ABSTRACT

Title of Dissertation: DEVELOPMENT OF A TRAFFIC INCIDENT MANAGEMENT SYSTEM FOR CONTENDING WITH NON-RECURRENT HIGHWAY CONGESTION

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Traffic incidents, including disabled vehicles, fire, road debris, constructions, police activities, and vehicle crashes, have long been recognized as the main contributor of congestion in highway networks and the related adverse environmental impacts. Unlike recurrent congestion, non-recurrent congestion is random in occurrence and duration owing to the nature of incidents so that it is highly unlikely to follow predetermined temporal and spatial patterns. These findings indicate the need to have an efficient and effective incident management system, including detection, response, clearance, and network-wise traffic management to contend with non-recurrent congestion.

In such a system, reliably estimated incident duration, the time difference between the onset of an incident and its complete removal, plays a key role to accomplish its goal – mitigating incident-related congestions and delays. However, due to the complex interactions between factors contributing to the resulting incident duration and the difficulty in recording data at the desirable level of quality, development of such a system for incident traffic management remains at its infancy. Thus, this research has developed a methodology for estimating incident duration and has identified critical variables and their interrelationships related to incident duration using the MDSHA (the Maryland State Highway) incident database. The proposed system is composed of the sequential

classifier with association rules (SCAR) and two supplemental models. This study has confirmed its reliability and robustness through a comparative study with several state-of-the-art approaches.

To minimize the incident impact, this study further pursued two additional objectives: (1) development of a deployment strategy for incident response units, and (2) design of a detour decision support model for control center staff to determine the necessity of detouring traffic. To achieve the second objective, an integer programming model has been developed from a new perspective of minimizing incident-induced delay, rather than minimizing total response time in the literature. Extensive tests of the developed model's performance and a comparative analysis with other existing models have confirmed the reliability and robustness of the proposed model. To achieve the third objective, this research has first explored key factors critical to the decision for implementing detour/diversion operations. Those factors have been integrated with an Analytical Hierarchy Process (AHP) to constitute the hybrid multi-criteria decision support system. A case study with the developed system has confirmed its reliability and flexibility.

The proposed incident estimation model integrated with a response unit allocation model and a detour decision model can enhance the current traffic incident management system for highway agencies to contend with freeway non-recurrent congestion and to assist traffic operators in answering some critical issues such as: *"what would be 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?", and "What would be the resulting operational costs and total* *socio-economic benefits due to the effective detour operations?"*. Furthermore, such a system will be able to substantially improve the quality and efficiency of motorists' travel over congested highways.

DEVELOPMENT OF A TRAFFIC INCIDENT MANAGEMENT SYSTEM FOR CONTENDING WITH NON-RECURRENT HIGHWAY CONGESTION

By

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Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, College Park, in partial fulfillment of the requirements for the degree of Doctor of Philosophy
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Dedication

To my mother (Jung-Ja Lee), my father (Byung-Wook Kim), my brother (Chamsub Kim),

my husband (Joon Woo Kim), and my daughter (Arin Lioba Kim)

for their endless love and support.

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Chapter 1: Introduction

1.1 Research Background

Traffic incidents, including disabled vehicles, fire, road debris, construction, police activities, and vehicle crashes, have long been recognized as the main contributors to congestion in highway networks and the related adverse environmental impacts. For example, Skabardonis et al. (2003) discovered that incident-related delay contributed from13 percent to 30 percent of the total congestion delay during peak periods, based on analysis of two freeway corridors in California. In a more comprehensive study, FHWA (2005) found that about 25 percent of congestion in the U.S. is incident-related. Furthermore, other research (Lindley, 1987) pointed out that non-recurrent traffic congestion due to incidents has contributed up to 60 percent of the total freeway delay in the United States.

Unlike recurrent congestion that is predictable and follows well-defined temporal and spatial patterns, non-recurrent congestion is random in occurrence and duration owing to the nature of the incidents (i.e., randomness in time, space and severity). These facts indicate the need to have an efficient and effective incident management system, including detection, response, clearance, and network-wide traffic management to contend with non-recurrent congestion.

A large body of studies has proved that a well-designed incident management program can substantially reduce non-recurrent congestion by reducing incident duration or diverting traffic. One successful example of incident management is the service patrol program in Hampton Roads, Virginia, which reduced the average incident duration by

70.7 percent (Ryan, 2007). Northern Virginia reported that its incident response units decreased the average incident duration by 15.6 percent 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 about 25 percent for the last seven years (Chang and Rochon, 2009). TIMS (Traffic and Incident Management System) is a detour operation system in Philadelphia that reroutes vehicles right after any detected major incident to reduce traffic flow and decrease the risk of spillback. Since its implementation in 1993, TIMS has contributed to reduction in freeway incidents by 40 percent, freeway closure time by 55 percent, and the incident-severity rate by 8 percent (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, to produce the estimated maximum impact area, the evolution of the traffic queue, the predicted travel time, and the resulting delays for en-route motorists. However, due to the complex interactions between factors contributing to the resulting incident impact and the difficulty in recording data at the desirable level of quality, development of such a system for incident management is a quite challenging task. Therefore, this dissertation intends to first investigate the characteristics of critical factors and their relationships with incident impacts. The results from such investigations will then serve as the basis for developing principal system components, including strategies for optimally allocating available resources and models to predict incident clearance durations, incident-induced impacts, and optimal detour plans.

1.2 Research Objectives

It is well recognized that the effectiveness of an incident management system relies highly on a reliable estimate of incident duration, the time difference between the onset of an incident, and its complete removal. In fact, incident duration is one of the key input variables for most models constituting a state-of-the-art incident management system. However, due to the complex interactions between factors contributing to the resulting incident duration and the difficulty in recording data at the desirable level of quality, development of a reliable model for estimating such information remains at its infancy. Therefore, the first objective of this research is to develop a system to predict the duration of a detected incident and to identify critical incident-associated factors as well as interrelationships.

The second research objective is to develop operational tools that can be used to minimize the incident impact, given the estimated incident duration. Such a tool will offer two essential functions: (1) producing an effective deployment strategy for available incident response units, and (2) offering a decision-making mechanism for control center staff to assess the necessity of detouring/diverting traffic. With a reliable model for predicting incident duration, coupled with an effective tool for response operations and managing incident-induced impacts, traffic operators will be able to efficiently and effectively contend with non-recurrent congestion in highway networks.

1.3 Dissertation Organization

Based on the proposed research objectives, this study has organized the primary research tasks into six chapters. Figure 1.1 illustrates the organization of this study and the logic relations between its principal tasks. A brief description of each chapter's focus is presented below:

- ***Chapter 2*** summarizes the results of a comprehensive literature review associated with each key component of an incident management system, including incident response management strategies, incident clearance duration estimation/prediction models, and detour decision support models.
- ***Chapter 3*** illustrates the overall structure of the proposed system. It includes how those key technical components are integrated to provide all essential system functions. The inputs and outputs for each component and the interrelations between all key models in the operational process are also reported in this chapter.
- ***Chapter 4*** first presents the results associated with the contributions of an effective incident response program. A detailed description of an integer programming model, developed to determine the optimal set of locations for available emergency response units, constitutes the core of this chapter. Extensive tests of the developed model's performance and a comparative analysis with other existing models are also reported in this chapter.
- ***Chapter 5*** summarizes the research findings on critical factors and their interrelationships related to incident clearance duration using the *Association Rules* technique. The chapter further presents the development procedure for an integrated system designed to estimate the clearance duration of a detected incident. The proposed integrated system is composed of the sequential classifier with association rules (SCAR) and two supplemental models. Also included in

this chapter are the evaluation of the proposed system and its comparison with several state-of-the-art approaches.

- ***Chapter 6*** discusses key factors critical to the decision for implementing detour/divert operations. Those factors are integrated with an Analytical Hierarchy Process (AHP) to constitute the hybrid multi-criteria decision support system. A case study with the developed system has been conducted and is reported in this chapter.
- ***Chapter 7*** discusses the contributions of this dissertation and indicates the directions for future research, including both theoretical refinement of the proposed models and development of operational tools to facilitate the system's applications in practice.

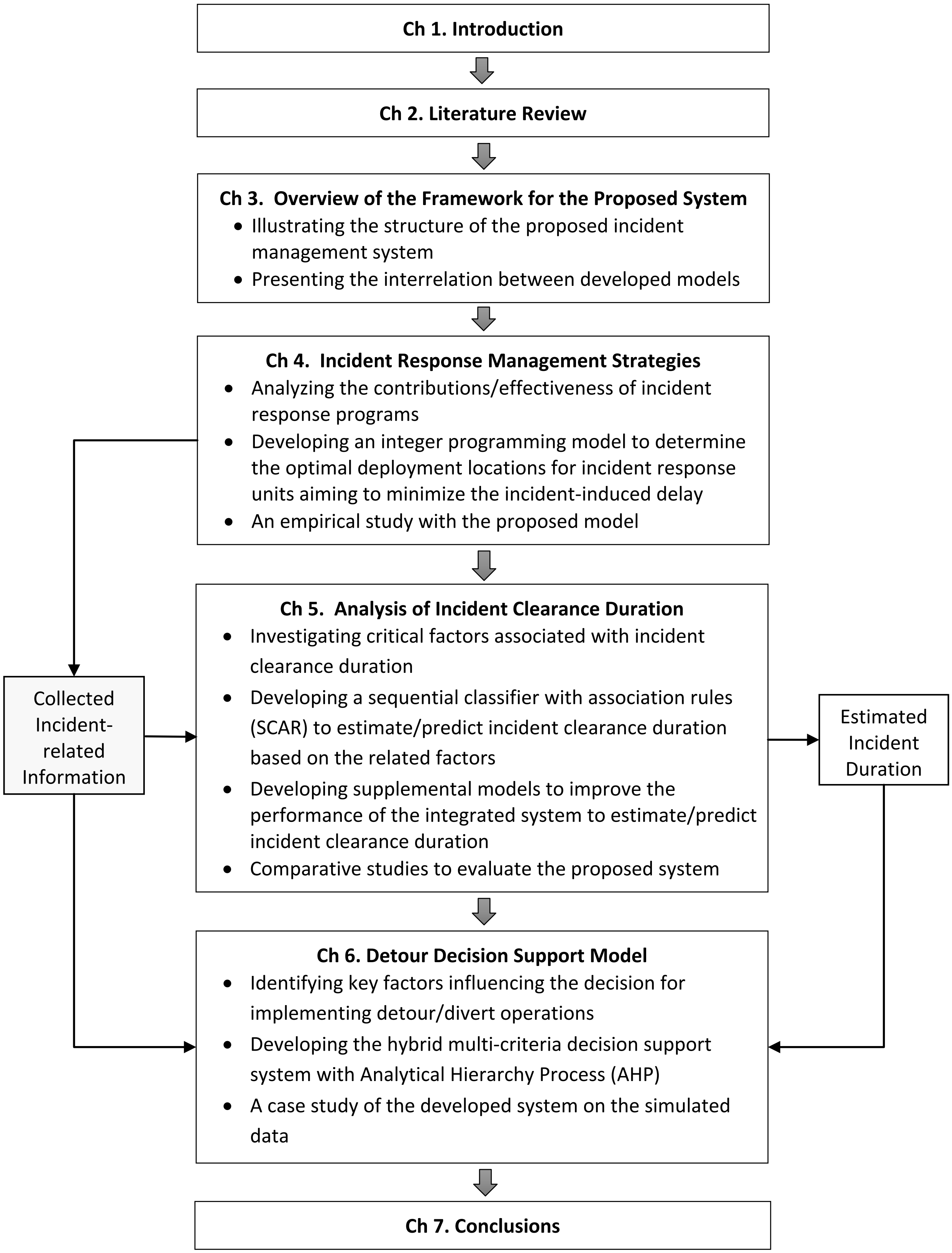


FIGURE 1.1 Dissertation Organization

Chapter 2: Literature Review

2.1 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: focusing on how best to use the available resources in response to detected and 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 brief summary of existing studies related to each category in sequence.

2.2 Incident Response Strategies

A large body of traffic studies has pointed out the critical role of efficient response to the total delay incurred by incidents and has 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) show that a reduction of ten minutes in emergency response time could result in 33 percent less probability of incurring vehicle collision and fatalities. 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 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).

Two main issues 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.

2.2.1 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 nature of emergency events. One approach that reflects the complexity and uncertainty of the response allocation issue uses 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 in order to maximize the average of demand coverage. MEXCLP was enhanced later by ReVelle and Hogan (1986). 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 the scenario planning methodology to handle multiple possibilities of a random event that 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.

Along the same line, 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, but with large coverage areas, such as rural communities.

2.2.2 *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 in order 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 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.

Along the same line of research, Carson and Batta (1990) developed a *P*-median model to produce the dynamic strategy that can 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) took into account 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 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) so as 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.

2.2.3 *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, seeks to identify the center of a circle with the smallest radius that can 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 in order to minimize the worst response time.

In addition to the aforementioned 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).

2.3 Incident Duration Estimation

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, and (6) time sequential models, and (7) unconventional methodologies. The rest of this section discusses each approach in detail.

2.3.1 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.

2.3.2 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.

2.3.3 Regression Models

Another simple methodology for predicting incident duration uses regression. Regression models usually include a number of 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:

$$Log(Duration) = 0.87 + 0.027 X_1 X_2 + 0.2 X_5 - 0.17 X_6 + 0.68 X_7 - 0.24 X_8$$

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.

2.3.4 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) in order 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.

2.3.5 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 a given 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 3.1) 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.

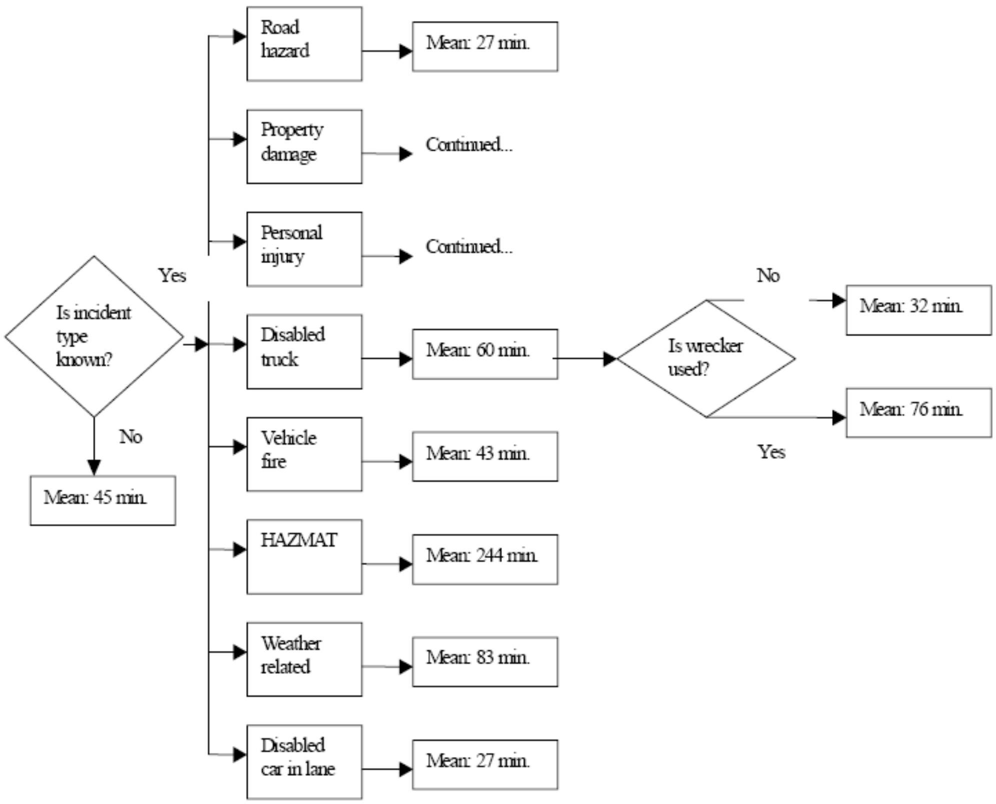


FIGURE 2.1 A Part of the Complete Decision Tree to Predict Clearance Time by Ozbay and Kachroo (1999)

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. They 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 a number of 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 of each other. However, they concluded that such a tree, developed on the basis of 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. In spite of relatively good model results, their tree model did not indicate decision criteria for each branching.

The recent noticeable 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 is able to describe the overall dependency structure of a large number of 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 immediate 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.

Similar to Ozbay and Noyan, Yang et al. (2008) include a Bayesian theorem to develop a decision tree, so-called Bayesian 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.

2.3.6 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 are capable of yielding 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.

2.3.7 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 in order 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

Chapter 3: The Structure of the Proposed Incident Management System

3.1 Introduction

As discussed in Chapter 1, a well-designed incident management system can substantially reduce non-recurrent congestion by reducing incident-induced impacts. Many states in the U.S. have established a traffic incident management system over the past several decades (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 an incident management system to be re-structured and tailored to the local needs for better operations in practice (Jin et al., 2014).

This chapter introduces the structure of an incident management system proposed in this study for the state of Maryland. The proposed system is developed to enhance the existing system, based on the available resources, infrastructure, and traffic environments. It consists of several individual modules and the embedded technical models to assist the responsible agents to maximize the effectiveness of their performance. In addition to illustrating the system's structure how the proposed incident management system will work to mitigate the impact of a detected incident with all embedded support models also constitutes the core of this chapter. Since such a system includes a large number of models and algorithms, the last section will highlight the key functions of those models developed in this study.

3.2 Incident Response and Operational Process

With the proposed incident management system illustrated in Figure 3.1, the traffic control center can take the following steps to effectively and efficiently respond to traffic incidents and the resulting impacts on freeways:

Step 1: An incident is detected through various detection sources (e.g., patrolling units, polices, CCTV, system alarms, etc.) and reported to the operation center.

Step 2: An incident response unit is dispatched to the incident site promptly to manage the affected traffic and to clear the incident.

Step 3: The operation 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 or not a detour/diverting operation is necessary will be made. A well-designed traffic diverting operation, grounded on rigorous assessment, can significantly reduce the network-wide incident impact.

Step 6: Once a favorable decision is made for taking the detour/diverting operation, the optimal detour/diversion plan needs to be implemented with the embedded models to generate proper control strategies.

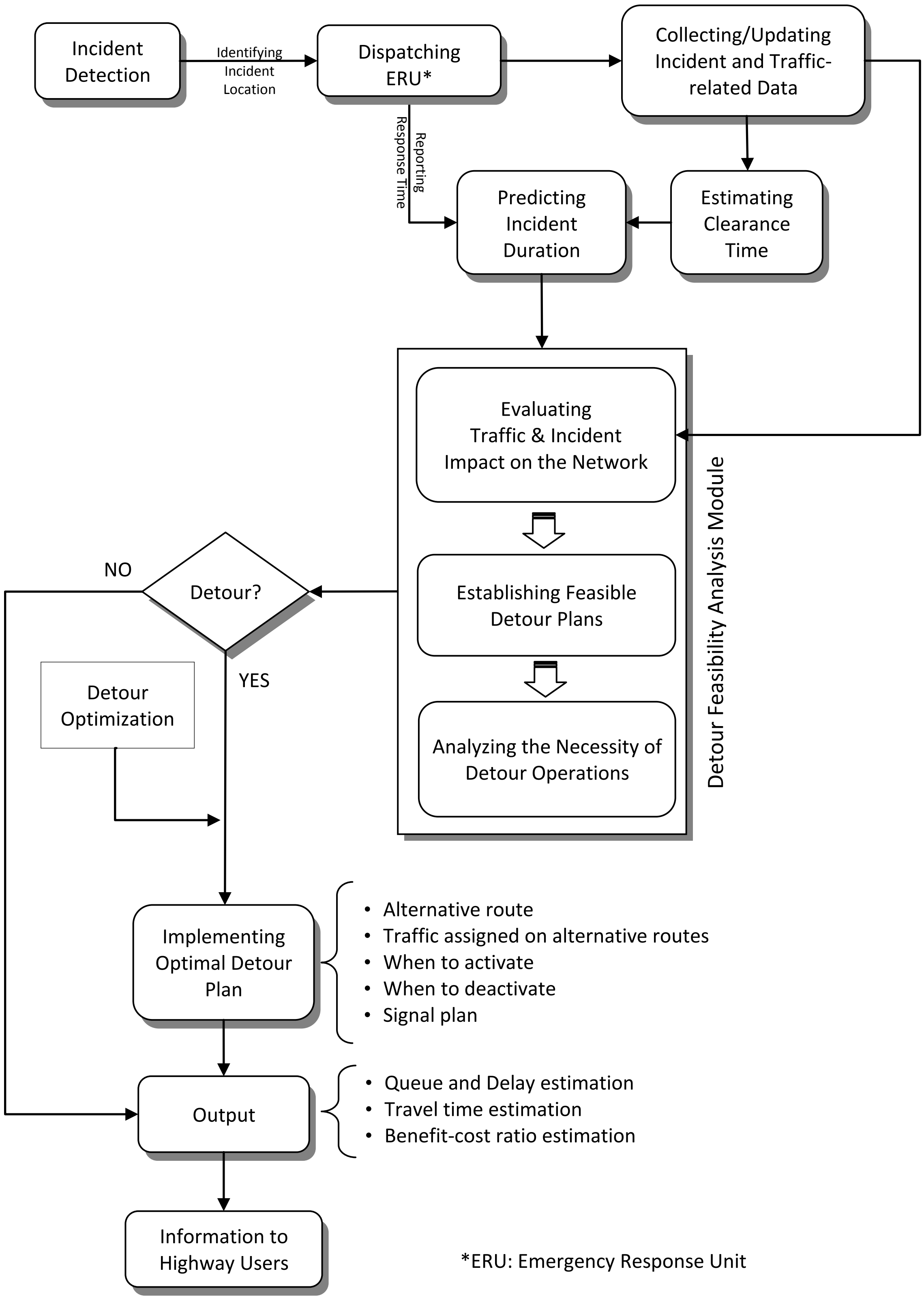


FIGURE 3.1 System Flowchart for the Incident Management Program

Step 7: Some useful traveler information will concurrently be provided to highway users to help them adjust their travel plans according to the up-to-date traffic conditions.

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

In brief, a complete incident management system can support highway agencies to contend with freeway non-recurrent congestion and to assist traffic operators in tackling some critical issues, such as: *"what would be 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?", and "What would be the resulting operational costs and total socio-economic benefits due to the effective detour operations?".*

3.3 Models Needed for the Proposed Incident Management System

Conceivably, to ensure efficient operations, such a system will have various technical models and algorithms to generate appropriate control 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 occurs, the first step to mitigate the non-recurrent congestion is to have a fast detection of incidents. Such a detection system should be capable of best using existing traffic sensors and various information sources such as GPS and cellular-phone uses, to minimize the potential false alarms and maximize the detection rate. A reliable system for incident detection can certainly reduce the incident response duration.

2. *Strategies for Emergency Responses:*

   Most incidents require emergency response services from first-aid staffs, wreckers/tow vehicles, police, and so on. Since most responsible agencies have only limited resources, an efficient strategy to best use them is needed to maximize their effectiveness. Hence, efficient operational models or algorithms need to be developed to optimally allocate the available resources and to maximize the resulting benefits.

3. *Databases for a Large Scale and Long Term Collection of Data:*

   By using the incident management and traffic monitoring system, the traffic control center can collect various incident and traffic related data. These data documented for the long-term period would be a valuable asset for relevant agencies to conduct essential studies for refining operational strategies and enhancing coordination between all involved agencies. An effective system for reporting the performance of incident response operations and the resulting benefits is also critical for sustaining support from policy makers and the general public.

4. *Models to Estimate/Predict Clearance Times of Detected Incidents:*

   A predicted incident clearance duration is one of the primary input parameters for estimating incident impacts and assessing the operational efficiency. A reliable estimate of a detected incident's clearance duration is essential for the design of traffic managing strategies in the network within the impacted area and for disseminating related traffic information to en-route and pre-route travelers. The benefits of having an efficient incident response and management system can also be estimated with such information.

5. *Models to Support the Decision for Whether a Detour/divert Operation Is Necessary Or Not:*

   In many severe lane-blockage incidents, traffic detour/diversion could be one of the most effective ways to reduce the network-wide non-recurrent congestion. However, a rigorous and comprehensive review for a wide range of associated variables should be preceded by an estimate of its resulting costs and benefits. To support and expedite the decision making in real time, it will be beneficial for control operators to have a reliable tool to assist them in assessing whether a traffic detour/diversion should be conducted or not from various perspectives.

6. *Models to Support the Optimal Detour/divert Plan:*

   If the traffic detour/diversion operations are assessed to be in need, then having a well-designed detour/diversion plan would be the most critical task. Hence, an ideal incident management system will also have an efficient operational model to generate the implementable optimal detour plan under the given traffic and network conditions. The outputs from such a model will include the optimal diversion rate, the adjusted signal plans, and the times to activate and deactivate the detour operations.

7. *Models to Produce Various Traveler Information:*

   Some models or algorithms introduced in the previous steps can produce 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 in *Steps 5* and *6*. Also, a model can be developed to predict the travel time under the up-to-date traffic conditions. Such information can be disseminated to motorists through an online traveler information system so that they can best select their routing strategies during the incident operational period.

8. *A Model to Evaluate Performance and Resulting Benefit of the Incident Management System:*

   To constantly improve the system's performance and have the sustainable support for the general public, it is imperative that the responsible agency have a convenient and reliable tool to conduct the performance evaluation and benefit assessment. The in-depth performance evaluation results can also help responsible agencies to identify the need for any additional resources and also have better coordination with other involved agencies.

3.4 Principal Models Selected for This Dissertation

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

(1) An operational model for optimizing incident response strategies

(2) A prediction model for estimating the incident clearance duration of a detected incident, and

(3) A decision support module for operating agencies to evaluate the need of implementing the detour/diversion operations.

Figure 3.2 illustrates those models and their relations. Key input data for developing and implementing these models are listed below:

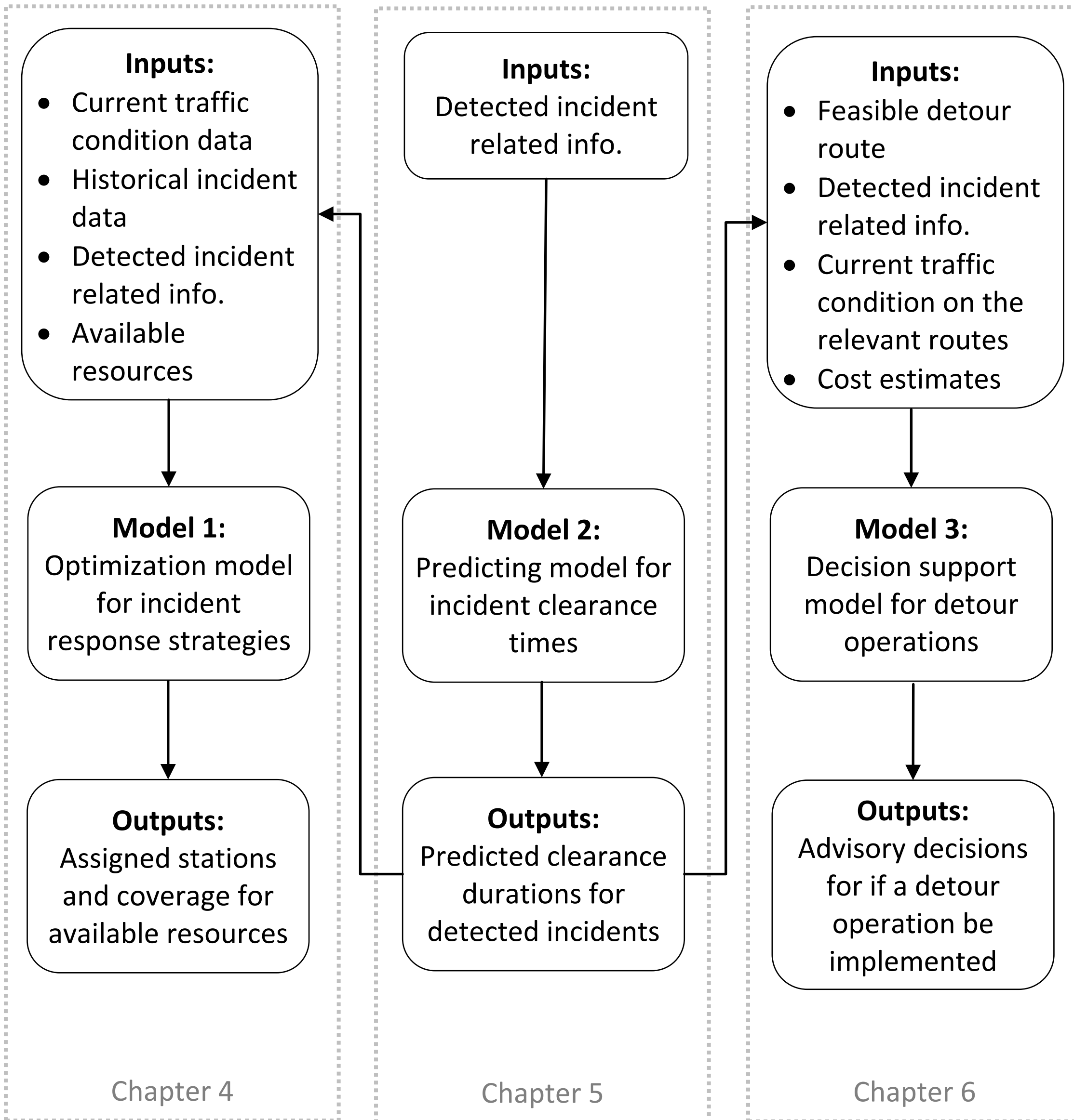


FIGURE 3.2 Frameworks for Main Models Covered in the Dissertation

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

The first model, the optimization model for generating incident response strategies, also requires information on available resources and historical incident frequencies as well as durations. This developed model seeks to identify the optimal stations and service coverage by each available response unit so that the total delay by incidents can be minimized with prompt response and effective clearance operation. A detailed description of the model structure, formulation, and evaluation is presented in Chapter 4.

The second model is designed to predict the clearance duration for a detected incident based mainly on the incident information. The predicted clearance duration will then serve as the key input of the third model, a decision support model for detour/diversion operations. Also, the information on the predicted durations of incidents will be documented in the incident database and used to update the response strategies. The model development process and its operating structure are presented in Chapter 5.

The third model, a decision support model for detour operations, is aimed to determine whether a detour/diversion operation is beneficial from various perspectives. The developed model is expected to provide an advisory assessment on the impacts of detour operations on the roadway users and other traffic within the boundaries of the incident impact area. Chapter 6 will present the developed model's structure, key features, case studies, and the results of validation.

Note that if the models developed in this dissertation are properly integrated with other systems, such as an incident detection system, a detour optimization system, and a travel time information system, then such an integrated system will be able to substantially improve the quality and efficiency of motorists' traveling over congested highways.

Chapter 4: Design of Incident Response Management Strategies

4.1 Introduction

As addressed in Chapter 1, a well-designed incident management program can substantially reduce non-recurrent congestion by reducing incident duration or diverting traffic. Various studies have shown that delay reduction can yield considerable benefits not only to roadway users but also to the environment (Roper, 1989; Maccubbin et al., 2008; Chang and Rochon, 2009). For this reason, many state transportation agencies have been stimulated to implement freeway incident management programs (Lindley, 1989), aiming to efficiently recover traffic conditions from an incident blockage to a normal state, and consequently, to decrease its impacts.

One of the key issues associated with the success of such systems is how to locate/allocate the available resources in order to minimize incident impacts. Numerous studies on this subject can be categorized into two types of strategies – patrolling and dispatching. In recent years, many transportation agencies have introduced patrol-based response programs, since they are effective in both detecting and responding to 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 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, this study intends to focus on developing an incident response model with the dispatching rather than patrolling strategies.

As reviewed in Chapter 2, many dispatching strategies have been introduced, mainly to minimize the number of service stations and the total operational costs, or to maximize the incidents covered by a pre-determined number of facilities. The objectives of those studies are mostly focused on minimizing response time or total costs.

However, research with extensive empirical data (Chang and Rochon, 2012; Olmstead, 1999) reported that prompt incident responses can reduce not only the response times but also the clearance times, and the total incident-induced delay. To my knowledge, since no studies in the literature related to the deployment strategies have made this finding in their model development, this study will first evaluate the effectives of a well-operated incident management system, using the incident data collected in Maryland. Based on the findings, this chapter will further present a new optimal location/allocation model for deploying available response units to minimize the total delay of detected incidents, rather than on minimizing the response time. The performance of the proposed model has been compared with the traditional *p*-median model aiming to minimize response times and the experienced-based patrolling strategy currently operated in Maryland.

4.2 Investigation on Contributions of Incident Management Program on Incident Duration

4.2.1 Incident Duration

Incident duration can be defined as the time difference 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 4.1. The first component 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 first arrival of any 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 includes only the first three components: detection/reporting time, response time, and clearance time.

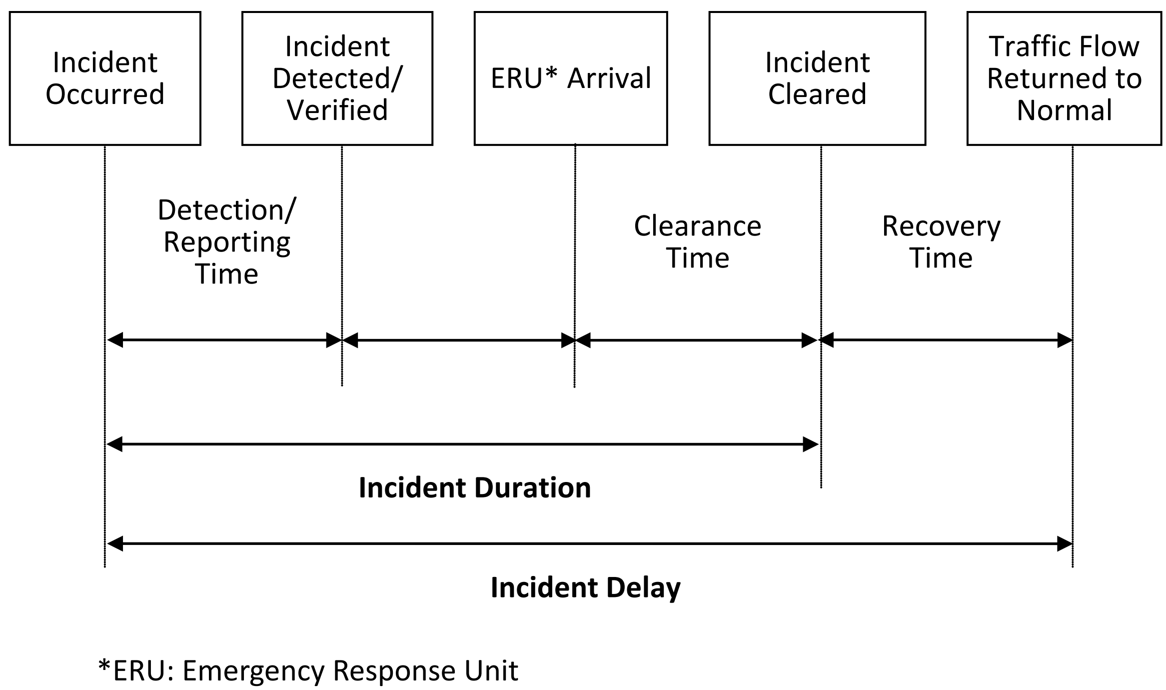


FIGURE 4.1 Components of Traffic Incidents

4.2.2 Effects of Incident Management Program on Reducing Incident Duration

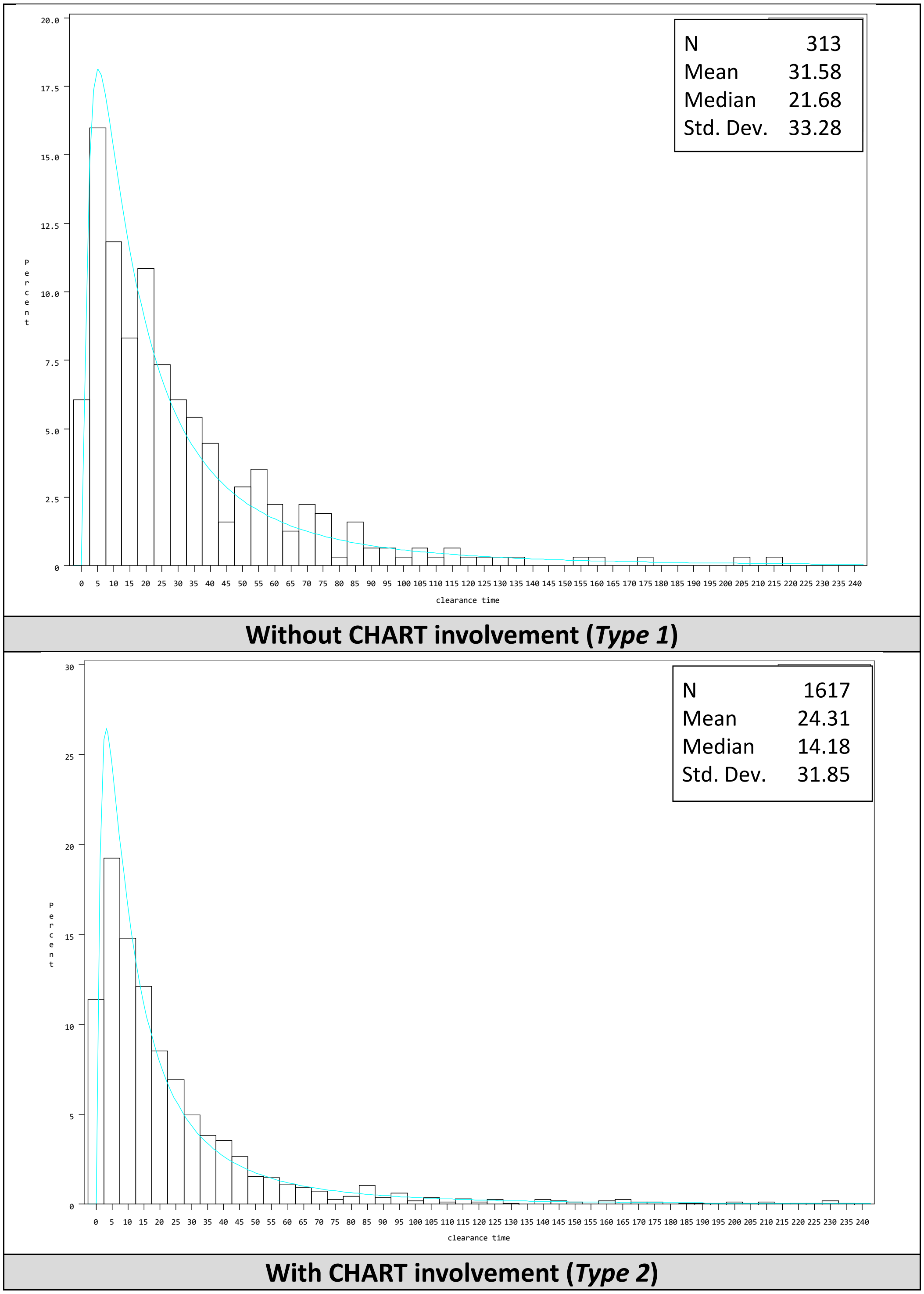
To investigate how an incident management program may have impact on the incident duration, this study has used Maryland incident data documented by the Coordinated Highway Action Response Team (CHART) over the past several years to perform the analysis.

CHART is an incident traffic management program operated by the Maryland State Highway Administration (MDSHA) in an effort to decrease the impacts of incidents on freeways by fast response, clearance, and appropriate traffic management. Their major tasks at incident sites include setting up traffic control devices, managing and controlling traffic flow passing the sites, and assisting the fire department, police, or other related agencies to expedite clearing incidents.

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

- ***Type 1***: incidents that CHART did not respond to; and
- ***Type 2***: incidents in which CHART was involved in the clearance

Figure 4.2 shows the clearance time distributions based on incidents' data from the 2012 CHART II Database. Notably, both *Type 1* and *Type 2* distributions are highly skewed toward the right, but the clearance times in *Type 2* concentrate on the range shorter than those in *Type 1*. The average clearance times for *Type 1* and *Type 2* are 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 are highly skewed, medians are also selected to test if their central tendencies are equivalent or not (laerd.com). The median clearance times for *Type 1* and



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 4.2 Distributions of Clearance Times (minutes) by CHART Involvement

Type 2 are 21.68 minutes and 14.18 minutes, respectively. The *t*-test results reject the null hypothesis that those values are equal, at the 95 percent significance level. Such statistical results confirm that clearance times of incidents in which CHART was involved are shorter than those in which CHART was not involved.

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

- ***Type 2-1***: incidents that CHART responded faster than other agencies; and
- ***Type 2-2***: incidents that other agencies responded faster than CHART

Figure 4.3 presents the distribution of clearance times for each group, where both are also highly skewed toward the right. However, the clearance times of incidents in *Type 2-1* concentrate more on a range shorter than those in *Type 2-2*. The average clearance times for *Type 2-1* and *Type 2-2* are 20.54 minutes and 33.02 minutes, respectively, while the medians are 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 confirm that the prompt response of an incident response team with sufficient traffic management expertise can indeed contribute to a reduction in the incident clearance duration and the resulting impacts.

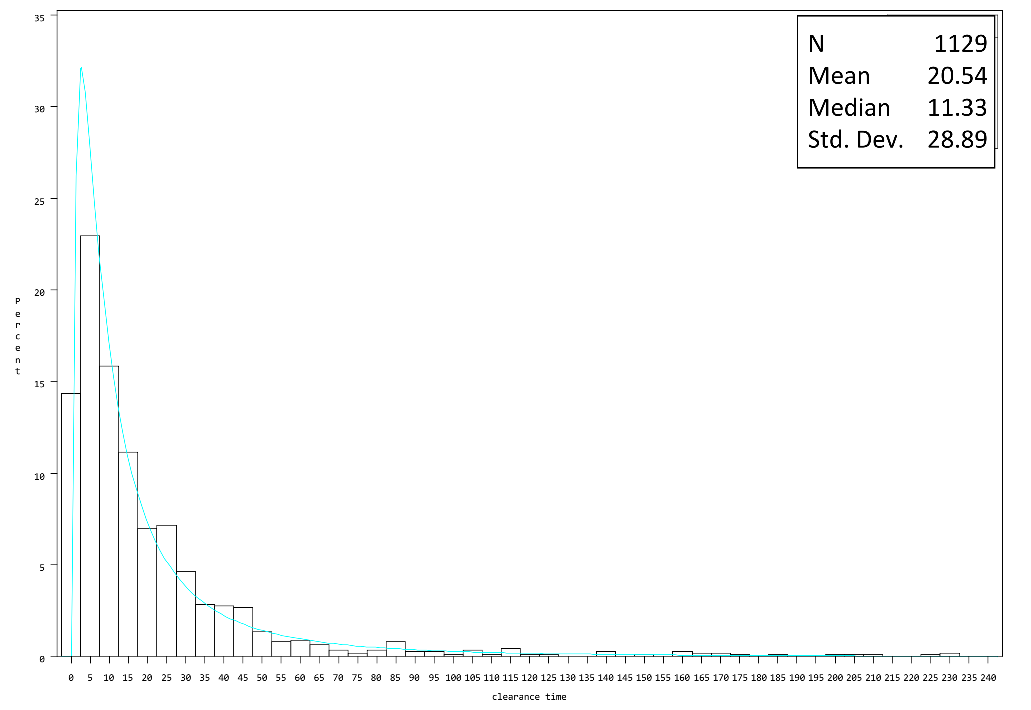
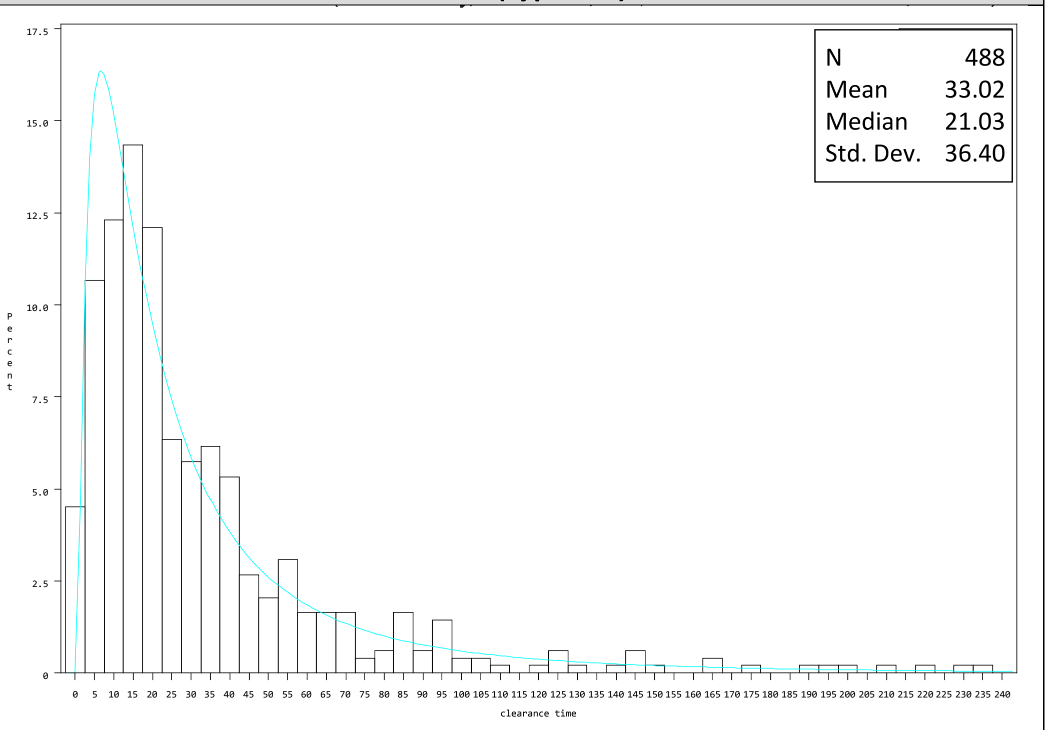


CHART (*Type 2-1*)



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

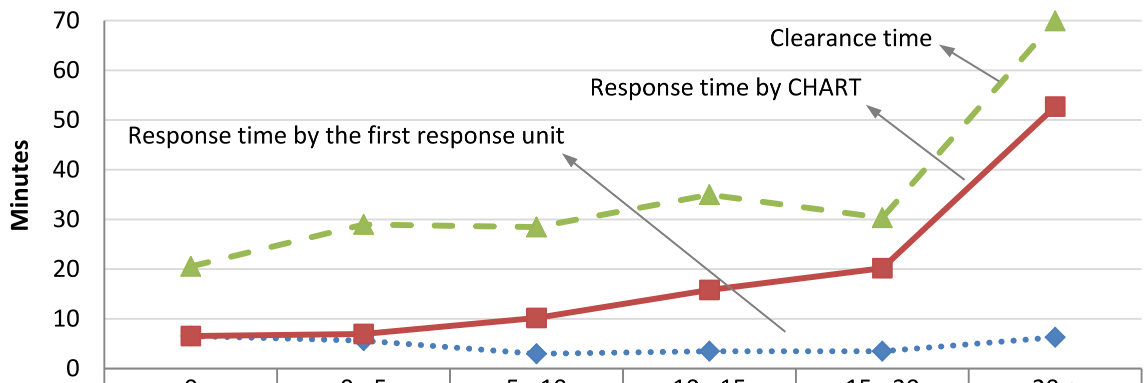
Interestingly, similar data patterns have also been observed throughout all traffic operations centers (TOCs) in Maryland, as shown in Table 4.1. Note that medians of clearance times in TOC-4 show a slightly different pattern from others owing to the relatively small sample size (only 9 data are used to estimate the median clearance time for *Type 1* incidents for TOC-4).

TABLE 4.1 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 only includes Maryland incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in 2012.
3. The analysis only includes clearance times between 1 minute and 4 hours.
4. MDSHA operates 7 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 operated on the seasonal basis during summer and winter, respectively.

Figure 4.4 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 has been delayed to arrive at the incident scene, regardless of other agencies' arrival. This further indicates that the incident 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 that 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 response agency.
2. Data include incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in Maryland in 2012.
3. The analysis only includes clearance times between 1 minute and 4 hours.

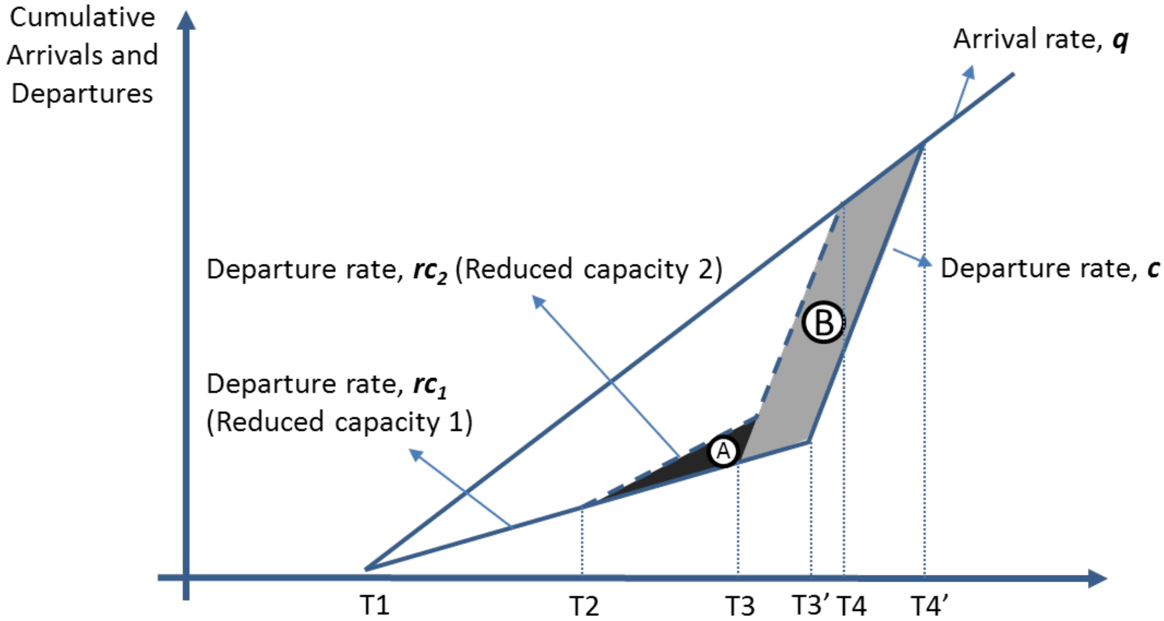
FIGURE 4.4 Relationships between Clearance Times and Delayed Response by CHART

Based on these findings, one could conclude that the effective response of incident management teams contributes to the reduction not only in response time but also in clearance time. Moreover, the reduction in clearance time would be increased if CHART has arrived at the scene faster than other agencies. Since not all incidents can be promptly responded to by the limited number of response units, it is necessary to develop a strategy that can optimally deploy available response units under various constraints.

4.3 Development of an Optimal Deployment Strategy

4.3.1 Incident Duration and Its Effect on Total Delay

To estimate the impact of an incident, this study uses the total delay induced by incidents 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 4.5, prompt incident response and efficient clearance can reduce the incident cleared 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 total delay as shown in the shaded area (*A* and *B*). Since the data to support the delay reduction due to the increased departure rate (rc_2), i.e., the area *A*, are not available, this study has focused mainly on the reduced delay contributed by the reduced incident clearance time (i.e., the area *B*).



T1: incident onset time
T2: arrival time of the response unit
T3: incident cleared with the assist of CHART
T3': incident cleared without the assist of CHART
T4: recovery time with the assist of CHART
T4': recovery time without the assist 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 by the assist of CHART

FIGURE 4.5 Reduced Incident Delay due to Effective Incident Response and Management

4.3.2 Model Formulation

This study has formulated a model for optimized allocation of incident response units under the following assumptions:

- Response units will stay at their designated stations and be dispatched after an incident is detected.
- They will return to their stations when the incident has been cleared.
- Every response unit is mainly responsible to take care of incidents in its

designated coverage area.

- Every freeway is divided into a number of segments and each segment is covered by only one unit.
- The demands (incidents) for a freeway segment are assumed to distribute uniformly over the segment.
- Response units are allowed to travel on shoulders during traffic congestion periods.

The network for model development consists of nodes and links that represent exits and freeway segments. The travel times from the assigned location to an incident site are 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 is designed to optimally assign the 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 a node *i*
- y_i: Binary decision variable, indicating if a unit stays at a node *i*
- f_j: Incident frequency at a node *j*
- t_{ij}: Travel time from *i* to *j*
- d_j: Predicted delay from incidents occurring at a node *j*
- T_{ij}: Incident duration, the sum of response time and clearance time

- α: Proportion of incidents that freeway incident management teams are involved in the clearance (*Type 2*) at a given time
- β: Proportion of incidents responded by freeway incident management teams 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 their 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 respond faster than freeway incident management teams (*Type 2-2*)
- q_j: Traffic volume at a node j
- c_j: Capacity at a node j
- rc_j: Reduced capacity due to the incident at a node j
- R: Available resources

As stated previously, this study has categorized incidents into the following three types:

(1) *Type 1*: incidents without assistance by the freeway incident management teams;

(2) *Type 2-1*: incidents when incident management teams respond faster than other agencies; and

(3) *Type 2-2*: incidents when other agencies respond faster than incident management teams

The proposed model is formulated as follows:

object to $$\min_{x,y} \sum_i \sum_j x_{ij} \cdot f_j \cdot d_j(t_{ij}) \quad \text{(Eq. 4-1)}$$

subject to

$$d_j(t_{ij}) = \frac{1}{2} T_{ij}{}^2 (q_j - rc_j) \left(\frac{c_j - rc_j}{c_j - q_j} \right) \qquad \forall (i,j) \in N \qquad \text{(Eq. 4-2)}$$

$$T_{ij}{}^2 = \begin{cases} Type\ 1\text{:}\ \ (RT_1 + \overline{CT}_1)^2 + Var(CT_1)\ , & 1-\alpha \\ Type\ 2-1\text{:}\ \ (t_{ij} + \overline{CT}_{2-1})^2 + Var(CT_{2-1}), & \alpha, \beta \\ Type\ 2-2\text{:}\ \ (RT_2 + \overline{CT}_{2-2})^2 + Var(CT_{2-2})\ , & \alpha, 1-\beta \end{cases} \qquad \forall (i,j) \in N \qquad \text{(Eq. 4-3)}$$

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

$$x_{ij} \le y_i \qquad \forall\ j \in N \qquad \text{(Eq. 4-5)}$$

$$\sum_i y_i \le R \qquad \text{(Eq. 4-6)}$$

$$x_{ij} = [0,1] \qquad \forall (i,j) \in N \qquad \text{(Eq. 4-7)}$$

$$y_i = [0,1] \qquad \forall\ i \in N \qquad \text{(Eq. 4-8)}$$

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

Constraint (Eq. 4-2) formulates the potential total delay induced by incidents on 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 in $(\overline{T_{ij}})^2 + Var(T_{ij})$ (Olmstead, 1996; Li et al., 2006). Constraint (Eq. 4-3) further describes the components of the incident duration for each type. As shown in the formulation, the response time can be represented with travel times if available.

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

4.4 Empirical Study

4.4.1 Study Site and Input Data

The proposed model is applied to segments of I-270, I-70, and US15 in Maryland (see Figure 4.6) to validate its performance. It is 63miles long with 30 distinct exits, managed by TOC-7 (Traffic Operation Center-7). Currently, TOC-7 operates 3 field units to manage incidents occurring 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 determines the optimal station and coverage for each response unit within the TOC-7's coverage to minimize the potential total delay based on the given incidents, during a.m. peak hours (7:00 – 9:30) on weekdays.

FIGURE 4.6 Study Segments of I-70, I-270 and US 50 in Maryland

This study assumes that incidents occurred along the highway segments, and response units are deployed at nodes (i.e., highway exits) for dispatching operations. The input parameters in the models vary with the location within the target area so that they should be re-estimated for different target areas based on the available data sources. This study uses the following two major data sources to estimate key model parameters:

- *CHART II Database (data from Year 2010 to Year 2012) for:*
  - Incident frequency on freeway segment *i* (f_i) (Figure 4.7)
  - Average response times for 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 to determine the reduced capacity (rc_j)
- *RITIS (Regional Integrated Transportation Information System) for:*
  - Traffic volume (q_j)

Note that the incident frequencies often fluctuate over the study site, as illustrated in Figure 4.7, which poses a challenge to the traffic operators in optimizing the deployment strategies if they lack an assist of proper tools. The average from the historical data are used for computing the response times of incidents for *Type 1* (RT_1) and *Type 2-2* (RT_2) (i.e., non-CHART response), whereas the travel times by CHART from its station i to an incident site j (t_{ij}) are used as the response times of incidents for *Type 2-1*. The parameters α and β have been estimated to be 0.87 and 0.75, respectively, based on the same data sources (Table 4.2). These estimates imply that about 87 percent of incidents have been responded to by CHART during a.m. peak periods in the study area, and for about 75 percent of them CHART has responded faster than other agencies.

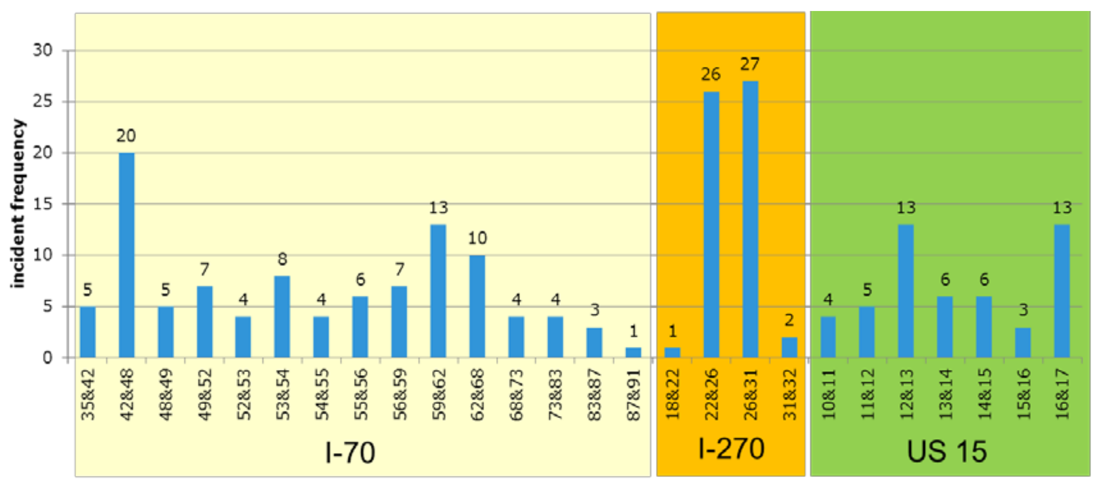


FIGURE 4.7 Average Annual Incident Frequency during AM Peak Hours by Location

TABLE 4.2 Estimations of Input Parameters α and β based on the Empirical Data

<table>
<tr><th colspan="2">CHART Involvement & Promptness</th><th>Frequency</th></tr>
<tr><td colspan="2">CHART Not Involved
(Type 1)</td><td>27</td></tr>
<tr><td rowspan="2">CHART Involved
(Type 2)</td><td>CHART is the first response agency
(Type 2-1)</td><td>130</td></tr>
<tr><td>CHART is NOT the first response agency
(Type 2-2)</td><td>43</td></tr>
<tr><td colspan="2">Total</td><td>200</td></tr>
<tr><td colspan="3">• α (proportion of incidents responded by CHART at a given time)
= (130+43)/200 = 0.87;
• β (proportion of incidents responded by CHART first at a given time)
= 130/(130+43) = 0.75</td></tr>
</table>

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, the reduced capacity due to incidents is estimated with 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 is set as 5 mph lower than a speed limit, since they are allowed to travel on shoulders even in cases of congestion. The proposed models are solved with CPLEX, a state-of-the-art optimization software package.

4.4.2 Model Results and Analyses for Model Robustness

This subsection presents the model outputs and its evaluation results, especially with respect to its robustness, using a comparative study and sensitivity analysis. In the comparative study, the proposed model's performance is compared with two existing strategies: (1) the dispatch strategy to minimize the average response times, and (2) the experience-based patrolling strategy operated by CHART. The key features of each strategy are summarized below:

- *Dispatching Strategy to Minimize the Average Response Time:*

  The traditional *p*-median model (Hakimi, 1964; ReVelle and Swain, 1970; Carson and Batta, 1990) is used as one of the comparative models that assigns the 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 freeway segment j. The above constraints (Eq. 4.4) – (Eq. 4.8) in subsection 4.3.2 are applied to this model under the same conditions.

- *Experience-based Patrolling Strategy*

  Currently, CHART is operated with the experience-based patrolling strategy that is to pay more attention to highway segments with a higher incident frequency or higher traffic volume. A brief description of their current practice is stated below:

  - The entire network of coverage is divided into several sub-networks. The scheme to divide the target network varies over time, based on the spatial distribution of total incidents in the historical data and the real-time traffic volumes.
  - Each available unit is then assigned by the supervisor to patrol those segments within each sub-network.
  - They will respond to incidents either by their own detection or receiving instructions from the operation center.

- The response strategy is on a first-come-first-serve basis, unless major incidents such as personal injuries or fatalities occur.

Moreover, the sensitivity analysis is conducted to evaluate the robustness of the proposed model in various network conditions using key factors - incident frequency and traffic volume on the target network. The results of sensitivity analysis are presented below.

Model Outputs

The proposed model produces two outputs – optimal stationary positions and assigned coverage for the given number of response units. Tables 4.3 and 4.4 compare these outputs under three strategies – minimizing the total delay (the proposed model), minimizing the average response time, and the CHART current practice. As shown in those tables, the assigned stations and service coverage based on the proposed model are somewhat different from those from the traditional p-median model. Note that *others* in Table 4.4 cover the junction area of three corridors (I-70, I-270, and US-15).

TABLE 4.3 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>

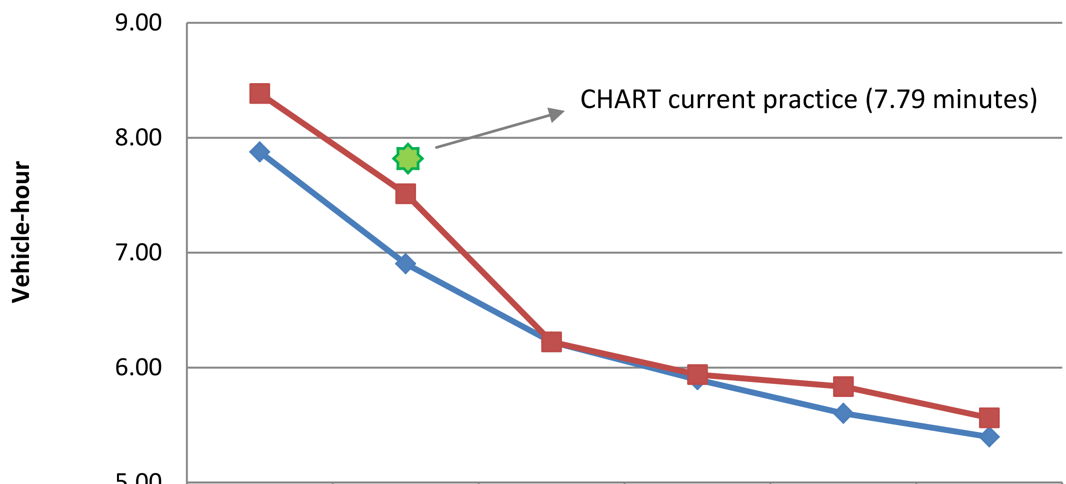
TABLE 4.4 Service Coverage Assigned for Each Response Unit by Strategy

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

Comparative Study for the Model Performance

Since the model outputs do not reflect the advantage of the proposed model over the traditional and the current strategies, the performance of these strategies is further compared with two measures of effectiveness (MOEs) – average travel time by given response units and the estimated total delay induced from given incidents. To compare the impact of the fleet sizes on the effectiveness of each strategy, those MOEs are estimated under the fleet sizes from 2 to 7 for the proposed and traditional models.

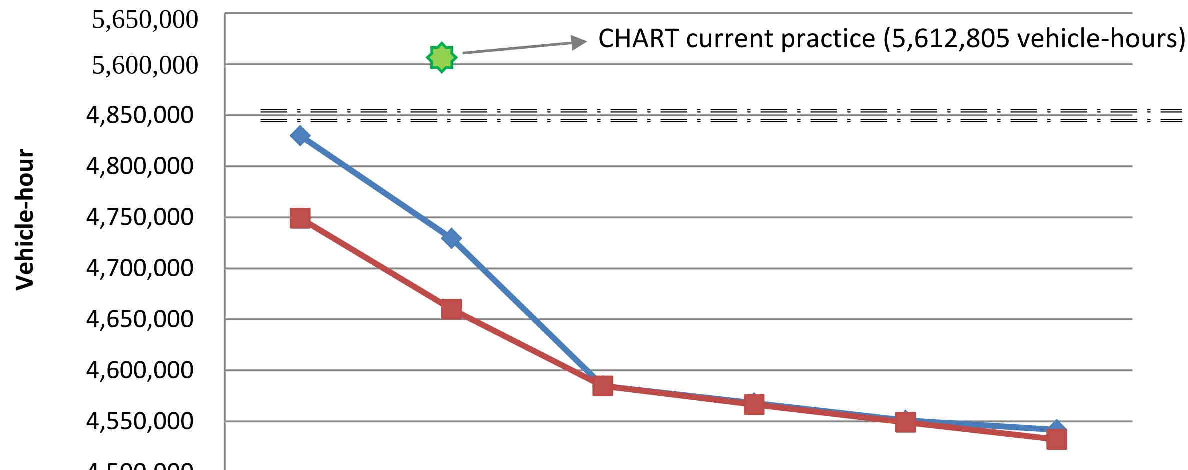
As displayed in Figure 4.8, the estimated average response time drastically decreases by adding a unit until reaching the size of 4 units, and the rate of decrease becomes less significant. As expected, the average response time with the proposed model is longer than that under the traditional *p*-median model over most fleet sizes explored in this study, since the traditional model aims to minimize the average response time. However, the difference progressively decreases and exhibits identical results at a fleet size of 4, and it increases again as the fleet size increases but not as much as under the size of small fleets. For the fleet size of 3 that CHART currently operates, the average response time by CHART's current practice is 7.79 minutes, which is3.6 percent and 11.4 percent larger 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 4.8 Average Travel Times (in minutes) by Incident Response Strategy

Similar patterns are also shown in the measurement of total incident delay in Figure 4.9. As expected, the total incident delay with the proposed model is less than that of the traditional model over the fleet sizes of 2 to 7. The fleet sizes of 2 or 3 operated with the proposed strategy show a significant reduction in the total delay of 80,857 and 69,390 vehicle-hours per year, respectively, compared with the traditional *p*-median model. The differences in the total delay between these two strategies are insignificant at a fleet size of 4, but it gradually increases again with more additional units. For the fleet size of 3 that CHART currently operates, the total delay by CHART's practice is 5,612,805 vehicle-hours, which is 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

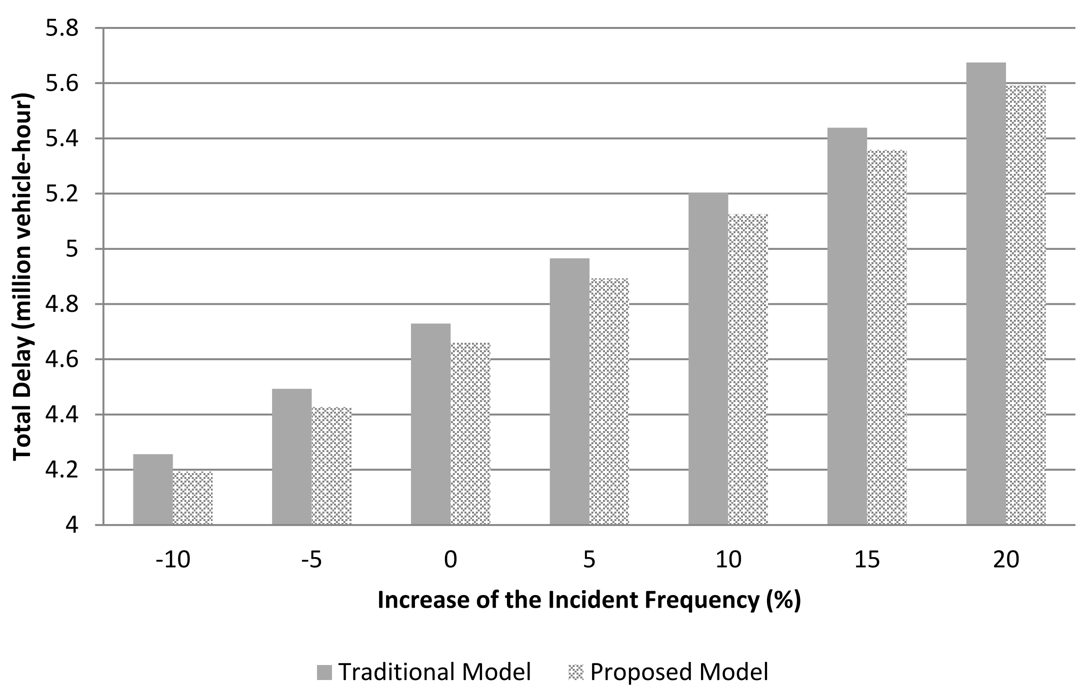
FIGURE 4.9 Total Delays (in vehicle-hour) by Incident Response Strategy

Based on these results, it is evident that the proposed model, if implemented in the TOC-7 region of Maryland, can outperform the traditional deployment model of minimizing the response time in terms of reducing the total incident-induced delay. It can also outperform 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 offer an effective tool to improve the performance of the freeway incident management programs, especially if the primary concern is to minimize the total delay, fuel consumption, and emissions.

Sensitivity Analysis for Key Parameters to Estimate Incident Delay

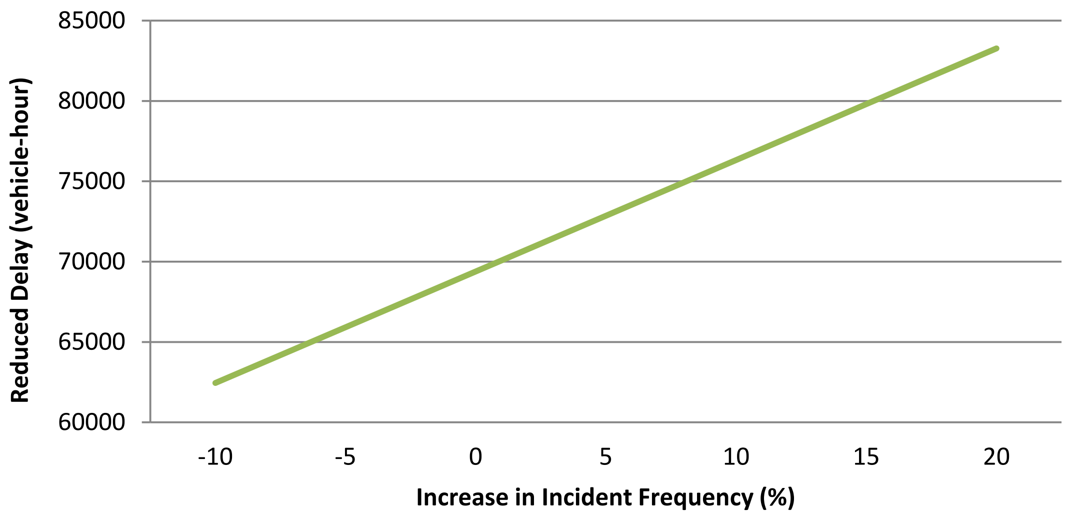
To investigate the performance of the proposed model in various network environments, this study has further conducted a sensitivity analysis with respect to key factors - incident frequency and traffic volume on the target network.

In Figure 4.10, the estimated incident delay from both traditional and proposed strategies exhibits an increasing trend with the total incident frequency in the target network, given that all other factors remain unchanged. Overall, the delays based on the proposed model are lower than those from the traditional *p*-median model through all examined incident frequencies. The magnitude of the reduction increases linearly, as shown in Figure 4.11, 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.

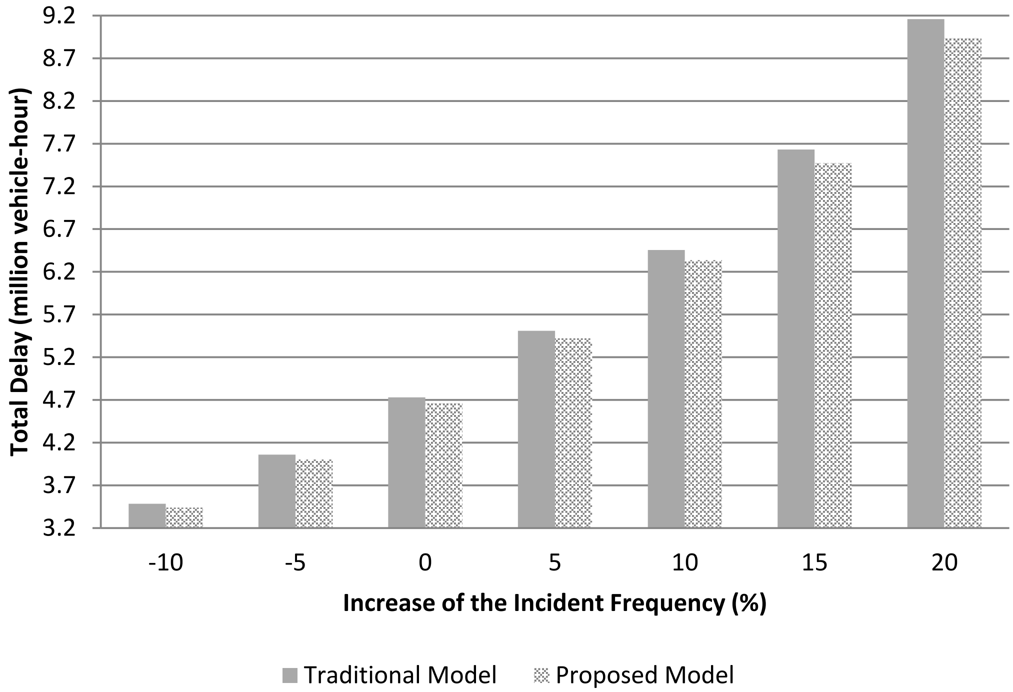
FIGURE 4.10 Model Performance (Incident Delay) by Various Incident Frequencies



* 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.

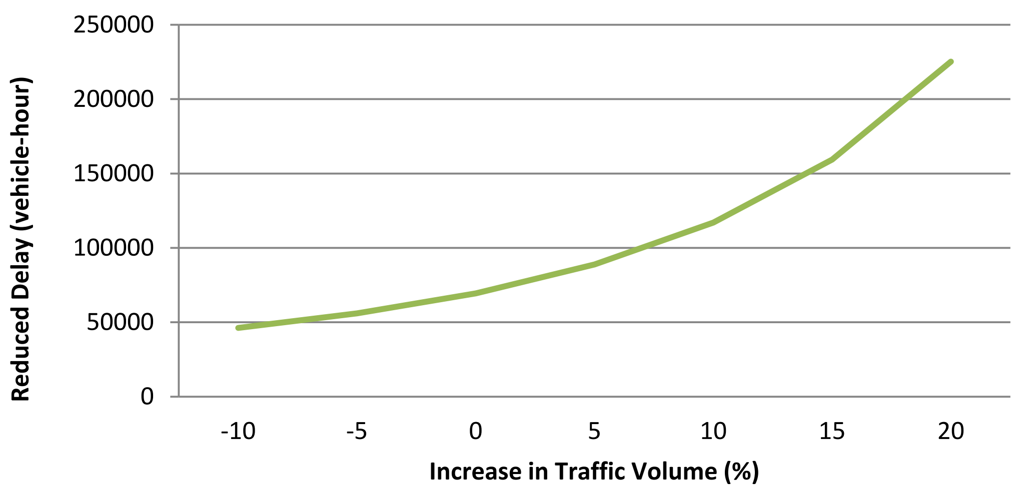
FIGURE 4.11 Reduced Incident Delay by the Proposed Model for Various Incident Frequencies

Similarly, a range of traffic volumes has been examined to assess their impacts on the resulting incident delay. Figure 4.12 exhibits that the estimated incident delays from both traditional and proposed strategies increase with the increase in traffic volume in the target network if all other factors are at the same level. The delays based on the proposed model remain lower than those from the traditional model over all listed traffic volumes, and the magnitude of the reduction exponentially increases, as displayed in Figure 4.13.



* 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 4.12 Model Results (Incident Delay) by 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 4.13 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 minimizing the total incident delay in most scenarios. Thus, the proposed deployment strategy offers the potential for use in different highway networks. To sum up, it is obvious that the proposed model outperforms the traditional deployment model of minimizing the response time, in terms of reducing the total incident-induced delay. It also outperforms the CHART's current practice with respect to reducing average response time and total delay. Thus, the proposed model could serve as an effective tool for traffic control centers to improve the performance of freeway incident management programs and consequently increase the benefits from socioeconomic and environmental perspectives with the resulting reduction in user delays, fuel consumption, and emissions.

Chapter 5: Analysis of Incident Clearance Duration

5.1 Introduction

As described in Chapter 4, 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 4. 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 has 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 closure and/or fatality 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 somehow 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 4 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.

5.2 Data

This study uses data on 6000 incidents collected in Maryland from 2006 to 2009 to develop the proposed model. The dataset is 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 MDSHA patrol (CHART);
- Operation Center: TOC 3, TOC 4, TOC 7, AOC, SOC, and others;
- Detection source: CCTV, system alarm, SHA, 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.

5.3 An Integrated Model to Predict Incident Clearance Duration

The proposed model is developed through three main phases as illustrated in Figure 5.1: 1) filtering out outliers, 2) identifying explicit associations between factors, and 3) developing models to predict unexplainable datasets. The final product from this development is the integrated system of SCAR (Sequential Classifiers with Association Rules) with supplemental models to predict incident clearance times. This algorithm is 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.

- The majority of 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.

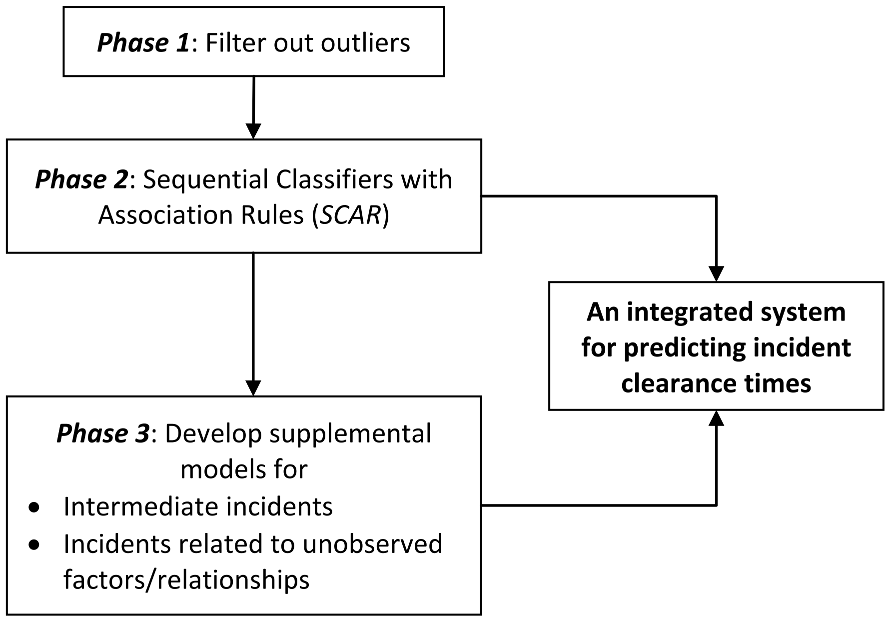


FIGURE 5.1 Flowchart to Develop the Proposed Model

The first phase of model development is focused on identifying potential outliers using a well-known algorithm, *PAM (Partitioning Around Medoids)*. The second phase mainly intends to investigate explicit relationships between the clearance duration and its associated factors and then develop a sequential classifier. The third phase aims to develop 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.

5.3.1 Phase 1: Filter out outliers

The dataset for this study has been examined to identify potential outliers with two approaches. First, incidents with unreliable or unreasonable information are excluded. For example, some incidents are recoded as being involved with more than 20 vehicles and some incidents have only limited information. Through this process, a total of 39 cases are excluded from the datasets. Furthermore, *Partitioning Around Medoids (PAM)*, is 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 in order 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 is 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:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \qquad \text{(Eq. 5-1)}$$

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. 5-1) 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* is capable of yielding good clusters that are not too stretched and isolating outliers in most cases (Kaufman and Rousseeuw, 1990).

Since *PAM* is mainly applied to identify potential outliers, this study focuses 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* is found to be 8 with the average *silhouettes* 0.13. According to Kaufman and Rousseeuw (1990), this value indicates that no significant structure has been found in the given dataset. However, since *PAM* is merely used to discover outliers, further analysis is conducted based on the selected structure.
2. *Select the weakest cluster from the selected structure:* a cluster with 293 elements is selected for further investigation, which shows 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* is found to be 3 with the average *silhouettes* of 0.23, and the weakest cluster with 36 incidents is chosen to be a set of outliers in this dataset.

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

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

Figure 5.2 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.

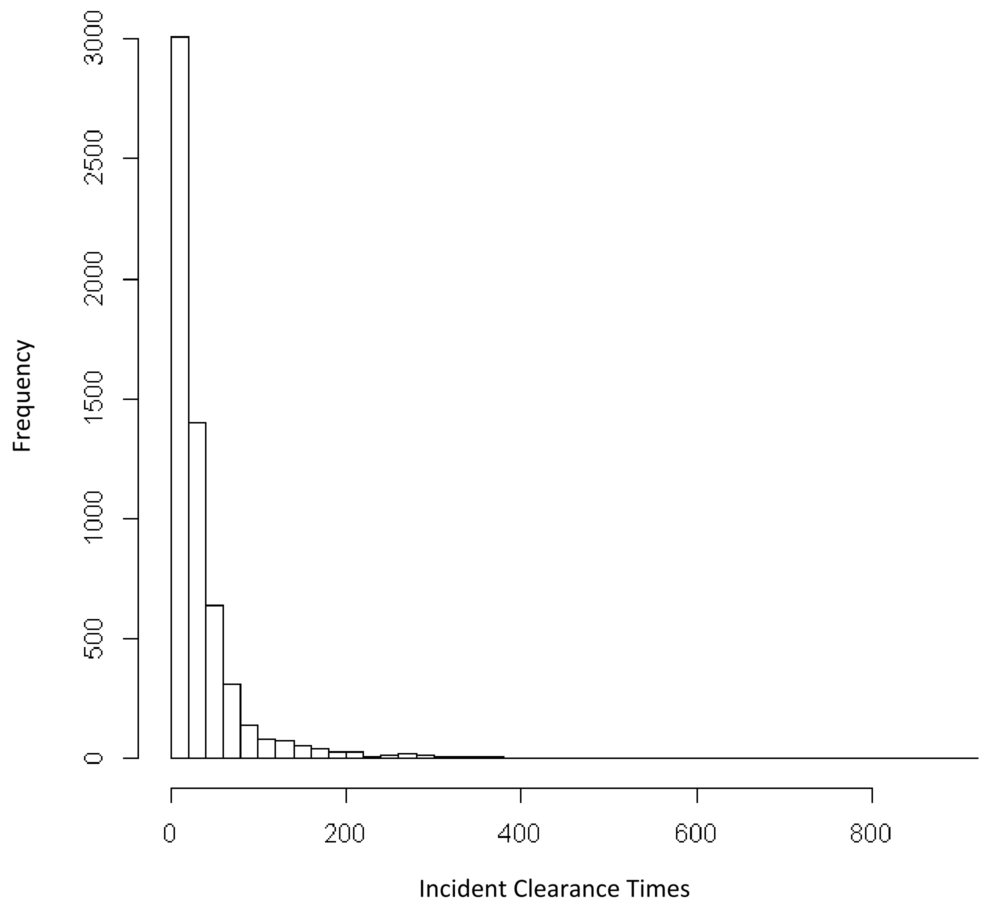


FIGURE 5.2 Distribution of Incident Clearance Times

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 the majority of response times on the study dataset (90 percent) lies within 10 minutes, this study considers that the incident duration could be replaced with the clearance time to categorize the incident classes.

Table 5.1 presents the distribution of incident clearance times when they are divided into three classes using the standards stated in MUTCD. As observed from Figure

5.2, 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 is 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 5.1 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 and purely concentrates on mining the potential associations between variables. Such characteristics are very effective for analyzing the incident duration, since one of primary objectives for such a study is 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 intends to discover any obvious associations of incident clearance durations with related variables using the *AR* technique. Furthermore, this study proposes a model that consists of rules defined by the mined associations and has 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→ 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 amount 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 5.3 presents the overview of procedures to develop the sequential classifiers with association rules. Details of each step are discussed below:

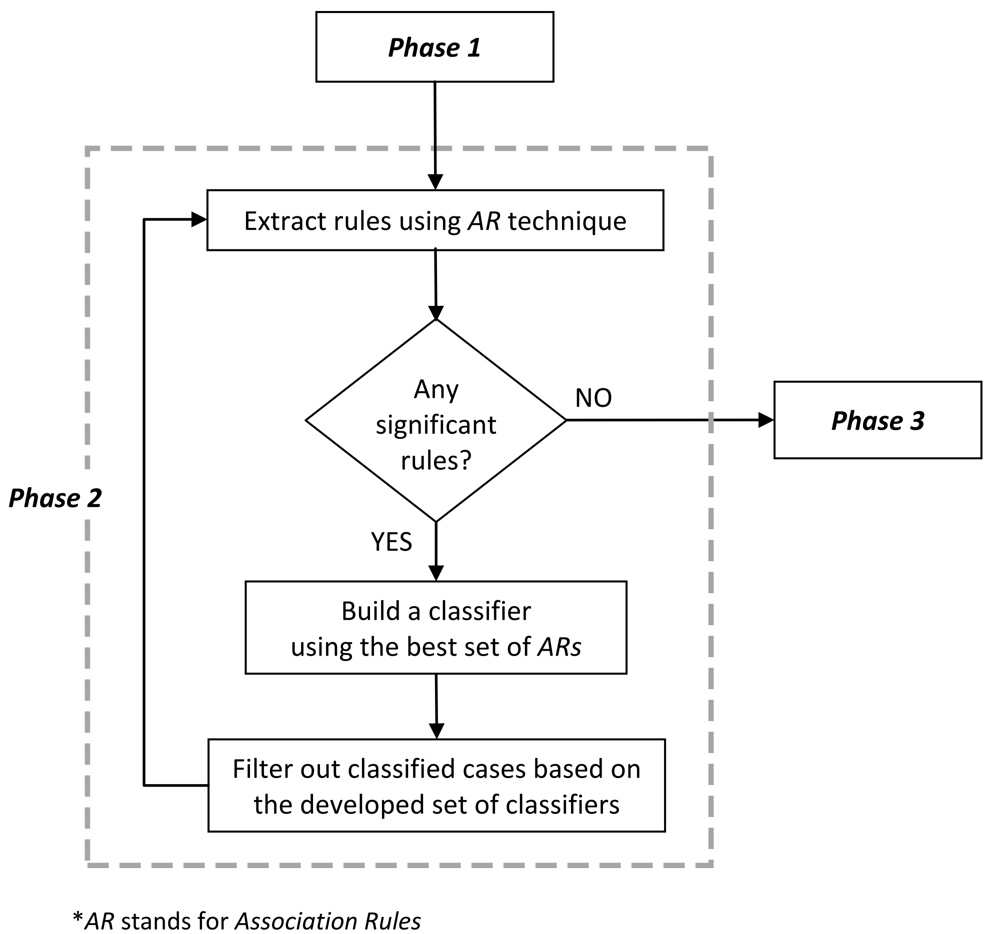


FIGURE 5.3 Flowchart to Develop the Sequential Classifiers with Association Rules (SCAR)

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 sets a relatively low value (0.005) for *support* in order 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* is set in from an intermediate to a high level (0.60 – 0.90) in order to discover reliable association rules.

Step 2: Investigate if there is any significant rule.

If *Step1* generates a large number of association rules, one may only need significant or interesting rules, based on the user-defined criteria. This study compares values for *confidence* and *support* among mined rules and chooses them with a higher *confidence* and *support*. This step is 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 selects the best set of *ARs* from the subset of rules constructed in *Step 2* and uses it as a classifier in *SCAR*. Suppose that a set of *m ARs* is generated from *Step 2* and denotes it by Ω. Then, *n ARs* are arbitrarily selected from Ω, and they are 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 $U_{ARs}^k = \bigcup AR_n^k$, and *confidence* and *support* values for U^k_{ARs} can be examined. After examining all possible U^k_{ARs} this study selects 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 it is clear that this step can be iterated at most $\binom{m}{n}$ times (= *k*) to examine all possible U^k_{ARs}, 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* is 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^k_{ARs}) from *Step 3* is added to the sequential classifiers to complete *SCAR*.

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

The incidents that are classified as supporting cases for the developed classifier through *Steps 3* and *4* are excluded from the input dataset, since their clearance times can be categorized by the developed *SCAR* system. The remaining incidents in the input dataset are 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 5.4. 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.

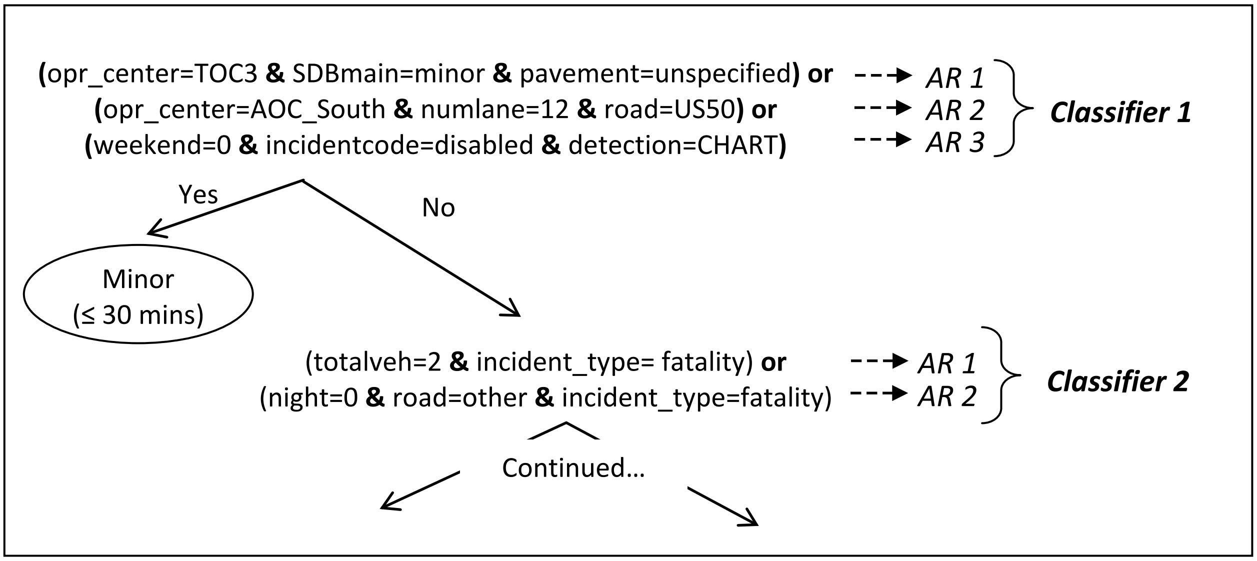


FIGURE 5.4 Illustration of a Single Classifier Composing *SCAR*

The system is able to 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 5.2 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 5.3 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 5.4 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 5.3 and 5.4 present contingency tables for more details of the system result. 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 those results, the *SCAR* system shows a good capability to correctly classify *Minor* and *Major* incidents. Classifiers embedded in the system have high confidence to classify *Intermediate* incidents, but their accuracy based on observations for the target class is relatively low, owing to misclassifications of classifiers that are targeting for *Minor* incidents.

As shown in the performance result (*Unclassified* in Tables 5.3 and 5.4), 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 5.2, 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 are 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 5.5 exemplifies *SCAR* in the arrangement of sequential IF-THEN-ELSE rules, while Figure 5.5 illustrates it in the form of the pruned tree. Since the developed *SCAR* includes a large number of classifiers, the full description of *SCAR* is presented in the format of sequential IF-THEN-ELSE rules in Appendix.

TABLE 5.5 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**			

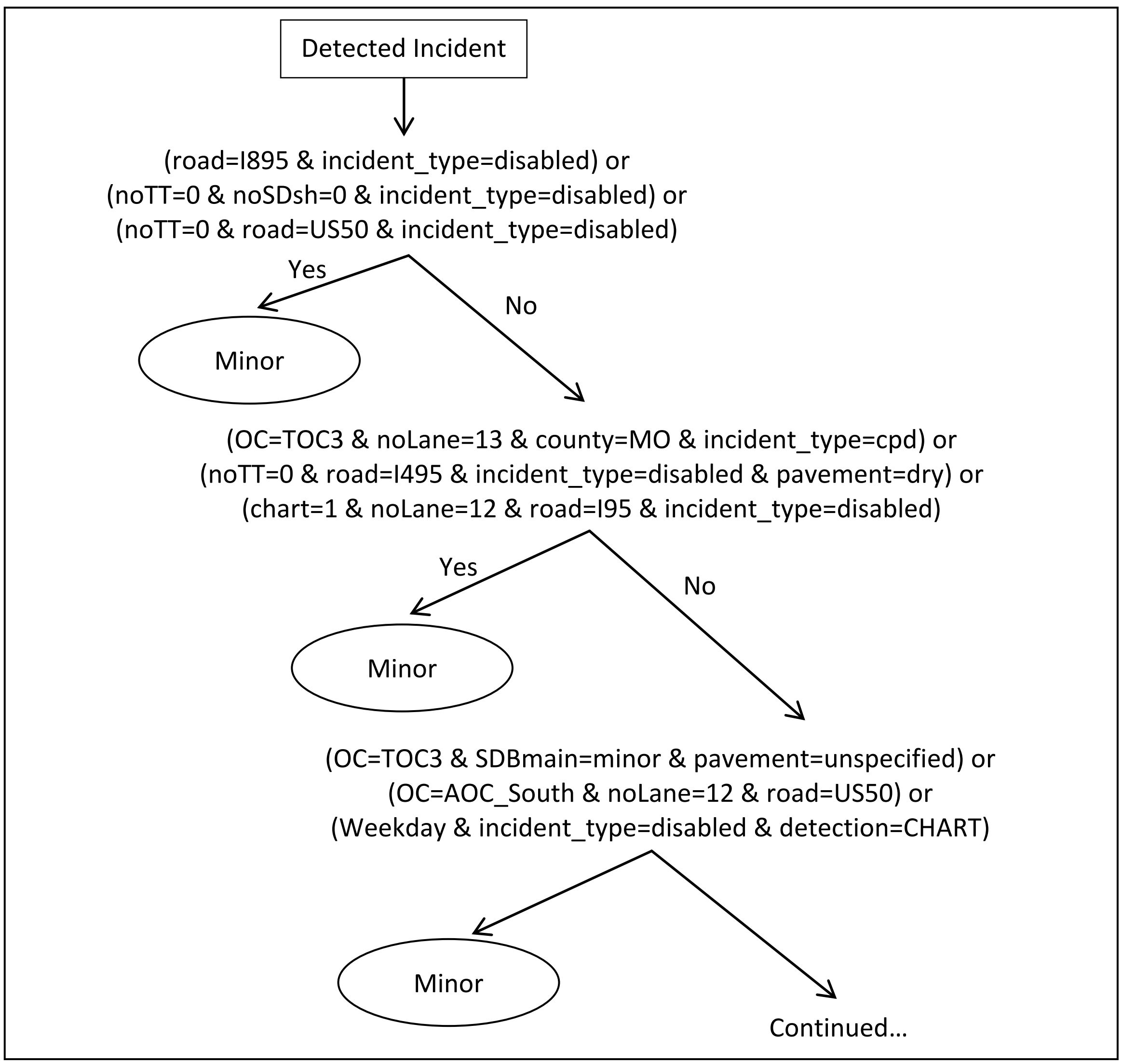


FIGURE 5.5 Presentation of *SCAR* II – Pruned Tree

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 are 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 <u>peak hours on major corridors</u> in the Washington and Baltimore Metropolitan regions and is involved with <u>property damage but no heavy vehicles</u>, its clearance duration is likely to end in 30 minutes (*Minor* class).
- If an incident is involved with <u>property damage and tractor-trailer</u>, its clearance duration is likely to be longer than 30 minutes (*Intermediate* or *Major* class).
- If an incident occurs during <u>off-peak hours or on minor roadways</u> in suburban areas in Maryland and is involved with <u>property damage</u>, 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 are consistent with observations that severe incidents causing multi-lane closure and/or fatalities are highly likely to last a long duration, while minor collisions are 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 is also a significant factor so that incidents in urban areas are likely to be cleared faster than those in suburban or rural areas. An interesting finding associated with detection sources is that incidents detected by CHART are likely to be cleared faster than those detected by other sources. It confirms the importance and contribution of incident management programs in addition to their prompt responses, as discussed in Chapter 4.

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 5.6. This feature in *SCAR* would be more critical as more factors are related to the interaction. As a result, it would significantly reduce the entire scale of the complete model to improve the interpretability of the model.

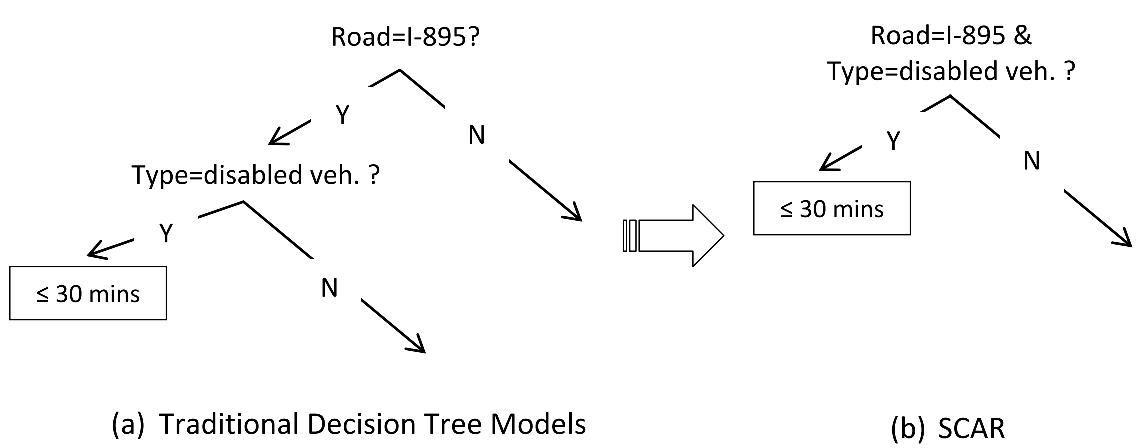


FIGURE 5.6 Reduction of the Presentation Scale and Complexity of *SCAR*

- *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 aforementioned feature (see Figure 5.7). Consequently, *SCAR* provides more opportunities to discover rules regarding the clearance time and its related factors.

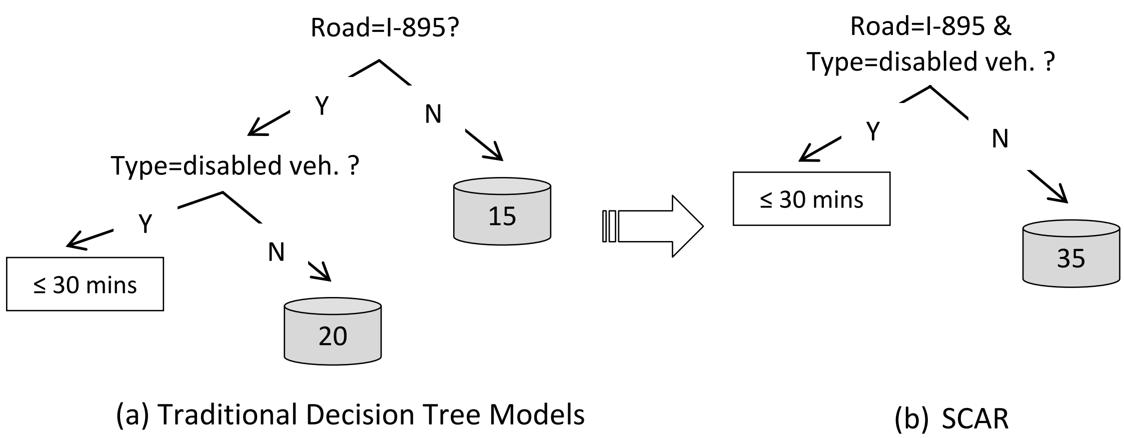


FIGURE 5.7 Prevention from the Lack of Samples in *SCAR*

- *Less sensitive to information loss:*

  Decision tree algorithms can construct multiple different models using the same data set, as exhibited in Figure 5.8, 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.

5.3.3 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.

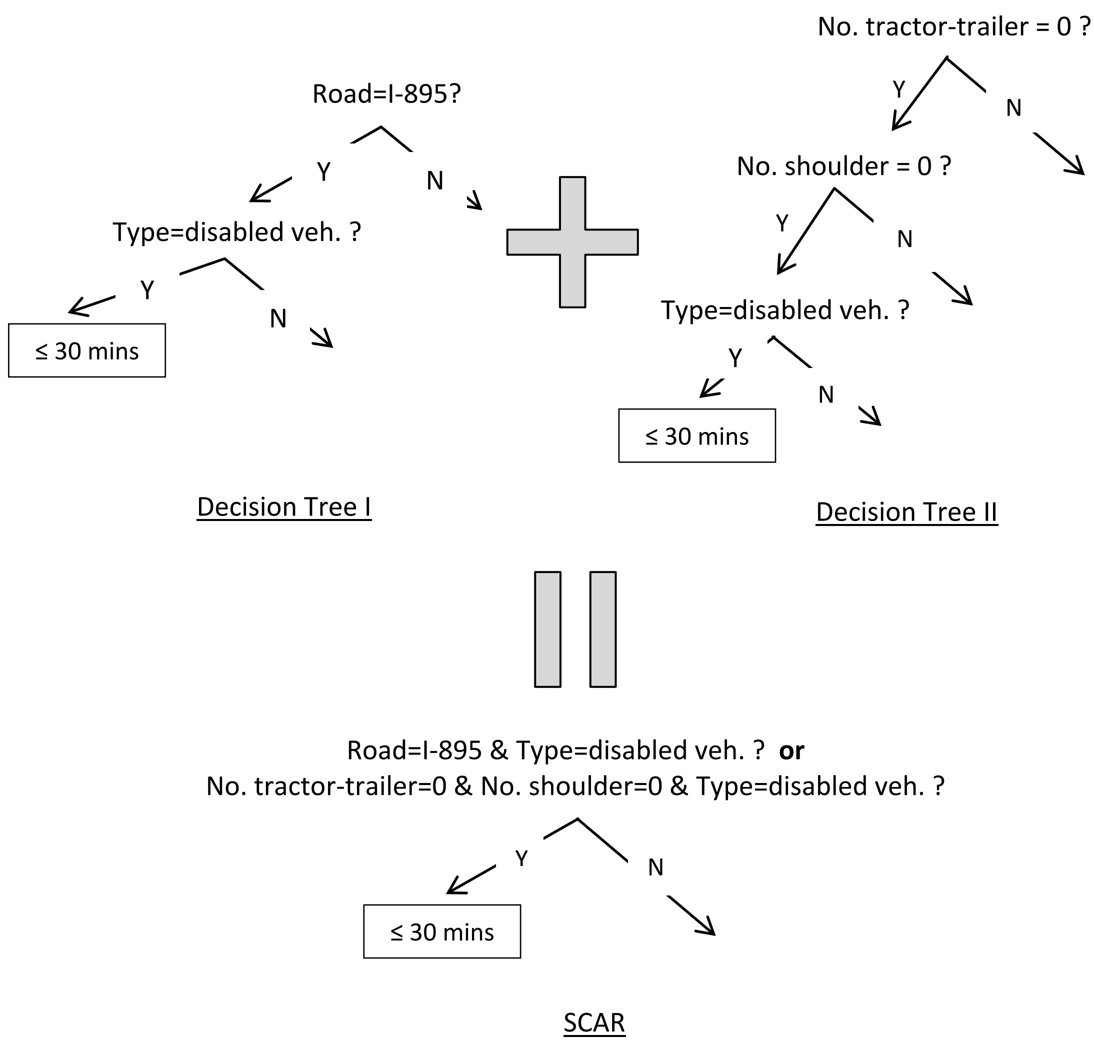


FIGURE 5.8 Prevention from the Information Loss in *SCAR*

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

Note that the data set used in this study only includes 344 major incidents (5.8 percent of the total), with clearance times ranging from 2 hours to 15 hours. This wide range of distribution poses 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 are applied to develop models with those data sets.

This section first 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, timevarying, 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 5.9 (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 5.9 (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 5.10.
- **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."

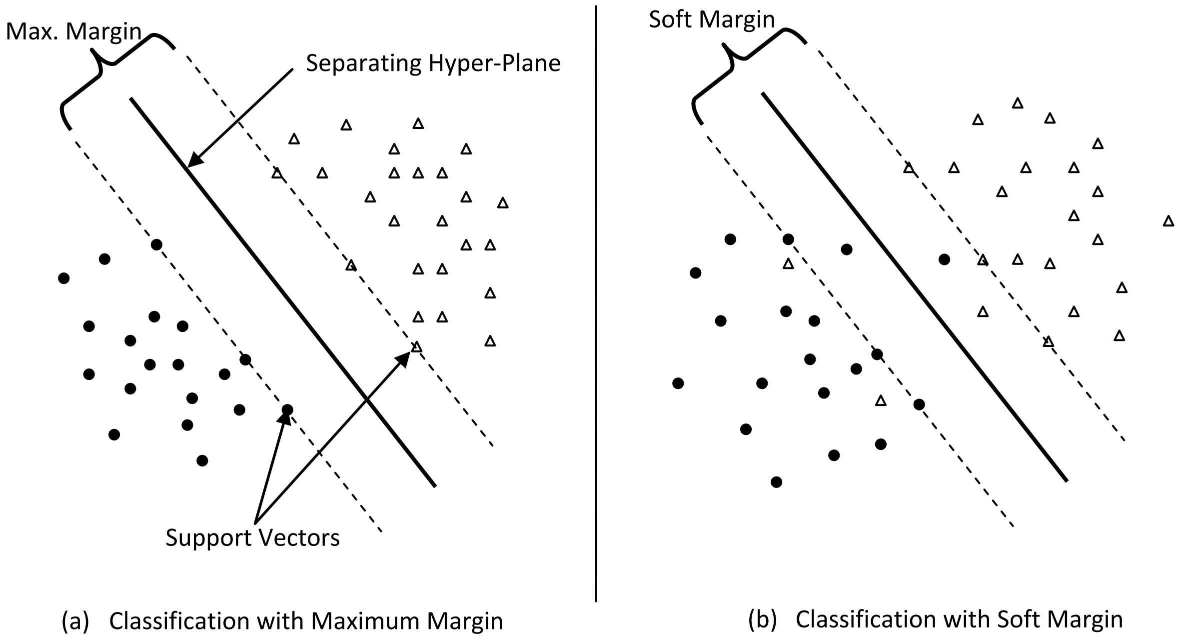


FIGURE 5.9 Illustrations of Support Vector Machines (Meyer, 2011)

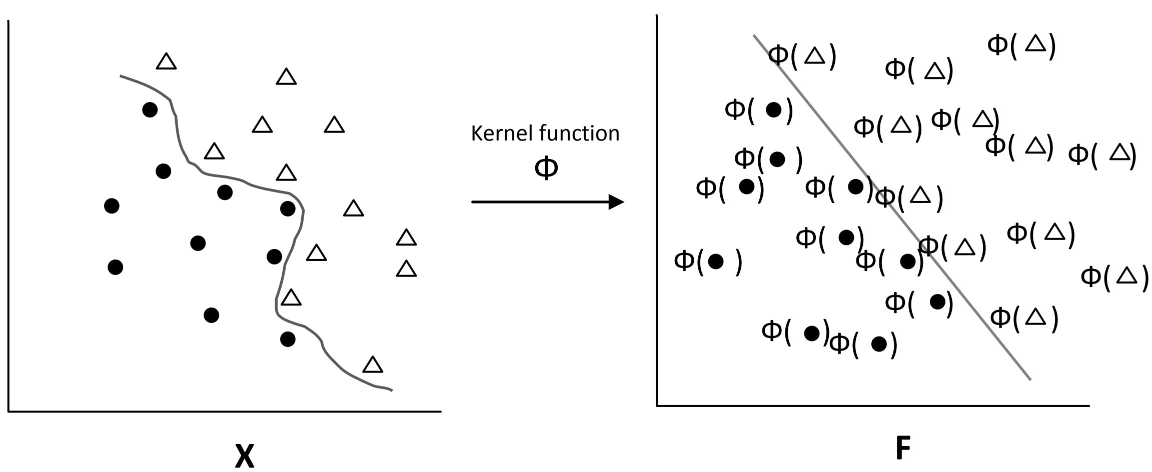


FIGURE 5.10 Illustration of Projection of Non-linearly Separable Cases to the Higher Dimensional Feature Space (Meyer, 2011)

Despite its strengths, the potential deficiency of SVMs lies 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, random forests show quite good results and are more robust with respect to noise and over-fitting (Breiman, 2001). They can also handle 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 are categorized as intermediate incidents having clearance times between 30 and 120 minutes in the development data set. Among those, 42 incidents (about 10 percent) are identified as misclassifications. Thus, the estimation/prediction model development for sub-classes of intermediate clearance times is conducted with the correctly categorized 379 intermediate incidents.

The sample sizes of sub-classes in intermediate incidents are also unbalanced, as shown in Table 5.6. The sub-class 1 (clearance times between 30 and 60 minutes) dominates the intermediate clearance times, while the sub-class 3 is only 10 percent of the total. Therefore, SVM and RF are highly likely to focus on the dominated class, sub-class 1, to increase their overall model accuracy. To balance sub-classes, weights are applied to observations, and SVM and RF models are developed based on the weighted observations. In addition, regression-type models are developed by using continuous values of clearance times, and the estimated/predicted clearance times are discretized with the same scheme as the one used for the proposed system.

Tables 5.6 and 5.7 summarize the performance results based on the model development data set and validation data set, respectively. SVM-1 is developed without weights (used the original class ratios), while SVM-2 and SVM-3 are 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 are developed based on the continuous value form of clearance times.

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

TABLE 5.6 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 5.7 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* is not able to categorize all incidents, since some incidents are associated with factors or their relationships that cannot be measured, observed, or identified. As presented in Table 5.2, *SCAR* is able to 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* is conducted in this phase.

Similar to supplemental model 1, SVM-1 is developed based on the original class ratios (no weights are applied), and SVM-2 uses a set of weights to balance the class ratio. SVM-reg and RF-reg are developed based on clearance times with the continuous value format. Tables 5.8 and 5.9 summarize the model performance results based on the development data set and validation data set, respectively. SVM-1 demonstrates its good performance only for minor and major incidents, while the overall result of SVM-2 is not acceptable. SVM-reg is over-fitted, and RF-reg only focuses on the intermediate-sub 2 class. Since RF-1 shows fairly good performance on intermediate and major incidents, it is selected to improve the estimation/prediction performance.

TABLE 5.8 Estimation Results from SVM and RF for Incidents Uncategorized by *SCAR*

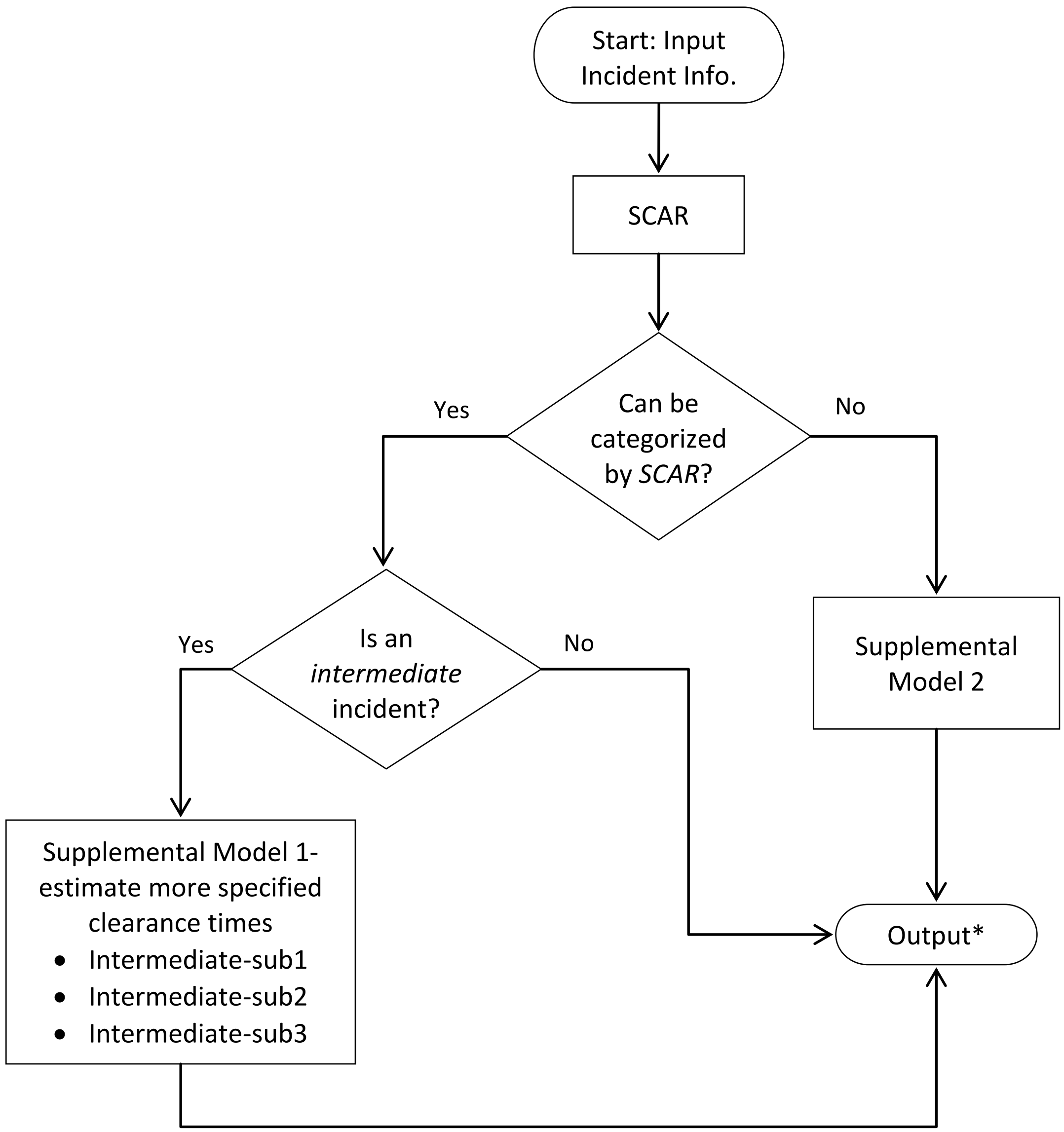
Clearance Duration Class (minutes)	Class ratio	Accuracy				
		SVM-1	SVM-2	SVM-reg	RF-1	RF-reg
Minor (≤ 30)	44.36%	96.% (468/487)	13.3% (65/487)	99.8% (486/487)	4.7% (23/487)	59.3% (289/487)
Intermediate-sub1 (30 – 60)	32.22%	26.2% (85/325)	46.8% (152/325)	9.8% (32/325)	50.8% (165/325)	82.5% (268/325)
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 5.9 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)

5.3.4 The Integrated System to Predict Incident Clearance Times

Figure 5.11 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 enter that 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 into 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 5.11 System Flowchart to Estimate/predict Incident Clearance Times Using the Proposed System

Table 5.10 shows that the overall performance of the proposed integrated system is promising. The system can well estimate/predict the *Minor* incident clearance, while its performance on the clearance times for the other classes is relatively poor. Considering the ratio of the original sample size in the data set, the probability that one can correctly classify an incident in *intermediate–sub3* by random guess is only 0.24. This value would not increase significantly even though the related agents have much experience. On the other hand, the proposed system can increase this probability nearly 10 times larger than the results with random guessing.

TABLE 5.10 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 5.11 and 5.12 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 5.10.

TABLE 5.11 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 5.12 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) are adopted. Cohen's kappa, denoted as K, is defined as follows:

$$K = \frac{P_o - P_e}{1 - P_e} \quad \text{(Eq. 5-2)}$$

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 is applied to evaluate the model's performance in estimating clearance times, K represents the true capability of the model.

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

$$K_w = \frac{P_{o(w)} - P_{e(w)}}{1 - P_{e(w)}} = 1 - \frac{\sum_i \sum_j w_{ij} p_{o,ij}}{\sum_i \sum_j w_{ij} p_{e,ij}} \quad \text{(Eq. 5-3)}$$

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 is very close to the accuracy of the proposed system. For both cases, however, K and K_w (with linear weights) are zero because their agreements are due to a random nature, whereas K and K_w for the developed system are approximately 0.4 and 0.5, respectively. These values can be interpreted as fair or moderate according to the most widely used index (Table 5.13). The best way to evaluate the true capability of the proposed system has been compared with those of other comparable models that are discussed in the next subsection.

TABLE 5.13 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 would be more practical. This is 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, these cases in the cells below the main diagonal in Tables 4.11 and 4.12 are acceptable to traffic operators. To provide only partial credits to these slightly overestimated results, the following weights (w_{ij}) are assigned to cells (i, j):

$$w_{ij} = 1 - \frac{|i-j|}{(n-1)} \qquad \text{(Eq. 5-4)}$$

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 are zero, since their misclassification is not acceptable.

TABLE 5.14 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 5.15:

$$acceptability = \frac{\sum_i \sum_j w_{ij} * c_{ij}}{\sum_i \sum_j c_{ij}} \qquad \text{(Eq. 5-1)}$$

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

TABLE 5.15 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 is a continuous variable, this study has calibrated a typical continuous model for comparison. To compare its performance with the proposed system, the clearance time has been discretized into five bins, based on the same discretization scheme as used in this study. Tables 5.16 and 5.17 summarize the performance of each model in estimation and prediction, respectively.

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

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

The random forests are 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 is selected after numerous experiments and it demonstrates good performance to estimate/predict those incidents with clearance times less than one hour, although it does 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:

TABLE 5.16 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 5.17 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%

1. *Transform the dependent variable (clearance times) to the normal distribution* − According to Figure 5.2, it is obvious that clearance times are not normally distributed. Since the linear regression model is based on the assumption 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 is 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 is adopted (Box and Cox, 1964). Figure 5.12 presents the distribution of the transformed clearance times.

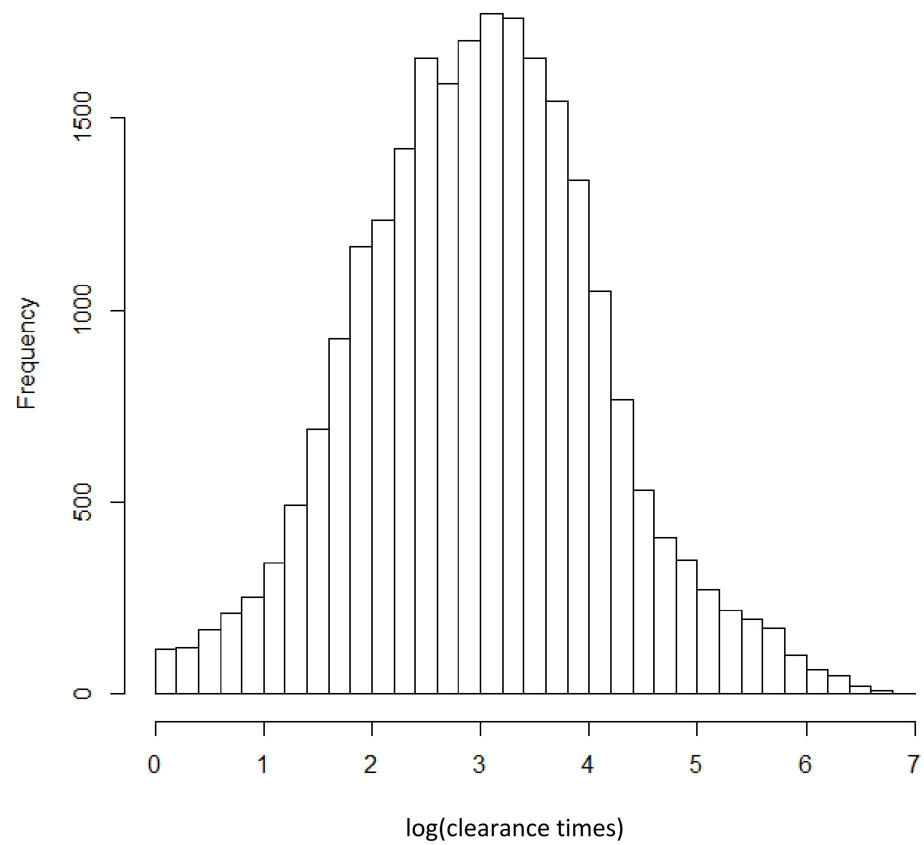


FIGURE 5.12 Distribution of the Transformed Clearance Times

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 have also been considered, but most of those are 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 show smaller than 10, indicating that no significant multicollinearity exists 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, is 2.006; thus, it does not reject the null hypothesis that the residuals are homoscedasticity. Figure 5.13 also confirms that no significant heteroscedasticity is 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 5.18 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*) shows the highest significance, reflecting that the clearance time increases 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 contribute significantly to increasing the clearance times. Obviously, the incident type is an important factor to determine the clearance times. The indicator for fatality involved (*CF*) is the second most significant variable, according to MLR.

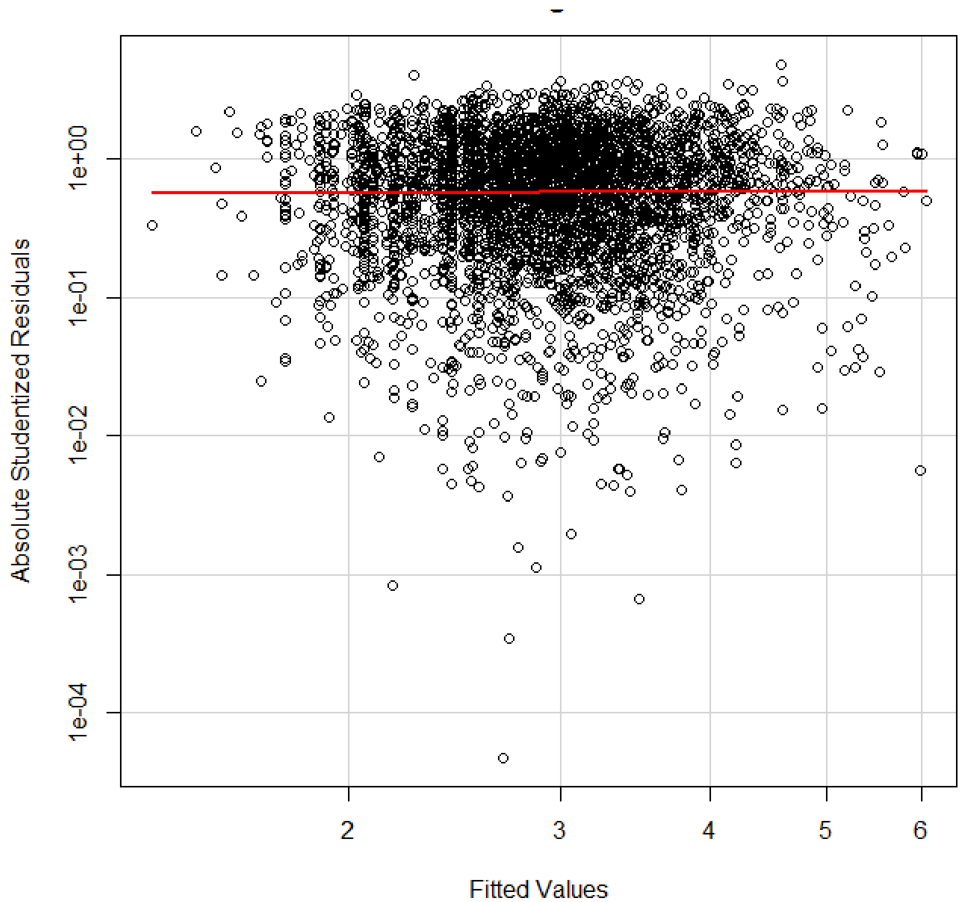


FIGURE 5.13 Distribution of Residuals versus Fitted Response Values

TABLE 5.18 (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 5.18 (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) show statistical significance to the incident clearance time. Note that the sign for the variable *Disabled* is negative, which indicates 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, includes variables related to regions (*Southern* and *Washington*). This implies that it would take longer time to clear incidents occurring in Southern Maryland, but exhibits 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 are included in the model. They imply 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 are consistent with some of the findings from *SCAR*. However, MLR is limited to catch interrelationships between factors since most variables are 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 does not show a good performance. However, using the same measures of performance, MLR demonstrates the results comparable with other models. The overall model accuracy is very close to the one from the proposed system owing to the high accuracy on clearance times less than 30 minutes, but the MLR is not reliable to estimate/predict clearance times between 1 hour and 2 hours. The acceptability of MLR is significantly lower than that of the proposed systems. It indicates 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 are better than other models. In addition, the proposed model can provide some insightful information on the impacts of related factors and their collective impacts on incident clearance times. Research findings listed in subsection 5.3.2 would be practically useful for traffic agencies to plan and improve their incident management programs.

Chapter 6: An Integrated Multi-criteria Support System for Assessing Detour Decisions during Non-recurrent Freeway Congestion

6.1 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 6.1 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.

In view of the strengths and limitations in the existing studies, this study is 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.

TABLE 6.1 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)

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.

6.2 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.

6.2.1 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 or not 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 suits 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 has developed a hybrid decision support system by integrating the traditional decision-making model with the AHP model, as shown in

Figure 6.1. Details for the system structure and supporting technical models are presented in the following subsections.

6.2.2 Architecture of the Proposed System

The developed system executes the decision on whether or not 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 6.1:

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.

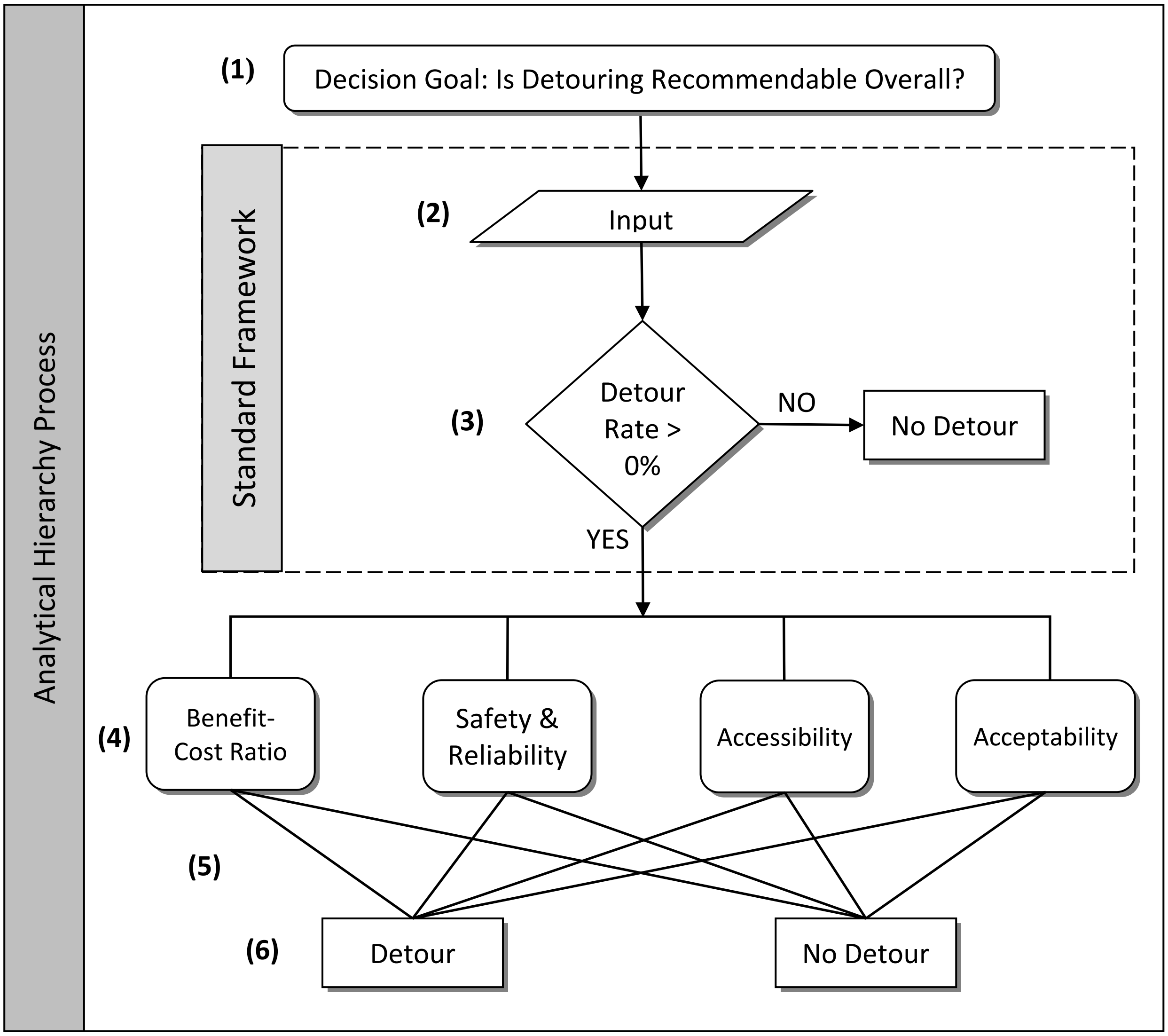


FIGURE 6.1 Overall Structure of the Proposed Detour Decision Support System

- 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 final conclusion.

As shown in Figure 6.1, 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 subcriteria, sub-subcriteria, 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 will measure the estimated travel times for the primary and alternative routes and use 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 aforementioned scenarios, this study uses 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.

6.2.3 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 6.2.2. Since the decision is made based on the estimated optimal detour rate, models or tools are needed to produce such measurements. For this sake, this study uses an integrated control model for freeway corridors under non-recurrent congestion developed by Liu and Chang (2011). This model can produce 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. Their 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 can also simulate 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 can provide the results for operations with and without the detour. While the third level uses the optimal detour rate for the initial decision making, the derived delay reduced by detour operations serves 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 conducts 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 can be 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 uses 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 includes 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 can be 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 can be 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 uses 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 uses 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 is 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 in order 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 a number of 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 6.2 and Figure 6.2 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 show 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 6.2) 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 6.2) 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 6.2) 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 6.2 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

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)

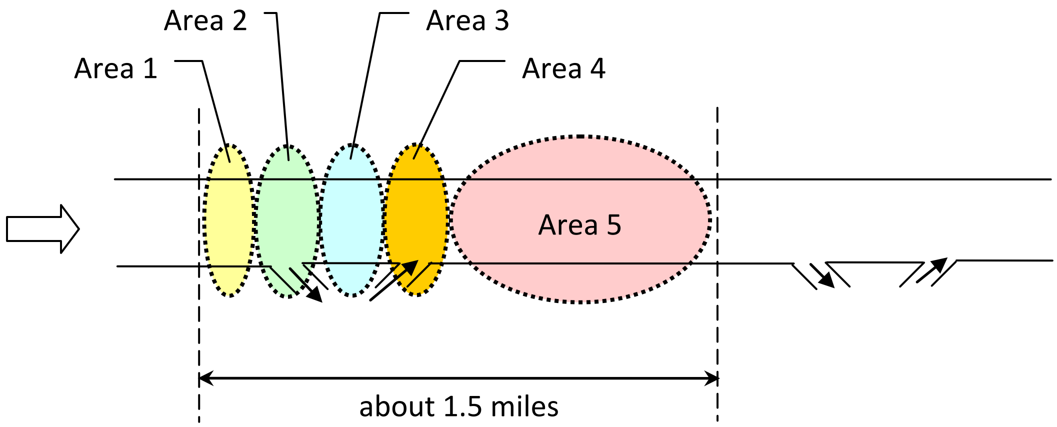


FIGURE 6.2 Illustrations of Incident Locations for the Queue Model

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

6.3 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.

6.3.1 Illustration of the System Performance and Evaluation by Comparative Analysis

To illustrate the system's performance this study has selected five experimental scenarios, as shown in Table 6.3 (Scenario No. 1 to 5). Simulation results show that proper detour operations can decrease the total travel time for all selected scenarios (see the row named "saved travel time" in Table 6.3). This analysis has further investigated

TABLE 6.3 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 6.4 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 6.5 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.

whether the detour operations are still beneficial from other perspectives and with different MOEs. Table 6.4 presents the system's outputs for those scenarios, and they are further compared with those by other state DOTs to evaluate the merit of the proposed system (see Table 6.5). For these experimental analyses the weights for benefit-cost ratio, safety and reliability, accessibility, and acceptability are set at 0.31, 0.31, 0.18, and 0.20, respectively.

The key incident characteristics associated with each scenario and the resulting recommendations by the proposed decision system are summarized below, which focuses mainly on the lane blockage status and incident duration, since they are 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 are 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 are 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 are 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 are 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 recommends that properly detouring traffic in Scenario 1, with only partial lane blockage over short incident duration, can still yield a sufficient total benefit if considered from the economic, environmental, and societal perspectives. The conclusion, however, would be quite different if one employs any of the state-of-the-practice methods shown in Table 6.1. The third column in Table 6.5 represents the discrepancy of decisions between different traffic agencies in the literature and the proposed system.

Similarly, based on those rules reported in Table 6.1, one may conclude that the incident condition in Scenario 3 justifies a detour operation (see decisions from New Jersey and Oregon DOTs in Table 6.5). However, the proposed decision support system, by applying multiple criteria from various perspectives, does not recommend the detour implementation with fairly high confidence (70 percent). The system considers 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 long 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 demonstrate 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 use a single factor to make a decision for detour implementation. Based on their decision criterion, these agencies would implement detour operations for both Scenarios 2 and 5, because of the complete closure of the primary route. However, the proposed system produces different recommendations for those two scenarios, since their incident durations and the traffic conditions on the freeway and the alternative route are quite different, which leads to significantly different benefit-cost ratios (see Table 6.3).

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, would make the opposite recommendations for those two scenarios. The major contributor to this discrepancy would be the number of signalized intersections on the alternative route. In Scenario 4, only two signalized intersections lie on the main detour route, whereas Scenario 5 has five of them. Signalized intersections on the alternative route tend to increase its travel times and delays. Thus, the optimization model is less likely to divert traffic to the detour route. Although the estimated optimal detour rate for Scenario 5 is about 54 percent, the total benefits from the saved total travel time are not sufficient to offset the operational expenses. Therefore, the multi-criteria decision-support system recommends 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 6.5.

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

This analysis demonstrates 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. Hence, this study has further used Scenario 6 in Table 6.3 as a base case and divided it into three sub-scenarios for further analyses. Table 6.6 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 implies that the decision maker should place higher weights on the **benefit-cost ratio** and on **safety and reliability**. Consequently, the decision support system will yield 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 will yield 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 are equally important, the system will then yield the following decision:

"Detour operations are recommended, with 53 percent confidence."

TABLE 6.6 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 seeks to highlight the fact that choosing whether or not 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 has presented a comprehensive decision system to rigorously incorporate all critical factors in making a timely detour decision to contend with non-recurrent congestion. The performance analysis results show that the proposed system makes 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 7: Conclusions and Future Research

7.1 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 administrations.

For this sake, this dissertation has 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 first-aid staffs, 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 has 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 has 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 has developed a decision support tool to assist control operators to tackle 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 can produce 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 aforementioned critical issues into account, this research has 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 of all responsible agencies. For such needs this study has proposed an enhanced freeway traffic incident management system and developed several efficient, reliable, and robust technical models for its operations. As long as properly integrated with other systems for incident detection, diversion optimization, and travel time information, the integrated system developed in this study will be able to substantially improve the quality and efficiency of motorists' travel over congested highways.

7.2 Future Research

Although this study has 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 done 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 operating 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

Descriptions of Classifiers Constituting *SCAR* (continued from TABLE 5.5)

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-	(noPVS=0 & noTT=0 & ODBmain=minor & incident_type=unknown) or	THEN	Minor (≤30)

	IF	(night=0 & noLane=12 & county=Baltimore & incident_type=disabled) or (OC=TOC3 & totalveh=2 & noSDsh=2 & pavement=unspecified)		
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)	THEN	Intermediate (30 – 120)

		or (night=1 & noSDBmain=1 & incident_type=cpi & non-holiday)		
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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