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New Framework and Decision Support Tool to Warrant Detour Operations During Freeway Corridor Incident Management

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by

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ABSTRACT

NEW FRAMEWORK AND DECISION SUPPORT TOOL TO WARRANT DETOUR OPERATIONS DURING FREEWAY CORRIDOR INCIDENT MANAGEMENT

by

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Under the Supervision of Professor Yue Liu

As reported in the literature, the mobility and reliability of the highway systems in the United States have been significantly undermined by traffic delays on freeway corridors due to non-recurrent traffic congestion. Many of those delays are caused by the reduced capacity and overwhelming demand on critical metropolitan corridors coupled with long incident durations. In most scenarios, if proper detour strategies could be implemented in time, motorists could circumvent the congested segments by detouring through parallel arterials, which will significantly improve the mobility of all vehicles in the corridor system. Nevertheless, prior to implementation of any detour strategy, traffic managers need a set of well-justified warrants, as implementing detour operations usually demand substantial amount of resources and manpower.

To contend with the aforementioned issues, this study is focused on developing a new multi-criteria framework along with an advanced and computation-friendly tool for traffic managers to decide whether or not and when to implement corridor detour operations. The expected contributions of this study are:

- Proposing a well-calibrated corridor simulation network and a comprehensive set of experimental scenarios to take into account many potential affecting factors on

traffic manager's decision making process and ensure the effectiveness of the proposed detour warrant tool;

- Developing detour decision models, including a two-choice model and a multi-choice model, based on generated optima detour traffic flow rates for each scenario from a diversion control model to allow responsible traffic managers to make best detour decisions during real-time incident management; and
- Estimating the resulting benefits for comparison with the operational costs using the output from the diversion control model to further validate the developed detour decision model from the overall societal perspective.

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Chapter 1

INTRODUCTION

1.1 Research Background

Traffic delays on freeway corridors due to congestion have significantly undermined the mobility and reliability of the highway systems in the United States. Most of those delays are due to non-recurrent traffic congestion caused by the reduced capacity and overwhelming demand on critical metropolitan corridors coupled with long incident durations. In such conditions, if proper detour strategies could be implemented in time, motorists could circumvent the congested segments by detouring through parallel arterials, which will significantly improve the mobility of all vehicles in the corridor system.

To contend with this vital operational issue, various types of optimal control models, focused on diversion control and integrated with other control strategies like ramp metering control and arterial signal control, have been proposed in the past several decades. Certainly, the previous research efforts have made an invaluable contribution to the development of control strategies and operational guidelines for freeway incident management. However, prior to implementation of any detour strategy, traffic managers need a set of well-justified warrants, as implementing detour operations usually demand substantial amount of resources and manpower.

In this regard, very limited information and tools are available in the literature to assist traffic managers in warranting detour operations from the system benefit perspective and with multiple affecting factors taken into account in the decision-making process, although numerous traffic safety and operation manuals have addressed the need of properly diverting traffic flows during major incidents or emergencies. Hence, prior to the potential implementation of detour operations, effective guidelines involving warranting the necessity of implementing such a detour plan considering the overall benefit and various potential affecting factors needs to be provided for traffic managers to make final decisions in freeway incident management.

1.2 Research Objectives

Based on the background introduced before, it is necessary to develop a new multi-criteria framework along with an advanced and computation-friendly tool for traffic managers to decide whether or not and when to implement corridor detour operations. This study has performed extensive analyses of the past 5-year major incident data in the stretch of interstate highway 94 (Madison - Milwaukee) using the Wisconsin Lane Closure System and the InterCAD Traffic Incident Data Exchange System and to obtain a comprehensive incident scenario dataset. Detour operations will be implemented for those real-world incident scenarios in a well-calibrated simulated environment with varying traffic demand levels, driving behavior patterns, geometric configurations, and traffic control parameters.

The detour decision will be evaluated and ranked for each experimental scenario by the developed detour decision model, and then benefit analyses will be performed to evaluate the benefits gained by the implementation of detour. The objectives of this research will focus on:

- Investigate the state-of-the art literature in order to synthesize available information on the analysis of incident management and diversion control under freeway non-recurrent congestion;

- Analyze newly collected or archived incident field data to build a comprehensive incident scenario dataset and identify key factors that affect driver's decision to divert;
- Develop a well-calibrated corridor simulation network;
- Determine the detour operational strategy for each experimental scenario;
- Develop and validate the detour decision models; and
- Estimate the benefits of detour operations for each scenario.

1.3 Research Organization

Based on the proposed research objectives, this study has organized all primary results and key findings into six subsequent chapters. A brief description of the information contained in each chapter is presented next.

Chapter 2 performs a comprehensive review of available literature associated with incident management, including incident detection algorithm, incident duration prediction, optimal control strategies and decision making for detour operations.

Chapter 3 illustrate the framework of the proposed multi-criteria detour decision system, based on critical issues that need to be taken into account in the design of detour decision process. It specifies the required system inputs, the principal system components and their key functional features, as well as the operational interactions.

Chapter 4 mainly presents the project background and data collection process, including data collection sites, introduction of data sources, procedure of combing databases, data extraction and analysis, and freeway segment division for experimental design.

Chapter 5 develops a well-calibrated corridor simulation network based on the divided segments and a comprehensive set of experimental scenarios according to the key factors that may affect the traffic manager's final decision on whether or not to implement detour operations.

Chapter 6 details the model development and validation, including an integrated division control model to determine the best set of division rates for each scenario, a 2-choice model that gives 2 types of decisions (i.e. Detour or No detour) and a multi-choice model that yields 5 types of decisions (i.e., "strongly recommended", "recommended", "neutral", "NOT recommended", and "strongly NOT recommended") and estimation model for benefits of each experimental scenario.

Chapter 7 summarizes the primary research findings and their potential applications to improving detour operational efficiency. Recommendations for future research were also made.

Chapter 2

LITERATURE REVIEW

In the Traffic Incident Management Handbook (FHWA, 2000), traffic incident management has been defined as the "*systematic, planned and coordinated use of human, institutional, mechanical, and technical resources to reduce the duration and impact of incidents, and improved the safety of motorists, crash victims, and incident responders*". This chapter summarizes major studies by transportation researchers over the past decades on various aspects of incident management. It focuses on both the critical issues and potential research directions identified in the existing literature on this vital subject.

To facilitate the presentation, this chapter will report the review results along the following lines:

- **Incident detection algorithm**: accurately detect an incident in an early time to reduce the congestion and incurred delay or costs by efficient algorithm ;
- **Incident duration prediction:** predict incident duration by developing a methodology under the certain traffic condition;
- **Optimal control strategies:** response to the detected incident by implementing appropriate control strategy, such as diversion, ramp metering, signal timing optimization; and
- **Decision making for detour operations:** explain why detour operations are needed and how to implement detour plan.

The remaining sections present a summary of existing methodologies associated with each of the above research lines. Based on the review results, the last section will outline the further research needs for this study.

2.1 Incident Detection Algorithm

Implicit to the response to an incident is its detection. In the Traffic Incident Management Handbook (FHWA, 2000), incident detection is defined as the process by which an incident is brought to the attention of the agency or agencies responsible for maintaining traffic flow and safe operations on the facility. Under medium to heavy traffic conditions, the effect of a lane-blocking incident on traffic is an inverse function of the time taken to clear it up. Again, the promptness of the response is a direct function of the time taken to detect the incident. Accurate and early detection of incidents is vital for subsequent management action plans that aim to reduce the congestion caused by incidents.

An incident detection algorithm is capable of providing fast and accurate detection with minimal investments on top of the current surveillance systems and has low maintenance and personnel requirements. In a study (Presley and Wyrosdick, 1998) conducted in Atlanta, Georgia it was observed that the Georgia Navigator system (Georgia's advanced traffic management system) has reduced the average incident duration time from 64 minutes to 41 minutes. This reduction of 23 minutes translated into a cost savings of 44.6 million dollars due to reduced delay time in 1997. Using a simple linear projection, it can be projected (approximately) that a decrease of 1 minute in overall incident duration on average would lead to 1.94 million dollars benefit. Use of an incident detection algorithm, involving a trivial deployment overhead of a few thousand dollars, has the potential to reduce the response time by faster detection of incidents. This alone provides enough motivation to invest in research of incident detection algorithms.

Depending on how an algorithm analyzes the operations data in order to detect incidents, an algorithm is usually classified into one of five major categories: comparative algorithms, statistical algorithms, time-series algorithms, traffic theory based algorithms, and advanced algorithms.

2.1.1 Comparative Algorithms

Comparative algorithms are designed to compare the value of measured traffic parameters (i.e., volume, occupancy or speed) to a pre-established threshold value. An incident alarm is prompted when the measured traffic parameter exceeds an established threshold. Comparative algorithms include the decision tree (DT) algorithms (Payne, 1976; Payne et al., 1976; Payne and Knobel, 1976; Tignor and Payne, 1977; Payne and Tignor, 1978; Levin and Krause, 1979 a, b), the pattern recognition (PATREG) algorithm (Collins et al., 1979), and the APID algorithm (Masters et al., 1991).

The DT algorithms, or so-called California algorithms, are the most widely known comparative algorithms. This type of algorithm is based on the principle that an incident is likely to cause a significant increase in upstream occupancy while simultaneously reducing occupancy downstream. The following occupancy differences of two adjacent fixed detectors locations in a decision tree structure are analyzed: 1) the absolute difference in occupancy between the upstream and downstream detectors; 2) the relative difference in occupancy between upstream and downstream detectors compared to the upstream occupancy; and 3) the relative difference in occupancy between upstream and downstream detectors compared to the downstream occupancy. In the California algorithm family, the modified #7 and #8 algorithms were shown to have the best performance (Payne and Tignor, 1978; Balke, 1993). California #7 replaces the temporal downstream occupancy difference in the above third test with the present downstream occupancy measurement. California #8 has the most complicated form (it involves 21 individual tests) in that it incorporates refining functions to deal with compressive waves.

The PATREG algorithm was developed by the Transport and Road Research Laboratory (TRRL) as part of their Automatic Incident Detection (AID) system. The algorithm estimates vehicle speeds by tracing and measuring travel times of particular traffic patterns between detectors. The algorithm compares these speed values to pre-established thresholds and triggers an alarm when they fall below the thresholds during a pre-set number of consecutive intervals.

The All-Purpose Incident Detection (APID) algorithm was developed for use in the COMPASS advanced traffic management system implemented in Metropolitan Toronto. It incorporates and expands the major elements of the California algorithms into a single structure. The algorithm includes the following major parts: 1) a general incident detection algorithm for use under heavy traffic conditions; 2) a light volume incident detection algorithm; 3) a medium volume incident detection algorithm; 4) an incident termination detection routine; 5) a routine for testing for the presence of compression waves; and 6) a routine for testing for the persistence of incident conditions. A primary feature of the algorithm, compared to the California algorithms, is that different algorithms are used under different traffic conditions.

2.1.2 Statistical Algorithms

The statistical algorithms use standard statistical techniques to determine whether observed detector data differ statistically from estimated or predicted traffic characteristics.

The standard normal deviate (SND) algorithm (Dudek et al., 1974) and Bayesian algorithm (Levin and Krause, 1978; Tsai and Case, 1979) are two representative types of statistical incident detection algorithms.

The SND algorithm was developed by the Texas Transportation Institute (TTI) in the early 1970s for use in the initial surveillance and control center in Houston, TX. The algorithm computes the SND of the traffic control measure, which is the number of deviations a particular value of a variable deviates from the mean of that particular variable. Its working principle is based on the premise that a sudden change in a measured traffic variable suggests that an incident has occurred. The algorithm compares 1-minute average occupancy measurements to archived occupancy values of the mean and SND that define thresholds for detecting incidents. An SND value which is greater than the critical value indicates the presence of an incident. Two successive intervals are used to make a consistency test.

The Bayesian algorithm uses Bayesian statistical techniques to compute the likelihood that an incident signal is caused by a lane-blocking incident. The algorithm makes use of the relative difference of the occupancies used in the California algorithms as the traffic measure, but computes the conditional probability using Bayesian statistics. Bayesian theory assumes that frequency distributions of the upstream and downstream occupancies during incident and incident-free conditions can be developed. Three databases are identified for satisfying the requirement of the Bayesian algorithm: 1) traffic occupancy and volume data during incident conditions; 2) traffic occupancy and volume data during incident-free conditions; and 3) archived data on the type, location, and severity of incidents.

2.1.3 Time Series Algorithms

Time series algorithms assume that traffic normally follows a predictable pattern over time. They employ time series models to predict normal traffic conditions and detect incidents when detector measurements deviate significantly from model outputs. Several different techniques have been used to predict time-dependent traffic for incident detection, including the autoregressive integrated moving-average (ARIMA) model (Ahmed and Cook, 1977, 1980, 1982) and high occupancy (HIOCC) algorithm (Collins et al., 1979).

The ARIMA model assumes that differences in a traffic variable measured in the current time slice (t) and the same traffic variable in the previous time slice (t-1) can be predicted by averaging the errors between the predicted and observed traffic variable from the past three time slices. These errors are expected to follow a normal pattern under incident-free conditions while an abnormal error indicates a potential incident occurrence. This model is used to develop short-term forecasts and confidence intervals of traffic variables. Incidents are detected if the observed occupancy values fall outside the established confidence interval.

The HIOCC algorithm also monitors detector data for changes over time, but relies on 1-second occupancy data. The algorithm is designed to examine the individual pulses from the detectors and seek several consecutive seconds of high detector occupancy in order to identify the presence of stationary or slow-moving vehicles over individual detectors. A computer scans detector occupancy data every tenth of a second and several consecutive values of instantaneous occupancies are then examined to see if they exceed a predetermined threshold.

2.1.4 Traffic Theory Based Algorithms

The traffic theory based algorithms depend on the relationship between the traffic variables for their analysis. The algorithms in this category include the McMaster algorithm and the Generalized Likelihood Ratio (GLR) algorithm.

The McMaster Algorithm was developed using data from Queen Elizabeth Way, Mississauga, Ontario. The basic McMaster Algorithm (Persaud and Hall, 1989; Persaud et al., 1990) (Persaud et al., 1990; Hall et al., 1993) is a congestion detection algorithm. It uses a catastrophe theory model for description of the flow-occupancy-speed relationship. This algorithm has the capability of identifying congestion even when traffic flow occurs below the critical occupancy value. Most of the other approaches depend on the critical occupancy as a threshold value for activation of the detection logic. Since this is a single station algorithm, it does not suppress detection of incidents at stations close to an incident.

Another algorithm in this category is the Generalized Likelihood Ratio (GLR) algorithm which is proposed by Chow et al. (Chow et al., 1977a; Chow et al., 1977b; Greene et al., 1977; Kurkijian et al., 1977). In the GLR algorithm only one extended Kalman filter is used corresponding to the normal operations scenario. Using some Incident Innovations Signatures (IIS) that are pre-determined from simulations, a correlation is drawn between the residuals of the filter to the corresponding IIS to obtain the likelihoods of different events. These likelihoods are used for the final isolation of incidents. Unlike the other algorithms that perform well in heavy traffic, this algorithm was found to perform well under light and moderate traffic as well.

2.1.5 Advanced Algorithms

The latest trend has been the development of algorithms with advanced mathematical formulation based techniques and algorithms that incorporate inexact reasoning and uncertainty into the detection logic. These algorithms are based on Artificial Intelligence which refers to a set of procedures that apply inexact or "black box" reasoning and uncertainty in complex decision-making and data-analysis processes.

The artificial intelligence techniques applied in automatic incident detection include neural networks (Ritchie and Cheu, 1993; Cheu and Ritchie, 1995; Stephanedes and Liu, 1995; Dia and Rose, 1997; Abdulhai and Ritchie, 1999; Adeli and Samant, 2000), fuzzy logic (Chang and Wang, 1994; Lin and Chang, 1998), and a combination of these two techniques (Hsiao et al., 1994; Ishak and Al-Deek, 1998).

Neural networks are data processing structures used to simulate the thought process and reasoning of the human brain. They consist of a number of simple processing elements (PEs) with parallel interconnections. The PEs receive input information, weighted by the strength of associated connection values, then make computations using a transfer function, and finally send output to other connected PEs in the next layer. The commonly used neural network algorithms for incident detection include multi-layer feed forward neural networks (MLF) and probabilistic neural networks (PNN). The MLF-based algorithm has three fundamental layers: input layer, hidden layer, and output layer. The inputs for PEs on the input layer generally include volume, occupancy, and/or speed at both upstream and downstream detectors. The PNN-based algorithm has the capability of incorporating prior probabilities of incident occurrence, road conditions, and misclassification cost for incident detection. The neural network algorithms require substantial training through trial-and-error processes to optimize weights in order to identify uncongested and congested traffic, both recurring and nonrecurring. In order to reduce the high dimensionality of a common neural network model and improve its computational efficiency, Adeli and Samant (2000) proposed using an adaptive conjugate gradient neural network (ACGNN) with a two-stage discrete wavelet transform and linear discriminant analysis preprocess (as described as the DWTLDA algorithm in this chapter) for incident detection to improve detection efficiency and performance.

In addition, Ivan and his colleagues (Ivan et al., 1995; Ivan and Chen, 1997; Ivan, 1997; Ivan and Sethi, 1998) applied neural networks to fuse loop detector and probe vehicle data for arterial incident detection. In these applications, neural networks are designed to work in two forms: 1) combining the raw traffic data; or 2) integrating the incident detection results (or incident occurrence probabilities) from a loop detector-based model and a probe vehicle-based model.

Fuzzy logic is another artificial intelligence technique used for incident detection. It provides a mechanism for applying inexact or imprecise data to a set of rules. It has been applied to eliminate strict decision thresholds and use membership functions to represent the degree of probability of the presence of an incident. Decisions on incident or incident-free states are allowed even though traffic data may be inexact or missing. The ability to make decisions based on incomplete data has the potential to significantly improve the performance of incident detection algorithms.

Fuzzy logic combined with neural networks (Hsiao et al., 1994) was applied to improve the performance of incident detection over either single technique. Ishak and Al-Deek (1998) applied a fuzzy neural network, a clustering algorithm that maps a set of input patterns to a set of categories, to improve the performance of incident detection. This method has the capability of overcoming the so-called stability-plasticity dilemma problem of the MLF-type neural networks.

2.2 Incident Duration Prediction

The Highway Capacity Manual (HCM) defines incident duration time with four segments: Detection, Response, Clearance, and Recovery. As showing in Figure 2.1, the detection time includes the time elapsed from when the incident occurs to when a responding agency is notified. The response time includes the time elapsed from when the responding agency is notified and when the first responder arrives on scene. The clearance time includes the time elapsed from when the first responder arrives on scene to when all elements of the incident are cleared from the roadway. The recovery time is defined as the time elapsed from when the incident is cleared until normal traffic operations are restored.

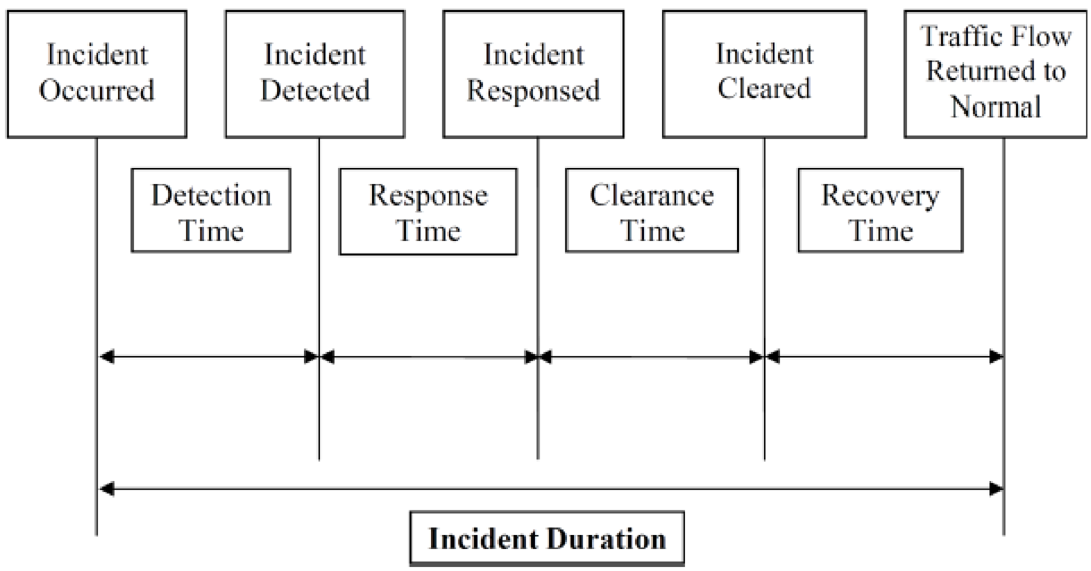


Figure 2. 1 Incident Duration

Incident duration has been studied by numerous researchers for several decades with various methodologies. The most representative approaches are (1) Probabilistic Distributions, (2) Conditional Probabilities, (3) Linear Regression Models, (4) Time Sequential Models, (5) Decision Trees and Classification Trees, and (6) Discrete Choice Models. Although there are a variety of existing techniques with acceptable results, they cannot be directly applied to incidents that occurred at any other locations. Each model was developed with different incident data sources and descriptive variables, and thus yields somewhat different results. Therefore, for any target application, it is necessary to develop a new model for different traffic conditions and available data sources.

The first approach for the incident duration reviewed in this study is the probabilistic model, which is relatively straightforward to use in forecasting the incident duration. The key aspect of this approach is to view the duration as a random variable and attempt to find a probability density function (PDF) that can fit to the data set. Golob et al. (1987) conducted their research using approximately 530 incidents that involved trucks, and found that the incident duration could be modeled with a log normal distribution. Their finding has been supported by other studies by Giuliano (1989), Garib et al. (1997) and Sullivan (1997) for freeway incident duration. In 1999, Ozbay and Kachroo also found that the distribution of incident duration from their data set shows a shape very similar to 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 follow a normal distribution. This finding has an important implication since it supports the theory that the 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. In 2000, Nam and Mannering learned that their data set can 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 time for their study data.

Probability models for incident duration can be extended to conditional probability models. The key idea of such models is to find the probability distribution of incident duration under certain given conditions; for example, the probability of incident duration lasting 30 minutes given the condition that the incident has already lasted for 10 minutes. Intuitively, it is noticeable that the probability of the end of incident duration would be different, depending on how long the incident has lasted (known as duration dependence in Nam and Mannering (2000)), and the incident characteristics. One of the interesting approaches under this concept is the hazard-based duration model. This model allows researchers to formulate incident duration with conditional probability models. Such models have been widely used in biometrics and industrial engineering fields to determine causality from the duration data. Due to its similarity with the nature of traffic incident duration, their theoretical concepts and models have recently been applied in the transportation field. With such approach, researchers' interests have been expanded from simply estimating and predicting the incident duration to computing the likelihood that the incident will finish in the next short time period, given its elapsed duration. One of the most representative studies using this methodology was conducted by Nam and Mannering (2000), using a set of two-year data from Washington State. Through their study, it is shown that each incident time (i.e. detection/reporting, response, and clearance times) is significantly affected by numerous factors, and different assumptions of distribution are recommended for different incident times. They also found that the estimated coefficients were unstable through the two-year data used in the model development. As concluded by Nam and Mannering, this approach is more useful to determine which variable has greater influence on incident duration, than to estimate or predict the incident duration for a set of given explanatory variables.

Another simple methodology to predict incident duration is linear regression models. These models usually include a number of binary variables as independent variables to indicate incident characteristics, and a continuous or categorical v ariable as a dependent variable (i.e., incident duration). One of the most well-known linear regression models for incident prediction was developed by Garib et al. (1997) using 277 samples 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). They also included all possible combinations of the independent variables to develop the best model. The final incident duration model from their research is as follows:

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

Where Duration = incident duration (minutes)

X1 = number of lanes affected by the incident

X2 = number of vehicles involved in the incident

X5 = truck involvement (dummy variable)

X6 = morning or afternoon peak hour indicator (0: morning peak hour; 1: afternoon peak hour)

X7 = natural logarithm of the police response time (minutes)

X8 = weather condition indicator (0: no rain; 1: rain)

This model showed 0.81 for adjusted R2. The logarithm form of incident duration indicates that the incident duration in this data set follows a log normal distribution which is supported by the Kolmogorov-Smirnov test. This result is similar to those from Golob et al. (1987) and Giuliano (1988). According to the authors, the police response time is the most significant factor in affecting the incident duration, which is followed by weather condition, peak hour, truck involvement, and the combined effect of number of lanes and vehicles involved in the incident.

Khattak et al. (1995) realized that the full set of variables for incident forecasts would be available at the moment the incident is cleared. Although prediction models based on this total set of variables will be more accurate and reliable, they are less practical for the real-time incident duration prediction because this full set of variables can only be available after the incident is cleared. Thus, they introduced a time sequential model, based on the idea that the prediction of incident duration made earlier in the incident life would be more informative to incident management even with lower accuracy and reliability. The model developed by Khattak et al. (1995) has ten distinct stages of incident duration, based on the availability of information. Each stage indicates different ranges of incident duration, and has a separate truncated regression model. At each stage, more variables are included progressively to explain the stage 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 intention of their study is to introduce and demonstrate the time sequential model rather than proving the performance of their model in traffic operations.

Another approach available in the literature is the Decision Tree Model. The purpose of applying this methodology is to discover patterns in a given data set without considering the fundamental probabilistic distribution (Smith and Smith, 2001). Smith and Smith (2001) pointed out that the pattern-recognition model has been used recently to develop the incident duration models. One of the representative models is developed by Ozbay and Kachroo (1999) for the Northern Virginia region. They began with developing a model to predict clearance time using linear regression, based on a large size of samples. Unfortunately, they completed the analysis with a poor result ($R2 \approx 0.35$), and learned that the incident duration follows neither a lognormal nor a log-logistic distribution. As an alternative method, they explored a decision tree model and finally generated the relation patterns shown in Figure 2.2 for predicting clearance times. It can be noted that the incident tree consists of a series of decision 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, the tree immediately provides 45 minutes for the clearance time. Otherwise, it goes to the next level to decide which type of incident it falls into. After that, it will face the next decision variable (e.g., "Is wrecker used?") and so on. Also, the outcome from this tree is an average clearance time under current conditions which is estimated from the past records.

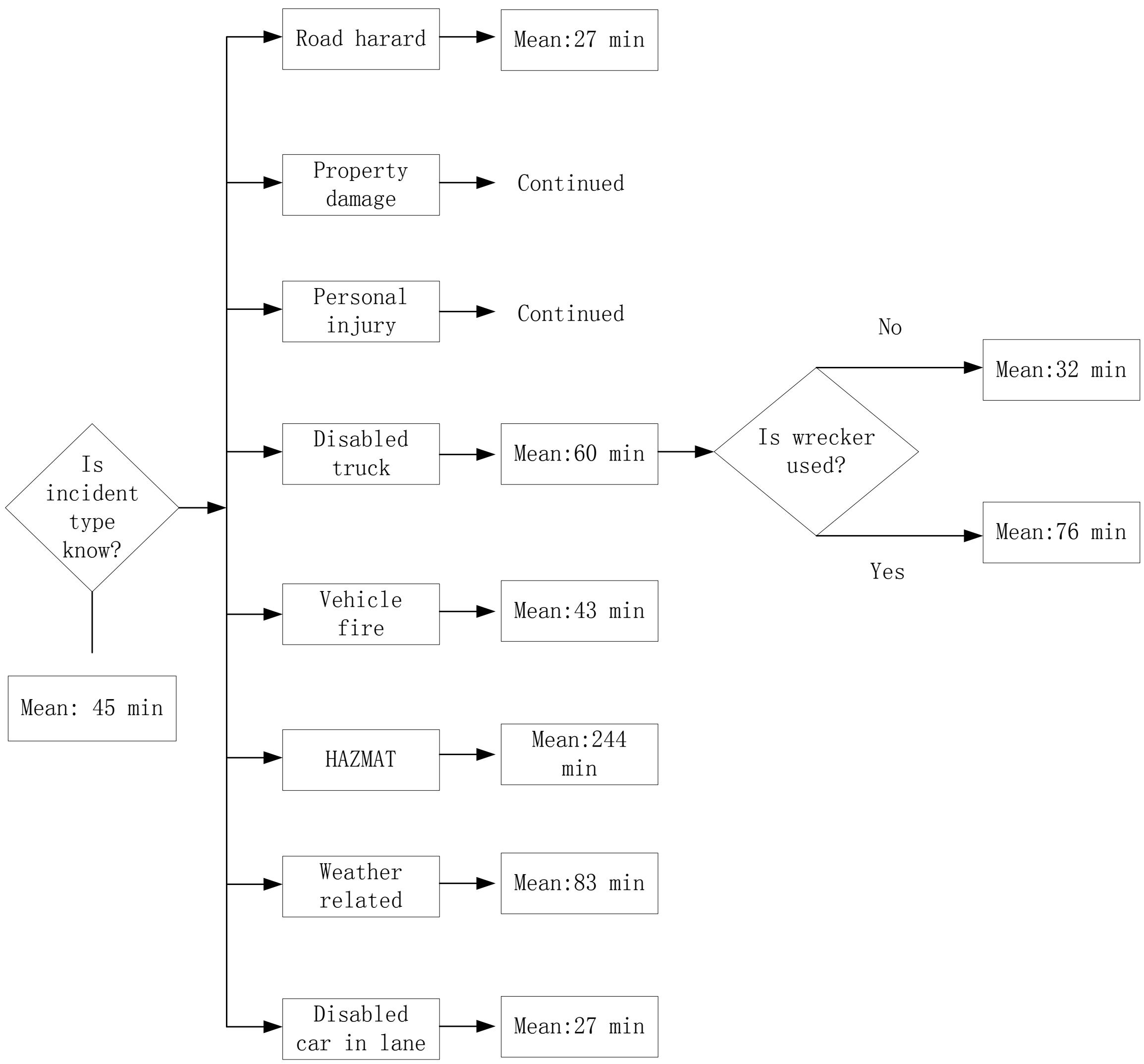


Figure 2. 2 A Part of the Complete Decision Tree to Predict Clearance Time by Ozbay and Kachroo (1999)

Ozbay and Kachroo were satisfied with the new tree, based on the test results since about 57.14 % (44 out of 77) of tested incidents were predicted within 10 minutes of prediction error. They also found that the large differences between predicted and actual clearance time were caused by numerous outliers.

Smith and Smith (2001) who were inspired by the study of Ozbay and Kachroo tried to develop a similar classification tree. They concluded that a classification tree developed on the basis of a reliable and sufficient database performs well, even though the results of their classification tree were not satisfactory due to poor data quality.

The last approach reviewed for this study is the discrete choice model. Most studies in the literature have treated incident duration as a continuous variable. Lin et al. (2004) developed a system that integrates the discrete choice model and the rule based model for predicting incident duration. They first adopted ordered probit models to classify sample data for incident duration into several time intervals, and then developed a rule-based supplemental model to enhance the accuracy of prediction results.

2.3 Optimal Control Strategies

Once the incident has been detected and the incurred duration has been forecasted, it is time to make proper response to the incident. The implementation of proper routing and control strategies in time can help motorists to circumvent the congested segments by detouring through parallel arterials. Such implementation involves diversion, ramp metering, and arterial signal which have been studied by many transportation researchers. Therefore, this study will review the control strategies from the three perspectives: diversion control, ramp metering, arterial signal, integrated control strategies.

2.3.1 Diversion Control

Diversion control can be viewed as an optimal loading balancing strategy to fully utilize the available capacity of a traffic corridor during non-recurrent congestion prioritizing either system-optimal or user-optimal traffic conditions. From the angle of system optimization, the control goal is to minimize or maximize a global performance index without considering whether the cost of taking the detour routes may exceed the regular route. In the view of user optimization, the recommended detour routes are never considered to be more costly than the regular route. Based on the differences among the reviewed diversion control studies in control logic and model formulations, four groups are included in this part: responsive strategies, predictive strategies, iterative strategies, and integrated strategies.

Responsive strategies usually provide guiding plans based on current measurements from the surveillance system, without using mathematical models in real time. Most responsive strategies are localized in nature, i.e., they only generate independent plans for each off-ramp or diversion point. Messmer and Papageorgiou (1994) have proposed several types of simple responsive strategies which assign more or less traffic to alternative routes according to the sign and value of the current travel time difference between both directions, thus aiming to reach optimum conditions for users. Operational systems that employ this kind of decentralized responsive strategy have also been developed and evaluated by the city of Aalborg, Denmark, where they have reportedly improved traffic conditions (Mammar et al., 1996; Dörge et al., 1996).

Extending such simple responsive strategies, multivariable responsive strategies, as well as heuristics and advanced feedback control concepts, have been proposed to address the low sensitivity issue with respect to varying demands and driver compliance rates. Hawas and Mahmassani (1995) proposed a procedure for real-time route guidance in congested vehicular traffic networks. Their decentralized approach envisions a set of local controllers scattered or distributed across the network, where every controller can only extract limited "raw" information from network detectors and utilizes this information to guide the within-territory vehicles to their individual destinations. The assignment procedure is driven by informed local search procedure with heuristics. An assessment undertaken to gauge the performance of this local responsive strategy has yielded encouraging results under different network structures and demand loading patterns. Pavlis and Papageorgiou (1999) developed a feedback-responsive route guidance strategy for complex, meshed traffic networks. Essential components of the strategy are simple, decentralized bang-bang control laws. Their simulation investigation demonstrated the efficiency of the proposed strategy for two example networks under different demand and incident conditions. Wang and Papageorgiou (2000) also examined the performance of multiple feedback routing regulators for freeway networks under different scenarios of disturbances and uncertainties. Some of the factors examined included compliance rate, demand, control interval length, and incidents. Simulation results for such studies also suggest that multivariable feedback routing controllers can efficiently equalize experienced travel times along the alternative routes within the network and perform robustly in many perturbed situations.

Responsive strategies have contributed to considerably reduce travel delays compared to the no-control case. However, they are unlikely to achieve the system optimal traffic state due to the local nature of their control. Their applications in a large traffic corridor network are also limited without the ability to provide information about future traffic conditions under current route guidance settings.

Predictive strategies are generally more robust and preferable compared with responsive strategies since they can employ a dynamic network flow model to predict future traffic conditions under the current route guidance settings, based on the current traffic state, control inputs, and predicted future demands.

A heuristic expert system with predictive route guidance strategies, OPERA (Morin, 1995), was designed to generate guidance information in cases of non-recurrent congestion in the Scottish interurban motorway network. An on-line motorway network simulation model for traffic pattern forecast and an online expert system module for strategy generation have been used in this system. Messmer et al. (1998) have also presented a control scheme which includes both feedback and feed forward terms subject to user-optimal constraints and applied it to the Scottish highway network. Such a system employs the feed-forward term to predict travel times and delays along long interurban highway links. Their simulation evaluation results demonstrate the potential for achieving improvements with these kinds of control measures and control strategies. Wang et al. (2002) has developed a more advanced predictive feedback routing control scheme with the feature of running a mathematical model only once at each time step depending on the predicted routing decisions, rather than the currently prevailing, traffic conditions.

The applicability of predictive strategies needs to be further verified under different topological and traffic conditions, especially under non-recurrent traffic congestion even these strategies are more effective than those relying on responsive logic alone.

Iterative strategies are considered to be predictive in nature and may aim at achieving either the system-optimal or user-optimal condition since they run a freeway network model in real time with a route guidance plan dynamically that adjusts at each time interval to ensure the successful achievement of the control goal.

For the system-optimal case, a set of control formulations usually aims at minimizing a specific network performance index under the constraints of splitting rates at diversion points over a preset time horizon. In this regard, Papageorgiou (1990c) developed a macroscopic modeling framework to resolve the dynamic assignment and the route guidance problem for a multi-destination freeway and/or for road networks with time varying demands. A key variable of the model at each network node is the splitting rates of each traffic sub-flow with a specified destination. On the other hand, several studies have also focused on establishing user-optimal conditions via iterative route guidance strategies (Mahmassani and Peeta, 1993; Ben-Akiva et al., 1997; Wisten and Smith, 1997; Wang et al., 2001). A key procedure embedded in those strategies modified the path assignment or splitting rates appropriately to reduce travel time differences among all alternative routes, which are evaluated by iteratively running a simulation model over a given time horizon.

In the past two decades, other control measures are integrated to diversion strategies. Several studies have documented the benefits of ramp metering with diversion over the scenario with no metering controls. Nsour et al. (1992) investigated the impacts of freeway ramp metering, with and without diversion, on traffic flow. Also, Moreno-Banos et al. (1993) presented an integrated control strategy addressing both route guidance and ramp metering, based on a simplified traffic flow model. The same problem was also addressed by Elloumi et al. (1996) using a linear programming approach. More advanced integrated control strategies have been developed to generate optimal route guidance schemes concurrently with other control measures (Cremer and Schoof 1989; Chang et al., 1993; Papageorgiou, 1995; Zhang and Hobeika, 1997; Wu and Chang, 1999b; Van den Berg et al., 2001; Kotsialos et al., 2002).

2.3.2 Ramp Metering

This part emphasizes the review of on-ramp metering strategies that include pre-timed metering strategies, traffic-responsive metering strategies, and coordinated ramp metering strategies.

Pre-timed metering strategies generally aim to determine the metering rates at off-line for different times of day, based on the normal daily demand pattern and freeway capacities. Wattleworth (1963) developed a ramp metering model using a linear programming method with the objective of maximizing total entering flow rates within the constraints of freeway mainline capacity and the physical upper and lower bounds of metering rates at each ramp. Lovell and Daganzo (2000) extended Wattleworth's steady-state mode to include time-dependency and developed a computationally-efficient greedy heuristic solution.

Pre-time ramp metering strategies are not suitable for addressing non-recurrent congestion scenarios since they are applied with the assumptions that the traffic demand patterns are static or time-dependent which is not available or is difficult to reliably estimate in real-world operations. However, traffic responsive strategies are designed to compute suitable ramp metering values based on real-time traffic measurements (freeway speed, volume, density and occupancy). Papageorgiou et al. (1991) proposed a closed-loop ramp metering strategy (ALINEA), using a well-known classical feedback theory in the following form:

$$r(k) = r(k-1) + K_R[\hat{o} - o_{out}(k)] \tag{2.1}$$

Where K_R is a positive regulator parameter; $\hat{o}$ is a desired value set for downstream occupancy (typically set to O_{cr} to have the downstream flow close to q_{CAP}). Compared with the demand-capacity strategy, the ALINEA strategy adjusts the metering rates in response to even slight differences of $\hat{o} - o_{out}(k)$ instead of to a threshold value of O_{cr}; thus, it may prevent congestion by stabilizing the traffic flow at a high throughput level.

Responsive metering strategies are effective in reducing freeway congestion. However, they need appropriate values or relations to be preset, and the scope of their actions is more or less local. Coordinated metering strategies are developed to avoid these deficiencies that have been studied in a large body of literature. a sophisticated macroscopic traffic flow model combined with optimal control theory to determine ramp metering rates has been employed in the literature (Blinkin, 1976; Papageorgiou and Mayr, 1982; Bhouri et al., 1990; Stephanedes and Chang, 1993; Chang et al., 1994; Papageorgiou, 1995; Chen et al., 1997; Zhang and Recker, 1999; Chang and Li, 2002; Kotsialos et al., 2002; Kotsialos and Papageorgiou, 2004). In general, a set of dynamic traffic flow models for both freeways and on-ramps to capture the evolution of traffic state variables and to model the physical boundaries or real-world operational constraints have been embedded in these strategies with an objective criterion to be optimized. Finally, numerical solution algorithms are developed to solve the optimal control model to yield the target metering rates.

In summary, ramp metering has direct and efficient measures to mitigate freeway congestion; proper implementation can achieve various positive effects on corridor operations, including an increase in the freeway mainline throughput and the effective utilization of excess capacity on parallel arterials. However, the implementation of ramp metering may increase the cost of excessive queues at the on-ramp which will spill back and block neighboring urban arterials and off-ramps. Therefore, optimal ramp metering strategies should be implemented jointly with other strategies, such as diversion control and arterial signal timing optimization, to achieve a better performance for the overall corridor network.

2.3.3 Arterial Signal Control

Signal control has been widely accepted as an effective strategy to increase arterial capacity and to mitigate congestion during daily traffic scenarios. Coordinated signal optimization practices have been employed by researchers to address non-recurrent congestion situations for normal traffic conditions at high demand levels. This part will review the key models for coordinated arterial signal optimization along the following three lines: mathematical models, simulation-based approaches, and dynamic traffic control formulations.

In the category of mathematical models, a mixed integer linear programming (MILP) model (Gartner et al. 1975a,b) has been developed to minimize intersection delay. With MILP as the underlying mathematical optimization model, MAXBAND (Little et al., 1981) has been designed to find the optimal cycle length, offsets, and left-turn phase sequence for preset green splits to maximize the bandwidth. This model has been further extended to deal with coordinated signal control in corridors by Chang et al. Despite the aforementioned progress in the literature, issues of having heavy or unbalanced turning movements that may disrupt the progression bandwidth for arterial through traffic have not been addressed.

Considering such limitations, some researchers proposed to use simulation-based models to minimize total system delays and stops or maximize the system throughput by combing nonlinear optimization with macroscopic traffic models. Examples of such models are TRANSYT (Robertson, 1969), TRANSYT-7F (Wallace et al., 1988), SIGOP (Lieberman et al.,1983), and SYNCHRO (Husch et al., 2003). Also, mesoscopic or microscopic traffic-simulation-based optimizers have been developed to design signal timings for arterials. Park et al.(1999) developed a mesoscopic-based optimizer with GA as the searching technique and it achieved promising results compared with TRANSYT-7F under different traffic demand patterns.

Dynamic traffic control formulations have been proposed to mathematically represent the complex interactions between traffic state evolution and key control parameters. Kashani and Saridis (1983) have developed an urban arterial traffic flow model based on horizontal queues over large time steps. Lo et al. (2001) has proposed and integrated the cell transmission models with a MILP model for signal optimization.

2.3.4 Integrated Control Strategies

The aforementioned research efforts on various aspects of traffic control have made an invaluable contribution to the development of control strategies and operational guidelines for freeway incident management Usually, diversion strategies, ramp metering and arterial signal timing optimization should be implemented jointly, rather than independently, when incidents occurs on freeway segments. Studies (Reiss et al., 1981; Van Aerde and Yagar, 1988) in such areas focused mainly on modeling and simulation analyses.

The above control strategies can make great contribution to reduce delay under freeway incidents. However, implementation such strategies usually demand substantial amount of resources and manpower which cannot be ignored. Hence, prior to implementation of such control strategy, traffic managers need a set of well-justified warrants. The following section will review some of previous studies to explain whether a decision needs to be implemented or not.

2.4 Decision Making for Detour Operations

This author mainly focused on implementing traffic diversion to reduce the congestion under freeway incidents. Hence this section will review literature on exploring the necessity of implementing detour operations for incident management.

Manual on Uniform Traffic Control Devices (MUTCD) states that major and intermediate incidents lasting more than 30 minutes usually require traffic diversion or detouring for road users due to partial or full roadway closures, while traffic diversion even into other lanes may not be necessary, or needed only briefly for minor incidents usually cleared within 30 minutes.

Another notable source for guiding the detour plan development is the Alternate Route Handbook. This report provides comprehensive and general guidelines for how to plan and execute the alternate route plan with various stakeholder agencies. According to this document, key factors to be considered in establishing criteria for detour plan implementation include incident duration, number of lane blockage, observed traffic condition, time of day, and day of week. The capacity of the proposed alternative route and its background traffic are also critical factors. It also summarizes the criteria currently used to decide whether or not to execute the pre-developed alternate route plan in a variety of states (see Table 2.1).

Table 2.1 Criteria for Deciding the Implementation of Detour Plans in Various States

AGENCY	CRITERIA
North Carolina DOT – main office	• A complete closure of the highway in either direction is anticipated for 15 minutes or longer.
North Carolina DOT – Charlotte regional office	• No action or discussion occurs until 15 minutes after the incident. After 15 minutes, an alternate route plan is deployed only if the highway is completely closed (all lanes closed, including the shoulder) and expected to last longer than an additional 15 minutes (30 minutes total).
New Jersey DOT	• Level 1: Lane closures on a State highway, expected to have prolonged duration and impact on traffic. • Level 2: Complete closure of highway, anticipated to last more than 90 minutes.

Oregon DOT	• Incident with two or more lanes blocked, or • Incident with one lane blocked and expected to last more than 20 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 2 hours.
ARTIMIS (Ohio/Kentucky)	• This plan has a detailed table with four different levels, based on criteria. The following represents a summary: - During the morning and afternoon peak hours, an advisory alternate route is deployed in the event of a two-lane closure for more than 2 hours, or a closure of more than two lanes for less than 30 minutes. - Mandatory alternate routes are deployed during the peak hours when more than two lanes are closed for at least 30 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 30-120 minutes from detection to fully restored traffic flow. - Level D is an incident taking over 2 hours from detection to fully restored traffic flow (including full freeway closure in one or both directions).
Wisconsin DOT (Blue Route)	• Incident causes delays that will exceed 30 minutes.

Source: *Alternate Route Handbook (2006)(FHWA, 2006)*

As indicated in Table 2.1, most state agencies use only the incident duration and lane blockage information for making the detour decision. Most importantly, there are many other factors that may affect the traffic manager's final decision on whether or not to implement detour operations during an incident, such as traffic volumes on the freeway and the detour route, percentage of trucks, the incident duration and number of lanes blocked, the number of signals on the detour route, level of driver compliance rates, the distance of the detour route, and the expected benefits if detour is implemented, etc. Detour operations without considering those potential affecting factors may result in waste of traffic management resources as well as exacerbation of corridor traffic congestion and economic loss.

To further illustrate how other factors may contribute to warranting detour decisions by different highway agencies, Kim et al. (2010) has performed a preliminary analysis based on an incident dataset in their study. Figure 2.3 presents the results on the distribution of detour/no detour decisions by several affecting factors other than the incident duration. In Figure 2.3, we can identify some observable relations between affecting factors and the detour decisions. For example, there exhibits trend that as the number of freeway lanes increases, it is less likely to make a decision for implementing detour operations, while when the number of lanes in the detour route increase, and it is more likely to make a decision for implementing detour operations. It can also be observed that some detour decisions have an obvious effect by the freeway volumes, indicating that the likelihood of implementing detour operations increases with the freeway volume. The lane blockage ratio also shows a fairly notable impact on detour decision-making in terms of increasing the likelihood of promoting the detour operation. However, there are few references to quantify such relations, or it is more likely to be determined by personal experience or judgment. Moreover, there must be some hidden joint effects of those affecting factors that have not been discovered yet by previous studies. Such findings indicate the need for more comprehensive criteria and tools based on rigorous analyses to support detour decisions that some time may have to be made even by non-experienced traffic mangers.

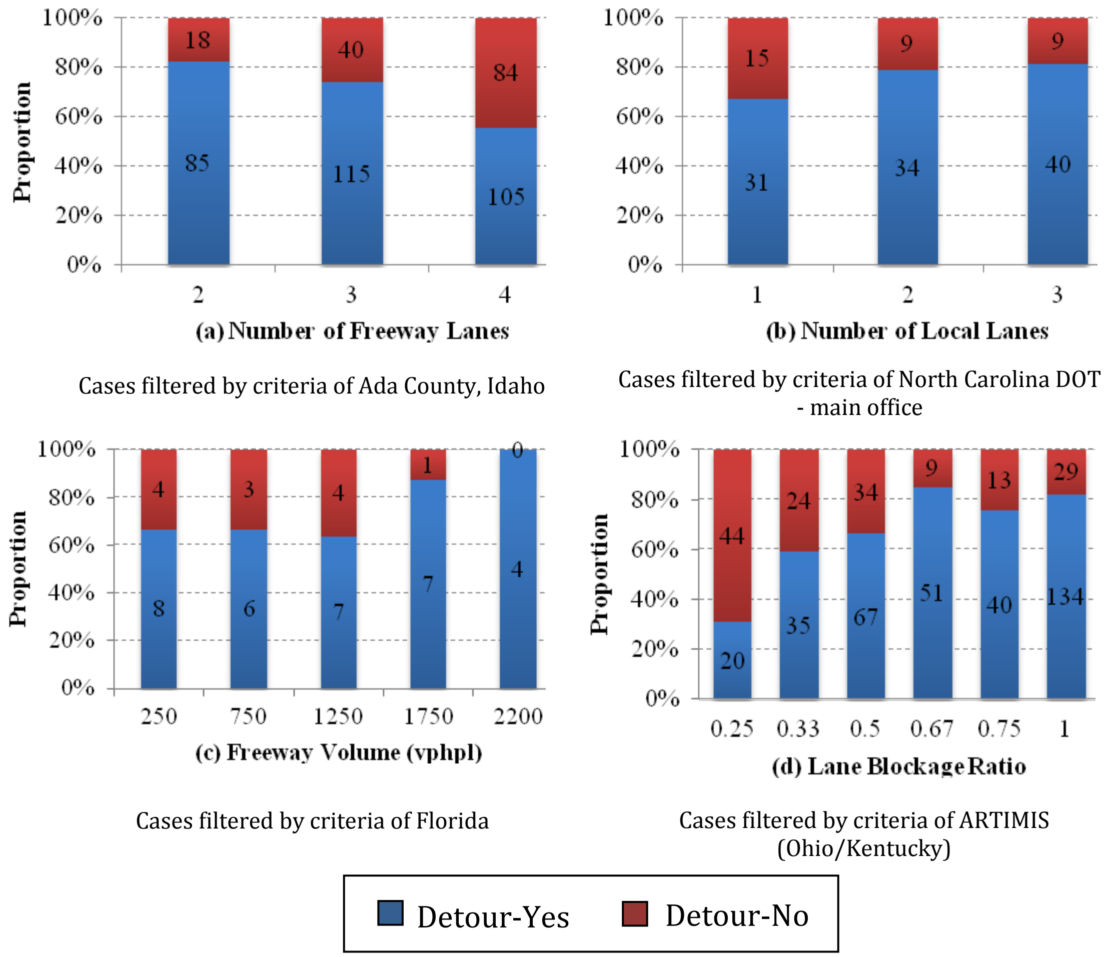


Figure 2.3 Proportional Distribution of Decisions by Potential Factors (Kim et al. 2010)

In review of the above limitations in the existing studies and the additional requirements for real-time incident management, this study aims to develop a new multi-criteria detour warrant tool for effectively ameliorating the impacts of incident and improving mobility of vehicles in the freeway corridor system contending with incident management.

Chapter 3

MODELING FRAMEWORK

The proposed multi-criteria detour framework aims to achieve best detour decisions for responsible managers to effectively ameliorate the impacts of incident and improving mobility of trucks and all other vehicles in the freeway corridor system. To achieve the intended objective, modeling efforts must effectively take into account the interactions between all critical system components under the incident conditions. Some major research issues to be addressed in developing such a multi-criteria framework system are listed below:

- Detection of an incident, which yields the time, location, severity, truck involvement, weather condition, duration of an incident occurring on the freeway mainline segment;
- Development of a well-calibrated corridor simulation network and a comprehensive set of experimental scenarios including the key factors that may affect the traffic manager's final decision whether or not to implement detour operations, such as freeway related factors, incident related factors, detour route related factors and driver related factors;
- Construction of optimal traffic control models, including identification of the proper control objectives based on the incident nature and available corridor capacity so as to effectively optimal detour strategies under an integrated operational framework;
- Development of a set of reliable and convenient statistical models that allow responsible traffic managers to make best detour decisions during real-time incident management; and

- Estimation of benefits from detour plans generated from the developed detour decision model so as to be served as one of the direct criteria to validate the detour decision.

It should be noted that all above tasks are interrelated and each is indispensable for the implementation of a multi-criteria detour system. In view of the large body of literature on incident detection and optimal detour operations under freeway incident, this study will focus on the development of detour decision-making models. The next section will identify critical requirements to be fulfilled by each proposed system component.

3.1 Required System Input

3.1.1 Incident Information

Incident information, which is key inputs of the proposed multi-criteria detour framework, can be generated as followings:

- Time and location of an incident that has occurred;
- Duration of the incident;
- Severity of incident
- Truck involvement during incident
- Weather condition during incident

3.1.2 Corridor Network

To ensure that the proposed detour warrant tool is effective under a wide range of incident scenarios and roadway geometric and traffic conditions, an experimental freeway corridor network that include segments of the freeway mainline experiencing an incident, on-ramps and off-ramps, upstream and downstream of the incident location, and connecting parallel detour route. This information can be summarized as following which will be showed in next chapter:

- Network Configuration
- Connectivity
- Signals

3.1.3 Experimental Scenarios Design

The above required input associate with other key factors that may affect the traffic manager's final decision on whether or not to implement detour operations are organized into the following groups to design a comprehensive set of experimental scenarios.

- **Freeway-related factors**: flow rate on the freeway mainline and the number of lanes on the freeway mainline;
- **Incident-related factors**: incident duration and the number of lanes blocked;
- **Detour route-related factors**: flow rate on the road connecting from freeway to detour route, flow rate on the parallel route, flow rate on the road connecting from the detour route back to the freeway, and the number of lanes and signals on the detour route; and

3.2 Modeling Framework

In view of the above input requirements, Figure 3.1 depicts the framework of the multi-criteria detour system for incident management, highlighting interrelations between principal system components. This study will focus on the detour decision models highlighted in the figure's dark gray box.

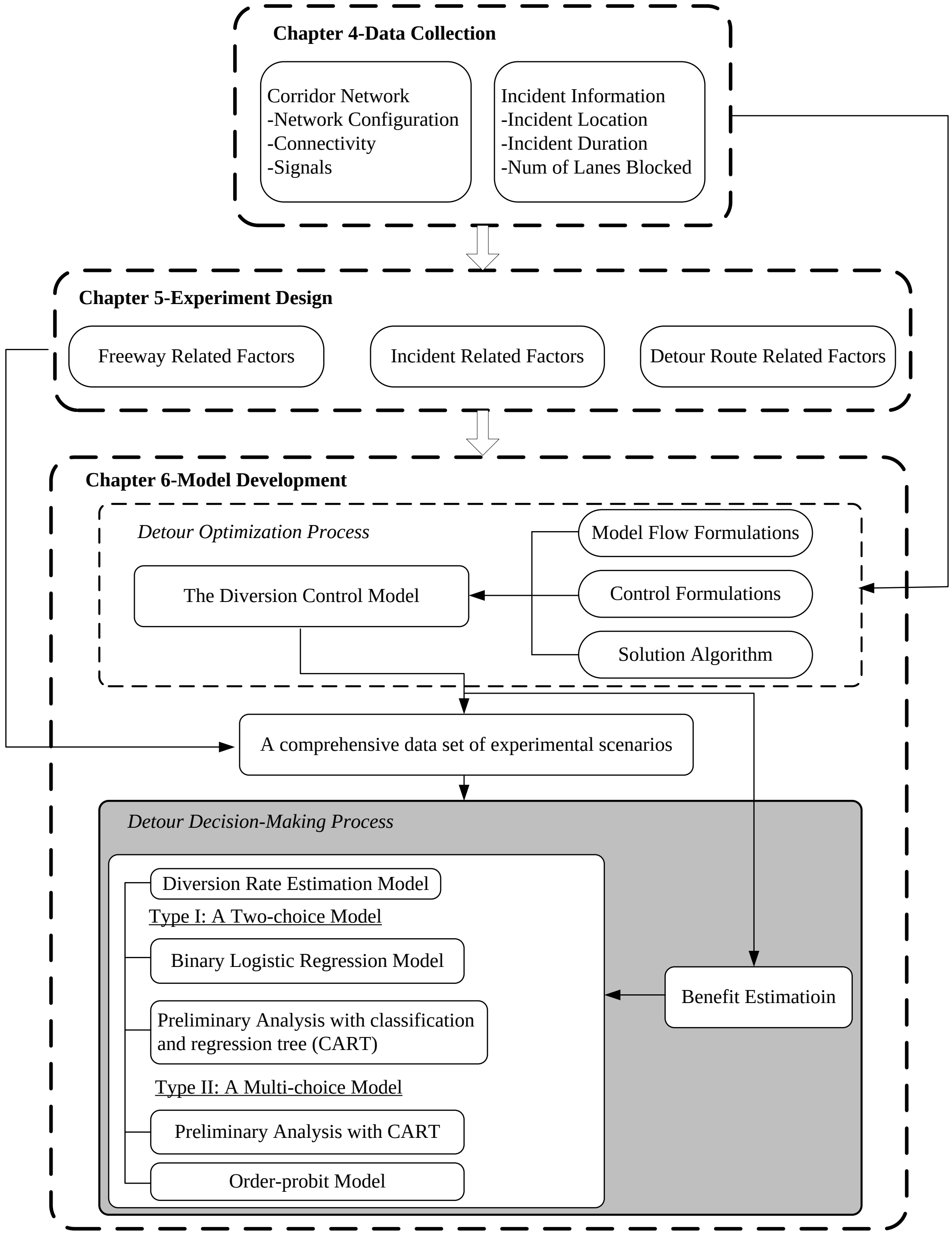


Figure 3. 1 A Modeling Framework of the Proposed System

Note this framework applies a hierarchical model development structure. Each previous component is necessary for the development of the following model. A brief description of each key system component is presented below:

- **The diversion control model**: This component is employed to determine the best diversion rate that yields the minimum total corridor delay for each scenario (designed in chapter 5). The diversion rate will be used in decision model Type I. This component will also generate the total travel time and total time in queue which can be as input to benefit estimation model.
- **Diversion rate estimation model**: This part is to figure out how the potential factors affect the final optimal detour rate in a given scenario, i.e. what trend (higher or lower) could the optimal detour rate be at a certain incident situation
- **Type I A two-choice model:** This model will apply the best diversion rate generated from the diversion control model and then set a minimum threshold value for the diversion rate on the alternative route to convert the decimal diversion rate into a binary decision. A preliminary analysis with classification and regression tree (CART) is embedded to better develop a binary logistic regression model. Details about this procedure will be presented in chapter 6.
- **Type II A multi-choice model:** This component aims to develop a hybrid multi-criteria decision process which consider multiple factors that may affect the traffic manager's final decision on whether or not to implement detour operations. It will yield 5 types of decisions (i.e., "strongly recommended", "recommended", "neutral", "NOT recommended", and "strongly NOT recommended"). A preliminary analysis with CART is embedded with the multi-choice model to classify the category of independent variables and select the category of dependent variables according to

overall prediction accuracy of every tree. Then the ordered-probit model is developed with results of the preliminary analysis. It will yield 5 types of decisions (i.e., "strongly recommended", "recommended", "neutral", "NOT recommended", and "strongly NOT recommended") based on the re -categorized independent variables and selected categories of dependent variable coming from CRT model.

- **Benefit estimation**: The primary goal of this component is to consider the resulting benefits for comparison with the operational costs using the output from the diversion control model. The benefit analysis can be a way to validate the developed detour decision model, since it shows us whether the implemented detour plan is truly beneficial or not from the overall societal perspective.

The applicability of the developed two types of models will be evaluated based on the statistical significance of their associated explanatory factors and the overall goodness of data fit. With such models one can reliably warrant the detour operation for any given incident scenario.

Chapter 4

DATA COLLECTION AND EXTRACTION

4.1 Highway Description

The area of study for this project consists of the IH-94 corridor between the city of Madison where IH-94 connects with IH-39/90 and the city of Milwaukee where it connects to IH-43. The segment covers approximately 70 miles of mostly rural highway from IH-39/90 until reaching Milwaukee County at which point it continues on as an urban highway.

4.2 Data Sources

All data collected for the initial dataset came from the Wisconsin TOPS Laboratory operated by the University of Wisconsin – Madison. There are multiple databases containing crash and incident information maintained by the TOPS Lab. The author chose two, the MV4000 Crash Data database as well as the InterCAD to complete the preliminary data set. While it would have been preferable to query and use only one database, neither of these databases was complete, and therefore needed to supplement each other. It is for this reason that the dataset is comprised of only two years of data rather than the originally intended 5 years. While the MV4000 database now covers over 18 years of incidents, the InterCAD database contains only 2 years and limits the scope of the data set accordingly.

4.2.1 MV4000

The MV4000 Crash Data Retrieval Facility is a database maintained by the TOPS Laboratory with crash data from all reportable crashes in Wisconsin with data available from 1994 to the present year. The MV4000 data set contains an abundance of information, and is what the majority of the preliminary data set was built using. The MV4000 database uses standardized data fields to describe each incident. A sample of what the retriever tool looks like is shown in Figure 4.1. Data was retrieved for the years 2010 and 2011 to match the time period that was available from other sources.

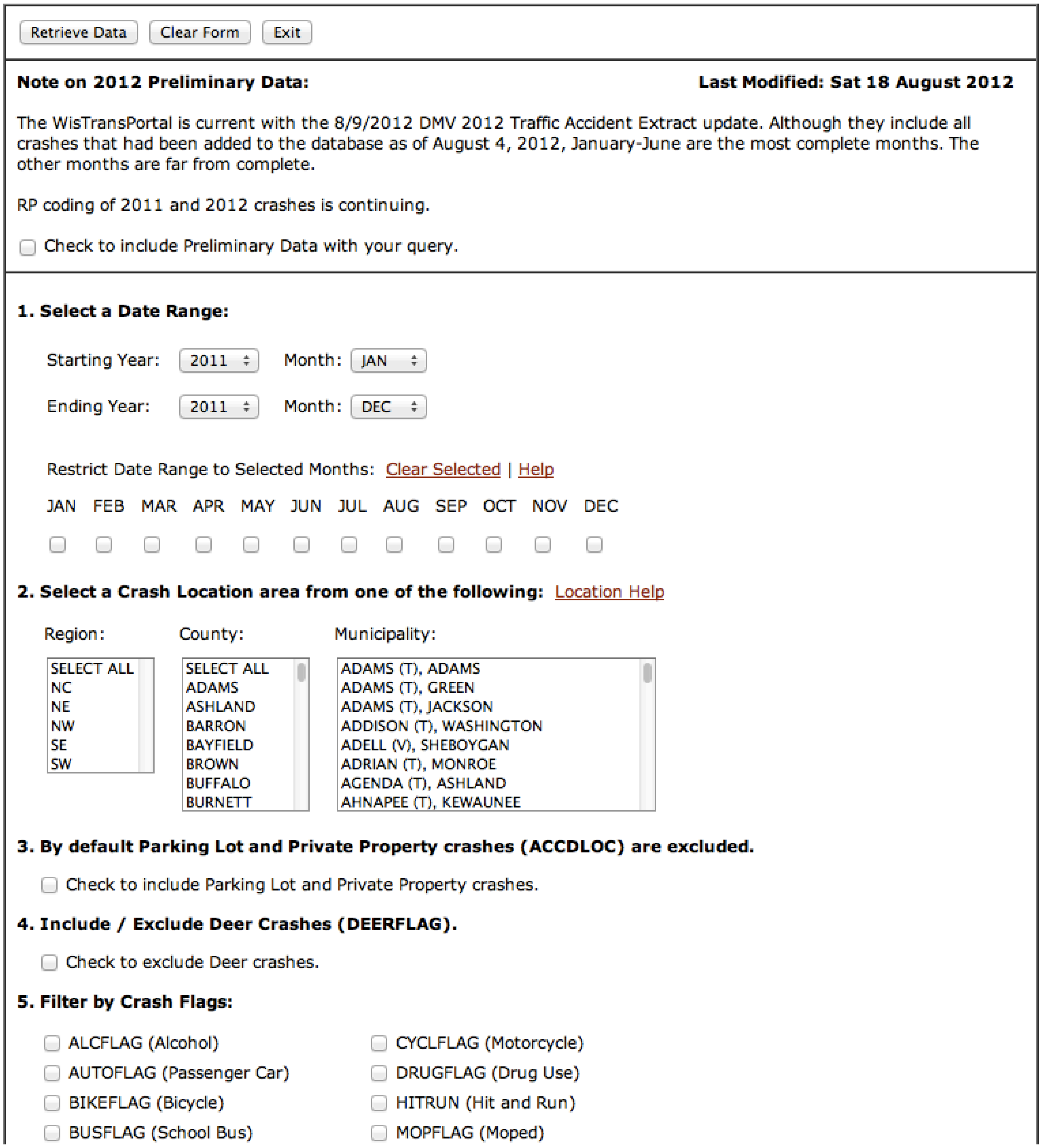


Figure 4. 1 Retriever Tool

The retrieval facility provides the user with information in a web based presentation of the data and allows the user to download the information in a comma separated values (.csv) format.

4.2.2 InterCAD Traffic Incident Data

The second database used for the study was the InterCAD Traffic Incident Data database (InterCAD). This database, while it contains much less data than the MV4000 database contains the detection and end time for each incident, which is absolutely necessary for a complete database. In rare cases the InterCAD database was able to act as a supplement to MV4000 due to missing or insufficient data. While InterCAD does contain a free text field, this data is not standardized in any way, and cannot be compared consistently to other data points. Figure 4.2 shows the user interface for the InterCAD Data Retrieval Facility.

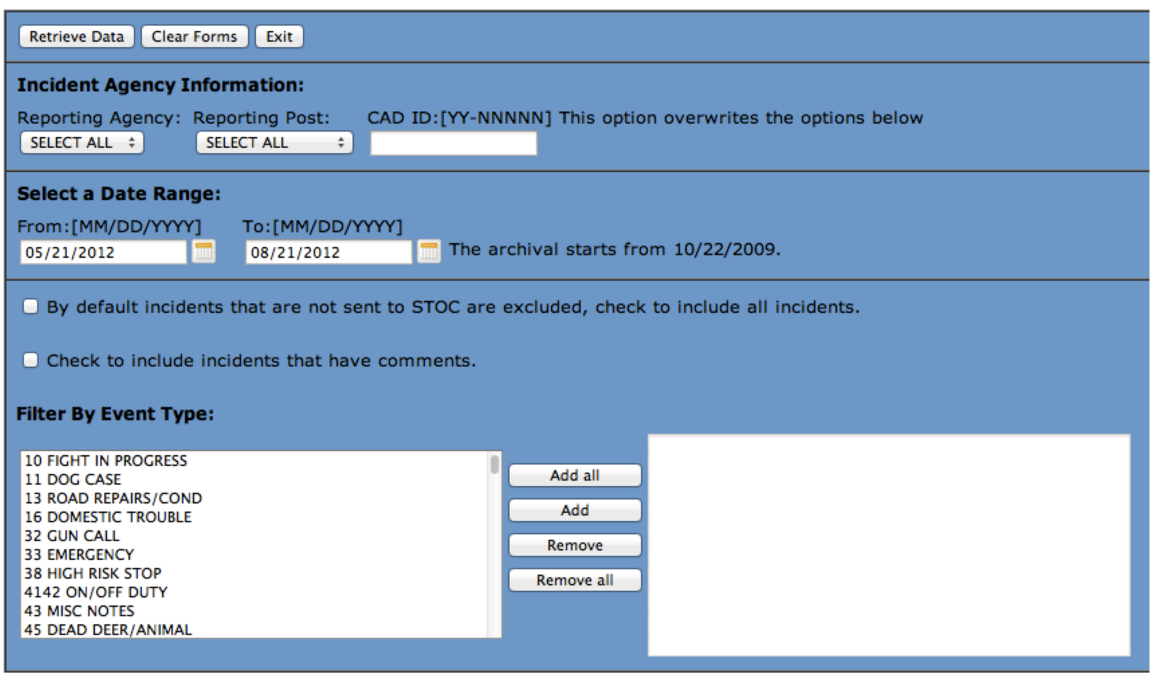


Figure 4. 2 InterCAD Data Retrieval Facility

InterCAD, like MV4000 provides users with both a web based interface as well as an option to download the data in a comma separated values format.

4.3 Data Compilation

4.3.1 Database Merging

As stated previously, two databases were used as sources for this project. The goal of the preliminary data collection was to produce a single data set from which to perform the analysis, so it was necessary to combine the two databases. There was no automated way to perform this task. The dataset was constructed by manually matching incidents between MV4000 and interCAD. Figure 4.3 is a screenshot of the databases combined into one spreadsheet.

	A	B	C	D	E	F	G	H	I	J
1	DOCTNMBR	ACCDDATE	ACCDTIME	ACCDYEAR	ACCDMTH	DAYNMBR	ACCDHOUR	ARHOUR	ARMIN	NTFYDATE
15015	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63134	11	50PD crash-pr	12/21/11 16:37	12/21/11 17:37	175 RAMP NB	
15016	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63147	12	AOA assist oth	12/21/11 17:56	12/21/11 18:11	CNTY H AND GLENN VALLE	
15017	A437781	12/21/11	1757	2011	DEC	WED	17	0	0	12/21/1
15018	P4V30FJ	12/21/11	1827	2011	DEC	WED	18	18	30	12/21/1
15019	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63152	11	50PD crash-pr	12/21/11 18:29	12/21/11 19:40	94 EB TO HWY 73 SB	
15020	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63168	19	50PD crash-pr	12/21/11 21:05	12/21/11 21:41	114EB	
15021	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63173	10	AOA assist oth	12/21/11 21:53	12/21/11 22:40	12/SHADY LANE	
15022	A132715	12/21/11	2330	2011	DEC	WED	23	0	0	12/21/1
15023	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63189	10	50PD crash-pr	12/22/11 2:04	12/22/11 3:32	I90 @ 112	
15024	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63193	9	50PD crash-pr	12/22/11 3:21	12/22/11 3:40	92.4 WB	
15025	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63199	7	50 crash	12/22/11 7:24	12/22/11 8:00	119.6NB	
15026	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63201	11	AOA assist oth	12/22/11 7:47	12/22/11 8:12	N5356 CTY J	
15027	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63202	8	50 crash	12/22/11 8:02	12/22/11 8:42	CTY F MI WOF DARLINGTO	
15028	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63211	7	50 crash	12/22/11 8:36	12/22/11 9:42	E SPRINGS AT HI XING.. A	
15029	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63242	4	AOA assist oth	12/22/11 11:03	12/22/11 12:13	147EB	
15030	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63265	11	50PD crash-pr	12/22/11 12:14	12/22/11 13:00	92WB	
15031	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63266	5	AOA assist oth	12/22/11 12:17	12/22/11 13:12	MILTON AV, JVL	
15032	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63299	7	70 fire	12/22/11 14:58	12/22/11 15:26	174EB	
15033	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63339	10	46D road debr	12/22/11 20:08	12/22/11 20:52	276WB	
15034	A437746	12/23/11	5	2011	DEC	FRI	0	0	0	12/23/1
15035	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63363	8	AOA assist oth	12/23/11 0:50	12/23/11 1:11	319 SOUTH ST APT 2 JC	
15036	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63367	9	AOA assist oth	12/23/11 2:57	12/23/11 4:06	327 LODI ST UNIT A	
15037	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63370	4	AOA assist oth	12/23/11 3:36	12/23/11 4:19	527 HILLSIDE RD	
15038	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63409	10	50PD crash-pr	12/23/11 10:50	12/23/11 11:25	132EB	
15039	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63418	8	AOA assist oth	12/23/11 11:22	12/23/11 11:49	29231 WILKINSON RD / N	
15040	P4V573C	12/23/11	1135	2011	DEC	FRI	11	23	35	12/23/1
15041	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63428	13	46D road debr	12/23/11 11:50	12/23/11 12:10	131.8WB	
15042	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63468	6	46D road debr	12/23/11 15:19	12/23/11 15:19	HY33/ CTH W	
15043	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63473	8	46D road debr	12/23/11 15:41	12/23/11 15:57	123 EB	
15044	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63475	4	AOA assist oth	12/23/11 16:09	12/23/11 16:56	DEFOREST POST	
15045	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63477	13	RO runoff/slid	12/23/11 16:43	12/23/11 18:02	HY 41NB AT HY 49 MEDIAN	
15046	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63480	12	50PD crash-pr	12/23/11 16:47	12/23/11 18:25	HY 41NB AT HY 49	
15047	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63494	8	50 crash	12/23/11 18:29	12/23/11 20:29	41 NB 1MI HWY 67	
15048	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63499	6	AOA assist oth	12/23/11 18:59	12/23/11 19:31	HWY B LOWER ROCK LAKE	
15049	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63501	11	50 crash	12/23/11 19:02	12/23/11 20:06	246 WB	
15050	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63502	5	50PD crash-pr	12/23/11 19:03	12/23/11 19:04	246WB AT BAXTER	
15051	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63514	11	50PD crash-pr	12/23/11 22:52	12/23/11 23:55	78 S OF WALKER RD	
15052	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63583	10	50PD crash-pr	12/24/11 11:39	12/24/11 12:17	KWIK TRIP, North Central E	
15053	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63597	8	AOA assist oth	12/24/11 12:49	12/24/11 13:17	WEST BARABOO	
15054	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63601	14	46D road debr	12/24/11 13:00	12/24/11 13:20	173EB	
15055	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63602	11	50CD crash-ca	12/24/11 13:05	12/24/11 13:43	251EB	
15056	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63645	13	50PD crash-pr	12/24/11 17:11	12/24/11 18:13	108 EB	
15057	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63655	5	AOA assist oth	12/24/11 20:04	12/24/11 21:08	OFFICER SAFETY ATL	
15058	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63661	4	AOA assist oth	12/24/11 20:33	12/24/11 20:34	CHECK WELFARE FOR MAD	
15059	A308924	12/24/11	2255	2011	DEC	SAT	22	0	0	12/24/1
15060	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63694	6	AOA assist oth	12/25/11 2:28	12/25/11 2:59	COST CUTTERS LAKE MILL	
15061	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63695	17	RO runoff/slid	12/25/11 2:51	12/25/11 4:49	148.5 WB	
15062	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63696	15	50PD crash-pr	12/25/11 2:52	12/25/11 3:27	95 WB	
15063	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63697	14	50PI crash-inj	12/25/11 3:36	12/25/11 4:37	147 EB	
15064	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63745	4	AOA assist oth	12/25/11 12:31	12/25/11 15:08	DEFOREST POST	
15065	C7VGV3K	12/25/11	1310	2011	DEC	SUN	13	13	26	12/25/1
15066	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63753	12	50 crash	12/25/11 13:13	12/25/11 14:31	EB AT JEFF CO REST AREA	
15067	WSP-D1P11-6	WSP Wisconsi	D1 DeForest	D1:P11-63804	11	50 crash	12/25/11 19:29	12/25/11 19:45	154 EB INTO MEDIAN	

Figure 4. 3 A Screenshot of the Databases Combined into One Spreadsheet

Figure 4.3 shows a screenshot if the databases after having been combined by the data team. An algorithm written by the data team encoded in a column the date and time of each incident regardless of what database it came from. One database was highlighted, and then they were sorted by date and time. By highlighting one database and sorting by date and time the process of matching data points that described a common incident became much easier. This process was very labor intensive, as each match must be evaluated on as many factors as possible to ensure that a false match is not made. At many times there were multiple crashes in an area in a fairly short time period. Identifying information such as whether the age of the driver is mentioned in both databases helps to make a positive match. The author was careful to reject a match when in doubt as to not throw off any of the data in the final data set.

4.3.2 Final Data Set

The merging of the database was not the final step in developing the dataset. The final data set consists of a new layout in the most advantageous manner for this study. Data fields that were deemed useful by the author were included in the final database, as well as fields generated by the author. Examples of fields generated include time parameters that were generated from existing fields in the data, some data that required a conversion from text to numeric form in cases where the author found that it would be more useful, as well as cases where it was necessary to generate a field that depended on multiple other fields. To create a field that tells the user whether or not trucks were involved in a given incident, that field must be dependent on all fields describing vehicle type.

4.4 Data Extraction and Analysis

Distributions of the data set were made for various data categories. These distributions are helpful to understand the data.

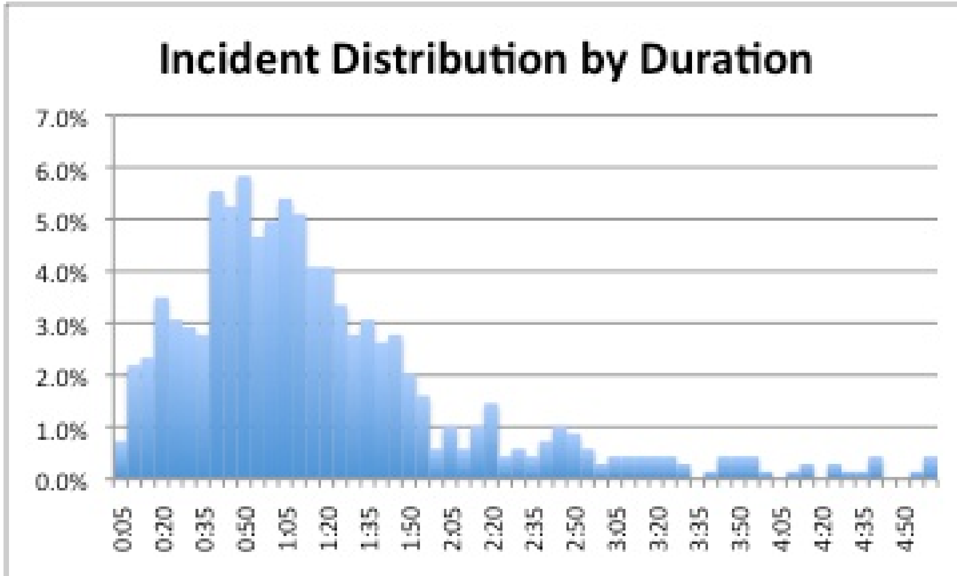


Figure 4. 4 Incident Distributions by Duration

Figure 4.4 indicates the distribution of incidents by the duration. This data appears to be distributed in a way that can be normalized using a translation.

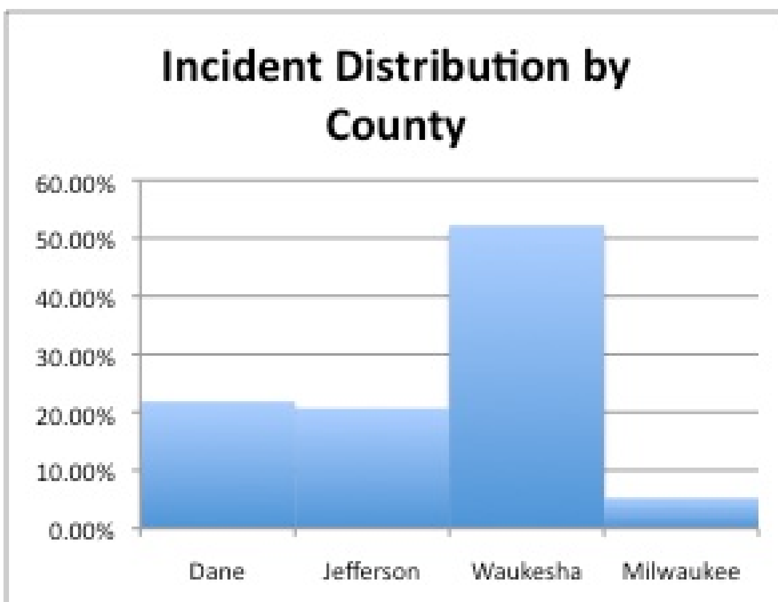


Figure 4. 5 Incident Distributions by County

As indicated by Figure 4.5, most of the incidents occurred in Waukesha County. While this would appear to indicate that Waukesha County experienced a higher rate of traffic incidents that would not be a correct assumption. This distribution simply means a large portion of the incidents studied in this manuscript occurred in Waukesha County, and that a relatively small portion occurred in Milwaukee County.

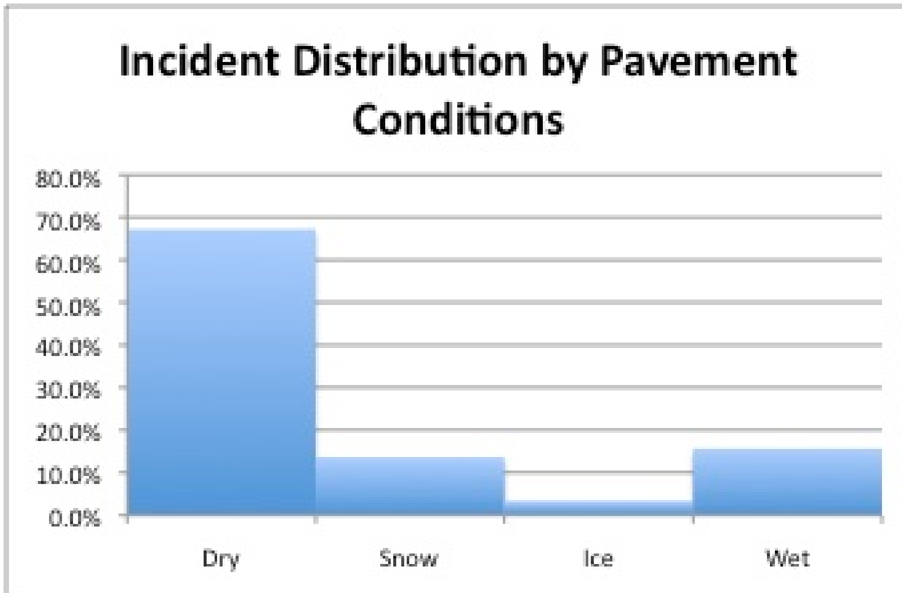


Figure 4. 6 Incident Distributions by Pavement Conditions

Figure 4.6 indicates the proportions of incidents that occurred in each pavement condition. This figure shows that the majority of incidents took place during dry conditions. While ice would seem to be the most detrimental road condition to safe travel, those pavement conditions most likely only prevailed during a very limited amount of time.

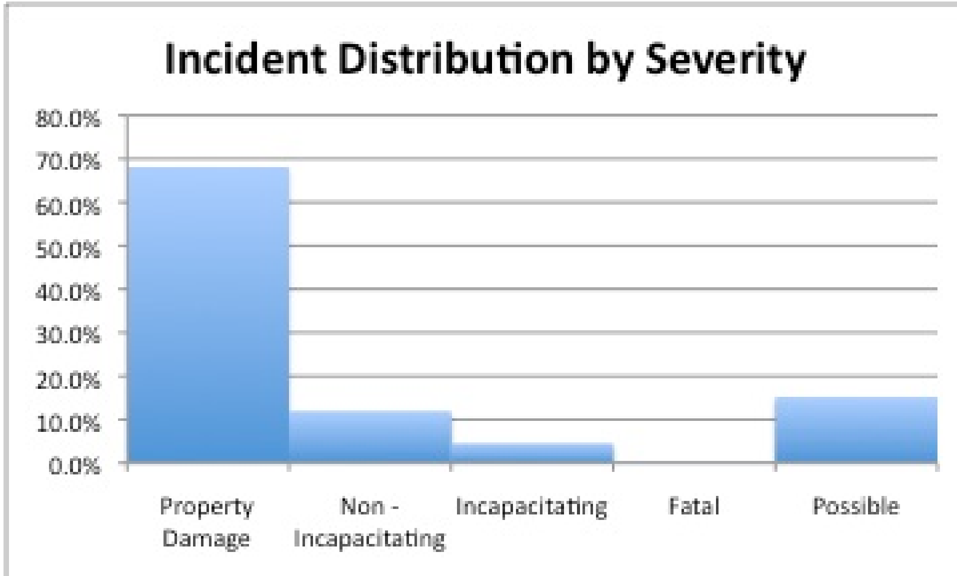


Figure 4. 7 Incident Distributions by Severity

The data set is made up of mainly property damage only crashes. The final category, "possible" appears to most likely represent incidents that were inconclusive to the responders, or that the investigation was completed after the MV4000 report was filed. While these incidents may have been anything from property damage to fatal crashes, it was apparent that these incidents described by "possible" were relatively minor incidents in which the injuries, if they existed were not a large factor in any aspect of the incident or its resolution.

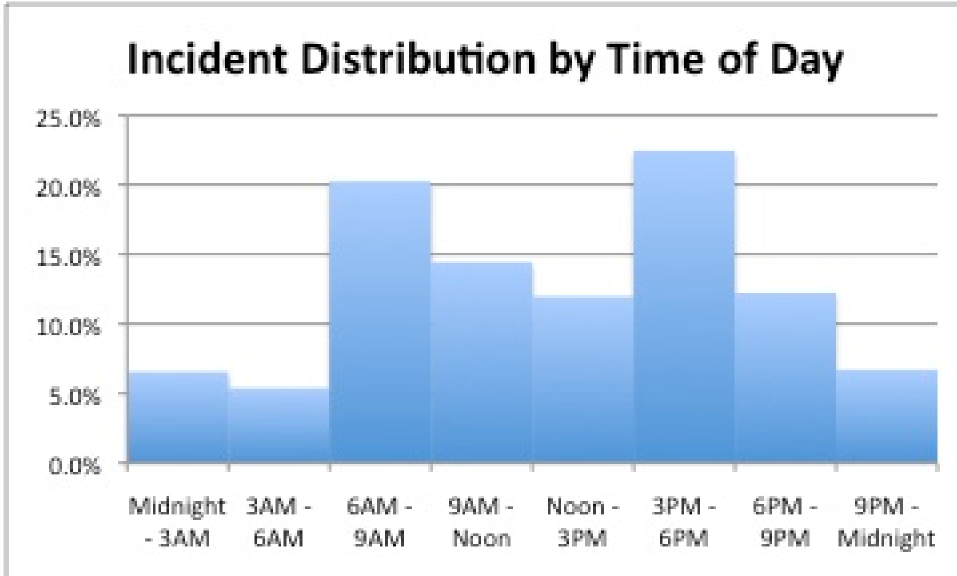


Figure 4. 8 Incident Distributions by Time of Day

Incidents are distributed in Figure 4.8 by the time that they occurred. The incidents occur most frequently from 6am to 9am and from 3pm to 6pm. This is to be expected as the highway is used the most during those time periods. Incidents occur least frequently during off peak hours.

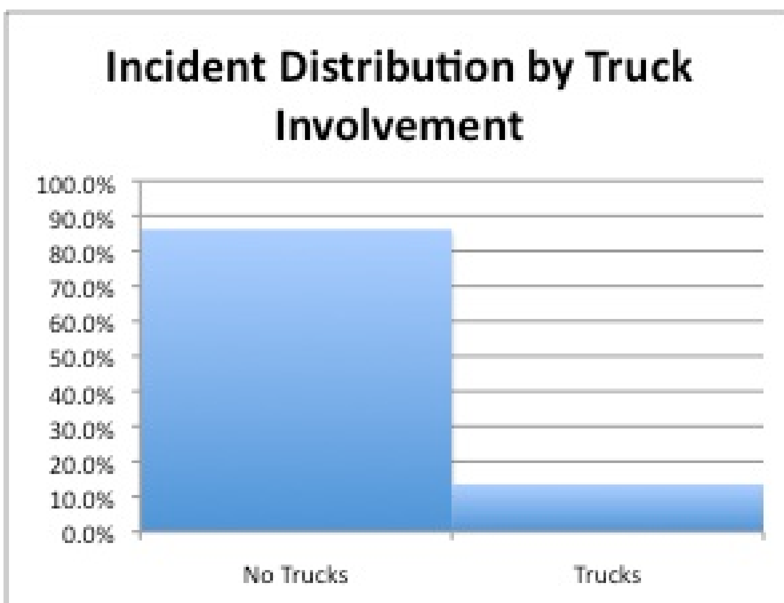


Figure 4. 9 Incident Distributions by Truck Involvement

Incidents are distributed by truck involvement in Figure 4.9. The majority of incidents involve cars only. The distribution seems to be fairly representative of the mixture of types of vehicles traversing this span of highway.

4.5 Freeway Segments

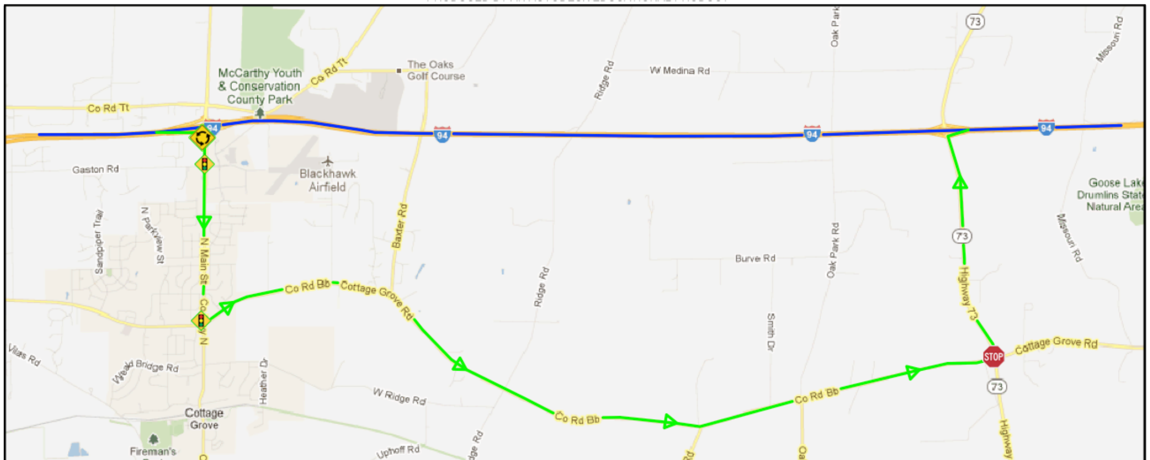
4.5.1 Segment Division

The area of the study, from Madison where I-94 meets I-90/39 to Milwaukee where I-94 meets I-43 and turns to the South towards Chicago, was divided into several segments in this study. The principle of the division is to make sure each segment includes the freeway mainline experiencing an incident, on-ramps, off ramps, upstream and downstream of the incident location, and the connecting parallel detour route. With this principle, all divided segments will be described in the following part.

4.5.2 Segments

This study has divided the target area into 18 segments. This section describes these segments one by one.

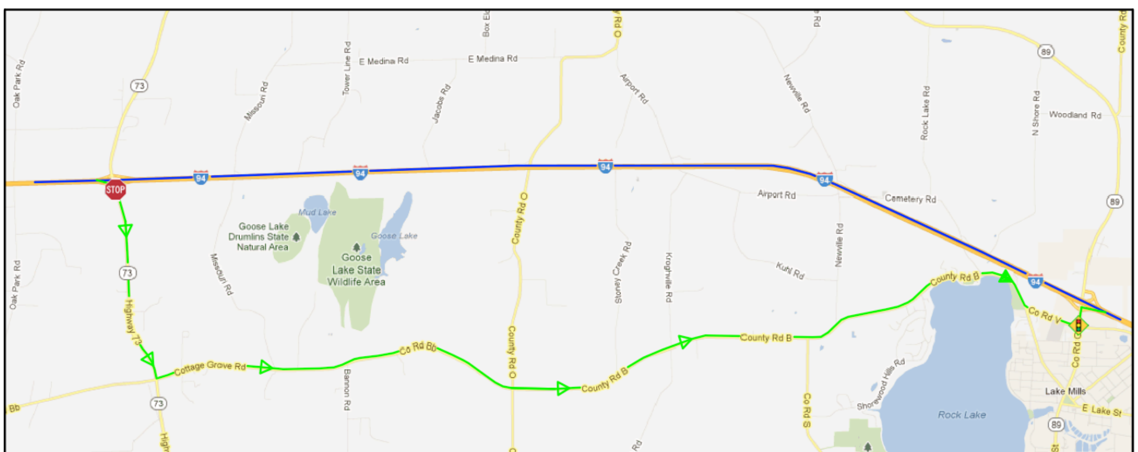
Figure 4.10 shows the configuration of the first segment. This segment starts at County Highway N in Dane County and ends it State Highway 73. Figure 4.10 indicates the east bound path and the west bound path utilize the same highway segments in reverse. Also noted in Figure 4.10 as well as the subsequent segment figures is the location of traffic control devices, stop signs as well as traffic signals.



SEGMENT: 1	IH-94 BETWEEN CTH N AND STH 73	DIRECTION: EB

Figure 4. 10 Segment 1

Figure 4.11 is shows the configuration of the second segment. This segment also utilizes the same route in both directions. Segment 2 traverses from Dane County to Jefferson County from West to East.



SEGMENT: 2	IH-94 BETWEEN STH 73 AND STH 89	DIRECTION: EB

Figure 4. 11 Segment 2

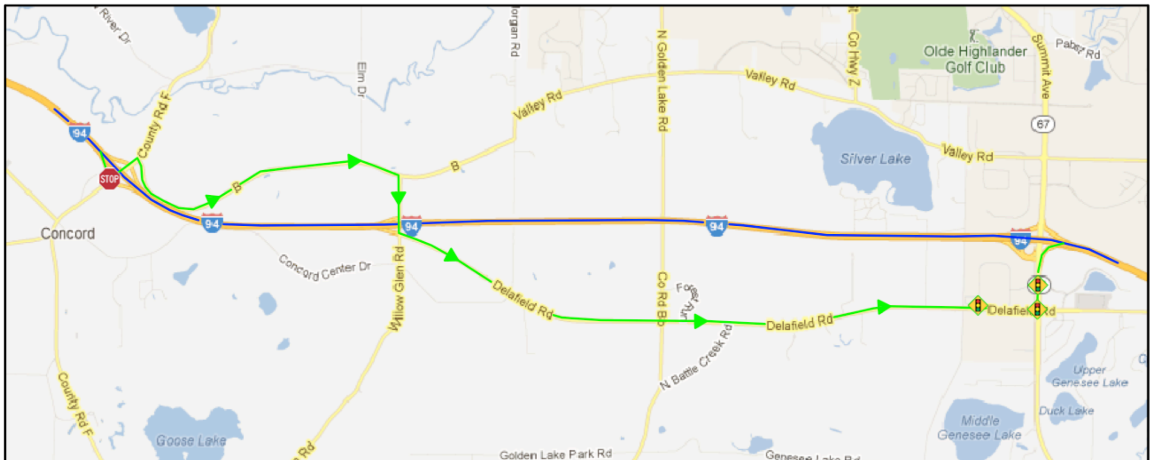
The third segment is shown in figure 4.12. Segment 3 located in Jefferson County uses the same route in both directions.

Figure 4. 12 Segment 3

Figure 4.13 describes segment 4. This segment also is located in Jefferson County and utilizes the same path in both directions.

Figure 4. 13 Segment 4

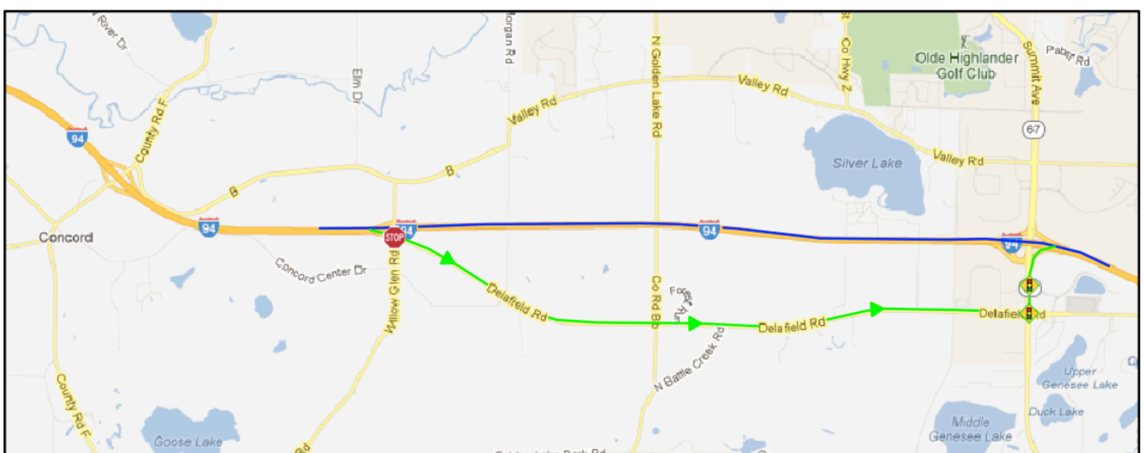
Segment 5 is the only segment in which traffic must be diverted to another segment in order to form a full diversion route. The reason that traffic cannot be contained in segment 5 is because of the lack of an eastbound on ramp and a westbound off ramp at the interchange with Willow Glen Rd. Because segment 6 has two viable diversion paths, segment 5 does also, because traffic must be diverted into segment 6. Segment 5 is also in Jefferson county.



SEGMENT: 5 B	IH-94 BETWEEN CTH F AND STH 67	DIRECTION: EB

Figure 4. 14 Segment 5

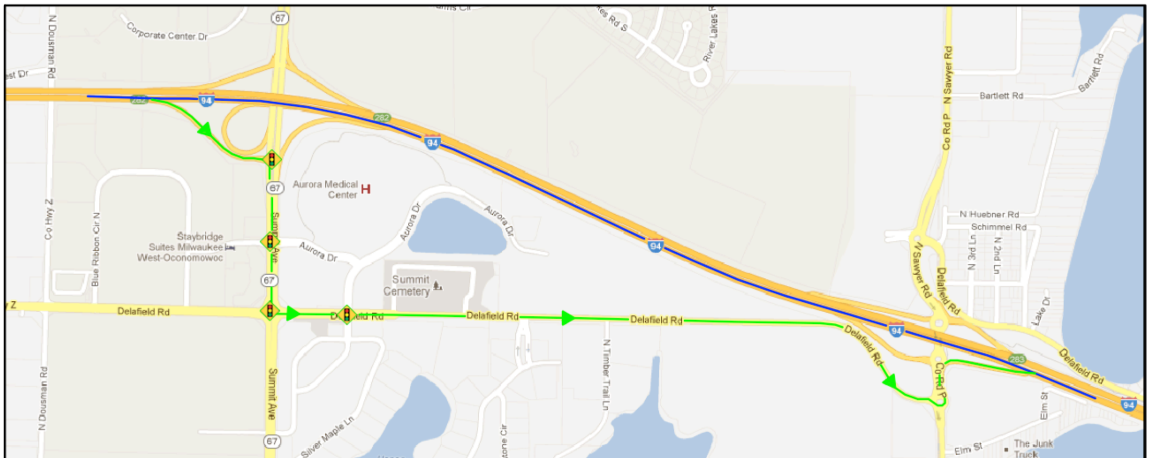
Segment 6, and shown in Figure 4.15 spans from Jefferson County to Waukesha county from West to East. Segment 6 is utilized by traffic diverting due to incidents located along segment 5, but is not affected by the nonstandard interchange configuration at Willow Glen Road when incidents occur within Segment 6.



SEGMENT: 6A	IH-94 BETWEEN WILLOW GLEN ROAD AND STH 67	DIRECTION: EB

Figure 4. 15 Segment 6

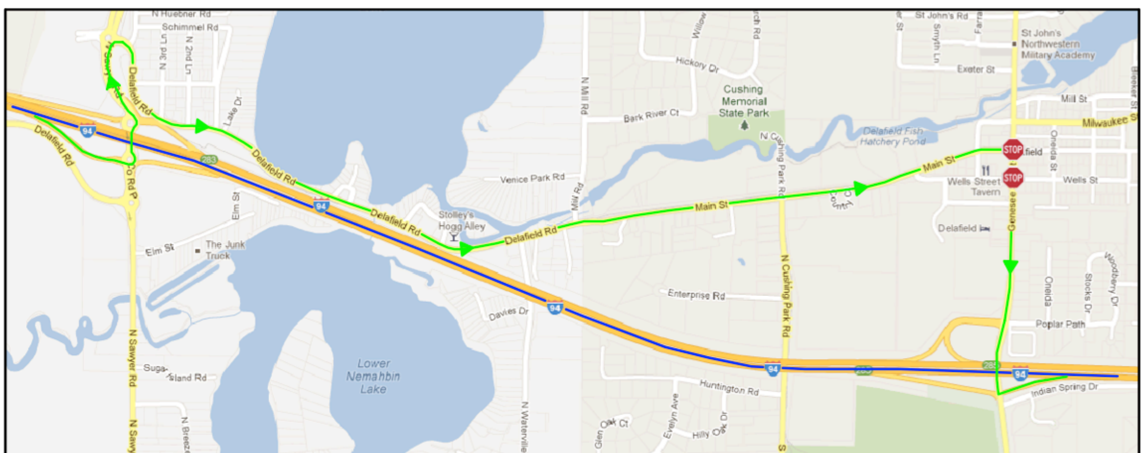
Figure 4.16 shoes Segment 7 located entirely in Waukesha County. Segment 7 utilizes the same route for traffic diverting in both directions.



SEGMENT: 7	IH-94 BETWEEN STH 67 AND CTH P	DIRECTION: EB

Figure 4. 16 Segment 7

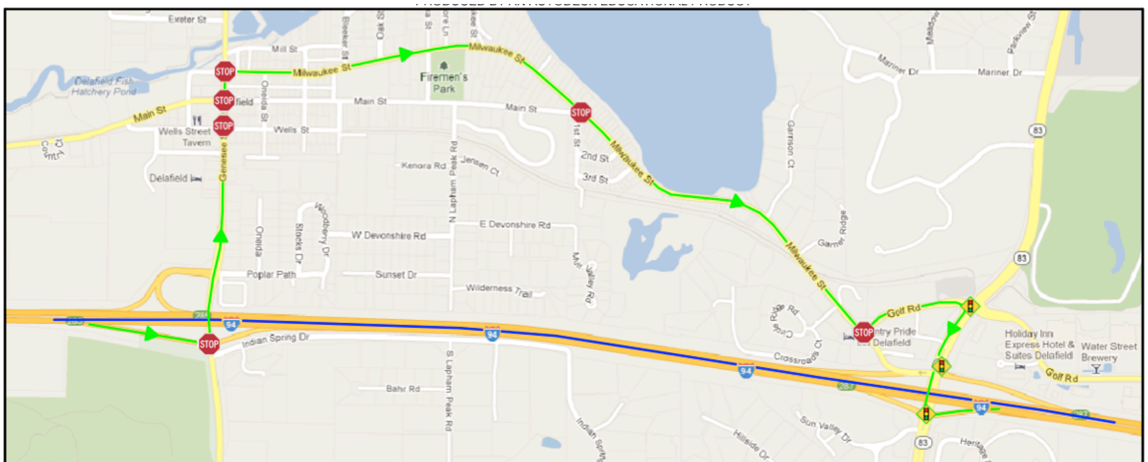
Segment 8 is shown in Figure 4.17. Segment 8 is also located in Waukesha county and utilizes the same route in both directions.



SEGMENT: 8	IH-94 BETWEEN CTH P AND GENESEE ST	DIRECTION: EB

Figure 4. 17 Segment 8

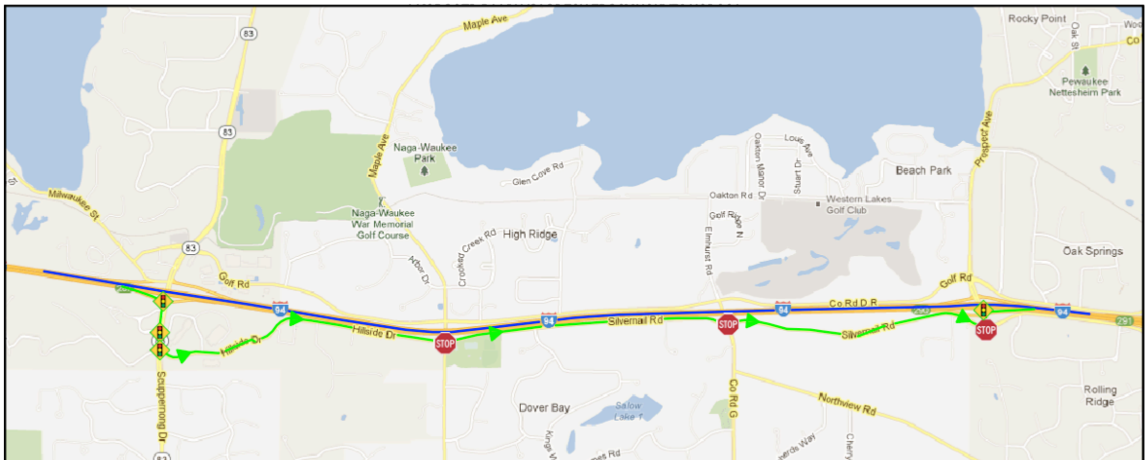
Segment 9 is shown in Figure 4.18. Segment 9 is located in Waukesha county and utilizes the same routes for diversion traffic in both directions.



SEGMENT: 9	IH-94 BETWEEN GENESEE ST AND STH 83	DIRECTION: EB

Figure 4. 18 Segment 9

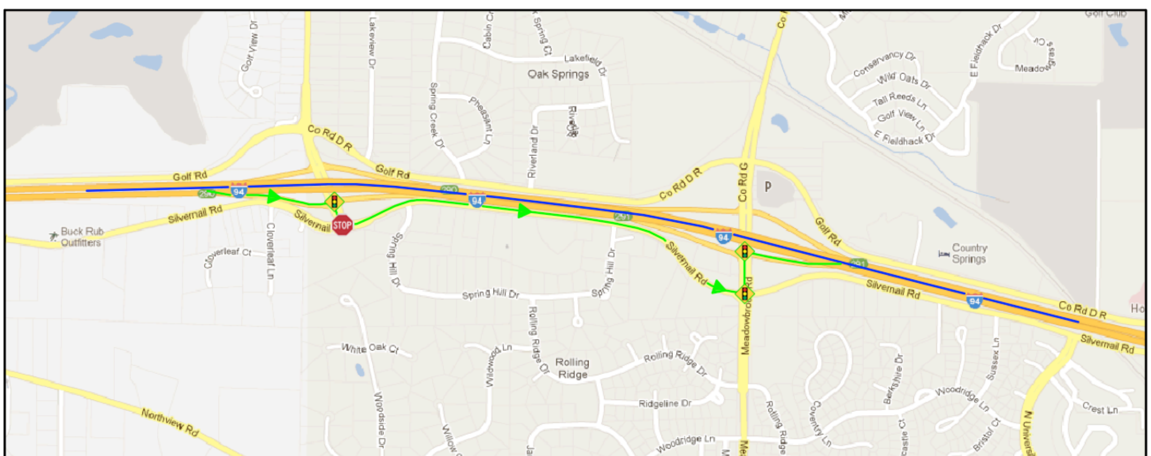
Figure 4.19 shows the configuration of Segment 10. Segment 10 is located in Waukesha county and diversion traffic can travel in either direction using either the road to the north of the freeway segment, Golf Road, or the road to the south of the freeway segment, Silvernail road. An exhaustive set of figure showing another diversion route can be found in the APPENDIX A.1. All possible routes were identified in order to find the optimal diversion route for any segment in which multiple routes were available for diversion traffic.



SEGMENT: 10	IH-94 BETWEEN STH 83 ST AND CTH SS	DIRECTION: EB

Figure 4. 19 Segment 10

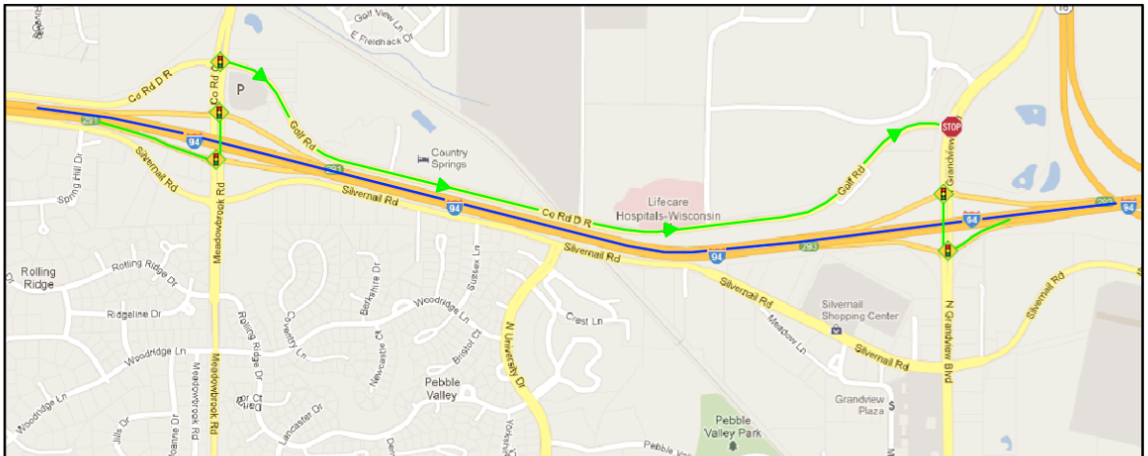
Figure 4.20 shows the eastbound route of diversion traffic for segment 11. Segment 11 is also located in Waukesha county and can accommodate two different diversion routes, Golf road to the North, and Silvernail Road to the south. Diversion traffic in another diversion route, and a full set of figure can be found in the APPENDIX A.2.



SEGMENT: 11	IH-94 BETWEEN CTH SS AND CTH G	DIRECTION: EB

Figure 4. 20 Segment 11

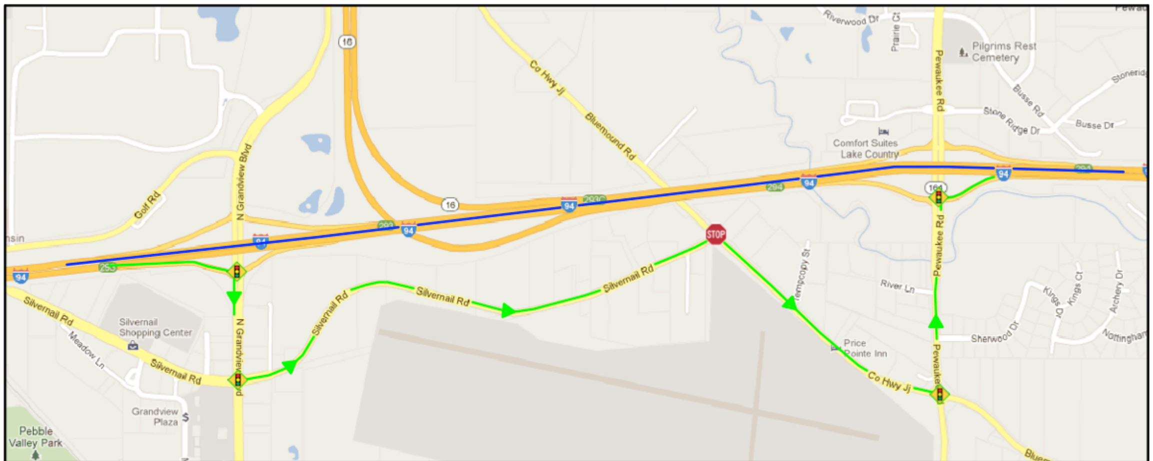
Figure 4.21 shows Segment 12. Again, segment 12 is located in Waukesha county, and allows diversion traffic to travel in two different routes, Golf Road located to the north of the freeway segment, and Silvernail Road located to the South of the freeway segment. Configuration of showing another route can be found in APPENDIX A.3.



SEGMENT: 12	IH-94 BETWEEN CTH G AND GRANDVIEW BLVD	DIRECTION: EB

Figure 4. 21 Segment 12

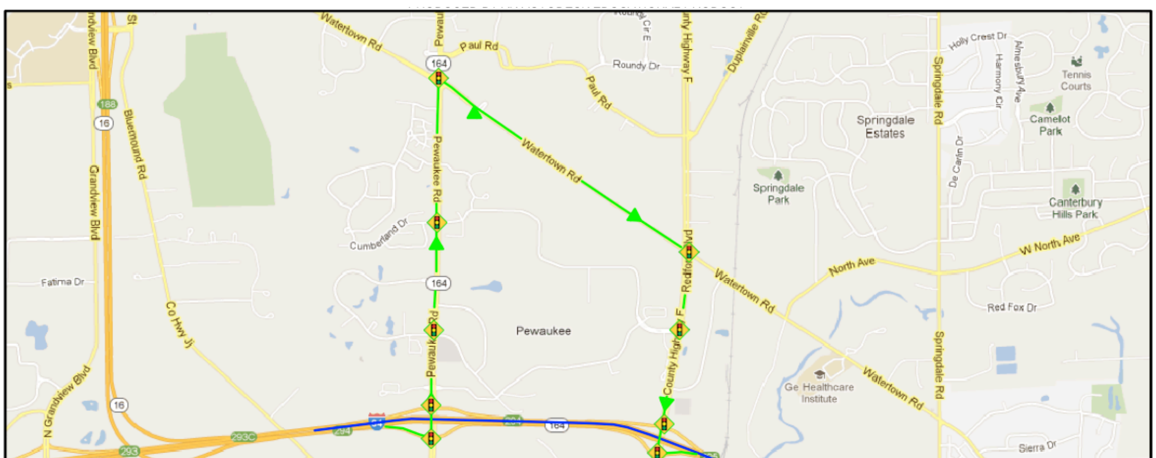
Segments 13 and 14 are both contained in Figure 4.22, as they are never utilized independent of one another. STH 16 forms an interchange with IH-94 at the dividing line between segments 13 and 14 and is used for a reference point to note incident locations, however STH 16 does not form any part of any diversion route. Segment 13-14 utilizes only one diversion path that accommodated diversion traffic in both directions. Segments 13 and 14 are located in Waukesha County.



SEGMENT: 13 -14	IH-94 BETWEEN GRANDVIEW BLVD AND WIS 164	DIRECTION: EB

Figure 4. 22 Segments 13 and 14

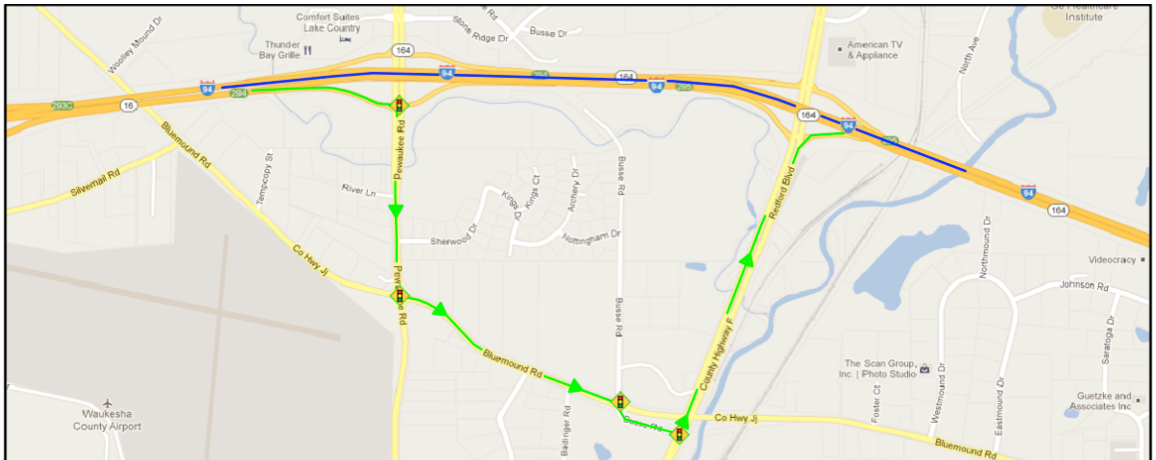
Segment 15 A is shown in Figure 4.23. Segment 15 has two different diversion paths and is represented in a separated figure for each. Figure 4.23 indicated the northern diversion route for segment 15 that utilizes Watertown Road. Segment 15 is located in Waukesha County, and both diversion paths can accommodate diversion traffic in both eastbound and westbound directions.



SEGMENT: 15	IH-94 BETWEEN PEWAUKEE RD (WIS 164) AND CTH F (WIS 164)	DIRECTION: EB

Figure 4. 23 Segment 15 A

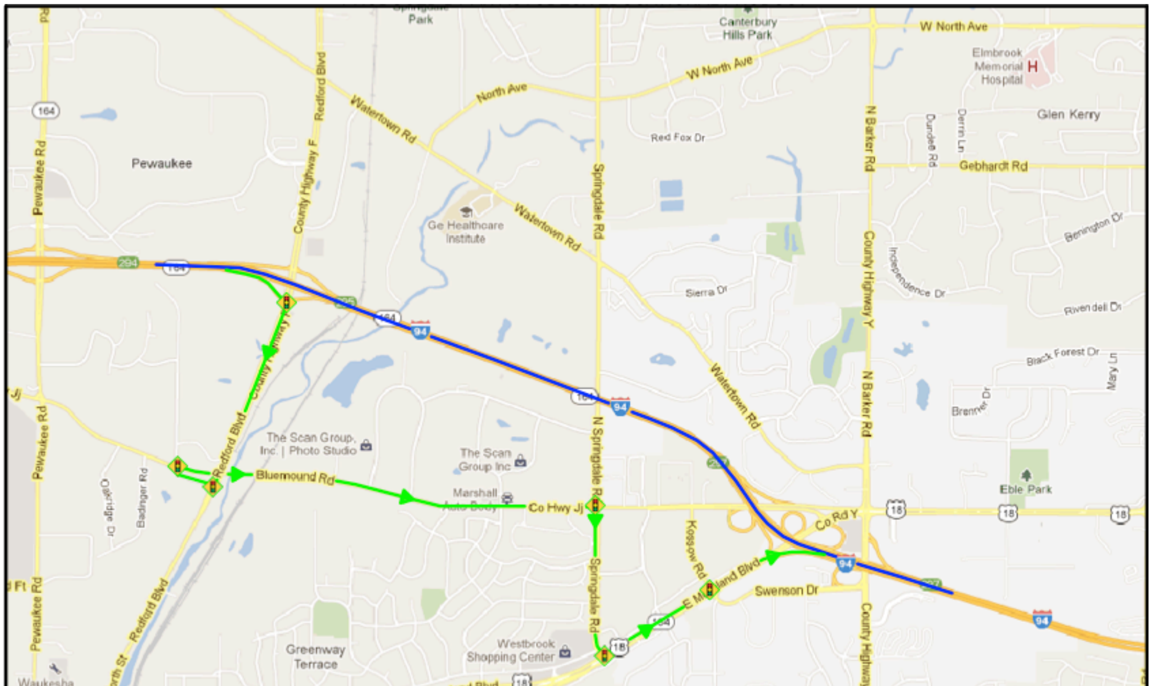
Figure 4.24 shows the southern diversion route for Segment 15 utilizing CTH JJ.



SEGMENT: 15	IH-94 BETWEEN PEWAUKEE RD (WIS 164) AND CTH F (WIS 164)	DIRECTION: EB

Figure 4. 24 Segment 15B

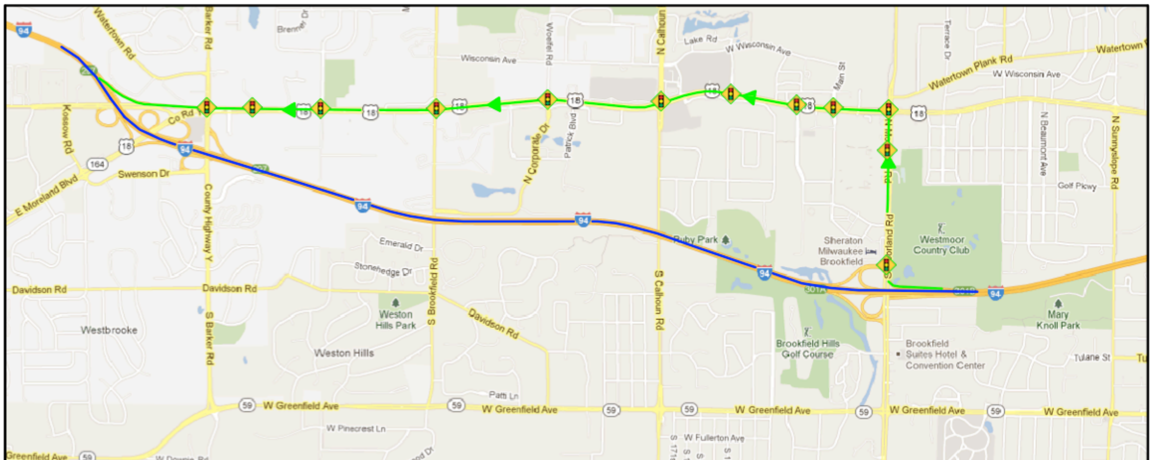
Figure 4.25 shows the southern diversion route for segment 16. This segment is located in Waukesha County as well. The northern diversion route utilizes Watertown Road instead, and the figure showing the Northern diversion route can be found in the APPENDIX A.5. Both diversion routes are capable of accommodating diversion traffic in both directions.



SEGMENT: 16	IH-94 BETWEEN CTH F AND E MORELAND BLVD (US-18)	DIRECTION: EB

Figure 4. 25 Segment 16

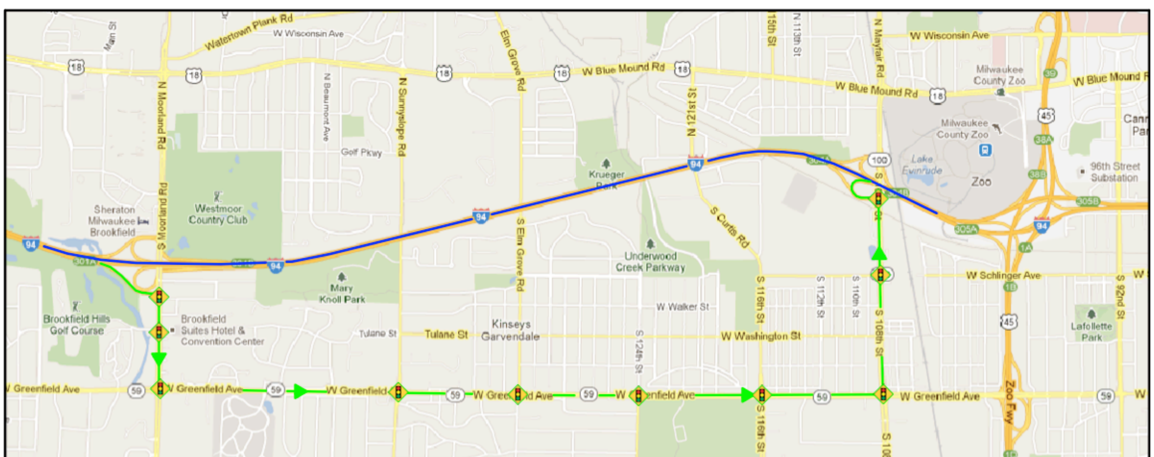
Figure 4.26 indicates the diversion plan for Segment 17. This segment is located in Waukesha County and also has 2 different diversion paths. In Figure 4.26 the northern diversion route is diagramed. The southern route utilizes Greenfield Ave. instead; the figure diagramming the southern route can be found in the APPENDIX A.6.



SEGMENT: 17	IH-94 BETWEEN E MORELAND BLVD (US - 18) AND S MORELAND RD	DIRECTION: WB

Figure 4. 26 Segment 17

Segment 18 is described in Figure 4.27. Segment 18 also has two diversion routes. The southern diversion route is shown in Figure 4.27, utilizing Greenfield Ave. The northern route utilizes Bluemound Road and a figure diagramming it can be found in the APPENDIX A.7.



SEGMENT: 18	IH-94 BETWEEN S MORELAND RD AND MAYFAIR RD (WIS 100)	DIRECTION: EB

Figure 4. 27 Segment 18

Chapter 5

EXPERIMENTAL DESIGN

During an incident, there are many factors that may affect the traffic manager's final decision on whether or not to implement detour operations, such as traffic volumes on the freeway and the detour route, the incident duration, the number of lanes blocked, and the number of signals on the detour route, etc. To ensure that the proposed detour warrant tool is effective under a wide range of incident scenarios and roadway geometric and traffic conditions, an experimental freeway corridor network that include segments of the freeway mainline experiencing an incident, on-ramps and off-ramps upstream and downstream of the incident location, and the connecting parallel detour route (see Figure 5.1) will be designed and calibrated. It will be quite cost-effective to use such an experimental environment to replicate a variety of complex and dynamic traffic patterns as well as the real-world operational characteristics (e.g. turning-bay, delay on ramps, and driving behavior) that may contribute to warranting a detour decision.

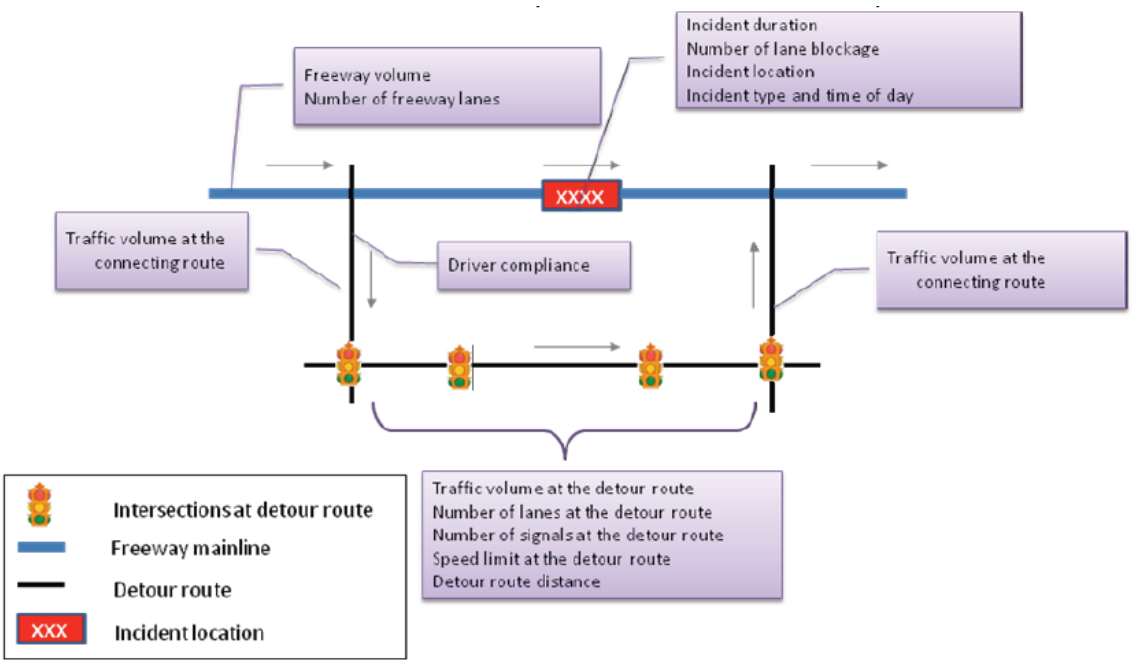


Figure 5. 1 Conceptual experimental design and key contributing factors

5.1 Simulation Network Construction

To realistically reflect the real-world operational characteristics in the study network (e.g., turning-bay, delay on ramps, and driving behavior), this study has modeled and calibrated each experimental scenario with the widely used micro-simulation package, CORSIM. The networks built with this the graphical interface TRAFED in the TSIS™ software represent the segments.

The simulation network for each segment can be graphically demonstrated given the proper dimension as TRAFED allows the user to use a bitmap image as a background to a network and to specify the real world width. For example, Figure 5.2 shows an overview of a network that has been created in the TSIS™ software package using TRAFED.

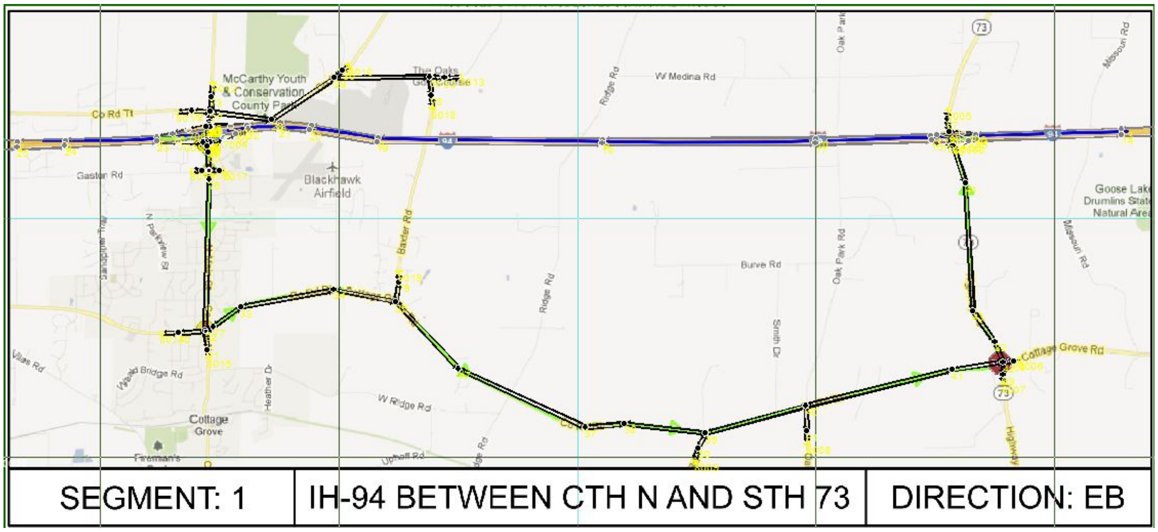


Figure 5. 2 An Overview of A Network

5.1.1 Simulation on Interchange

Interchange is a special geometry which needs more efforts to deal with in constructing simulation network. Figure 5.3 is a close in view of an interchange created in TRAFED that is part of segments 17 and 18. While the radii are displayed in TRAFVU, they are not considered in the simulation model. The length of the segment is however considered. For example, if a segment's end points are 500 feet apart, but the user specifies that the length of segment is 785 feet (if those two points were opposite each other in a semi-circle) the simulation will treat that segment as if it were 785 feet, and if the user chooses to display it as a half circle. TRAFVU. Unless specified, TSIS™ does not necessarily treat a vehicle leaving a segment to enter another at an angle as a turning vehicle, so the lack of consideration in a curved segment does not matter.

Figure 5. 3 A Close in View of An Interchange

5.1.2 Simulation on Intersection

Intersection geometries are important factors in the performance of a high volume traffic network. Figure 5.4 shows a typical intersection layout found in an urban segment as laid out in TSIS™ to represent real world conditions. TRAFVU was not an important tool in ascertaining the performance of the networks. Numerical output parameters were used instead of any graphically observed measures in determining network performance. While TRAFVU was not necessary for any data collection, it was very important when verifying that the network had been laid out correctly. In the TRAFED view, a segment or an intersection would have to be examined in a dialogue box individually to verify that it had been specified correctly. TRAFVU allows the user to examine the entire network by panning it around with parameters such as number of lanes and correctly specified number of turning bays easily verified without having to enter into a dialogue box for each component.

Figure 5. 4 A Typical Intersection Layout

5.1.3 Technique on Geometric Parameter Estimation

Google Maps was a very important part of the data collection of this study. Without Google Maps, the process of ascertaining the properties described in this section would have become onerous, or the degree of accuracy attained would have been severely diminished.

Using Google Maps, geometric data was collected for each of the segments. In addition to geometric data such as the number of lanes that a road segment is made up of, using the Distance Measurement Tool it is easy to obtain distances for turn bays, freeway auxiliary lane, and any other critical dimension.

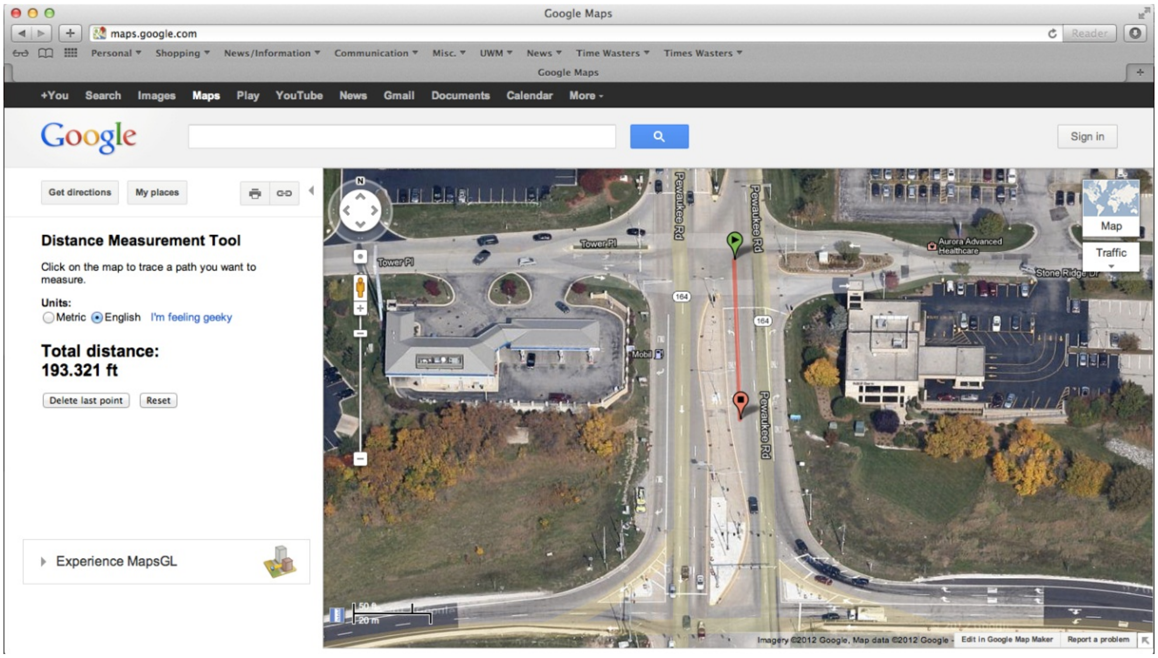


Figure 5. 5 Demonstration of Using Distance Measure Tool

Figure 5.5 demonstrates the use of the Distance Measuring Tool. It is worth noting that while the simulation animation software TRAFVU renders networks in an aesthetically pleasing manner, such as rendering tapers at freeway lane drops, TSIS™ does not recognize partial lanes, or assign vehicles to multiple lanes at once. For this reason, features such as turn bays must be measured from the point at which a usable lane width exists not at the point where the taper begins as shown in Figure 5.5.

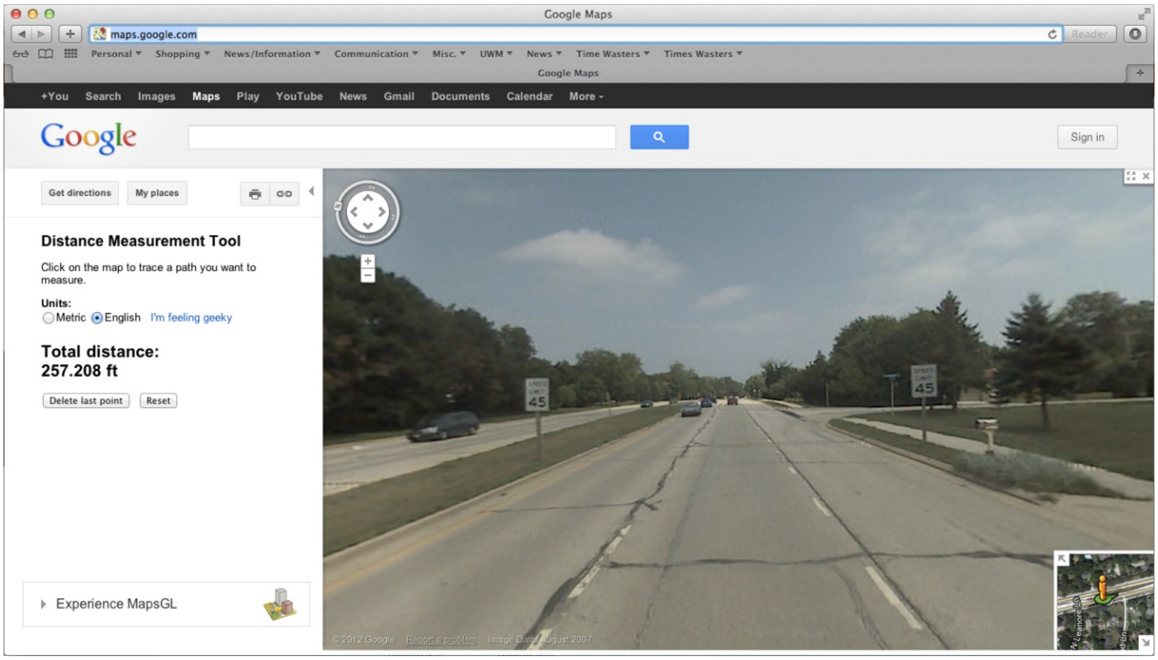


Figure 5. 6 A Screen Shot of Street View

Some features of the segments such as the speed limit of a local road, or freeway segment were ascertained using Google's Street View feature. Figure 5.6 is a screen shot of a road segment in segment 18. Using street view, one can see that the speed limit on this segment is 45 miles per hour. One other use Street View is as to corroborate with aerial photos to clarify attributes of a segment. Because not all photos used in Google Maps were taken at the same time, different views can also be useful to make sure that the newest data used.

In overall, Google map is great tool in this study to estimate important geometric parameters such as the distances for turn bays, freeway auxiliary lane, speed limit of a certain corridor and many other critical geometric attributes. Other parameters such as turn volumes, entrance node volumes and exit percentages on the freeways were necessary only to test that the network performed without any errors, as those parameters would be later specified in the running of the experiment, and many different combinations of values would be used.

5.2 Category of Key Variables

With well-established simulation network for each segment, it is necessary to define the category of key factors that may potentially affect detour operations. This study organizes all the potential factors associated with each experimental scenario into the following groups:

- **Freeway-related factors**: flow rate on the freeway mainline and the number of lanes on the freeway mainline;
- **Incident-related factors**: incident duration and the number of lanes blocked;
- **Detour route-related factors**: flow rate on the road connecting from freeway to the detour route, flow rate on the parallel route, flow rate on the road connecting from the detour route back to the freeway, and the number of lanes and signals on the detour route; and
- **Driver related factors**: level of driver compliance rates to the detour operations.

5.4 Range of Variables Values

The range of values of some key factors which will be used in the model development is summarized in Table 5.1, note that these variables and corresponding ranges are original; they may be re-categorized for model construction if needed.

Table 5. 1 Key Variables and Range of Values for the Experimental Design

VARIABLES	DESCRIRPTION	RANGE OF VALUES
FR_VOL	Freeway mainline volume rate (in vphpl)	250, 750, 1250, 1750, 2200
FR_LN	Number of lanes on the freeway mainline	2, 3, 4
INC_DUR	Incident duration (in mins)	15, 30, 45,60, 75, 90,105, 120
LN_BLK	Number of lanes blocked	1, 2, 3, 4
LC_VOL1	Flow rate on the road connecting from freeway to detour route (in vphpl)	200, 300, 400, 500, 600, 700, 800
LC_VOL2	Flow rate on the detour route (in vphpl)	200, 300, 400, 500, 600, 700, 800
LC_VOL3	Flow rate on the road connecting from detour route to freeway (in vphpl)	200, 300, 400, 500, 600, 700, 800
LC_LN	Number of lanes on the detour route	1, 2, 3
NUM_SIGNAL	Number of signals on the detour route	2, 3, 4, 5, 6, 7

5.5 Scenarios Generating

Considering the wide range of values taken by each contributing factor, the total number of experimental scenarios that can be generated from all possible combination of key factors will be extremely large. For example, assuming each factor takes 5 possible values, one can generate a total of 5^{13} = 1,220,703,125 scenarios. It will be impossible to evaluate all those scenarios and further use them for decision model development. To contend with this problem, the author has adopted a probability sampling approach to randomly select scenarios from the sample space and assure that all scenarios have equal probabilities of being chosen. Using this procedure, this study has generated an experimental scenario set with a relatively compact size of 500. The generated scenario set will then be divided into two subsets, one subset containing 400 experimental scenarios for detour optimization model and decision model development and another subset containing 100 experimental scenarios for model validation.

Chapter 6

MODEL DEVELOPMENT AND VALIDATION

This chapter will develop and calibrate detour decision models that include a two-choice model and a multi-choice model for the multi-criteria detour system. Before the development of detour decision models, a detour optimization model developed by Liu et al. (2011) that can generate optimal detour rate will be presented is section 6.1. The generated optimal detour rate will be used to explore how various potential factors affect transportation managers' final decision making.

Section 6.2 provides a diversion rate estimation model which shows how potential factors affect optimal detour rate in each scenario. Though the proposed analysis presents the relationship between these factors and optimal detour rate, it is still hard for transportation mangers to make final decision due to the continuity of optimal detour rate and the lack of an exact criterion to implement detour decision.

Considering the aforementioned limitation, section 6.3 proposes a two-choice model which helps transportation managers decide whether a detour decision should be made or not given a certain experimental scenario. A preliminary analysis with Classification and Regression Tree (CART) will be embedded in this section to analyze the significance of selected variables and re-group the variables to better develop the proposed two-choice model. Obviously, this model provides transportation mangers with a result of "detour" or "not detour" which is an effective guidance in the process of incident management. However, even this model gives a decision of "detour", transportation mangers still want to know whether this detour decision is highly recommended or just recommended in real-time operation. Considering this situation, it is necessary to develop a multi-choice model to provide more criteria for transportation mangers to make final decision.

In regard of this requirement, a multi-choice model has been developed which will be presented in section 6.4. To better develop this model, CART will be used again to re-categorize the independent variables and select different criteria as dependent variables as the input of the multi-choice model.

In section 6.5, benefit analysis is presented to validate the developed detour decision model to show that whether the implemented detour plan is truly beneficial or not from the overall societal perspective.

6.1 Detour Optimization Model

As stated before, it is necessary to know the optimal detour rate for the development of detour decision model. This study employs an integrated diversion control model developed by Liu et al. (2011) that can determine the best diversion control strategy (i.e. diversion rate, signal timing optimization, ramp metering) that yields the maximum utilization of corridor capacity for each experimental scenario, and the optimal detour rate to the local route. The connection of such model and CORSIM is illustrated in Figure 6.1. The experimental scenarios are severed as inputs for the proposed model, the outputs (diversion rate, signal timing optimization, ramp metering) of such model associated with the experimental scenarios are severed as the inputs for CORSIM. With this process, the outputs from CORSIM, including total throughputs, total vehicles in queue, total travel time, and total time in queue can be generated which will be used for benefit estimation at the end of this chapter.

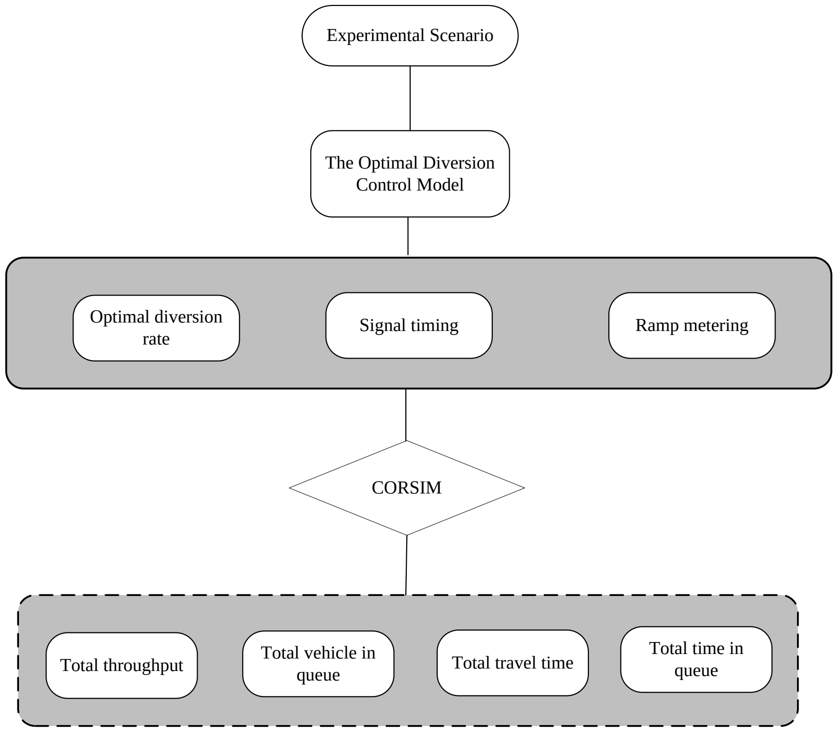
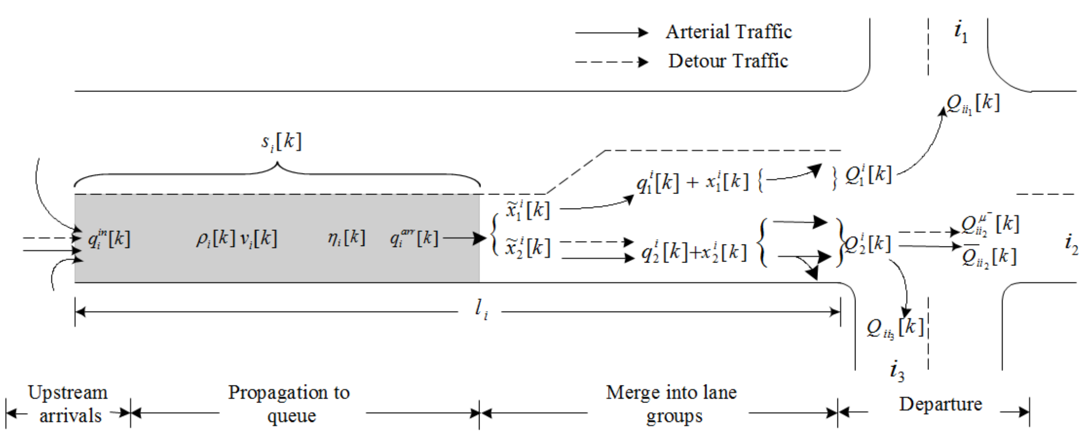
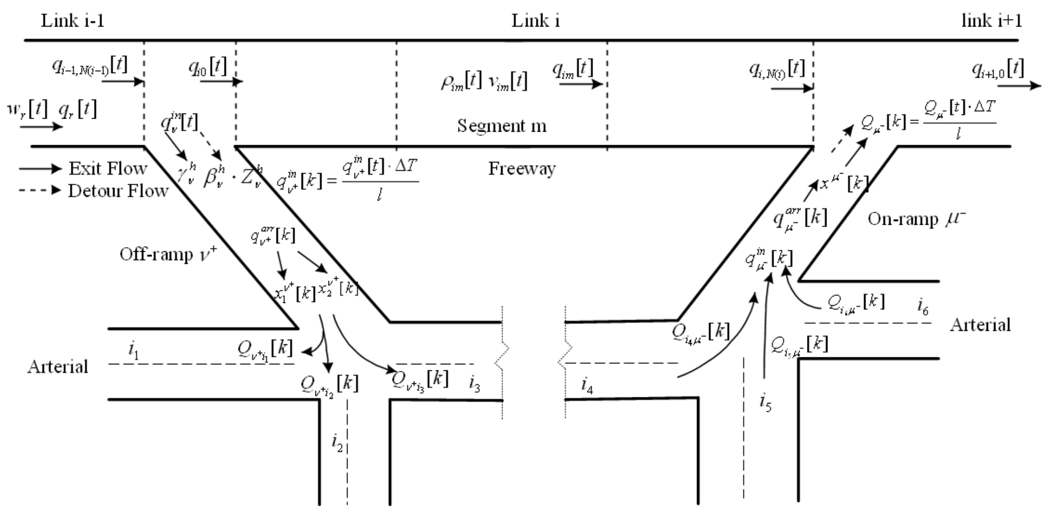


Figure 6. 1 Connection of Detour Optimization Model and CORSIM

The integrated diversion control model has effectively integrated a set of macroscopic traffic flow models that can precisely model and predict the traffic evolution along the freeway mainline, arterial link, and on–off ramps (see Figure 6.2).



(a) Arterial Model



(b) Freeway and Ramps

Figure 6. 2 Macroscopic Network Flow Modeling in the Integrated Diversion Control Model (Liu et al., 2011)

To facilitate the model presentation, the notations used hereafter are summarized below:

Notation

Δt	: Time step for updating arterial status (secs);
T_h	: Length of the control time interval h (#. of Δt);
H	: The entire control time horizon;
k	: Time step index of arterial system corresponds to time $t = k\Delta t$;
S_N	: Set of arterial intersections;
$n, n \in S_N$	: Index of arterial intersections;
S^U	: Set of arterial links;
S^{OUT}	: Set of outgoing arterial boundary links;
$i, i \in S^U$	: Index of links,
S_r	: Set of traffic demand entries;

P_n : Set of signal phases at intersection n;

$p, p \in P_n$: Index of signal phase at the intersection n;

$\Gamma(i), \Gamma^{-1}(i)$: Set of upstream and downstream links of link i;

l_i : Length of link i (ft);

n_i : Num. of lanes in link i;

N_i : Storage capacity of link i (vehs);

Q_i : Discharge capacity of link i (veh/h);

$\rho^{\min}, v_i^{free}$: Minimum density (veh/mile/lane) and the free flow speed at link i (mph);

$\rho^{jam}, v^{\min}$: Jam density (veh/mile/lane) and the minimum speed (mph);

α, β : Constant model parameters;

S_i^M : Set of lane groups at link i;

$m, m \in S_i^M$: Index of lane groups at link i;

$\delta_m^{ij}, j \in \Gamma^{-1}(i)$: A binary value indicating whether the movement from link i to j uses lane group m;

Q_m^i : Discharge capacity of lane group m at link i (veh/h);

$d_r[k], r \in S_r$: Demand flow rate at entry r at step k (veh/h);

$q_r[k], r \in S_r$: Flow rate enter the link from entry r at step k (veh/h);

$w_r[k], r \in S_r$: Queue waiting on the entry r at step k (vehs);

$q_i^{in}[k]$: Upstream inflows of link i at step k (vehs);

$\gamma_{ij}[k],\ j \in \Gamma^{-1}(i)$: Relative turning proportion of movement from link *i* to *j*;

$N_i[k]$: Num. of vehicles at link *i* for at step *k* (vehs);

$v_i[k]$: Mean approaching speed of vehicles from upstream to the end of queue at link *i* at step *k* (mph);

$\rho_i[k]$: Density of the segment from upstream to the end of queue at link *i* at step *k* (veh/mile/lane);

$q_i^{arr}[k]$: Flows arriving at end of queue of link *i* at step *k* (vehs);

$s_i[k]$: Available space of link *i* at step *k* (vehs);

$x_i[k]$: Total num. of vehicles in queue at link *i* at step *k* (vehs);

$q_m^i[k]$: Flows join the queue of lane group *m* of link *i* at step *k* (vehs);

$x_m^i[k]$: Queue length of lane group *m* of link *i* at step *k* (vehs);

$\lambda_m^{ij}[k],\ j \in \Gamma^{-1}(i)$: Percentage of movement from link *i* to *j* in lane group *m*;

$Q_m^i[k]$: Flows depart from lane group *m* of link *i* at step *k* (vehs);

$Q_{ij}^{pot}[k]$: Flows potentially depart from link *i* to *j* i at step *k* (vehs);

$Q_{ij}[k]$: Flows actually depart from link *i* to *j* i at step *k* (vehs);

$g_n^p[k]$: Binary value indicating whether signal phase *p* of intersection *n* is set to green at step *k*.

μ^+, ν^+ : Index of the incident upstream on-ramp and off-ramp, respectively

μ^-, ν^- : Index of the incident downstream on-ramp and off-ramp, respectively

$\bar{\gamma}_{ij}[k], j \in \Gamma^{-1}(i)$: Relative turning proportion of normal arterial traffic from link i to j

$\gamma_{ij}^{\mu^-}, j \in \Gamma^{-1}(i)$:A binary value indicating whether detour traffic at link i heading to downstream on-ramp μ^- will use downstream link j or not

$\bar{N}_i[k]$:Num. of vehicles from normal arterial traffic at link i at step k

$N_i^{\mu^-}[k]$:Num. of detour vehicles heading to downstream on-ramp μ^- at link i at step k

$\eta_i[k]$:Fraction of normal arterial traffic in total traffic at link i at step k

$\bar{\lambda}_m^{ij}[k], j \in \Gamma^{-1}(i)$:Percentage of normal arterial traffic in lane group m going from link i to j

$\bar{Q}_{ij}[k]$:Normal arterial traffic flows actually depart from link i to link j at step k

$Q_{ij}^{\mu^-}[k]$:Detour traffic flows heading to downstream on-ramp μ^- actually depart from link i to link j at step k

$\{C^h, h \in H\}$:Common cycle length for all intersections in the control interval h

$\{\Delta_n^h, \forall n \in S_N, h \in H\}$:Offset of intersection n for each control interval h

$\{G_{np}^h, \forall n \in S_N, p \in P_n, h \in H\}$:Green time for phase p of intersection n for each control

	interval h
$\{R^h_{\mu^+}, h \in H\}$	:Metering rate at the incident upstream on-ramp μ^+ for each control interval h
$\{Z^h_{\nu^+}, h \in H\}$	:Diversion rate at the incident upstream off-ramp ν^+ for each control interval h

The integrated control model aims to maximize the utilization of the corridor capacity so as to minimize congestion on the freeway mainline due to an incident with the following control objective:

$$\max \quad \sum_{t=1}^{H} q_{i+1,0}[t] \cdot \Delta T + \sum_{k=1}^{H} \sum_{i \in S^{OUT}} q_i^{in}[k]$$

$$\text{s.t.} \quad s:[C^T, \Delta_n^T, G_{np}^T, Z_{\nu^+}^T] \in S \tag{6-1}$$

where $q_{i+1,0}[t]$ is the flow rate entering the freeway link (i+1) downstream of the on-ramp μ^-; S^{OUT} is the set of outgoing links in the arterial network (see Figure 6.1); S denotes the feasible solution set defined by the following network flow and operational constraints:

1) *Arterial Demand Entries*

$$IN_r[k] = \min\left[D_r[k] + \frac{w_r[k]}{\Delta t}, Q_i, \frac{s_i[k]}{\Delta t}\right] \tag{6-2}$$

$$w_r[k+1] = w_r[k] + \Delta t[D_r[k] - IN_r[k]] \tag{6-3}$$

2) *Arterial Upstream Arrivals*

$$q_i^{in}[k] = \sum_{j \in \Gamma(i)} \bar{Q}_{ji}[k] + \sum_{j \in \Gamma(i)} Q_{ji}^{\mu^-}[k] \tag{6-4}$$

3) *Arterial Joining Queue End*

$$q_i^{arr}[k] = \min\left\{\rho_i[k] \cdot v_i[k] \cdot n_i \cdot \Delta t, \bar{N}_i[k] + N_i^{\mu^-}[k] - x_i[k]\right\} \tag{6-5}$$

4) *Arterial Merging Into Lane Groups*

$$q_m^i[k] = \min\{\max\{N_m^i - x_m^i[k], 0\}, \max\{q_m^{i,pot}[k] \cdot [1 - \sum_{m' \in S_i^M} \omega_{m'm}^i[k]], 0\}\} \tag{6-6}$$

5) *Arterial Departing Process*

$$Q_{ij}[k]=\min\left\{Q_{ij}^{pot}[k],\frac{Q_{ij}^{pot}[k]}{\sum_{i\in\Gamma(j)}Q_{ij}^{pot}[k]}\cdot s_j[k]\right\} \tag{6-7}$$

$$Q_{ij}^{pot}[k]=\sum_{m\in S_i^M}\min\left\{q_m^i[k]+x_m^i[k],Q_m^i\cdot g_n^p[k]\right\}\cdot\lambda_m^{ij}[k] \tag{6-8}$$

6) Arterial Flow Conservation

$$x_i[k+1]=\sum_{m\in S_i^M}\left(x_m^i[k+1]+\tilde{x}_m^i[k+1]\right) \tag{6-9}$$

$$\bar{N}_i[k+1]=\bar{N}_i[k]+\sum_{j\in\Gamma(i)}\bar{Q}_{ji}[k]-\sum_{j\in\Gamma^{-1}(i)}\bar{Q}_{ij}[k] \tag{6-10}$$

$$N_i^{\mu^-}[k+1]=N_i^{\mu^-}[k]+\sum_{j\in\Gamma(i)}Q_{ji}^{\mu^-}[k]-\sum_{j\in\Gamma^{-1}(i)}Q_{ij}^{\mu^-}[k] \tag{6-11}$$

$$\eta_i[k+1]=\frac{\bar{N}_i[k+1]}{\bar{N}_i[k+1]+N_i^{\mu^-}[k+1]} \tag{6-12}$$

$$s_i[k+1]=N_i-\bar{N}_i[k+1]-N_i^{\mu^-}[k+1] \tag{6-13}$$

7) Freeway Mainline Dynamics

$$\rho_{im}[t+1]=\rho_{im}[t]+\frac{\Delta T}{l_{im}n_{im}}(q_{i,m-1}[t]-q_{im}[t]) \tag{6-14}$$

$$q_{im}[t]=\rho_{im}[t]\cdot v_{im}[t]\cdot n_{im} \tag{6-15}$$

$$V_{im}(\rho_{im}[t])=v_f^i\exp\left[-\frac{1}{\alpha_f}\left(\frac{\rho_{im}[t]}{\rho_{cr}^i}\right)^{\alpha_f}\right] \tag{6-16}$$

$$v_{im}[t+1]=v_{im}[t]+\frac{\Delta T}{\tau}[V(\rho_{im}[t])-v_{im}[t]]+\frac{\Delta T}{l_{im}}v_{im}[t][v_{i,m-1}[t]-v_{im}[t]]-\frac{\eta\cdot\Delta T[\rho_{i,m+1}[t]-\rho_{im}[t]]}{\tau\cdot l_{im}[\rho_{im}[t]+\kappa]} \tag{6-17}$$

8) On-off Ramps

$$Q_{\mu^-}[t]=\min\left\{\frac{x^{\mu^-}[l\cdot t]+\sum_{k=lt}^{l(t+1)-1}q_{\mu^-}^{arr}[k]}{\Delta T},Q_{\mu^-}\cdot R_{\mu^-},Q_{\mu^-}\cdot\min\left[1,\frac{\rho^{jam}-\rho_{i+1,0}[t]}{\rho^{jam}-\rho_i^{crit}}\right]\right\} \tag{6-18}$$

$$q_{\nu^+}^{in}[t]=\min\left\{\rho_{i-1,N(i-1)}[t]\cdot v_{i-1,N(i-1)}[t]\cdot n_{i-1,N(i-1)}\cdot(\gamma_{\nu^+}^T+\beta_{\nu^+}^T\cdot Z_{\nu^+}^T),Q_{\nu^+},\frac{s_{\nu^+}[l\cdot t]+\sum_{k=lt}^{l(t+1)-1}\sum_{j\in\Gamma^{-1}(\nu^+)}Q_{\nu^+j}[k]}{\Delta T}\right\} \tag{6-19}$$

9) Operational Constraints for Control Parameters

$$C^{min}\le C^T\le C^{max},\forall T\in H \tag{6-20}$$

$$G_{np}^{min}\le G_{np}^T<C^T\quad,\ \forall n\in S_N,p\in P_n,T\in H \tag{6-21}$$

$$\sum_{p \in P_n} G_{np}^{T} + \sum_{p \in P_n} I_{np} = C^{T}, \forall n \in S_N, p \in P_n, T \in H \tag{6-22}$$

$$0 \le \Delta_n^{T} < C^{T}, \forall n \in S_N, T \in H \tag{6-23}$$

$$\beta_{v^+}^{T} \cdot Z_{v^+}^{T} + \gamma_{v^+}^{T} \le Z^{max}, T \in H \tag{6-24}$$

The arterial dynamics in the diversion optimization model consists of six modules: demand entries, upstream arrivals, joining the end of queue, merging into lane groups, departing process, and flow conservation (see Figure 6.2a). Eq. (6-2) updates the flow entering arterial link i from demand entry r at time step k. Eq. (6-3) calculates the queue waiting at the demand entry during each time step. The arrival flows to link i at time step k can be formulated as the sum of actual departure flows from all upstream links, including both normal arterial traffic and detour traffic, given by Eq. (6-4). Eq. (6-5) models the evolution of upstream inflows to the end of queue with the average approaching speed. Eq. (6-6) gives the number of vehicles that can actually merge into their destination lane group m at time step k considering the potential queue blockage effects from other lane groups (e.g. a fully occupied through lane group may completely block the left-turn traffic). Eqs. (6-7) and (6-8) give the actual departing flows from link i to link j at time step k. The arrival and departure flows at link i should be subject to the flow conservation law, given by Eqs. (6-9)-(6-13).

Eqs. (6-14)-(6-17) capture the network flow dynamics on the freeway mainline (see Figure 6.2b). The key concept is to divide the freeway link into homogeneous segments, and update the flow, density, and speed within each segment at every time interval (Messmer and Papageorgiou, 1995). As on-ramps and off-ramps function to exchange diversion flows between the freeway and arterial systems, Eqs. (6-18)-(6-19) are employed to model their interactions.

The integrated diversion control model aims to optimize the diversion rates and retime the signals along the detour route so as to accommodate the detour traffic. Eqs. (6-20)- (6-24) is the restriction for the control decision variables, including the cycle length (C^T), the offsets (Δ_n^T), the green splits (G_{np}^T), diversion rates ($Z_{V^+}^T$).

A genetic algorithm (GA)-based heuristic integrated with a rolling horizon framework has been employed to yield reliable model solutions. Note that the control model has been validated under various traffic conditions and incident scenarios, showing promising properties in freeway corridor incident management. More details about the formulations and solution algorithm of the diversion optimization model can be found in the work by Liu et al. (2011).

6.2 Division Rate Estimation Model

The diversion rate estimation model is to explore how factors in each scenario affect the corresponding optimal detour rate. To achieve this goal, a linear regression model is applied in which the independent variables are 9 original factors and dependent variables are optimal detour rate.

Table 6. 1 Estimation Results for Linear Regression Model

Variables	Coefficient Estimation	Stand Error	P-value
Intercept	1.765	0.002	0.001
FR_VOL (250, 750, 1250, 1750, 2200)	-2.649	0.239	0.004
FR_LN (2, 3, 4)	6.982	11.300	0.006
INC_DUR (15, 30, 45,60, 75, 90,105, 120)	-3.238	0.963	0.002

LN_BLK (1, 2, 3, 4)	-0.831	1.245	0.003
LC_VOL1 (200, 300, 400, 500, 600, 700, 800)	0.239	16.897	1.230
LC_VOL2 (200, 300, 400, 500, 600, 700, 800)	0.802	2.900	0.003
LC_VOL3 (200, 300, 400, 500, 600, 700, 800)	0.644	20.456	2.098
LC_LN (1, 2, 3)	-6.230	18.908	1.560
NUM_SIGNAL (2, 3, 4, 5, 6, 7)	0.454	1.043	0.002
R Square		0.81	
Adjusted R Square		0.82	
Observation		400	

Table 6.1 shows the estimation results for the linear regression model. R square is 81% which makes this model acceptable. Among 9 independent variables, flow rate on the freeway, incident duration, number of lane blocked, flow rate on the detour route and number of signal on the detour route are significant. From the estimated coefficients for each significant variable, the following conclusions can be derived:

- The increase of flow rate on the freeway has a negative impact on the optimal detour rate which means it will get a lower optimal detour rate when the flow rate on the freeway is higher;
- Incident duration and number of lanes blocked show a negative impact on the optimal detour rate which implies vehicles are suggested to detour to alternate route in an early time when the incident duration is large and too many lanes are blocked on the freeway; and
- Flow rate on the detour route and number signal on the detour route have a positive impact on the optimal detour rate which shows that higher optimal

detour route is derived when the flow rate is higher in the detour route and there are more signals on the detour route.

The above analysis can assist transportation managers to figure out how these factors in a given scenario affect the final optimal detour rate, i.e. what trend (higher or lower)could the optimal detour rate be at a certain incident situation. However, this information cannot help transportation mangers make final decision because of the continuity of optimal detour rate and the lack of an exact criterion to implement detour decision. In real-time incident management, transportation mangers prefer to make a decision according to a binary decision variable, i.e. "yes" or "no". This requirement boosts the selection of a criterion to separate the continuous optimal detour rate to make a final decision.

6.3 A Two-choice Detour Decision Model

According to the requirement mentioned in section 6.2, this section is to provide a two-choice detour decision model to determine how to decide whether a detour decision should be made or not based on each generated experimental scenario in the previous chapter and the optimal detour rate derived from section 6.1.

6.3.1 Concept of Two-choice Detour Decision Model

The principle of two-choice detour decision model is to set a minimum threshold value for the diversion rate on the alternate route to convert the decimal diversion rate into a binary decision. Figure 6.3 illustrates the procedure to make the detour decision for each experimental scenario which will be used for the two-choice detour decision model development. The author assumes that an incident scenario would be warrant a detour operation if its optimal flow distribution state demands more than the summation of this threshold and a normal detour rate of 5% to divert to the local arterial.

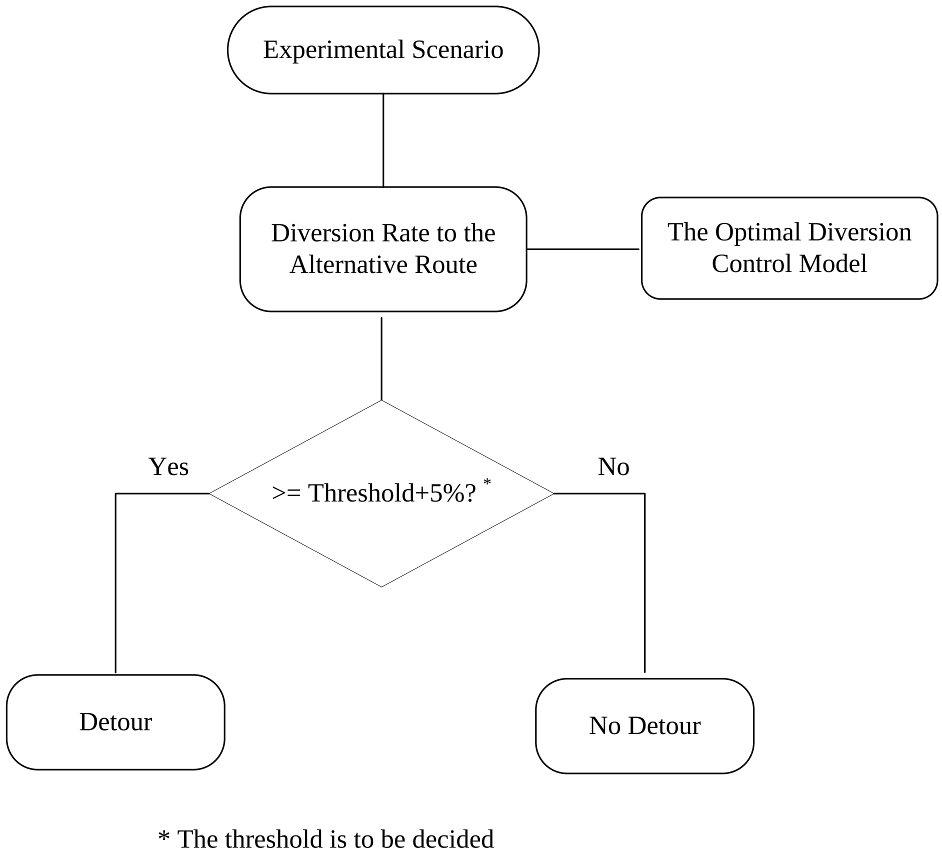


Figure 6. 3 The Procedure to Determine the Detour Decision

Since the detour decision is binary in nature, this study adopts a logistic regression, a commonly used methodology to study a binary dependent variable. The following parts will briefly present the principle of binary logistic regression and detail its development and validation in this study.

6.3.2 Principle of Binary Logistic Regression

The output of a linear regression can be transformed to an appropriate probability using a logit link function as follows:

$$\text{logit } p = \log \ o = \frac{\log p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \quad (6\text{-}25)$$

where p is a probability to succeed, and o is the odds representing the ratio of p to 1-p.

Since the odds (o) can be any value in (0, ∞), the log odds (log o) can vary in (-∞, ∞). This value represents what we get from the linear regression on the right hand side of Eq. (6-25). The inverse of the logit function is the logistic function, thus logit (p) = z can be transformed to:

$$p = \frac{e^z}{1+e^z} \quad (6\text{-}26)$$

Then, the logistic function maps any value of the right-hand side in Eq. (6-26) to a proportional value in (0, 1). The parameters included in the model (βi) can be estimated with the maximum likelihood method (Allison, 2001). The aforementioned theory implies that a unit additive change in the value of the variable changes the odds by a constant multiplicative amount. More detailed discussion regarding logistic models would be found in many references (Ben-Akiva and Lerman, 1985; Venables and Ripley, 2002; Washington et al., 2003).

6.3.3 Model Development

The dependent variables are series of binary variables indicating whether a detour decision should be made or not (1 represents "yes", 0 represents "no"). Note that the minimum threshold has not been set yet. This study will select one from the set (5%, 10%, 15%, 20%, 25%, 30% and 35%) with the principle of providing the greatest performance of the binary logistic regression model. Detour rates smaller than 5% and greater than 35% are not selected into a threshold set since when the detour rate is smaller than 5%, the incident is considered trivial, no detour needs to be implemented while when the detour rate is greater than 35%, the incident should be considered as special case since there should be severe incidents happened that incur long incident duration, great freeway volume and so on. Obviously, a detour plan needs to be implemented in such situation.

6.3.3.1 Calibration with Original Groups of Variables

This study first applied the original groups of independent variables and their values from Table 5.1 in the previous chapter. Table 6.1 show the estimation results when the minimum threshold is set as 5%. Among 9 independent variables, only incident duration is demonstrated to be significant. Moreover, the predicated model accuracy is only 49.3% which should be determined to be unacceptable. Other estimation results when the minimum threshold is set as 10%, 15%, 20%, 25%, 30%, 35% can be found in APPENDIX B which show the similar effects as Table 6.2. This is mainly because the independent variables are not well-categorized. Therefore, it is necessary to re-group the independent variables to better develop the binary logistic regression model.

Since the overall prediction accuracy is relatively low, it fails to select the optimal minimum threshold. This requires further analysis to get the optimal minimum threshold.

Considering the aforementioned model requirement, the following part will present a preliminary analysis to re-group the independent variables and select the optimal minimum threshold.

Table 6. 2 Calibrated Logistic Decision-Model with the Minimum Threshold of 5%

Variables included in the final model	Estimate	Exp(estimate)	Std. Error	z value	p-value
(Intercept)	-2.34500	0.2514	12.54390	-8.54	0.01
FR_VOL (250, 750, 1250, 1750, 2200)	0.45021	0.9738	56.00234	-9.62	1.51
FR_LN (2, 3, 4)	1.78294	3.5678	15.89535	5.08	0.60
INC_DUR (15, 30, 45,60, 75, 90,105, 120)	0.11725	0.7728	0.10723	-2.74	0.04
LN_BLK (1, 2, 3, 4)	-6.72811	1.6958	10.53119	9.02	1.74
LC_VOL1 (200, 300, 400, 500, 600, 700, 800)	0.00036	1.0004	20.00018	6.99	5.05
LC_VOL2 (200, 300, 400, 500, 600, 700, 800)	0.53490	1.8635	58.22140	10.33	7.02
LC_VOL3 (200, 300, 400, 500, 600, 700, 800)	-5.57560	1.8985	23.89450	7.34	2.78
LC_LN (1, 2, 3)	7.50390	4.8565	58.22140	10.33	7.02
NUM_SIGNAL (2, 3, 4, 5, 6, 7)	4.69900	2.9680	13.31660	2.98	0.13
The number of observations used for calibration			400		
Likelihood with constants only			-507.93		
Final value of Likelihood			-1161.605		
Fitted model accuracy			0.520		
Predicted model accuracy			0.493		

6.3.3.2 Preliminary Analysis for Binary Logistic Regression Model

The goal of this section is to re-categorize the independent variables and select the optimal minimum threshold for the development of binary logistic regression. Classification and Regression Tree (CART) has the ability to organize by variables and identify patterns in the data (Smith and Smith, 2001) which was chosen as a tool of preliminary analysis in this study. The basic concept of CART was attached in APPENDIX C.1.

The original independent variables were used as inputs for the building tree. The dependent variable is the same with the binary logistic regression model. Each threshold was used to build a tree. Thus totally, there are 7 trees developed for the preliminary analysis. The estimation results can be found in APPENDIX C.2. It shows that the significant independent variables are incident duration (INC_DUR) which is categorized into the duration under 45 minutes and above 45 minutes, number of signals on alternative (NUM_SIGNAL) which is categorized into number under 2 and above 2, volume of the roadway connecting from freeway to detour route (LC_VOL1) which is categorized into volume under 600 vphpl and above 600 vphpl. Other variables like number of lane blocked, freeway volume for each lane, number of freeway lanes, volume on the detour route, and number of local lanes were still not significant. This boosts the combination of the volume of each lane and the number of lanes to model development. Also, this study will try the percentage of capacity drop instead of number of lane blocked to analyze its impact on detour decision.

Table 6.3 summaries the overall prediction accuracy for each developed tree under different minimum threshold. From the table, it is obvious tree 2 has the highest prediction accuracy of 75.9% in which 10% was set as the minimum threshold. This study will select 10% as the final optimal minimum threshold to develop the binary logistic regression model.

Table 6. 3 The Overall Prediction Accuracy of Each Tree

Tree Number	1	2	3	4	5	6	7
Minimum Threshold	5%	10%	15%	20%	25%	30%	35%
Prediction Accuracy	55.1%	75.9%	57.6%	72.4%	65.4%	69.5%	63.8%

6.3.3.3 Calibration with Re-grouped Variables

With the contribution of preliminary analysis, the final binary logistic regression model used the re-grouped independent variables and minimum threshold of 10% to calibrate. Table 6.4 summarizes specifications of the model which demonstrates about 76 percent and 73 percent accuracies for model estimation set and validation set, respectively. The accuracy is determined by whether or not the optimal traffic distribution during the incident management period needs more than twenty percent (additional normal detour volume of five percent) of its total volumes to the local street. In addition, all variables included in the model are significant at a 95 percent confidence level which also confirms the necessity of re-grouping independent variables. The calibrated results also offer the following information:

- All variables included in the final model show positive relations with the response variable.

- When the flow rate on the roadway connecting from freeway to detour route (denoted in LC_VOL1) is not heavy, it has a strong positive effect on the decision.

- The binary variable, indicating whether the primary detour route includes more than two traffic signals or not, has a positive and significant sign. This implies that it is more likely to implement detour plans if the primary detour route has less number of signalized intersections.

Table 6. 4 Calibrated Logistic Decision-Model

Variables included in the final model	Estimate	Exp(estimate)	Std. Error	z value	p-value
(Intercept)	-1.38300	0.2508	0.54490	-2.64	0.01
IF(INC_DUR>45) TRUE[1]	0.00725	0.9928	0.00383	-2.34	0.03
IF(NUM_SIGNAL <= 2)TRUE[2]	0.67700	1.9680	0.31220	2.18	0.02
IF(LC_VOL1 < 600)TRUE[3]	0.51490	1.6735	0.22540	2.33	0.01
PER_CAP_DROP	3.42800	1.5958	0.59110	7.02	0.01
LC_VOL2*LC_LN	0.00036	1.0004	0.10018	1.99	0.05
FR_VOL*FR_LN	0.00021	0.9998	0.00304	-4.62	0.04
The number of observations used for calibration			400		
Likelihood with constants only			-317.93		
Final value of Likelihood			-361.605		
Fitted model accuracy			0.765		
Predicted model accuracy			0.733		
The number of observations used for validation			100		

<Note> [1] IF(INC_DUR >45 2)TRUE: 1 if INC_DUR<= 45 ; 0 otherwise
[2] IF (NUM_SIGNAL <= 2) TRUE: 1 if NUM_SIGNAL<= 2; 0 otherwise
[3] IF (LC_VOL1 < 600) TRUE: 1 if LC_VOL1 < 600; 0 otherwise

From aforementioned findings, it can be concluded that the incident duration alone should not be a sole criterion to decide the need of implementing the detour operation.

Table 6.5 details the re-calibrated logistic model with interaction terms, including INC_DUR:FR_VOL (0.00002/p-value=0.000) and INC_DUR: PER_CAP_DROP (0.05154/p-value=0.000). Although these two interaction terms are not included in the final logistic regression model due to their multicollinearity, the information still can be derived regarding how they interact with each other. It can be observed that both interaction terms are related to incident duration, which confirms its significance again.

Table 6. 5 Re-calibrated Logistic Decision Models with Excluded Interaction Terms

Variables included in the final model	Estimate	Exp(estimate)	Std. Error	z value	p-value
(Intercept)	2.29900	9.9642	0.472	4.869	0.000
IF(INC_DUR>45)TRUE	-0.06469	0.9374	0.008	-7.692	0.000
IF(NUM_SIGNAL <= 2)TRUE	0.71610	2.0464	0.316	2.269	0.023
IF(LC_VOL1 < 600)TRUE	0.54460	1.7239	0.227	2.404	0.016
LC_VOL2*LC_LN	0.00043	1.0004	0.000	2.337	0.019
FR_VOL*FR_LN	-0.00047	0.9995	0.000	-5.921	0.000
INC_DUR:FR_VOL	0.00002	1.0000	0.000	4.219	0.000
INC_DUR: PER_CAP_DROP	0.05154	1.0529	0.008	6.766	0.000
The number of observations used for calibration			400		
Likelihood with constants only			-307.93		
Final value of Likelihood			-250.42		
Fitted model accuracy			0.774		
Predicted model accuracy			0.773		

To determine the detour decision, first, it is needed to estimate the probability of being a "yes" for a decision regarding a given scenario (e.g., Scenario 1 in Figure 6.4). Using Eq. (6-27) and the estimated coefficients in Table 6.4, it is able to estimate u, e^u, and p. Values for u, e^u, and p for Scenario 1 are 1.103, 3.012, and 0.751, respectively. Since p >= 0.5, one shall decide to implement detour plans.

$$p = \frac{e^u}{1+e^u} \tag{6-27}$$

where variable u is a measure of the total contribution of all affecting variables used in the model (listed in Table 6.4), and

u = -1.383 + 0.00725*IF(INC_DUR>45)TRUE + 0.677*IF(NUM_SIGNAL<=2)TRUE + 0.5149*IF(LC_VOL1<600)TRUE + 3.728*PER_CAP_DROP + 0.00036* LC_VOL2*LC_LN + 0.00021* FR_VOL*FR_LN.

6.3.4 Summary of Findings

This section focuses on exploring whether a detour decision should be made or not by developing a logistic regression model with incident scenarios that yields binary variables "yes" or "no" to indicate the final decision. The estimated results presents an accuracy of 73.5% and all independent variables included are significant which made the following findings extremely convincing:

- Less number of signals on the alternative arterial will increase the probability of implementing detour plan;
- It is more likely to detour to arterial with larger percentage of capacity reduction on freeway and

- When the flow rate on the roadway connecting from freeway to detour route is slight, it is more likely to make detour decision.

To justify the proposed detour operations, one can further conduct the analysis of resulting benefits, which can be estimated with the procedure presented in section 6.4.

6.4 A Multi-choice Model

This section is to develop a multi-choice model to yield 5 types of decisions (i.e. "strongly not recommended", "not recommended", "neutral", "recommended", "strongly recommended") so that transportation mangers have more criteria to make final detour decision. Figure 6.4 describes the procedure to determine detour decision with 5 thresholds. If the optimal detour rate generated from the optimal diversion control model for a certain scenario is smaller than threshold 1 plus normal detour rate (5%), then "strongly not recommended" is presented so that transportation mangers will implement "no detour" without any hesitation; if the optimal detour rate is located in threshold 1 plus 5% and threshold 2 plus 5% , "not recommended" is presented, transportation mangers will implement "no detour"; when the optimal detour rate is in the range of threshold 2 plus 5% and threshold 3 plus 5%, transportation mangers can either implement "detour" or "not detour" since both implementations are reasonable under this situation. While when the decision is "recommended", the "detour" is implemented, when the decision is "strongly recommended", "detour" is implemented without any hesitate.

Ordered probit model has the ability to rank criteria which is chosen as developing a multi-choice detour decision model. The 5 types of decisions are assigned with numeric labels (0, 1, 2, 3, and 4). 0 indicates "strongly not recommended", 1 indicates "not recommended" , 2 indicates "neutral", 3 indicates "recommended" and 4 indicates "strongly recommended".

Note that the values of five thresholds will be decided in model development. The following parts in this section will introduce the basic concept of ordered probit model and its development and validation.

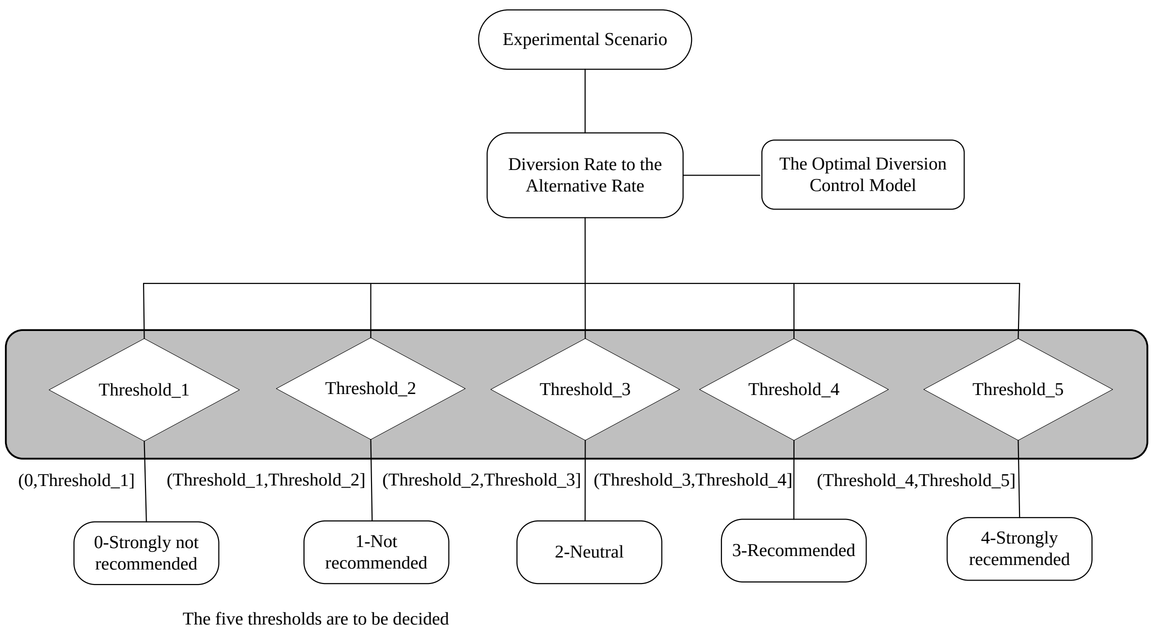


Figure 6. 4 The Procedure to Determine Detour Decision with 5 Thresholds

6.4.1 Basic Concept of Ordered Probit Model

The ordered model is appropriate in applications in which the respondent expresses a preference with an ordinal ranking. Although the outcome is discrete, the multinomial logit models would fail to account for the ordinal nature of the dependent variable. If the situation being modeled is unordered, an ordered model can create serious biases in the estimation of the probabilities. On the other hand, if the type of event under study is ordered, an unordered model loses efficiency rather than consistency.

The ordered model given by:

$$P(y=j/x,\theta)=p(S_j) \tag{6-28}$$

For some probability measure (p) depending on x and θ, and a finite sequence of successive interval {Sj}, depending on x and θ. In most cases, the ordered model takes a simpler form for some distribution functions.

$$\begin{gathered}P(y=j/x,\mu,\beta)=F(\mu_j-x\beta')-F(\mu_{j+1}-x\beta') \\ j=0,1,\ldots\ldots,m, \qquad \mu_0=-x, \qquad \mu_j\leq \quad \mu_{j+1}, \qquad \mu_{m+1}=x\end{gathered} \tag{6-29}$$

If F = Φ (i.e., a standard normal distribution), equation 25 defines the ordered probit model. The model depicted in equation (6-29) is motivated by consideration of an unobserved continuous random variable (y*), which determines the outcome of y by the rule y = j if and only if $\mu_j<y^*<\mu_{j+1}$ with j = 0, 1... m. With a normal distribution, the probabilities can be shown as follows:

$$\begin{aligned}&P(y=0)=\Phi(-\beta' x),\\&P(y=1)=\Phi(\mu_1-\beta' x)-\Phi(-\beta' x),\\&P(y=2)=\Phi(\mu_2-\beta' x)-\Phi(\mu_1-\beta' x),\\&\qquad\qquad\vdots\\&P(y=j)=1-\Phi(\mu_{j-1}-\beta' x).\end{aligned} \tag{6-30}$$

The computations of marginal effects of changes in the categories can be computed as:

$$f(P(y=0), fx) = -\Phi(\beta' x)\beta,$$

$$\frac{fP(y=1)}{fx} = (\Phi(\beta' x) - \Phi(\mu - \beta' x))\beta$$

$$\frac{fP(y=2)}{fx} = \Phi(\mu - \beta' x)\beta$$

...

6.4.2 Model Development and Validation

To develop the multi-choice model, it is necessary to decide the values of independent variables and dependent variables. As the analysis in two-choice model, those original independent variables are not well categorized. Though the original variables might have a better significance when they used in multi-choice model than used in two-choice model, it is still assumed the ultimate significance of these variables is not very promising. Underlying this assumption, a preliminary analysis will be first introduced before the development of the multi-choice model.

This study also selects different thresholds from a predetermined set of threshold from 5% to 60% with the increment of 5%. Table 6.6 lists all the cases with the selected thresholds and corresponding dependent variables based on the range of the optimal detour rate. The preliminary analysis will select the best case for the development of multi-choice model.

Table 6. 6 Cases of selected threshold for model development

Case	Category of selected thresholds (%)	Definition of dependent variables based on the optimal detour rate
1	(5,10,15,20,25)	(0,10%]-0; (10%,15%]-1; (15%,20%]-2; (20%,25%]-3; (25%,100%]-4
2	(5,15,20,25,30)	(0,10%]-0; (10%,20%]-1; (20%,25%]-2; (25%,30%]-3; (30%,100%]-4
3	(5,10,20,25,30)	(0,10%]-0; (10%,15%]-1; (15%,25%]-2; (25%,30%]-3; (30%,100%]-4
4	(5,10,20,25,35)	(0,10%]-0; (10%,15%]-1; (15%,25%]-2; (25%,30%]-3; (30%,100%]-4
5	(5,10,25,30,35)	(0,10%]-0; (10%,15%]-1; (15%,30%]-2; (30%,35%]-3; (35%,100%]-4
6	(10,15,20,30,35)	(0,15%]-0; (15%,20%]-1; (20%,25%]-2; (25%,35%]-3; (35%,100%]-4
7	(10,15,20,25,30)	(0,15%]-0; (15%,20%]-1; (20%,25%]-2; (25%,30%]-3; (30%,100%]-4
8	(10,20,25,30,35)	(0,15%]-0; (15%,25%]-1; (25%,30%]-2; (30%,35%]-3; (35%,100%]-4
9	(10,20,30,35,40)	(0,15%]-0; (15%,25%]-1; (25%,35%]-2; (35%,40%]-3; (40%,100%]-4
10	(10,30,35,40,45)	(0,15%]-0; (15%,35%]-1; (35%,40%]-2; (40%,45%]-3; (45%,100%]-4
11	(15,20,25,30,35)	(0,20%]-0; (20%,25%]-1; (25%,30%]-2; (30%,35%]-3; (35%,100%]-4
12	(15,20,30,35,40)	(0,20%]-0; (20%,25%]-1; (25%,35%]-2; (35%,40%]-3; (40%,100%]-4
13	(15,20,35,40,45)	(0,20%]-0; (20%,25%]-1; (25%,40%]-2; (40%,45%]-3; (45%,100%]-4
14	(20,25,30,35,40)	(0,25%]-0; (25%,30%]-1; (30%,35%]-2; (35%,40%]-3; (40%,100%]-4
15	(20,30,35,40,45)	(0,25%]-0; (25%,35%]-1; (35%,40%]-2; (40%,45%]-3; (45%,100%]-4
16	(20,35,40,45,50)	(0,25%]-0; (25%,40%]-1; (40%,45%]-2; (45%,50%]-3; (50%,100%]-4

17	(25,30,35,40,45)	(0,30%]-0; (30%,35%]-1; (35%,40%]-2; (40%,45%]-3; (45%,100%]-4
18	(25,35,40,45,50)	(0,30%]-0; (30%,40%]-1; (40%,45%]-2; (45%,50%]-3; (50%,100%]-4
19	(5,25,35,45,55)	(0,10%]-0; (10%,30%]-1; (30%,40%]-2; (40%,50%]-3; (50%,100%]-4
20	(5,20,30,40,50)	(0,10%]-0; (10%,25%]-1; (25%,35%]-2; (35%,45%]-3; (45%,100%]-4
21	(10,20,30,40,50)	(0,15%]-0; (15%,25%]-1; (25%,35%]-2; (35%,45%]-3; (45%,100%]-4
22	(15,25,35,45,55)	(0,20%]-0; (20%,30%]-1; (30%,40%]-2; (40%,50%]-3; (50%,100%]-4
23	(20,30,40,50,60)	(0,25%]-0; (25%,35%]-1; (35%,45%]-2; (45%,55%]-3; (55%,100%]-4

Note: 0 -strongly not recommended; 1-not recommended, 2-neutral; 3-recommended; 4 –strongly commended.

6.4.2.1 Preliminary Analysis for Ordered Probit Model

CART is selected again to categorize the original variables (see Table 5.1) and choose the best category of threshold for model development. All the original variables and each case in Table 6.6 are used to build tree with CART. The growing method of CART is selected for developing the tree model which has the ability to choose the most significant variables for splitting. The CART model selected the appropriate variable for each decision level based on the highest variance in distribution. Therefore, the tree model will stop when a specific variable is unknown.

The results can be found in APPENDIX C.3, among the 9 independent variables, the significant variables are freeway volume, number of lane blocked, incident duration, number of signal on detour route. Moreover, freeway volume rate is re-categorized into under 500 and above 500 vplph in most of trees. Number of lane blocked is re-categorized into under 1 and above 1 in all of trees. Incident duration is re-categorized into under 60 minutes and above 60 minutes. Number of signal on detour route is re-categorized into under 2 and above 2. Other variables like flow rate on the detour route, number of lanes on detour route are not demonstrated to be significant. This study will again use the total volume of detour route which is the combination of number of lanes and flow rate on detour route to develop the multi-choice model. Other insignificant variables such as number of signal on detour route will still use their original values. Table 6.7 lists all the re-grouped variables for multi-choice model.

Table 6. 7 Re-grouped Variables and Range of Values for Multi-choice Model

VARIABLES	DESCRIPTION	RANGE OF VALUES
FR_VOL	Freeway mainline volume rate (in vphpl)	0 IF (FR_VOL<=500); 1 Otherwise
FR_LN	Number of lanes on the freeway mainline	2, 3, 4
INC_DUR	Incident duration (in mins)	0 IF (INC_DUR <=60); 1 Otherwise
LN_BLK	Number of lanes blocked	0 IF (LN_BLK <=1); 1 Otherwise
LC_VOL1	Flow rate on the road connecting from freeway to detour route (in vphpl)	200, 300, 400, 500, 600, 700, 800
LC_VOL2* LC_LN	Volume on the detour route (in vph)	[200, 2400]
LC_VOL3	Flow rate on the road connecting from detour route to freeway (in vphpl)	200, 300, 400, 500, 600, 700, 800
NUM_SIGNAL	Number of signals on the detour route	0 IF (NUM_SIGNAL <=2); 1 Otherwise

Table 6.8 summaries the overall prediction accuracy of each tree. Note that the number of tree is consistent with the case number in Table 6.6. Obviously, tree 1 in which (5%, 10%, 15%, 20%, and 25%) is set as the five thresholds to make the final decision has the highest accuracy of 75.2%. Therefore, (5%, 10%, 15%, 20%, 25%) is chosen as the final threshold used in the ordered probit model.

Table 6. 8 The Overall Prediction Accuracy of Each Tree

Tree number	Prediction accuracy	Tree number	Prediction accuracy
1	75.2%	13	63.2%
2	71.8%	14	67.3%
3	68.0%	15	68.5%
4	49.0%	16	71.8%
5	49.0%	17	68.5%
6	56.8%	18	71.8%
7	41.8%	19	65.8%
8	65.3%	20	62.7%
9	64.0%	21	62.7%
10	68.5%	22	65.8%
11	65.3%	23	68.5%
12	64.0%		

6.4.2.2 Calibration Results of Ordered Probit Model

Note that the independent variables used in ordered probit model are coming from Table 6.7 and dependent variables are determined with threshold (5%, 10%, 15%, 20%, and 25%). Table 6.9 describes the estimation results of the ordered probit model. The overall prediction accuracy is 78.5%, making the performance of the model acceptable. Moreover, according to P-value of every independent variable, number of lanes on freeway, number of lane blocked, incident duration, freeway flow rate and number of signal on detour route are very significant in this model. The negative coefficient of number of lanes on freeway indicates that vehicles are recommended to stay at freeway with more lanes on freeway. This conclusion is obvious since more lanes on the freeway can hold higher capacity which can be utilized by more vehicles without detouring to alternative route. The positive coefficients of number of lanes blocked, freeway volume and incident duration give a reasonable conclusion that vehicles should be suggested to detour to alternative with the increase of number of lanes blocked, incident duration and freeway flow rate. Number of signal on detour route has a negative impact on detour decision that means it should not be suggested to detour with more number of signals on detour route.

Table 6. 9 Estimation Results for Ordered Probit Model

Variable*	Estimated Coefficients	Standard Error	P-value
Constant	1.3632	.3.120	.001
LN_BLK IF (LN_BLK >1) TRUE	.9911	4.725	.002
IN_DUR IF (INC_DUR >60) TRUE	.0101	-4.592	.000
FR_LN (2, 3, 4)	-.3800	-4.246	.001
FR_VOL IF(FR_VOL>500) TRUE	.9679	-6.134	.000
LC_VOL1	-.0001	-.0780	.938
LC_VOL2* LC_LN	.0003	.1210	.904
LC_VOL3	.0006	1.888	.059
NO_SIGNA IF (NUM_SIGNAL >2) TRUE	-.0048	-.1190	.025
Threshold u_1	.0962	.0300	.000
Threshold u_2	.2169	.0439	.000
Threshold u_3	.3620	.0548	.000
Restricted log likelihood		-381.4406	
Log likelihood function		-328.1631	
Number of observations		400	
Overall prediction accuracy		78.5%	

* Dependent variable is "Whether detour decision should be made given the optimal detour rate r?"

If r ∈(0, 10%]: strongly not recommended, y=0;
r ∈ (10%, 15%]: not recommended, y=1;
r ∈ (15%, 20%]: neutral, y=2;
r ∈ (20%, 25%]: recommended, y=3;
r ∈ (25%, 100%]: strongly recommended, y=4.

6.4.3 Summary of Findings

This section focuses on selecting the most appropriate category of criteria to assist transportation mangers to make a final decision and exploring how factors influence transportation mangers' final decision given the selected category of criteria. The calibration results show an accuracy of 78.5% and 5 variables are significant, the following conclusions can be come up:

- It is less likely to be recommended to implement detour decision with more number of lanes on freeway;
- When the number of lanes blocked increase, the final decision tends to "strongly recommended";
- If the freeway volume or the incident duration increases, it tends to be strongly recommended to alternative route and
- Vehicles are recommended to stay on freeway mainline if there are too signals on the detour route.

The proposed detour operations will be further justified by benefit estimation in the next section.

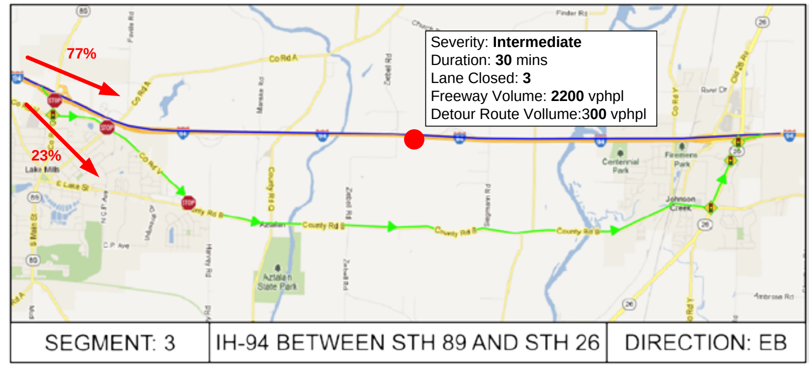
6.5 Benefit Estimation

The primary goal of implementing detour plans is to mitigate the congestion and the resulting delay due to an unexpected lane closure. Thus, responsible traffic managers need to consider the resulting benefits for comparison with the operational costs. This section briefly illustrates how to estimate the benefits resulted from detour operations. This benefit analysis can be a way to validate the developed detour decision framework, since it shows us whether the implemented detour plan is truly beneficial or not, from the overall system perspective.

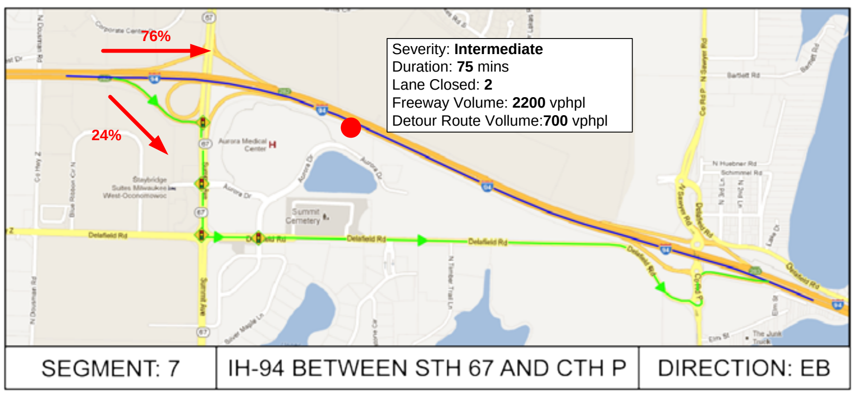
6.5.1 Scenario Selection

To illustrate how benefits from detour plans would vary depending on different traffic conditions and incident severities, this study selected four different scenarios that have been decided to implement detour plans based on the proposed detour decision model. Figure 6.5 illustrates the situation of these four scenarios which are located in segment 1, 3, 7 and 9, independently. Note that the segments presented here are consistent with those in section 4.5, chapter 4. The main flow rate and detour flow rate which were derived from the integrated diversion control model have been marked on each scenario in this figure. Table 6.10 summaries the outputs for the four scenarios with developed detour decision model (the two-choice model and the multi-choice model).The output for all scenarios is "Yes" with the two choice model, which means they needs to be implemented with detour plan. Note that, in scenario 1, the detour flow rate is 19%, obviously, it needs to implement detour plan according to the developed two-choice model in which the threshold is 10%. However, in the developed multi-choice model, the decision is "neutral" since it is slightly smaller than the bound between "neutral" and "recommended". In this case, it is still suggested to implement detour plan. The following part will explain how the benefit is estimated and whether the selected scenarios deserve the implementation of detour plan.

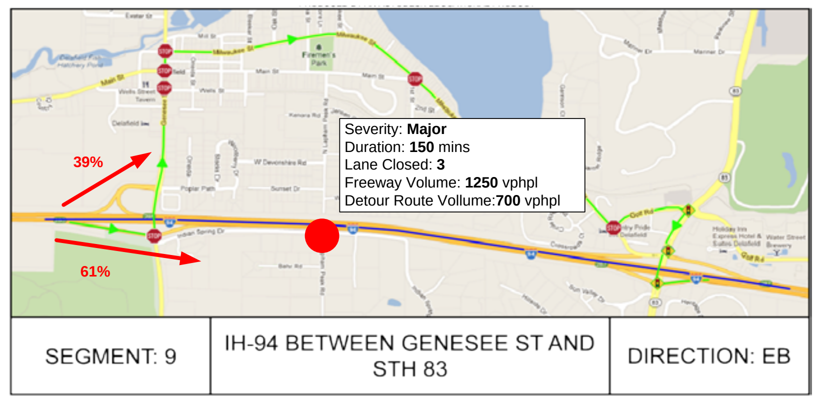
Scenario 1



Scenario 2



Scenario 3



Scenario 4

Figure 6. 5 Selected Scenarios of Implemented Detour Plan

Table 6. 10 Detour Decision for the Selected Scenarios

Scenario	Two-choice Model	Multi-choice Model
1	Yes	Neutral
2	Yes	Recommended
3	Yes	Recommended
4	Yes	Strongly Recommended

6.5.2 Benefit Analysis

This study has estimated benefits of selected scenarios with the following procedure:

Step 1: Compute the difference in delay between with and without detours

In this research the ***total travel time*** and ***total time in queue*** from the integrated corridor control model output are used to compute the reduced delay due to detour operations.

Step 2: Select other impacts that could be also parts of the benefit analysis

Once the delay decreases for any reason, associated by-products also decrease. This study include reduced fuel consumptions and emissions (i.e., HC, CO, NO, and CO2) in this benefit estimation procedure.

Step 3: Estimate the reduced amount of each by-product based on related references

Assuming that all vehicles are passenger cars, the author estimates the fuel consumption reduction directly from the reduced delays using a conversion factor, 0.156 gallons of gasoline / hour, which is provided by the *Ohio Air Quality Development Authority* (Koerner, 2008). It should be mentioned that the assumption of passenger car only is made for convenience of presentation and has nothing to do with the presented methodology and the proposed decision model. The inclusion of truck data will change only the estimated parameter values, but not the model structure as well as the research methodology.

Similarly, the reduced emissions can be estimated based on either the reduced delay or fuel consumption using conversion factors as follows:

- HC: 13.073 grams / hour of delay (provided by MDOT in 2000)
- CO: 146.831 grams / hour of delay (provided by MDOT in 2000)
- NO: 6.261 grams / hour of delay (provided by MDOT in 2000)
- CO2: 19.56 lbs CO2 / gallon of gasoline (Energy Information Administration in 2009)

Step 4: Convert the saved delay, fuel, and emissions to the monetary value

Similar to Step 3, we use monetary conversion factors to estimate the reduced delay and associated by-products in a monetary value. Followings are values and sources for factors.

- Delay: $27.37/ hour (U.S. Census Bureau in 2008)
- Fuel: $2.32/gallon (Energy Information Administration in 2009)
- HC: $6,700/ton (DeCorla-Souza, 1998)
- CO: $6,360/ton (DeCorla-Souza, 1998)
- NO: $12,875/ton (DeCorla-Souza, 1998)
- CO_2: $23 / metric ton (CBO (Congressional Budget Office)'s cost estimate for S. 2191, America's Climate Security Act of 2007)

Table 6.11 further displays the details for selected scenarios and corresponding outputs from the integrated diversion control model, while Table 6.12 shows the benefits estimated from aforementioned procedure.

Table 6. 11 Descriptions of Scenarios for Benefit Analysis Illustrations

Categories		Scenario 1	Scenario 2	Scenario 3	Scenario 4
Freeway : Detour Route Volume Level		L:L*	H:L	H:H	L:H
Incident Severity		Minor	Intermediate	Intermediate	Major
Lane Closure Status		Moderate	Severe	Light	Severe
Simulation Model Inputs	Number of Freeway	4	4	4	4
	Number of Lane Closures	2	3	2	3
	Incident Duration (minute)	15	30	75	150
	Freeway Volume (vphpl)	1250	2200	2200	1250
	Local Volume 1 (vphpl)	300	300	500	600
	Local Volume 2 (vphpl)	300	300	700	700
	Local Volume 3 (vphpl)	200	200	200	800
	Number of Signal on Primary Detour Route	2	4	2	5
	Ratio of Lane Closures	0.50	0.75	0.50	0.75
	Percentage Capacity Reduction	0.75	0.87	0.75	0.87
Flow Distribution for Each Route	Main Flow Rate	0.81	0.77	0.76	0.61
	Detour Flow Rate	0.19	0.23	0.24	0.39
Saved Outputs (w/o – w/ Detour)	Total Throughput	11432	12583	12492	15180
	Total vehicles in queue	3873	1035	1317	1252
	Total travel time (veh-hr)	1204.70	1548.04	1738.93	1964.18
	Total queue time (veh-hr)	432.85	407.72	571.75	910.16
	Total delay reduction (veh-hr)	**1637.55**	**1955.76**	**2310.78**	**2874.34**

* L: Light H: Heavy

Table 6. 12 Estimated Benefit Based on Saved Delays

Estimated Benefit ($)	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Delay	44,819.77	53,529.24	63,243.33	78,670.76
Fuel	592.66	707.83	836.28	1,040.28
HC	143.43	171.30	202.39	251.76
CO	1,529.22	1,826.38	2,157.82	2,684.19
NO	132.00	157.65	186.26	231.70
CO_2	52.13	62.26	73.56	91.50
Total	**47,269.21**	**56,454.70**	**66,699.65**	**82,970.20**

As shown in Table 6.11, selected scenarios cover four combinations of traffic conditions (heavy and light volumes) on both freeway and alternate routes. A significant reduction in delay and its resulting benefits has been showed in Table 6.12. Notice that considerable savings ($47,269.21) have been demonstrated in the first scenario which just reflects a minor incident case with relatively light volumes on both the freeway and detour route. This saving also indicates implementing detour plan when the output from multi-choice model is "neutral" under this situation. Since the detour rate of this scenario is 19% which is very close to threshold of "recommended".

The second scenario with a greater detour flow rate and a higher level of incident shows a more considerable saving than scenario 1. Both benefits savings of scenario 2 and 3 are considerable which further validate the proposed multi-choice model since both of these scenarios are suggested with "recommended" from the multi-choice model.

The last scenarios are suggested with "strongly recommended" from the multi-choice model which demonstrate more promising benefits of implementing detour plan than the first three scenarios. The benefits of almost $ 83,000 are observed in the last scenario which suffers a major incident with a long duration. These results also confirm the decision for detour implementation should be made after considering various aspects of related factors and given environments.

Chapter 7

CONCLUSIONS

Despite the increasing attention to minimizing incident-incurred congestion with optimal detour operations, effective guidelines for determining when and how to make such decisions are quite limited. Most existing guidelines are based mainly on the incident duration alone as the primary factor, offering no reliable procedure to consider the compound impacts of all related factors on the resulting detouring effectiveness and the overall system benefits.

This study proposes a multi-criteria decision-support system that can be implemented by any responsible agency to develop a convenient yet effective tool to determine the necessity of implementing detour operations during non-recurrent congestion. The proposed system has been applied with an actual freeway corridor (the IH-94 corridor between the city of Madison where IH-94 connects with IH-39/90 and the city of Milwaukee where it connects to IH-43). Different segments divided from the corridor and various actual incident scenarios for each segment have been demonstrated to achieve significant overall benefits. With this giant experimental scenario to develop and validate the proposed detour decision model embedded in the multi-criteria decision-support system, it should be fully recognized that any operational model intended for use in practice certainly can achieve its best performance if calibrated properly with local data. Notwithstanding that the proposed two-choice and multi-choice decision model, calibrated extensively with Wisconsin's incident data, can still serve as a useful reference tool for any other highway agencies in developing a similar model or in contending with non-recurrent congestion on traffic corridors with similar geometric features and incident characteristics.

The presented detour decision model plays a significant role in the integrated incident management system for contending with non-recurrent congestion, ranging from the prediction of incident duration to the computation of operational benefits. The proposed model, with features of computational convenience and operational flexibility, has the ability to allow potential users to customize its application depending on the operational requirements in the target region. Although the proposed model is calibrated from simulation data, the estimation results of its parameters clearly indicate that incident duration itself has a great impact on making detour decision, but it needs to be associated with following additional variables, whose significances have been demonstrated in this study, to make the proper decision for the responsible highway agency to minimize the congestion incurred by the detected incident:

- Number of signals on the detour route show its significance on both two-choice detour decision model and multi-choice detour decision model which leads to higher probability to implement detour decision given a detour route with less than 2 signals;
- Freeway volume also has significant impact on decision making process according to the estimation results on two detour decision models; and
- Percentage of capacity drop should be considered in the decision making process according to its significance in the two-choice detour decision model, though it is not involved in the multi-choice model, number of lane blocked, which is used to compute the percentage of capacity drop, has been demonstrated to be significant in the multi-choice model.

Due to the limitation of data collection, more potential factors (variance of driver compliance rate, percentage of truck involved, etc.) have not been explored in this study. Moreover, the comparison of estimated benefits between implementing detour operation and without implementing detour operation when the given scenario is not suggested to detour to alternate route from the two decision models needs to be presented to further confirm the proposed detour decision models.

According to aforementioned limitation of this study, the future research along this line is to include more potential factors that may affect transportation mangers' decision and enhance the proposed decision model with more available field data.

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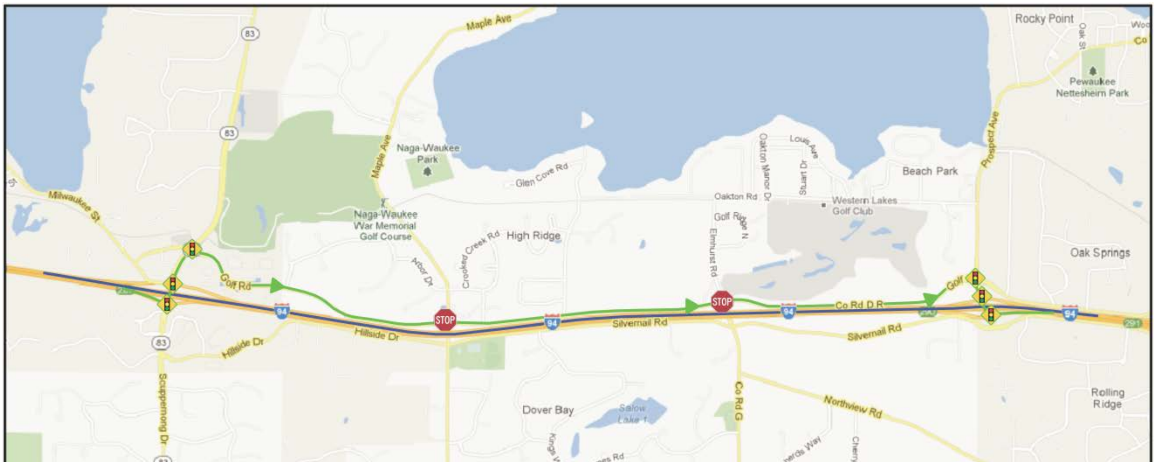
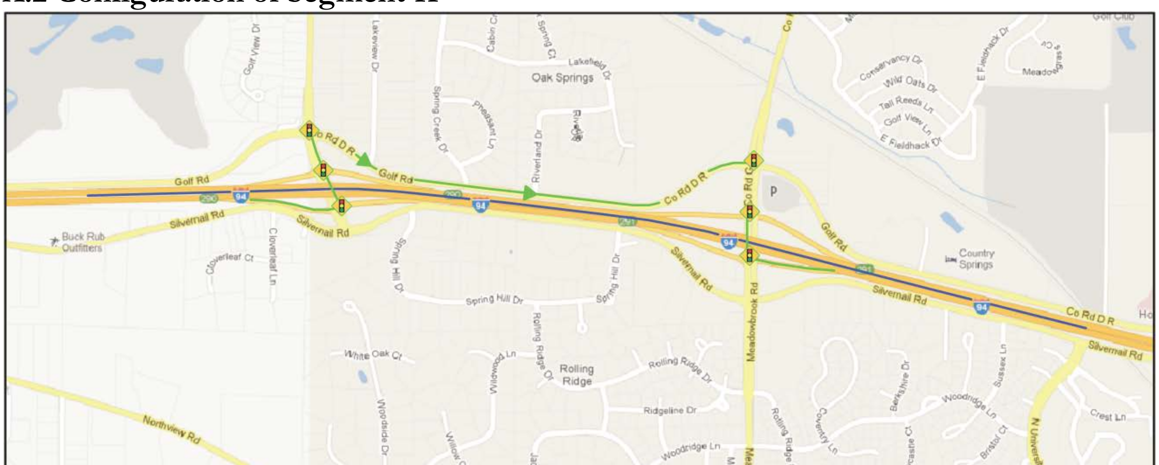
APPENDIX A: Configuration of Segments

A.1 Configuration of Segment 10



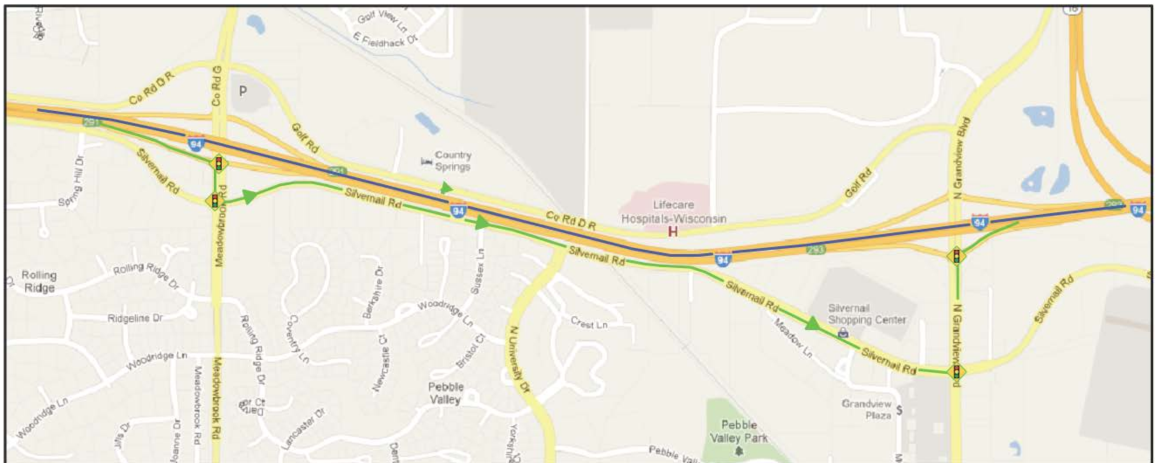
SEGMENT: 10 B	IH-94 BETWEEN STH 83 ST AND CTH SS	DIRECTION: EB

A.2 Configuration of Segment 11



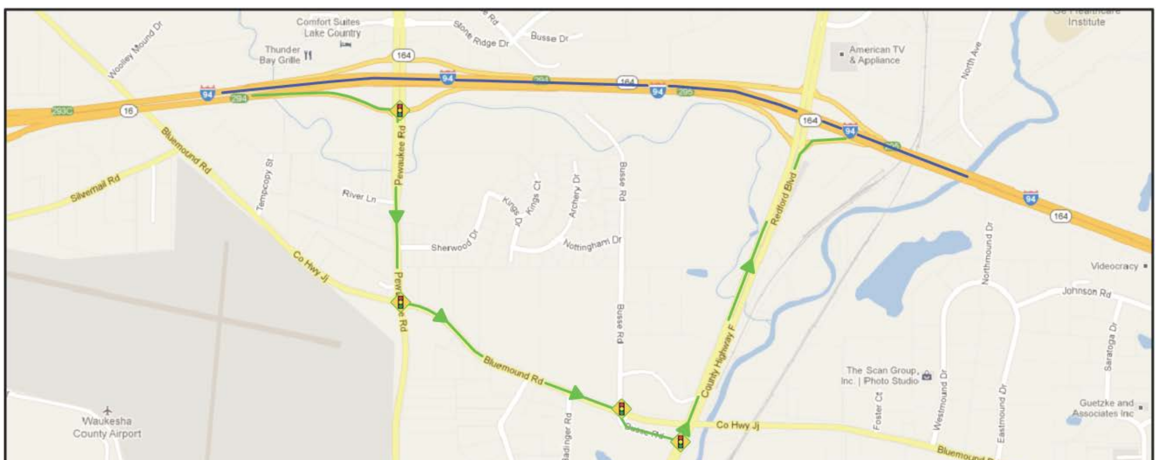
SEGMENT: 11 B	IH-94 BETWEEN CTH SS AND CTH G	DIRECTION: EB

A.3 Configuration of Segment 12



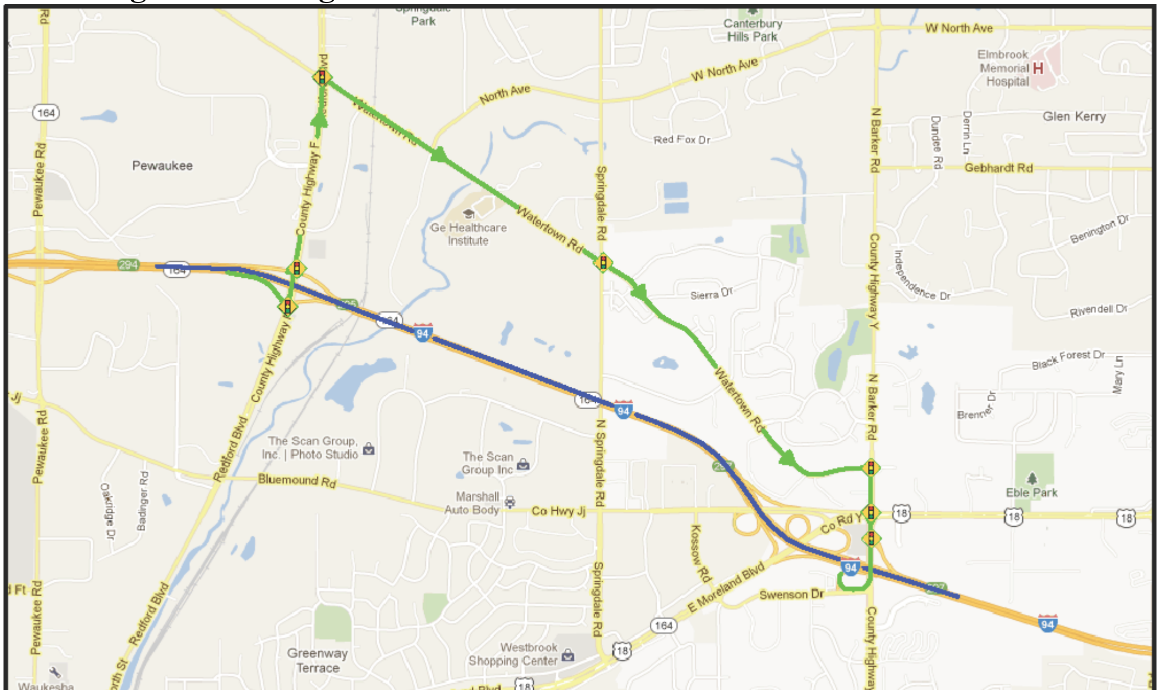
SEGMENT: 12 B	IH-94 BETWEEN CTH G AND GRANDVIEW BLVD	DIRECTION: EB

A.4 Configuration of Segment 15



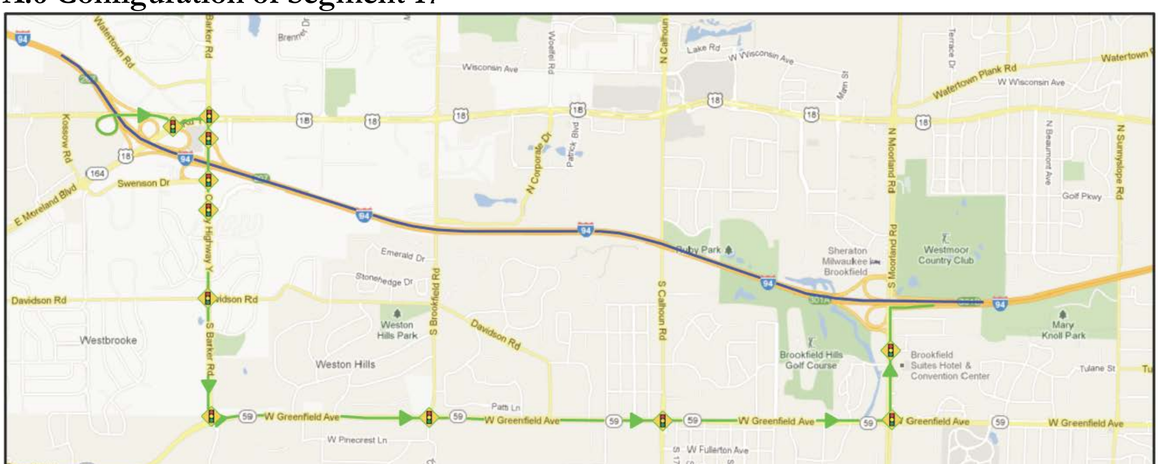
SEGMENT: 15 B	IH-94 BETWEEN PEWAUKEE RD (WIS 164) AND CTH F (WIS 164)	DIRECTION: EB

A.5 Configuration of Segment 16



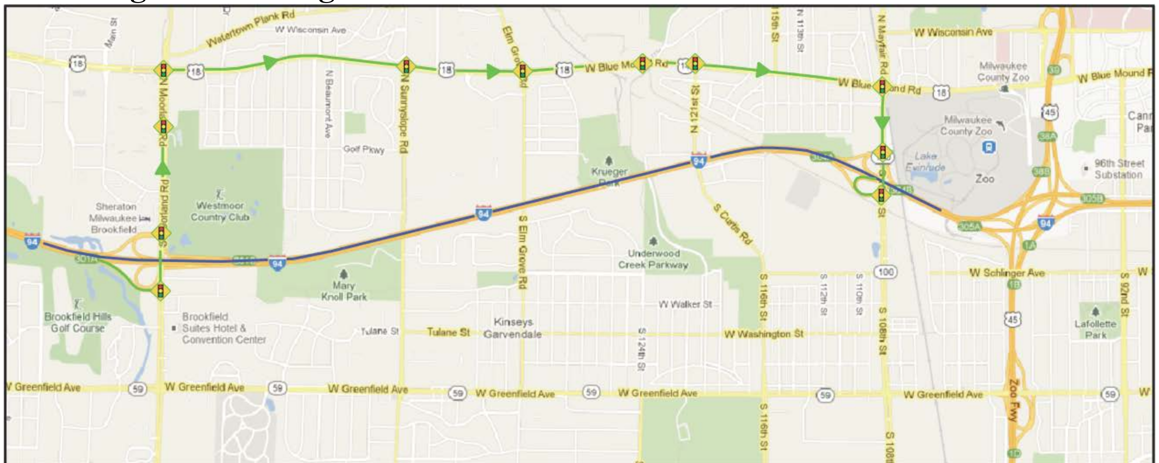
SEGMENT: 16 B	IH-94 BETWEEN CTH F AND E MORELAND BLVD (US-18)	DIRECTION: EB

A.6 Configuration of Segment 17



SEGMENT: 17 B	IH-94 BETWEEN E MORELAND BLVD (US - 18) AND S MORELAND RD	DIRECTION: EB

A.7 Configuration of Segment 18



SEGMENT: 18 B	IH-94 BETWEEN S MORELAND RD AND MAYFAIR RD (WIS 100)	DIRECTION: EB

APPENDIX B: Binary Logistic Regression with Original Variables

B.1 Calibrated Logistic Decision-Model with the Minimum Threshold of 10%

Variables included in the final model	Estimate	Exp(estimate)	Std. Error	z value	p-value
(Intercept)	-3.34600	0.2674	12.54390	-9.54	0.01
FR_VOL	0.46421	0.9838	56.00434	-10.62	1.51
FR_LN	1.73294	3.9878	75.89155	6.08	2.60
INC_DUR	0.18625	0.1228	0.11233	-2.74	0.04
LN_BLK	-6.72911	1.7858	11.53119	10.02	1.79
LC_VOL1	0.04536	1.0097	21.00018	6.99	5.56
LC_VOL2	0.53760	3.8635	59.22140	10.38	7.19
LC_VOL3	-5.57010	1.8685	29.89450	7.34	2.79
LC_LN	5.50390	4.8895	58.98140	10.36	7.56
NUM_SIGNAL	4.67890	2.9090	13.38560	2.90	0.98
The number of observations used for calibration			400		
Likelihood with constants only			-617.93		
Final value of Likelihood			-1870.605		
Fitted model accuracy			0.490		
Predicted model accuracy			0.487		

B.2 Calibrated Logistic Decision-Model with the Minimum Threshold of 15%

Variables included in the final model	Estimate	Exp(estimate)	Std. Error	z value	p-value
(Intercept)	-3.37900	0.2674	12.56540	-9.54	0.01
FR_VOL	0.23421	0.9754	56.00867	-10.62	1.51
FR_LN	1.9694	3.9854	75.89879	6.08	2.60
INC_DUR	0.19825	0.1285	0.112987	-2.74	0.04
LN_BLK	-9.72911	1.7823	11.53187	10.02	1.79
LC_VOL1	1.04536	1.0032	21.00010	6.99	5.56
LC_VOL2	4.56560	3.8614	59.22430	10.38	7.19
LC_VOL3	-9.87910	1.8667	29.89450	7.34	2.79
LC_LN	6.53490	4.8886	58.98195	10.36	7.56
NUM_SIGNAL	7.64390	2.912	13.38544	2.90	0.98
The number of observations used for calibration		400			
Likelihood with constants only		-787.93			
Final value of Likelihood		-18970.605			
Fitted model accuracy		0.451			
Predicted model accuracy		0.440			

B.3 Calibrated Logistic Decision-Model with the Minimum Threshold of 20%

Variables included in the final model	Estimate	Exp(estimate)	Std. Error	z value	p-value
(Intercept)	-3.34600	0.2674	12.54390	-9.54	0.34
FR_VOL	0.23421	0.9838	56.00434	-10.79	1.98
FR_LN	1.67294	3.9878	75.89155	6.32	2.32
INC_DUR	0.86625	0.1228	0.11233	-2.74	0.05
LN_BLK	-6.23911	1.7858	12.53119	10.93	1.89
LC_VOL1	1.86536	1.0097	29.67018	6.37	5.12
LC_VOL2	1.23376	3.8635	60.22980	11.67	7.80
LC_VOL3	-9.58810	1.8685	30.89320	7.44	2.50
LC_LN	7.54390	4.8895	58.98140	10.96	7.40
NUM_SIGNAL	5.67290	2.9090	14.38560	2.21	0.25
The number of observations used for calibration			400		
Likelihood with constants only			-623.93		
Final value of Likelihood			-1764.60		
Fitted model accuracy			0.501		
Predicted model accuracy			0.497		

B.4 Calibrated Logistic Decision-Model with the Minimum Threshold of 25%

Variables included in the final model	Estimate	Exp(estimate)	Std. Error	z value	p-value
(Intercept)	-3.34693	0.2674	12.54390	-9.54	0.03
FR_VOL	0.46412	0.9838	56.00434	-19.62	1.78
FR_LN	1.93232	3.9878	75.89155	7.08	2.54
INC_DUR	0.48625	0.1228	0.11233	-3.74	0.03
LN_BLK	-9.92911	1.7858	11.53119	11.02	1.80
LC_VOL1	2.14536	1.0097	21.00018	7.99	5.69
LC_VOL2	1.93760	3.8635	59.22140	19.38	7.26
LC_VOL3	-6.97010	1.8685	29.89450	5.34	2.98
LC_LN	9.50390	4.8895	58.98140	11.36	7.45
NUM_SIGNAL	3.67890	2.9090	13.38560	3.90	0.43
The number of observations used for calibration			400		
Likelihood with constants only			-617.93		
Final value of Likelihood			-1870.605		
Fitted model accuracy			0.587		
Predicted model accuracy			0.576		

B.5 Calibrated Logistic Decision-Model with the Minimum Threshold of 30%

Variables included in the final model	Estimate	Exp(estimate)	Std. Error	z value	p-value
(Intercept)	-3.35600	0.2674	12.54390	-9.54	0.01
FR_VOL	0.47421	0.9838	56.00434	-10.62	1.56
FR_LN	2.73294	3.9878	75.89155	6.08	2.61
INC_DUR	1.13625	0.1228	0.11233	-2.74	0.05
LN_BLK	-7.76911	1.7858	11.53119	10.02	1.98
LC_VOL1	2.06536	1.0097	21.00018	6.99	5.98
LC_VOL2	1.53760	3.8635	59.22140	10.38	7.20
LC_VOL3	-6.57010	1.8685	29.89450	7.34	2.80
LC_LN	7.50390	4.8895	58.98140	10.36	7.65
NUM_SIGNAL	5.67890	2.9090	13.38560	2.90	0.99
The number of observations used for calibration			400		
Likelihood with constants only			-657.93		
Final value of Likelihood			-1560.605		
Fitted model accuracy			0.576		
Predicted model accuracy			0.521		

B.6 Calibrated Logistic Decision-Model with the Minimum Threshold of 35%

Variables included in the final model	Estimate	Exp(estimate)	Std. Error	z value	p-value
(Intercept)	-3.34600	0.2674	12.54390	-10.54	0.02
FR_VOL	0.46421	0.9838	56.00434	-11.62	2.32
FR_LN	2.73294	3.9878	75.89155	7.08	1.78
INC_DUR	1.18625	0.1228	0.11233	-2.74	0.04
LN_BLK	-5.72911	1.7858	11.53119	10.02	1.98
LC_VOL1	0.14536	1.0097	21.00018	6.99	3.56
LC_VOL2	0.54760	3.8635	59.22140	10.38	7.43
LC_VOL3	-6.57010	1.8685	39.89450	7.34	3.65
LC_LN	7.50390	4.8895	59.98140	11.36	4.92
NUM_SIGNAL	5.67890	2.9091	12.38560	2.90	1.98
The number of observations used for calibration			400		
Likelihood with constants only			-717.93		
Final value of Likelihood			-1970.623		
Fitted model accuracy			0.570		
Predicted model accuracy			0.496		

APPENDIX C: Classification and Regression Tree

C.1 Basic Procedure of Classification and Regression Tree

Classification and Regression Tree (CART) is a nonparametric statistical method which first determines a sequence of if-then logic conditions that was developed based on analysis of the relationships between the dependent and independent variables. Based on the set of logic conditions, it builds a classification tree for categorical dependent variables, and a regression tree for continuous dependent variable.

CART consists of four steps – tree building, stopping the tree building, pruning, and optimal tree selection. Using learning dataset, the optimal tree is built for the outcome and predictor variables. The test dataset is required to validate the classification and decision rule.

In the tree building step, first, the root node, including all data set, is split into two child nodes according to the best possible variable to split, called a splitter. The best splitter is used to maximize the average "purity" of the two child nodes. After splitting, each node including the root node is assigned a predicted outcome category, based on a function shown below.

Node is category *i*, if $\frac{C(j|i)\pi(i)N_i(t)}{C(i|j)\pi(j)N_j(t)} > \frac{N_i}{N_j}$ for all values of *j*,

where $C(j|i)$ is cost of classifying *i* as *j*,

$\pi(i)$ is the prior probability of *i,*

N_i is number of category *i* in dataset,

and $N_i(t)$ is number of category *i* in node.

Procedures of node splitting and assigning for a predicted category are repeated for each node until it is impossible to carry forward.

To stop building a tree, at least one of the following criteria should be satisfied:

- There is only one observation left in each child node.

- The distributions of predictor variables for all observations within each child node are identical which makes the further splitting impossible.

- Reaches the maximum tree level that is externally set by users.

C.2 CART Results for Two-choice Model

C.2.1 Tree 1 (Minimum threshold= 5%)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	45	0.019
NUM_SIGNALS	2	2	0.007
LC_VOL1 (vphpl)	3	600	0.005
Tree Accuracy		55.1%	
Total Cases		400	

C.2.2 Tree 2 (Minimum threshold= 10%)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	2	45	0.008
NUM_SIGNALS	3	2	0.010
LC_VOL1 (vphpl)	1	600	0.019
Tree Accuracy		75.9%	
Total Cases		400	

C.2.2 Tree 3 (Minimum threshold= 15%)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	45	0.027
NUM_SIGNALS	3	2	0.009
LC_VOL1 (vphpl)	2	600	0.007
Tree Accuracy		57.6%	
Total Cases		400	

C.2.2 Tree 4 (Minimum threshold= 20%)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	45	0.015
NUM_SIGNALS	2	2	0.034
LC_VOL1 (vphpl)	3	600	0.078
Tree Accuracy		72.4%	
Total Cases		400	

C.2.2 Tree 5 (Minimum threshold= 25%)

Variables Included	Split Order	Division Threshold	Split Improvement

IN_DUR (min)	1	45	0.098
NUM_SIGNALS	3	2	0.056
LC_VOL1 (vphpl)	2	600	0.017
Tree Accuracy		65.4%	
Total Cases		400	

C.2.2 Tree 6 (Minimum threshold= 30%)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	45	0.049
NUM_SIGNALS	3	2	0.078
LC_VOL1 (vphpl)	2	600	0.004
Tree Accuracy		69.5%	
Total Cases		400	

C.2.2 Tree 7 (Minimum threshold= 35%)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	45	0.029
NUM_SIGNALS	3	2	0.021
LC_VOL1 (vphpl)	2	600	0.045
Tree Accuracy		63.8%	
Total Cases		400	

C.3 CART Results for Multi-choice Model

C.3.1 Tree 1 (5,10,15,20,25)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.015
NUM_SIGNALS	3	2	0.009
LN_BLK	2	1	0.023
FR_VOL (vphpl)	4	500	0.020
Tree Accuracy		63.8%	
Total Cases		400	

C.3.2 Tree 2 (5,15,20,25,30)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.023
NUM_SIGNALS	3	2	0.019
LN_BLK	2	1	0.003
FR_VOL (vphpl)	4	500	0.021
Tree Accuracy		71.8%	
Total Cases		400	

C.3.3 Tree 3 (5,10,20,25,30)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.041
NUM_SIGNALS	3	2	0.003
LN_BLK	2	1	0.004
FR_VOL (vphpl)	4	500	0.043
Tree Accuracy		68.0%	
Total Cases		400	

C.3.4 Tree 4 (5,10,20,25,35)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.001
NUM_SIGNALS	3	2	0.003
LN_BLK	2	1	0.013
FR_VOL (vphpl)	4	500	0.024
Tree Accuracy		49.0%	
Total Cases		400	

C.3.5 Tree 5 (5,10,25,30,35)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.032
NUM_SIGNALS	3	2	0.017
LN_BLK	2	1	0.009
FR_VOL (vphpl)	4	500	0.010
Tree Accuracy		49.0%	
Total Cases		400	

C.3.6 Tree 6 (10,15,20,30,35)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.042
NUM_SIGNALS	3	2	0.007
LN_BLK	2	1	0.009
FR_VOL (vphpl)	4	500	0.020
Tree Accuracy		56.8%	
Total Cases		400	

C.3.7 Tree 7 (10,15,20,25,30)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.041
NUM_SIGNALS	3	2	0.008
LN_BLK	2	1	0.003
FR_VOL (vphpl)	4	500	0.021
Tree Accuracy		41.8%	
Total Cases		400	

C.3.8 Tree 8 (10,15,20,25,30)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.041
NUM_SIGNALS	3	2	0.003
LN_BLK	2	1	0.002
FR_VOL (vphpl)	4	500	0.021
Tree Accuracy		65.3%	
Total Cases		400	

C.3.9 Tree 9 (10,20,30,35,40)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.008
NUM_SIGNALS	3	2	0.003
LN_BLK	2	1	0.001
FR_VOL (vphpl)	4	500	0.020
Tree Accuracy		64.0%	
Total Cases		400	

C.3.10 Tree 10 (10,30,35,40,45)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.049
NUM_SIGNALS	3	2	0.005
LN_BLK	2	1	0.001
FR_VOL (vphpl)	4	500	0.023
Tree Accuracy		68.5%	
Total Cases		400	

C.3.11 Tree 11 (15,20,25,30,35)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.043
NUM_SIGNALS	3	2	0.005
LN_BLK	2	1	0.008
FR_VOL (vphpl)	4	500	0.021
Tree Accuracy		65.3%	
Total Cases		400	

C.3.12 Tree 12 (15,20,30,35,40)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.045
NUM_SIGNALS	3	2	0.004
LN_BLK	2	1	0.010
FR_VOL (vphpl)	4	500	0.020
Tree Accuracy		64.0%	
Total Cases		400	

C.3.13 Tree 13 (15,20,35,40,45)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.041
NUM_SIGNALS	3	2	0.006
LN_BLK	2	1	0.003
FR_VOL (vphpl)	4	500	0.024
Tree Accuracy		63.2%	
Total Cases		400	

C.3.14 Tree 14 (20,25,30,35,40)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.021
NUM_SIGNALS	3	2	0.004
LN_BLK	2	1	0.005
FR_VOL (vphpl)	4	500	0.021
Tree Accuracy		67.3%	
Total Cases		400	

C.3.15 Tree 15 (20,30,35,40,45)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.014
NUM_SIGNALS	3	2	0.008
LN_BLK	2	1	0.001
FR_VOL (vphpl)	4	500	0.021
Tree Accuracy		68.5%	
Total Cases		400	

C.3.16 Tree 16 (20,35,40,45,50)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.043
NUM_SIGNALS	3	2	0.008
LN_BLK	2	1	0.010
FR_VOL (vphpl)	4	500	0.021
Tree Accuracy		71.8%	
Total Cases		400	

C.3.17 Tree 17 (25,30,35,40,45)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.041
NUM_SIGNALS	3	2	0.009
LN_BLK	2	1	0.003
FR_VOL (vphpl)	4	500	0.027
Tree Accuracy		68.5%	
Total Cases		400	

C.3.18 Tree 18 (25,35,40,45,50)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.000
NUM_SIGNALS	3	2	0.001
LN_BLK	2	1	0.002
FR_VOL (vphpl)	4	500	0.020
Tree Accuracy		71.8%	
Total Cases		400	

C.3.19 Tree 19 (5,25,35,45,55)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.042
NUM_SIGNALS	3	2	0.007
LN_BLK	2	1	0.009
FR_VOL (vphpl)	4	500	0.020
Tree Accuracy		65.8%	
Total Cases		400	

C.3.20 Tree 20 (5,20,30,40,50)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.041
NUM_SIGNALS	3	2	0.008
LN_BLK	2	1	0.001
FR_VOL (vphpl)	4	500	0.020
Tree Accuracy		62.7%	
Total Cases		400	

C.3.21 Tree 21 (10,20,30,40,50)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.041
NUM_SIGNALS	3	2	0.005
LN_BLK	2	1	0.003
FR_VOL (vphpl)	4	500	0.021
Tree Accuracy		62.7%	
Total Cases		400	

C.3.22 Tree 22 (15,25,35,45,55)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.049
NUM_SIGNALS	3	2	0.002
LN_BLK	2	1	0.003
FR_VOL (vphpl)	4	500	0.020
Tree Accuracy		62.7%	
Total Cases		400	

C.3.23 Tree 23 (20,30,40,50,60)

Variables Included	Split Order	Division Threshold	Split Improvement
IN_DUR (min)	1	60	0.042
NUM_SIGNALS	3	2	0.007
LN_BLK	2	1	0.008
FR_VOL (vphpl)	4	500	0.020
Tree Accuracy		68.5%	
Total Cases		400	