PREDICTIVE ACCIDENT MODELING FOR HIGHWAY TRANSPORTATION SYSTEM USING BAYESIAN NETWORKS

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ABSTRACT

The highway network, as a critical infrastructure in our daily life, is an important component of the public transportation system. In the face of a continuously increasing highway accident rate, highway safety is certainly one of the greatest concerns for transportation departments worldwide. To better improve the current situation, several studies have been carried out on preventing the occurrence of highway accidents or reducing the severity level of highway accidents.

The principal causes of highway accidents can be summarized into four categories: external environment conditions, operational environment conditions, driver conditions and vehicle conditions. This research proposes a representational Bayesian Networks (BNs) model which can predict and continuously update the likelihood of highway accidents, by considering a set of well-defined variables belonging to these principal causes, also named risk factors, which directly or indirectly contribute to the frequency and severity of highway accidents. This accident predictive BNs model is developed using accidents data from Transport Canada's National Collision Database (NCDB) during the period of 1999 to 2010.

Model testing is provided with a case study of Highway #63 site, which is from 6 km southwest of Radway to 16 km north of Fort Mackay in north Alberta, Canada. The validity of this BNs model is established by comparing prediction results with relevant historical records. The positive outcome of this exercise presents great potential of the proposed model to real life applications. Furthermore, this predictive BNs accident model can be integrated with a Safety Instrumented System (SIS). This integration would assist in predicting the real-time probability of accident and would also help activating risk management actions in a timely fashion. This research also simulates 10 scenarios with different specific states of variables to predict the probability of fatal accident occurrence, which demonstrates how the BNs model is integrated with SIS.

The major objective of this research is to introduce the predictive accident BNs model with the capabilities of inferring the dependent causal relations and predicting the probability of highway accidents. It is also believed that this BNs model would help developing efficient and effective transportation risk management strategies.

Key words: Bayesian network (BNs), highway safety, predictive accident model, Safety Instrumented System (SIS).

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LIST OF ABBREVIATIONS

BNs	Bayesian Networks
DAG	Directed, Acyclic Graph
SIS	Safety Instrumented System
SIF	Safety Instrumented Function
SILs	Safety Integrity Levels
CPT	Conditional Probability Tables
NCDB	Transportation Canada's National Collision Database
WHO	World Health Organization
Ex. En	External Environmental condition
Op. En	Operational Environmental condition
DR	Driver condition
VE	Vehicle condition
IRTAD	International Road and Traffic Database
IEC	International Electronic Commission
AADT	Annual Average Daily Traffic
DBN	Dynamic Bayesian network

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Chapter 1

1. Introduction

1.1 Highway Transportation Safety

Nowadays, as the development of public transportation system networks involving aircraft, ships, trains and motor vehicles grow, millions of fatalities and injuries occur each year worldwide due to various types of transportation accidents. Particularly, with the increasing vehicle usage in our daily life, the road transportation system alone causes a tremendous number of fatalities and injuries. According to Transportation Canada's National Collision Database (NCDB), there were 2,026 road accident fatalities and 123,141 injuries in total ranging from minimal to serious injuries in 2010, in which 56.7% of fatalities took place on primary or secondary highways (Canadian Motor Vehicle Traffic Collision Statistics report, 2011). Based on the annual statistical report from the World Health Organization (WHO) in 2010, the highway accident will be the third largest cause of death globally by 2020 and this trend will continue (World Health Report, 2010). Needless to say, highway transportation safety and reliability is as important now as ever before, which certainly becomes one of the greatest concern for transportation departments worldwide. In order to improve the current situation, the potential risk of highway transportation accidents is required to be predicted quantitatively, along with a safety management to be implemented to reduce this risk effectively.

The word "accident" has been used consistently to describe an unintentional injury or fatal event which is random and therefore unpreventable (Elvik & Vaa, 2002). However, the occurrence of highway accidents is never completely random. Based on empirical studies, male drivers under the age of 18 years are frequently involved in highway accidents (Morgan & Mannering, 2011); additionally, drunk drivers regardless of age or gender, and people driving over the speed-limit, are primary causes of highway accidents (Vanlaar & Robertson, 2011). In other words, highway accidents can be predicted with the appropriate information of causal factors and the relationships among them. The unexpected accidents could be prevented or at least minimized damage if the causes are known and predicted accurately.

In a theoretical sense, the highway safety problem can be described in terms of a number of highway accidents, a highway accident rate or a high proportion of fatal or serious injuries. Highway accidents can be modeled as a three dimensional space of influencing factors which are exposure, accident rate and injury severity (Nilsson, 2002). Figure 1 illustrates these three main factors to determine the number of people who are killed or injured in highway accidents.

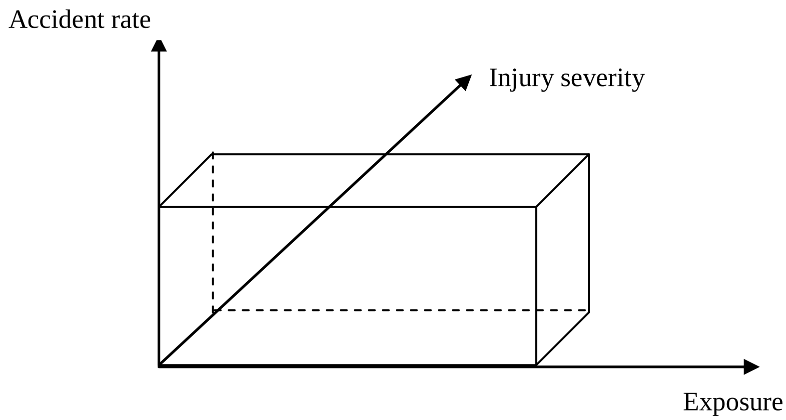


Figure 1 Three dimensions affecting highway safety (Nilsson, 2002)

Here, the exposure denotes the amount of activities which may occur during highway accidents. Usually the activity refers to the number of kilometers travelled and irrespective of whether the victims are drivers or passengers.

The accident rate is the risk of accident per unit of exposure and serves as an indicator of the probability of accidents occurrence. Generally, the higher the accident rate, the higher probability of a highway accident in a given region. Sometimes the terms "level of risk", or "accident risk" are used synonymously with accident rate. The international Road and Traffic Database (IRTAD, 2010) provides two measures of accident rate which are labeled "traffic risk" and "health risk". Traffic risk is the number of accidents (fatalities) per year per 100,000 motor vehicles and health risk is the number of accidents (fatalities) per year per 100,000 inhabitants in a specific region. Due to the difficulties in estimating the number of inhabitants, traffic risk is usually chosen for highway accident study. Hence, the traffic risk measure is used through the whole modeling and related calculations in this research.

Regarding the consequences of highway accidents, these can be defined and evaluated in terms of accident severity, which has a variable range from disasters with fatalities to the minor damage of fender benders. There are official accident statistics in most countries which classify accidents by severity along the following simple scale: fatal accident, accident resulting in serious injury, accident resulting in slight injury, accident resulting in property damage only (Elvik & Vaa, 2002). These crude categories are not comparable among countries and the severity level is initially determined when the accidents are recorded. In Canada, the definition of fatality is given as who died as a result of a reported traffic accident within 30 days of its occurrence, except in Quebec (eight days) and a serious injury describes an injured person who is admitted to hospital for treatment or observation, respectively (Canadian Motor Vehicle Traffic Collision Statistics report, 2010).

The highway transportation system is a complex dynamic system consisting of "people", "vehicle" and "road" (Lemaire et al., 2002). The prediction of accidents on a highway should take into account the key causes within these three dimensions. Specifically, in order to develop this system to cover more explanatory variables for risk analysis and clarify the dependent relationships among these variables, a novel classification is adopted to divide the principal causes into four categories which also act as main variables in predictive accident model: the external environmental condition, the operational environmental condition, the driver condition and the vehicle condition. For simplicity, these four main variables are shortly denoted as Ex. En condition, Op. En condition, DR condition and VE condition. Apparently, any failure of these four main variables would increase the probability of highway accident occurrence. Furthermore, there are various specific causal factors under each main variable, which are background variables contributing to highway accidents, including weather information, road surface friction coefficient, traffic density, driving speed, driver's gender and age, on-board safety equipment and so on. The selection of these background variables depends on data collection which contains as much necessary information as possible to develop the predictive accident model.

1.2 Previous approaches on highway safety

The application of safety and reliability approaches to transportation system is tracked back to the 1970s. (Dhillon, 2011). The goal was to eliminate transportation accident risk in principle, which was obviously never reached. The risk can only be reduced to an acceptable level and never be completely eliminated. In the field of highway safety over the last few years, several studies have been carried out on reducing the highway accident rate or preventing the occurrence of highway accidents. Some researchers focus on the contribution of major causes to highway accidents, such as the impact of weather conditions on driving safety (Brodsky & Hakkert, 1987; Sigbjornsson, 1998; Brijs et al., 2008), driving speed and the traffic flow involved (Jiang & Wang, 2010; Akintayo & Agbede, 2012; Golob & Recker, 2003), alcohol-impaired driving (Evans, 1990; Vanlaar & Robertson, 2011; Ramamath & Sudharsan, 2010), and the age, gender and physical/physiological condition of driver (Skyving & Berg, 2009; Talbot et al., 2012; Elvik, 2012; Morgan & Mannering, 2011; Unal et al., 2012). Other studies have proposed applications of different intelligent transportation systems to ensure safe driving. These applications include Adaptive Cruise Control (ACC) (Potts & Okurowski, 1995), Antilock Brake System (ABS) (Lin & Hsu, 2003), Collision Warning System (CWS) (Bella & Russo, 2011), the modeling of Time-To-Collision (TTC) (Farah et al., 2009; Kiefer et al., 2006), an intelligent data fusion system using vision/GPS sensing (Chang et al., 2009) and on-board safety monitoring system (Horrey & Lesch, 2011). Moreover, especially for the highway predictive accident model, statistical methods have been frequently developed using approaches such as multivariate analysis, empirical Bayes, fuzzy logic and artificial neural networks (ANNs). These approaches are utilized for various purposes such as establishing relationships between variables, screening covariates and predicting values. Chueh (1996) developed the multi-linear regression model which can give a negative number or a zero accident number, which leads to a fault indication of absolute safety. Shankar et al. (1995) developed the accident frequency prediction model by incorporating geometric variables which are horizontal alignment, vertical alignment and environmental factors such as rainfall, number of rainy days, snowfall. Greibe (2003) and Caliendo et al. (2007) proposed the crash prediction model for urban areas and multilane roads in Italy, which used the Poisson regression model, Negative Binomial (NB) regression model and Negative Multinomial regression model.

With a critical review of these literatures, previous studies usually focused on statistical regression techniques which can produce interpretable coefficients for each variable included in the prediction model. However, most of these regression models are constrained by assumptions and pre-defined underlying relationships between dependent and independent variables, i.e. linear relations between the variables. (Chang & Wang, 2006) This limitation often leads to incorrect prediction results of the likelihood of highway accidents. Xie et al. (2006) have made a comparison of the Bayesian neural networks (BNNs) and regression-based models. This study confirmed that the Bayesian networks (BNs) model are capable of identifying the relationships and structures of independent or dependent variables which cause highway accidents, without knowing any pre-defined relationships or making unnecessary assumptions. In addition, the BNs model alike a statistical model makes it easy to infer the probabilistic result and derive bi-directional induction (Ona, 2011). Recently, BNs model has been utilized to build a predictive accident model for rural highways and also to model the microscopic traffic characteristics of overtaking on two-lane highways (Vahogianni & Golias, 2012; Ona, 2011). This review also confirmed that BNs model has received much less attention compared to statistical regression models.

1.3 Fundamentals of Bayesian network (BNs)

The Bayes' theorem has played an important role in probability theory and statistical inference because it enables us to infer the probability of a cause when its effect is observed (Neapolitan, 2009). The Bayes' Theorem can be expressed as follows. The conditional probability of causal event C_i given event E is

$$P(C_i|E) = \frac{P(E|C_i)P(C_i)}{P(E|C_1)P(C_1) + P(E|C_2)P(C_2) + \cdots + P(E|C_n)P(C_n)} (1 \leq i \leq n)$$

(Eq 1.1)

where,

C_i - the i^th^ mutually exclusive and exhaustive event such that $P(C_i) \neq 0$ for all i.

Based on the definition of conditional probability and the chain rule, this theory is extended to model the probabilistic relationships among many causally related variables. These relationships can be described by graphical structures known as Bayesian networks (BNs).

All probabilistic networks have both qualitative and corresponding quantitative aspects. The qualitative aspect in BNs is given by a graphical structure in the form of a directed acyclic graph (DAG) that represents the conditional dependent and independent properties of a joint probability distribution over a set of variables that are indexed by the vertices of the DAG (Kjarulff & Madsen, 2008). More precisely, Kjarulff (2008) has proposed a mathematical definition of BNs as follows.

For a DAG, $\mathcal{G} = (V, E)$, where V denotes a set of nodes (or vertices) and E denotes a set of directed links (edges) between pairs of nodes, a joint probability distribution $P(\chi_v)$ over the set of variables χ_v (typically discrete) indexed by V can be factorized as

$$P(\chi_v) = \prod_{v \epsilon V} P\left(\chi_v \middle| \chi_{pa(v)}\right)$$

(Eq 1.2)

where,

$\chi_{pa(v)}$ - the set of parent variables of variable χ_v for each node $v \epsilon V$.

The BNs are capable of predicting and estimating future behavior based on past experience learned from a historical data source, characteristics of which precisely satisfies the requirements of predictive accident modeling. On the other hand, BNs can reduce the uncertainty of prior beliefs through probability updating (Koski & Noble, 2009).

In recent years, BNs model as a graphical inference methodology, has been increasingly used in many fields such as clinical pathology, genetics, statistical economics and for engineering applications, etc. In terms of safety and risk engineering , BNs has a great impact on the construction of system reliability models, risk management and safety analysis based on probabilistic and uncertain knowledge (Khakzad, et al., 2011), which can be used for either probability prediction or probability updating for dynamic safety analysis.

1.4 Objective of the research

The objective of this research is to introduce the predictive BNs accident model with the capabilities of inferring the dependent causal relations and predicting the probability of highway accidents occurrence. This research attempts to extend previous studies to combine the multivariate analysis and BNs model which considers more contributing causes, also named risk factors and to determine the dependable relations between them. Furthermore, this predictive BNs accident model can be integrated with a Safety Instrumented System (SIS). This integration would assist in predicting the real-time probability of accident occurrence and would also help activating risk management actions in a timely fashion. This research also simulates 10 scenarios with different specific states of variables to predict the probability of fatal accident occurrence, which demonstrates how the BNs model integrated with SIS. It is believed of this BNs model would help developing efficient and effective transportation risk management strategies.

1.5 Organization of the thesis

This thesis is organized with seven sections as follows.

Chapter 1 is a brief introduction of highway transportation safety and fundamentals of BNs. It also reviews previous approaches related to highway predictive accident models and BNs' applications.

Chapter 2 presents the methodologies which are used in this research including BNs inference and updating, discretizing continuous variable, BNs simulation tools and safety analysis within SIS.

Chapter 3 gives the integral concept of the highway predictive accident model and provides the development procedure of that the probabilistic methodology BNs implement to the highway predictive accident model.

Chapter 4 is devoted to mode testing with a specific case study on Highway #63 from southwest of Radway to north of Fort Mackay approximately 443 Km in north Alberta, Canada. This section also presents the simulation results and model analysis based on the comparison of simulation results and historical data.

Chapter 5 explains the integration of this proposed predictive BNs accident model with Safety Instrumented System (SIS). It also simulates 10 scenarios to predict the probability of fatal accident occurrence which demonstrating this integration.

Chapter 6 is a conclusion of this research and summarizes further efforts need to be done in the future work.

Chapter 2

2. Methodology

2.1 Causal accident theory

The scientific study of accidents began about 100 years ago when Bortkiewicz published his book entitled "The Law of Small Numbers" (Leipzig, 1898), and which has sought to explain the different aspects of accident occurrence. Until 1960, it was widely believed that it was not possible to reduce the road accidents effectively without knowing the real causes of traffic accidents and this idea was proposed in the first parliamentary report on traffic safety in Norway (Ministry of Justice, Parliamentary report 83, 1961-62). More researches based on the probabilistic concept have proved that accidents are the outcome of a vastly complex random process, whose general characteristics can be modeled statistically (Elvik and Vaa, 2002).

There are five different accident theories presented chronologically as follows in Figure 2.

1. The theory of accidents as purely random events;

2. Statistical accident theory and accident proneness theory;

3. Causal accident theory as expresses in the in-depth case study approach to accidents;

4. Systems theory and epidemiological accident theory;

5. Behavioral accident theory including the theory of risk homeostasis.

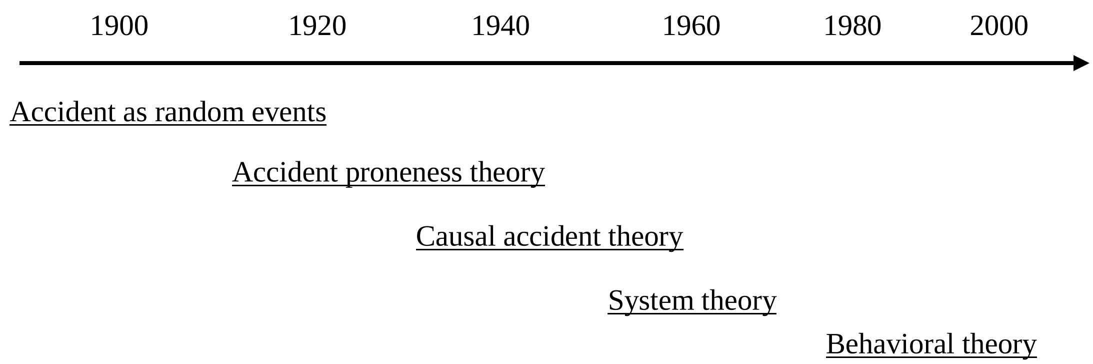


Figure 2 Five accident theories chronology (Rune and Truls, 2002)

Briefly concluded from these theories above, their objective was to explain variation in the number of accidents within a certain condition, to seek the statistical relationships between the causes that lead to accidents and to make improvements systematically for the process.

2.2 Bayesian networks (BNs) model

2.2.1 Graphical structure

As introduced earlier, BNs consists of a DAG as illustrated in Figure 3, that each variable is represented by a node "X", "Y_1", "Y_2", $\cdots$, "Y_n" in the graph, the direct dependencies between the variables are represented by directed edges between the corresponding nodes and the conditional probability tables (CPT) are assigned to the nodes specifying how strongly the connected nodes influence each other.

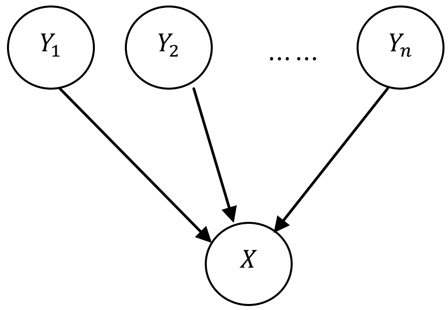
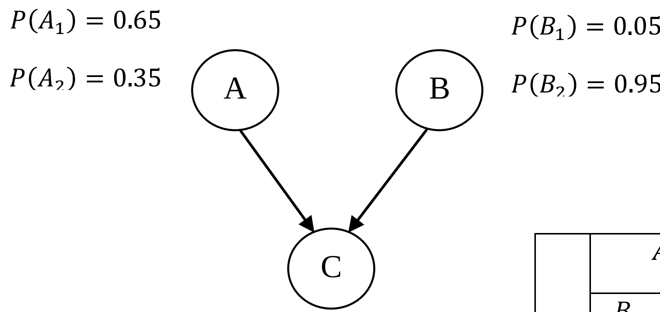


Figure 3 Graphical representation of P(X/(Y$_1$, Y$_2$, Y$_3$, ...Y$_n$))

The child vertex is labeled "X" and the parent vertex is labeled "$Y = \{Y_1,\ Y_2, \cdots\ Y_n\}$". Sometimes they are called the head and the tail, respectively. In causal BNs, X and Y can be described as the events concerned such as accidents, failures, malfunction, etc. and the risk factors contributing to these events. This can be better described with a simple example as shown in Figure 4. Here assuming the possible contributing causes for event C are events A and B with an independent probabilities and assuming all events only have two states of state 1 and state 2. The CPTs expresses the probabilities of the occurrence of event C if either event A or event B has taken place. For a general case, the states of each event can be extended according to the characteristic of events.



$P(C|A, B) =$

	A_1		A_2	
	B_1	B_2	B_1	B_2
C_1	0.12	0.25	0.05	0.3
C_2	0.88	0.75	0.95	0.7

Figure 4 A simple Bayesian Networks example

2.2.2 Inference in causal BNs

BNs represents joint probability models among given variables and the graph theory helps to illustrate and utilize independent structures within interacting sets of variables (Koski and Noble, 2009). Information about the observed value of variables is propagated through the network to update the probability over other variables that are not observed directly. In many situations, the directed edges between variables in BNs can have a simple and natural interpretation as the causal relationships, which is probabilistic and can be specified by a conditional probability distribution. BNs can be used to assess the effects of an intervention, where the manipulation of a cause will influence the effect.

To be roughly stated is that X is a cause of Y if a manipulation of X results in a change in the probability distribution of Y. The causal BNs is a DAG which contains a set of causally related random variables V such that for every $X, Y \in V$ there is an edge from X

to Y if and only if X is a cause of Y, and there is no subset of variables W_{XY} of V such that if the values of the variables in W_{XY} is known, a manipulation of X would no longer change the probability distribution of Y (Neapolitan, 2009).

As noted previously, the standard application of Bayes' Theorem is inference in BNs. Additionally, it is noticed that sophisticated algorithms including the Law of Total Probability, the Markov Condition and some basic probability definitions are required to accomplish this inference. There is another simple example to explain the method of inference in BNs as shown in Figure 5.

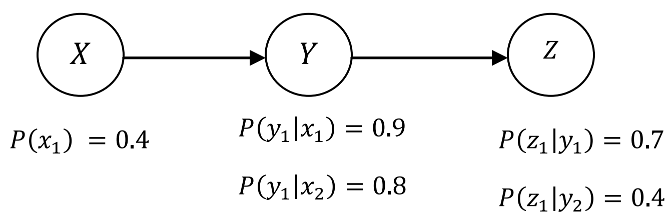


Figure 5 A simple example of causal BNs inference

Assuming all variables in the causal BNs only have two states and the calculations only present the probability.

The prior probabilities can be computed as:

$$P(y_1) = P(y_1|x_1)P(x_1) + P(y_1|x_2)P(x_2) = 0.9 \times 0.4 + 0.8 \times 0.6 = 0.84$$

$$P(z_1) = P(z_1|y_1)P(y_1) + P(z_1|y_2)P(y_2) = 0.7 \times 0.84 + 0.4 \times 0.16 = 0.652$$

This method is a message-passing algorithm in which each node passes its child a message needed to calculate the child's probabilities and it can be applied to an arbitrarily long linked list and to trees.

Then it can also be calculated the conditional probability of variable Z by the chain rule.

$$\begin{aligned} P(z_1|x_1) &= P(z_1|x_1, y_1)P(y_1|x_1) + P(z_1|x_1, y_2)P(y_2|x_1) \\ &= P(z_1|y_1)P(y_1|x_1) + P(z_1|y_2)P(y_2|x_1) \\ &= 0.7 \times 0.9 + 0.4 \times 0.1 = 0.67 \end{aligned}$$

Suppose X is instantiated for x_1.

This proceeding example shows how to use downward propagation messages to compute the conditional probabilities of variables below the instantiated variables. BNs can also be used for upward propagation of messages to compute the conditional probabilities of the remaining variables as illustrated below.

$$P(y_1|z_1) = \frac{P(z_1|y_1)P(y_1)}{P(z_1)} = \frac{0.7 \times 0.84}{0.652} = 0.902$$

Using Bayes' theorem,

$$P(x_1|z_1) = \frac{P(z_1|x_1)P(x_1)}{P(z_1)} = \frac{0.67 \times 0.4}{0.652} = 0.411$$

This algorithm helps to solve the problem of that when the values of outcomes/effects are observed, the probabilities of the causal events are available to be obtained. In other words, the information of major causes with high probability value can be determined and appropriate responses to change or improve the current events can be estimated to reduce the probability of occurrence of any hazardous outcomes/effects. Sometimes this proceeding is also called learning the probability or updating the probability.

2.2.3 BNs simulation tools

All these algorithms discussed previously are developed for inference in BNs. However, to some extent, they are worst-case non-polynomial time if applying to a complex BNs with numerous variables in practical case. Researchers do not need concern about this problem since a number of simulation tools for doing inference in BNs have been developed. GeNIe (Graphical Network Interface), which is a versatile and user-friendly development environment for graphical models, is ordinarily used to illustrate BNs model. The highway predictive BNs accident model in this research is developed using the simulation tool GeNIe. The values of marginal distribution for each variable and CPTs for all dependable nodes are inputted to the interface of "Node Properties". Once the model is completed in GeNIe, it is capable of taking both upward and downward propagations of messages. It computes the conditional probability of any node given any specific condition.

2.3 Methods of discretizing continuous variables

Both discrete and continuous random variables exist in BNs which compose hybrid networks. There is no requirement to consider continuous density function if they could be discretized, This would help to obtain a simpler and better inference by considering all variables as discrete. For example, driving speed is basically a continuous variable but it can be represented using three ranges with a given probability value of each range in the BNs. There are two of the most popular methods of discretizing continuous variables: the Bracket Medians Method and the Pearson-Tukey Method. The difference between these two methods is in how they divide the current continuous distribution function into several intervals and how they keep the indicated data items.

In the Bracket Medians Method, the mass in a continuous probability distribution function $F(x) = P(X \leq X)$ is divided into n equally spaced interval as $[x_i, x_{i+1}]$, for each interval, the bracket median d_i can be computed, which is the value such that

$$P(x_i \leq X \leq d_i) = P(d_i \leq X \leq x_{i+1})$$

then the discrete variable D can be defined with the same probability $P(D = d_i) = {}^{1}/_{n}$ (Neapolitan, 2009). Here is an example of taking n=4 for the explanation of this method procedure.

1. Determine four equally intervals which are $[0, 0.25]$, $[0.25, 0.50]$, $[0.50, 0.75]$, $[0.75, 1.0]$ (as shown in Figure 6)

2. Determine points x_1, x_2, x_3, x_4, such that

$$P(X \leq x_1) = 0.25$$

$$P(X \leq x_2) = 0.5$$

$$P(X \leq x_3) = 0.75$$

$$P(X \leq x_4) = 1.0$$

where the values on the right in these equalities are the endpoints of the four intervals.

3. Define the discrete variables D with the following probabilities:

$$P(D = d_1) = 0.25$$

$$P(D = d_2) = 0.25$$

$$P(D = d_3) = 0.25$$

$$P(D = d_4\,) = 0.25$$

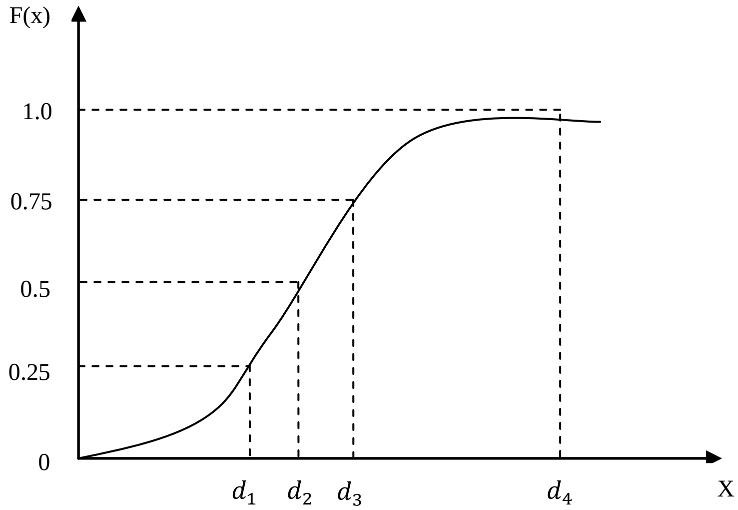


Figure 6 The Bracket Medians Method when n=4

In some special applications, more attention need to be paid on the data items fall in the tail of density function, such as driving speed, traffic flow and temperature, etc.. Values in the middle are not indicative one way or the other and have to group the data in each tail together. However, this cannot be done with the Bracket Medians method. Keefer (1983) proposed another discretizing method which called the Pearson-Tukey method.

In the Pearson-Tukey method, the mass in a continuous probability distribution function $F(x) = P(X \leq X)$ is divided into three intervals (Figure 7) and proceeds as follows (Neapolitan, 2009)

1. Determine points x_1 , x_2 , x_3 such that

$$P(X \leq x_1\,) = 0.05$$

$$P(X \leq x_2\,) = 0.50$$

$$P(X \leq x_3\,) = 0.95$$

2. Define the discrete variable D with the following probabilities:

$$P(D = d_1\,) = 0.185$$

$$P(D = d_2\,) = 0.63$$

$$P(D = d_3) = 0.185$$

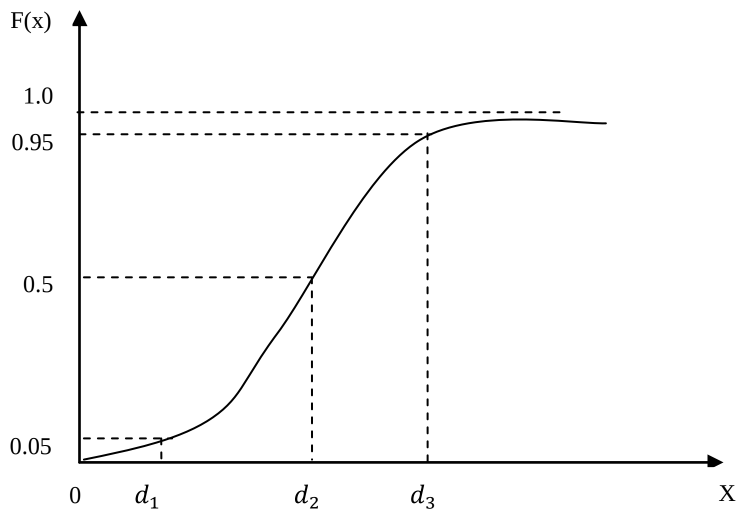


Figure 7 The Pearson-Tukey Method

In this research, the Pearson-Tukey method is used to discretize variables of temperature, wind speed and traffic density while the Bracket Medians method is used for variables of driver's age, driving experience and vehicle produced year.

2.4 Safety Instrumented System (SIS)

SIS is defined as a system comprising sensors, logic solvers and actuators for the purpose of taking a process to a safe state when normal predetermined set points are exceeded, or safe operating conditions are violated (IEC 61805, 2000). The basic SIS structure is illustrated in Figure 8.

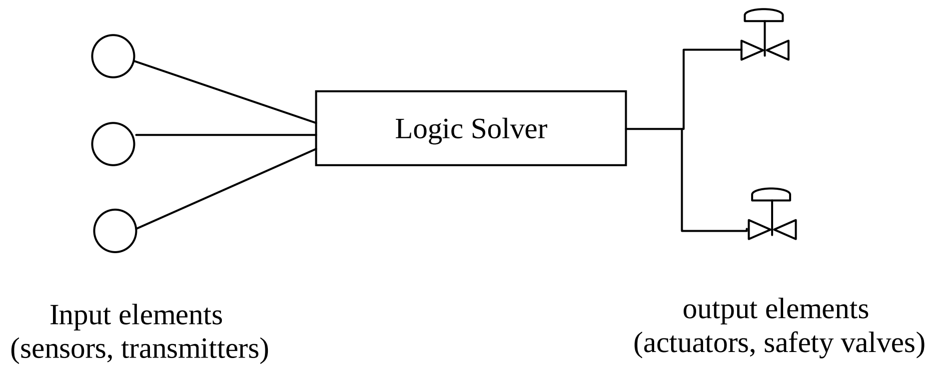


Figure 8 The basic SIS structure

SIS provides one or more Safety Instrumented Function (SIF) to monitor and maintain the safety of any equipment under its control in response to hazardous event(s). The SIF works as a safety protection which defines the relationships between the input and output in SIS. The generic safety standard IEC 61805 for Electrical/Electronic/Programmable Electronic (E/E/PE) safety-related system, defined these functional safety requirements in a quantitative expression of Safety Integrity Levels (SILs). SILs range from 1 to 4 and they are set to ensure that the specific risks are not exceeded in safety evaluation (IEC 61511, 2000). With respect to transportation system, SILs provide a range of threshold values for accident rates and severity levels, whose measures have been implemented into the model during design process. The application of SIS has been widely used for railway systems including railway signaling system, driverless automatic system and positioning system. However, it seems that less attention is paid on SIS implementation for highway transportation system. In this research, the prediction result from BNs model is utilized to set the ranges of SILs, along with safety analysis to make an optimal response to reduce the probability of accident occurrence and mitigate the severity of the consequences.

Chapter 3

3. Model development

3.1 Conceptual framework

From the perspective of highway safety study and causal accident theory mentioned previously, the basic idea of predictive accident modeling is sketched in Figure 9 as follows.

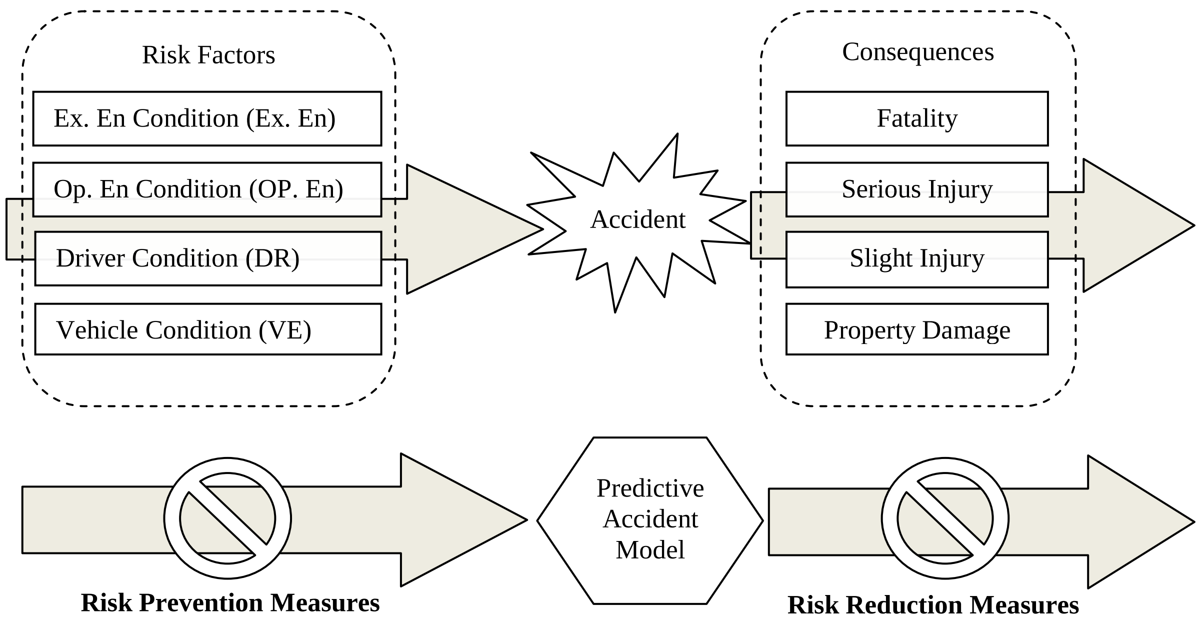


Figure 9 Conceptual framework of predictive accident model

As shown in this figure, the predictive accident model would help in preventing accidents through the control of source risks and also reduce the severity level of consequences.

Both of these measures follow the fundamental principles of risk management. The probabilities of the occurrence of highway accidents would be predicted based on the considerations of four main variables of Ex. En condition, Op. En condition, DR condition and VE condition.

3.2 Risk factor definition

Risk factors can be defined as the causes contributing to a highway accident and they are classified into four categories as discussed earlier and denoted as four main variables in BNs model. Based on earlier work on the causes of highway accidents and information from collected accident cases, there are 28 background variables and these variables represented as risk factors which could explain the variations in accident occurrences and causalities. The definition of these variables including the name, statistical classification and state descriptions are presented in Table 1. These variables are used subsequently in the model development.

Table 1 Highway accident risk factors (28 background variables) definition

Item	Category	Name	Abbreviation	Statistical Type	State Description
1	EX. En	Light condition	L	Binary	1= daylight
					0= darkness
2	EX. En	Road construction	RC	Binary	1= there is road construction
					0= otherwise
3	EX. En	Temperature	T	Continuous	Average daily temperature °c
4	EX. En	Wind speed	WS	Continuous	Average daily wind speed km/h
5	EX. En	Rainfall	RF	Binary	1= yes
					0= no
6	EX. En	Snowfall	SF	Binary	1= yes
					0= no

Table 1 continued

Item	Category	Name	Abbreviation	Statistical Type	State Description
7	EX. En	Visibility	V	Binary	1= positive 0= negative
8	Op. En	Road curve	RCU	Binary	1= if there is a road curve 0= otherwise
9	Op. En	Road surface	RS	Discrete	0= Dry 1= Wet 2= Snow/ice
10	Op. En	Road sign	RSI	Discrete	1= yes 0= no
11	Op. En	Traffic density	TD	Continuous	Average traffic density
12	Op. En	Driving speed	DS	Continuous	vehicle driving speed, km/h
13	Op. En	Manoeuvre	MA	Discrete	0= No action 1= change lane 2= overtake
14	DR	Age	A	Continuous	years
15	DR	Gender	G	Binary	1= male 0= female
16	DR	Driving experience	DE	Continuous	years
17	DR	Distraction	DI	Discrete	1= yes 0= no
18	DR	Driving purpose	DP	Binary	1= work 0= leisure
19	DR	Alcohol intake	AL	Binary	1= yes 0= no
20	DR	Physical condition	PC	Discrete	1= positive 0= negative
21	VE	Produced year	PY	Continuous	years
22	VE	Vehicle type	VT	Discrete	0= Motorbike 1= Passenger car 2= Bus/truck
23	VE	Engine condition	EG	Binary	1= positive 0= negative
24	VE	Brake condition	BC	Binary	1= positive 0= negative
25	VE	Steering wheel	SW	Binary	1= positive 0= negative
26	VE	Tire pressure	TP	Binary	0= Positive 1= Low pressure 2= Burst
27	VE	Vehicle light	VL	Binary	1= positive 0= negative
28	VE	Safety equipment	SE	Binary	1= positive 0= negative

The choice of variables and related definitions may vary depending on collected accident data. For a specific region, some variables may contribute more to the occurrence of highway accident. On the contrary, some variables barely appear and would not affect the probability of accident occurrence. These variables would be removed from the list after sensitivity analysis. For example, while estimating the effects of freezing weather on highway accidents, the variable "weather condition W" is a major cause not only of the occurrence of an accident but also affecting frozen temperature, the friction of the road surface, traffic density and driving speed. When the target region is changed to a tropical area, there are more concerns about the distraction of dazzling sunlight or driver's fatigue during burning hot weather.

Moreover, in order to reduce the complexity of the computational process and to better present the dependences among these variables, a few auxiliary variables are introduced to combine these background variables and connect them with the four main variables of Ex. En condition, Op. En condition, DR condition and VE condition.

Table 2 Auxiliary variables and main variables definition

Item	Category	Name	Abbreviation	Parents
1	Auxiliary	Weather condition	W	T, WS, RF, SF, VI
2	Auxiliary	Vehicle-side	V-side	MA, DS
3	Auxiliary	Road-side	R-side	RSI, TD, RS, RCU
4	Auxiliary	Power system	PS	EC
5	Auxiliary	Chassis	CH	TP, BC, SW
6	Auxiliary	Electrical system	ES	SE, VL
7	Main	External environmental condition	Ex. En	L, RC, W
8	Main	Operational environmental condition	Op. En	R-side, V-side
9	Main	Driver condition	DR	DP, PC, AL, DE, A, G
10	Main	Vehicle condition	VE	ES, CH, PS

The definition of auxiliary variables and main variables which are associated with are described in Table 2. All these variables are defined as binary variables only with states of positive and negative, which are represented as "1" and "0" in BNs model.

3.3 Data collection and processing

The accident data for highway predictive accident modeling is collected from Transport Canada (www.tc.gc.ca), Statistics Canada (www.statcan.gc.ca), TIRF (Traffic Injury Research Foundation, tirf.ca/index.php), and annual road accident published reports from some provincial governments. Transport Canada's National Collision Database (NCDB) contains data on all police-reported motor vehicle collisions on public roads in Canada since 1999. The historical highway accident data during the period of 1999 to 2010 are collected from the NCDB online database and the accident data are further refined and reorganized with distinct values according to 28 background variables mentioned earlier. Preliminary analysis of highway accident data is used to define the basic structure and relationships among the consequences and risk factors.

The original database list most fatal highway accidents in detail. However, accidents involving slight injury or property damage are not well described. This research collected the information of 293 highway accidents with fatalities from NCDB for the period of 1999 to 2010 and the statistical information is shown in Figure 10. The developed predictive accident model focuses on fatal accidents. This method can be extended for accident prediction with the other three levels of outcomes only if the historical data are available and could be used for initial severity and define relationships among 28 background variables as discussed earlier.

There are a few continuous variables in proposed model needing to be discretized. In this research, the Bracket Medians Method is used for discretizing variables DR and VE and the Pearson-Tukey Method is used for discretizing variables T, TD and DS. These variables are redefined with discrete intervals as mentioned in Table 3.

Table 3 Discretized variables

Item	Category	Variables	State Description
1	EX. En	Temperature (T)	0: Low= <-15 1: Medium= -14~25 2: High=>26
2	Op. En	Traffic density (TD)	0: Low= < 801 1: Medium=-802~1374 2: High=> 1375
3	Op. En	Driving speed (DS)	0: Low= < 42 1: Medium= 43~87 2: High=> 88
4	DR	Driving experience (DE)	0= <1 1=19-35 2=36-65 3=>65
5	VE	Produced year (PY)	0=<1 1=2-5 2=6-10 3=>10

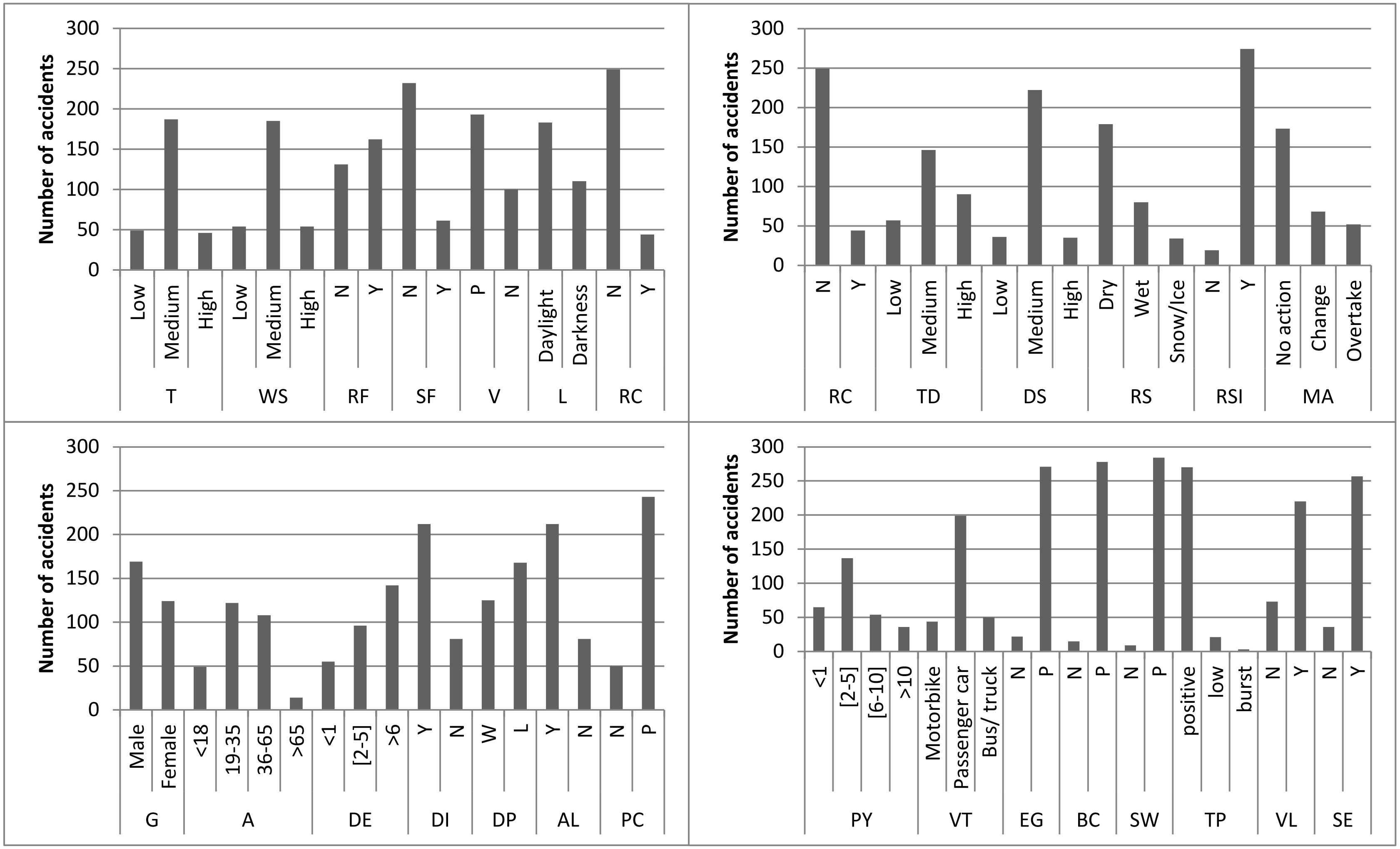


Figure 10 Statistical Information of 293 fatal accidents on Canadian highway during 1999-2010

3.4 Model development procedure

Essentially, highway safety problems can be characterized as an explanation of highway accidents and finding ways of preventing them. To achieve the first objective, explanation of highway accidents, it is important to identify the joint contributions of various risk factors. This helps to predict the real-time probability of highway accident occurrence by continuously updating information of variables Ex. En, Op. En, DR and VE. The general procedures of constructing BNs model is summarized in six steps and the complete procedure of highway predictive accident modeling is illustrated in Figure 11.

Step 1. Data collection and processing;

Step 2. Identify the number of variables including effects and causes;

Step 3. Define each variable (category, states and probability of each state);

Step 4. List the available causal relations among these variables;

Step 5. Quantify the relations by conditional probability table (CPT);

Step 6. Build the network with nodes which denote the variables and a directed edge denote the relationships among them.

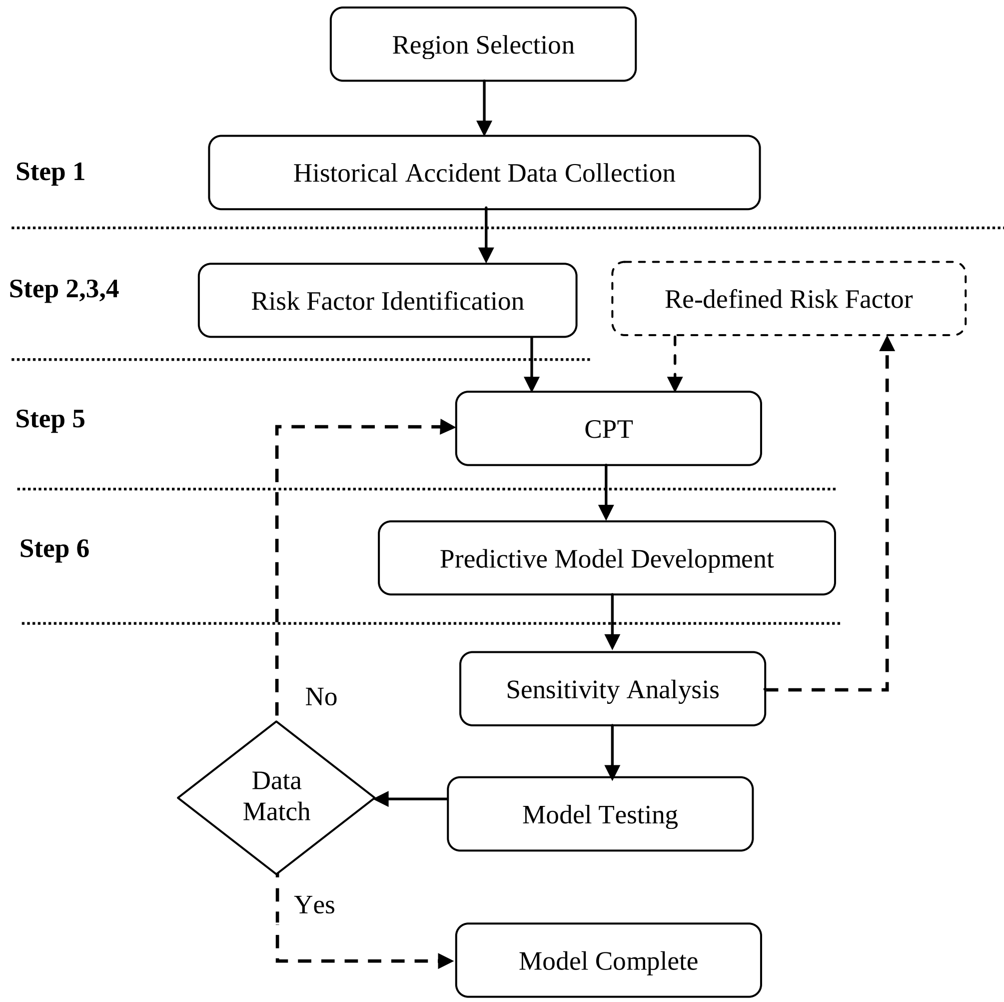


Figure 11 The flow chart of highway predictive accident model development

3.5 Sensitivity analysis

It is ideal to build a BNs model considering a complete set of variables. However, having a large number of parameters makes BNs model difficult to update efficiently. To better solve this problem, the most common method is sensitivity analysis which aims to describe changes in the network associated with small changes in parameter values. The sensitivity of variables in a network strongly influences the accuracy and rates of convergence of numerical methods for estimating probability values associated within BNs (Koski & Noble, 2009). The simplest way of identifying a sensitive variable is to consider one free variable and keep changing the single conditional probability potentials (CPPs). All probabilities in one of the CPPs may vary whereas other CPPs remain fixed. The measure of sensitivity is used to assess the performance of the developed BNs model. After estimating of sensitivities of variables, non-sensitive variables can be removed and sensitive variables can be redefined with updated CPTs.

The sensitivity analysis results for all variables are presented in Table 4 Sensitivity analysis results. The variable is chosen in turns with different states to obtain the related probability potentials, of which the changes helps to determine the sensitivity of this variable. In this research, the variables of PS (power system) and RCU (road curve) were picked out as the non-sensitive variables and removed from the variable list. The relationship between the probability of accident occurrence and these two variables are approximately linear with similar slopes and different intercepts. As shown in Table 4, the state of RCU changes from "1" to "0"can only make change of probability potentials in auxiliary variable Road-side (R-side) from 0.17176 to 0.17171. Additionally, the state change of PS leads to the changes of main variable vehicle condition (VE) with probability potentials values from 0.09211 to 0.09214. In a word, the state changes of those two parameters can only make 10^{-5} changes in the values of probability potentials and they would barely affect the probability of top event which is highway accident occurrence in this research.

Table 4 Sensitivity analysis results

Node		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
T		2	1	0	/	/	/	/	/	/	/	/	/
WS		/	/	/	2	1	0	/	/	/	/	/	/
SF		/	/	/	/	/	/	1	0	/	/	/	/
RF		/	/	/	/	/	/	/	/	1	0	/	/
VI		/	/	/	/	/	/	/	/	/	/	1	0
W	0	0.1564	0.1594	0.1512	0.1616	0.1586	0.1486	0.2019	0.1457	0.2153	0.0856	0.1223	0.2253
	1	0.8436	0.8406	0.8488	0.8384	0.8414	0.8514	0.7981	0.8543	0.7847	0.9144	0.8777	0.7747
Node		**S1**	**S2**	**S3**	**S4**	**S5**	**S6**						
W		0	1	/	/	/	/						
L		/	/	1	0	/	/						
RC		/	/	/	/	1	0						
EEC	0	0.146	0.1207	0.1152	0.1405	0.1347	0.1229						
	1	0.854	0.8793	0.8848	0.8595	0.8653	0.8771						
Node		**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**		
RS		0	1	2	/	/	/	/	/	/	/		
RCU		/	/	/	1	0	/	/	/	/	/		
TD		/	/	/	/	/	0	1	2	/	/		
RSI		/	/	/	/	/	/	/	/	1	0		
R-side	0	0.1701	0.1771	0.1588	0.17176	0.17171	0.1703	0.1909	0.1194	0.1701	0.179		
	1	0.8299	0.8229	0.8412	0.8411	0.8283	0.8297	0.8091	0.8806	0.8299	0.821		
Node		**S1**	**S2**	**S3**	**S4**	**S5**	**S6**						
MA		0	1	2	/	/	/						
DS		/	/	/	2	1	0						
V-side	0	0.1129	0.1108	0.1098	0.0833	0.1267	0.0512						
	1	0.8871	0.8892	0.8902	0.9167	0.8733	0.9488						
Node		**S1**	**S2**	**S3**	**S4**								
R-side		0	1	/	/								
V-side		/	/	0	1								
OEC	0	0.1478	0.0897	0.1378	0.0948								
	1	0.8522	0.9103	0.8622	0.9052								

Table 4 Continued

Node		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17
A		0	1	2	3	/	/	/	/	/	/	/	/	/	/	/	/	/
G		/	/	/	/	0	1	/	/	/	/	/	/	/	/	/	/	/
DP		/	/	/	/	/	/	0	1	/	/	/	/	/	/	/	/	/
PC		/	/	/	/	/	/	/	/	0	1	/	/	/	/	/	/	/
DI		/	/	/	/	/	/	/	/	/	/	1	0	/	/	/	/	/
AL		/	/	/	/	/	/	/	/	/	/	/	/	1	0	/	/	/
DE		/	/	/	/	/	/	/	/	/	/	/	/	/	/	0	1	2
DC	0	0.196	0.197	0.196	0.195	0.196	0.196	0.182	0.207	0.249	0.190	0.234	0.096	0.252	0.179	0.228	0.200	0.181
	1	0.803	0.802	0.803	0.804	0.803	0.803	0.817	0.792	0.750	0.809	0.765	0.904	0.747	0.820	0.771	0.799	0.818

Node		S1	S2	S3	S4	S5	S6	S7
TP		0	1	2	/	/	/	/
BC		/	/	/	0	1	/	/
SW		/	/	/	/	/	0	1
VCH	0	0.209	0.156	0.149	0.168	0.207	0.162	0.206
	1	0.790	0.844	0.850	0.831	0.792	0.837	0.793

Node		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
PY		0	1	2	3	/	/	/	/	/	/	/
VL		/	/	/	/	0	1	/	/	/	/	/
VT		/	/	/	/	/	/	0	1	2	/	/
SE		/	/	/	/	/	/	/	/	/	0	1
ES	0	0.144	0.141	0.142	0.142	0.150	0.140	0.144	0.141	0.145	0.102	0.148
	1	0.855	0.858	0.857	0.857	0.849	0.859	0.855	0.858	0.854	0.891	0.851

Node		S1	S2	S3	S4
PY		0	1	2	3
EC	0	0.001	0.015	0.189	0.277
	1	0.999	0.985	0.811	0.723

Node		S1	S2	S3	S4	S5	S6
VCH		0	1	/	/	/	/
ES		/	/	0	1	/	/
PS		/	/	/	/	0	1
VC	0	0.104	0.091	0.109	0.091	0.09211	0.09214
	1	0.896	0.908	0.890	0.908	0.884	0.907

Table 4 Continued

Node		S1	S2
EEC		0	1
ACC	1	0.0446	0.029
	0	0.9554	0.971
Node		**S1**	**S2**
OEC		0	1
ACC	1	0.0497	0.0288
	0	0.9503	0.9712
Node		**S1**	**S2**
DC		0	1
ACC	1	0.0614	0.0235
	0	0.9386	0.9765
Node		**S1**	**S2**
VC		0	1
ACC	1	0.0476	0.0255
	0	0.9524	0.9745

3.6 Results and model analysis

The highway BNs predictive accident model is simulated in GeNIe and the structure of BNs is shown in Figures 12 and 13. The relationships among variables can be presented clearly in the icon view in Figure 12. The occurrence of highway accident is considered as the top event (effects) in this BNs model, which has four main variables Ex. En, Op. En, DR and VE as its parents variables. After sensitivity analysis, there are 27 background variables remained under these four categories which connected with the main variables through five auxiliary variables. The directed edges between pairs of variables represent the causal relationships, which are obtained from data analysis and empirical studies. As discussed earlier, the selection of variables and the dependent relationships will be changed based on the target region and historical accident database. It can be easily modified in the current BNs model by adding/reducing the nodes (variables) and changing the direction of edges. The marginal discrete distribution can be read from the bar chart view in Figure 13. Each node contains the possible states of random variable and it has a preset CPT representing independent and dependent relationships quantitatively. The CPT of a variable includes the probabilities of the variable being in a specific state or value given the states of its parents.

The prediction of highway accident occurrence is a procedure of inference and updating in BNs model. It consists of computing the conditional probability of the top event (highway accident), given that other variables are set to evidences. For example, the states of some variables such as "rainfall", "age" and "driving speed" can be set as evidences if they are observed from real case. The conditional probability of highway accident could be seen that given evidence for the "rainfall" to be "Yes", the "age" to be "between 19 to 35" and the "driving speed" to be "medium". Table 6 shows the inference result of this example presented in BNs model. This table can be extended with more evidences of specific values or states for variables. The inference in BNs can be used not only for variable "highway accident" but also for any variable in the network.

Table 5 An accident prediction example in BNs model

<table>
<tr><td colspan="2" rowspan="2">Evidence</td><td colspan="2">Highway accident</td></tr>
<tr><td>Yes</td><td>No</td></tr>
<tr><td>Rainfall</td><td>yes</td><td rowspan="3">0.027538728</td><td rowspan="3">0.97246127</td></tr>
<tr><td>Driving Speed</td><td>medium</td></tr>
<tr><td>Age</td><td>19-35</td></tr>
</table>

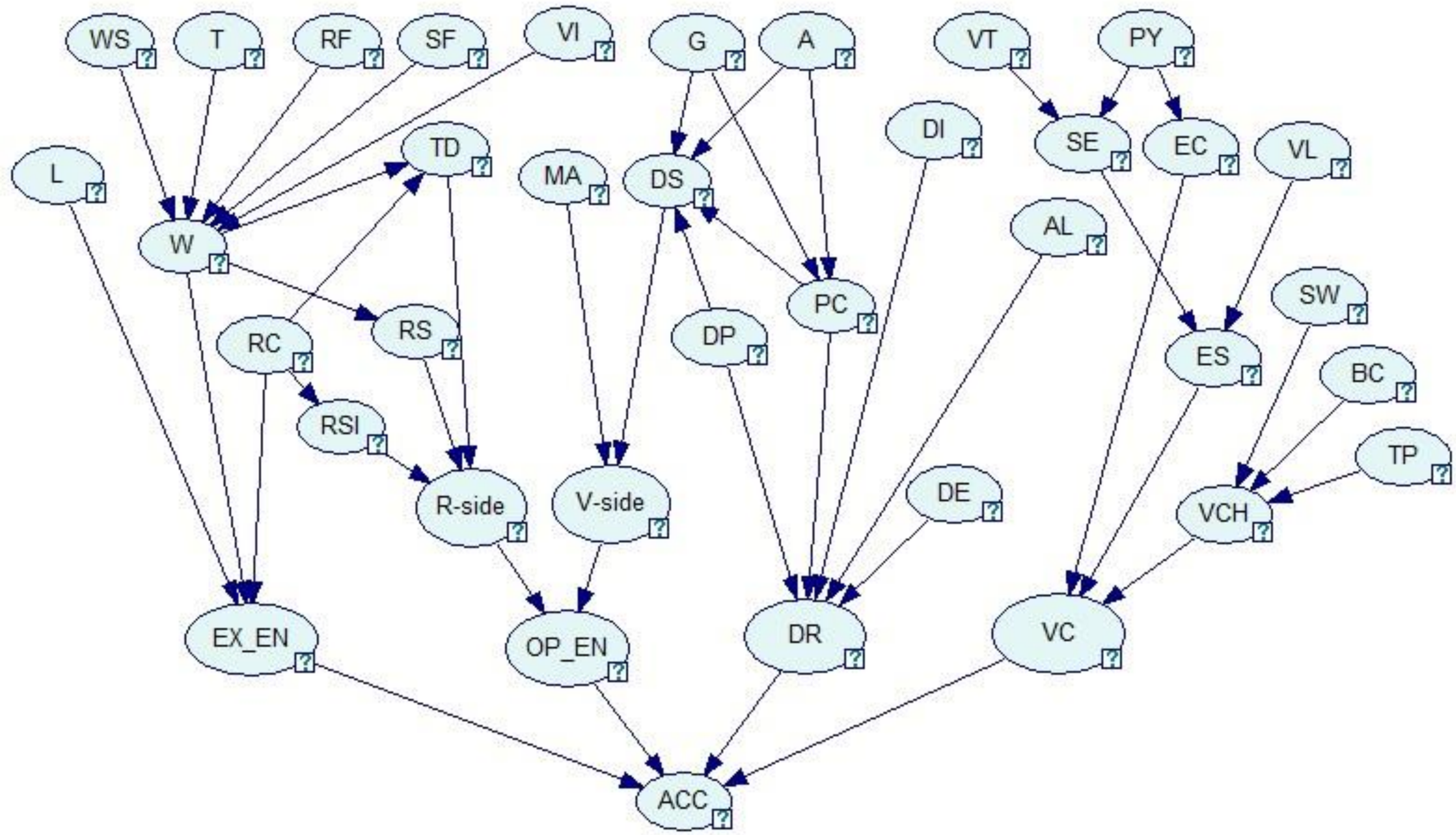


Figure 12 Highway predictive accident model (Icon view)

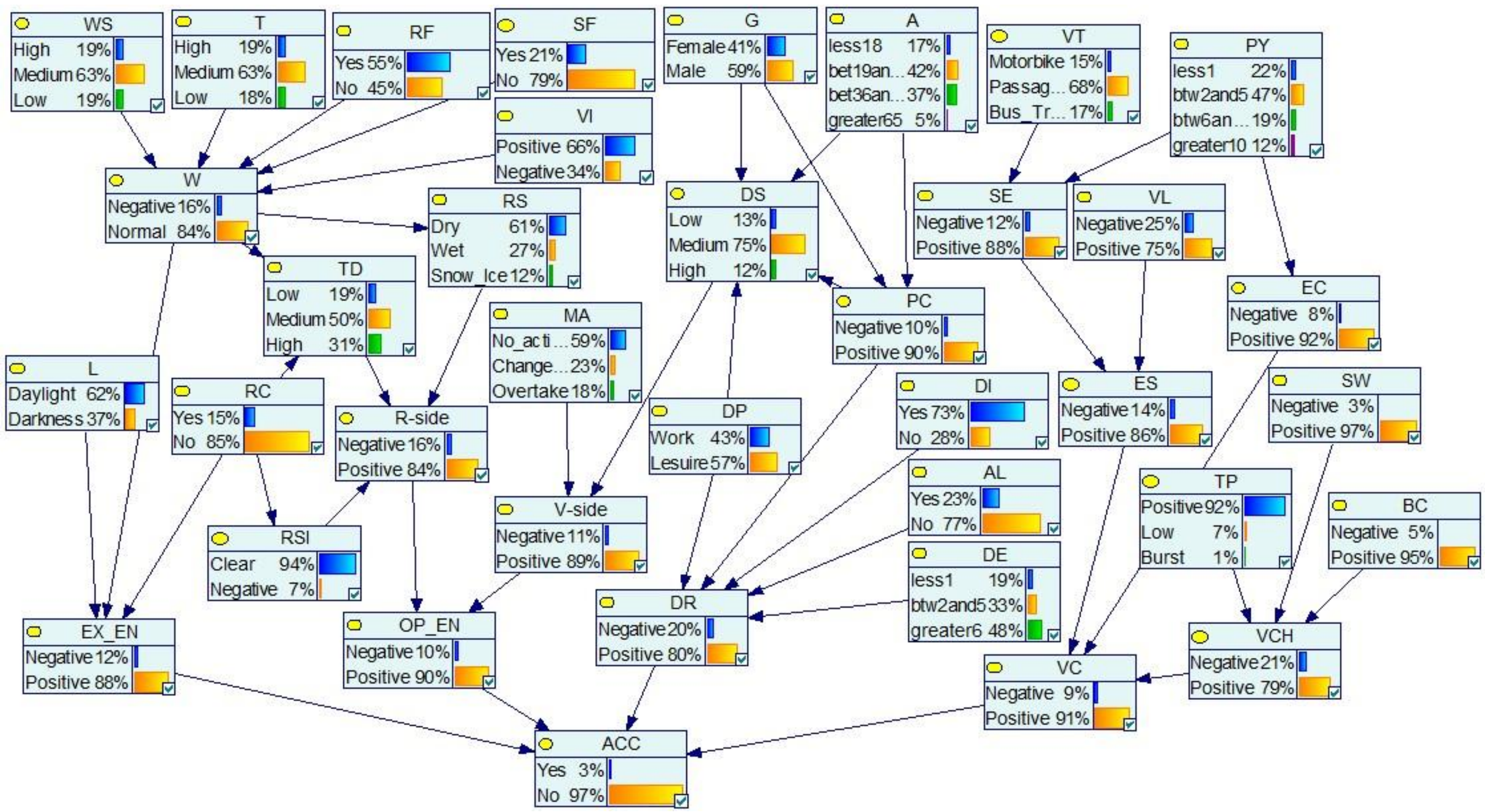


Figure 13 Highway predictive accident model (Bar chart view)

Chapter 4

4. Model Testing

4.1 Test case study

To test the predictive BNs accident model, a specific highway region Highway #63 is selected as the case study in this research. This highway is from 6 km southwest of Radway to 16 km north of Fort Mackay in north Alberta, Canada and the length is approximately 443 km. There are 79 determined points to gather information of traffic destity, which are officially assigned by Alberta Transportation department. Based on the highway accident records from governmental statistics, there were 798 reported highway accidents in this region during 1990-2012 and detailed records of 121 fatal accidents are available to be used in BNs model testing.

The original information obtained from accident database need to be further processed and categorized into distinct values to be able to work with BNs model. Initially, there are 27 background variables in the developed BNs model. Therefore, the focus is mainly on collecting information with respect to these 27 variables. The fatal accident data is organized in the way that coming with a specific state for each background variable. For example, one fatal accident information can be rewritten as "Rainfall: 1 (yes)", "Light condition: 1 (daylight)" and "Driver gender: 0 (female)" if these information are obtained from available accident records.

Figure 14 presents the statistical information of 121 fatal accidents based on classifications of 27 background variables. As can be seen from Figure 14, male driver involved in highway fatal accident is more frequently which accounts for 57.02% of the total than female drivers (42.97%). It also shows that most of fatal accidents occurred with high driving speed (50.61%) and under the situation of changing lane or overtaking other vehicles which constitutes around 51.39% and 36.11% of the total, respectively. Noticeably, the huge proportion of fatal accidents (82.89%) happened along the highway when the driver has negative physical/psychological condition. Similar result is also noticed for the distraction involved accidents (82.55%). Considering the causes contributed to highway fatal accidents, the statistical results shown in Figure 14 imply that these variables mentioned previously are significant risk factors responsible for the likelihood of highway fatal accidents.

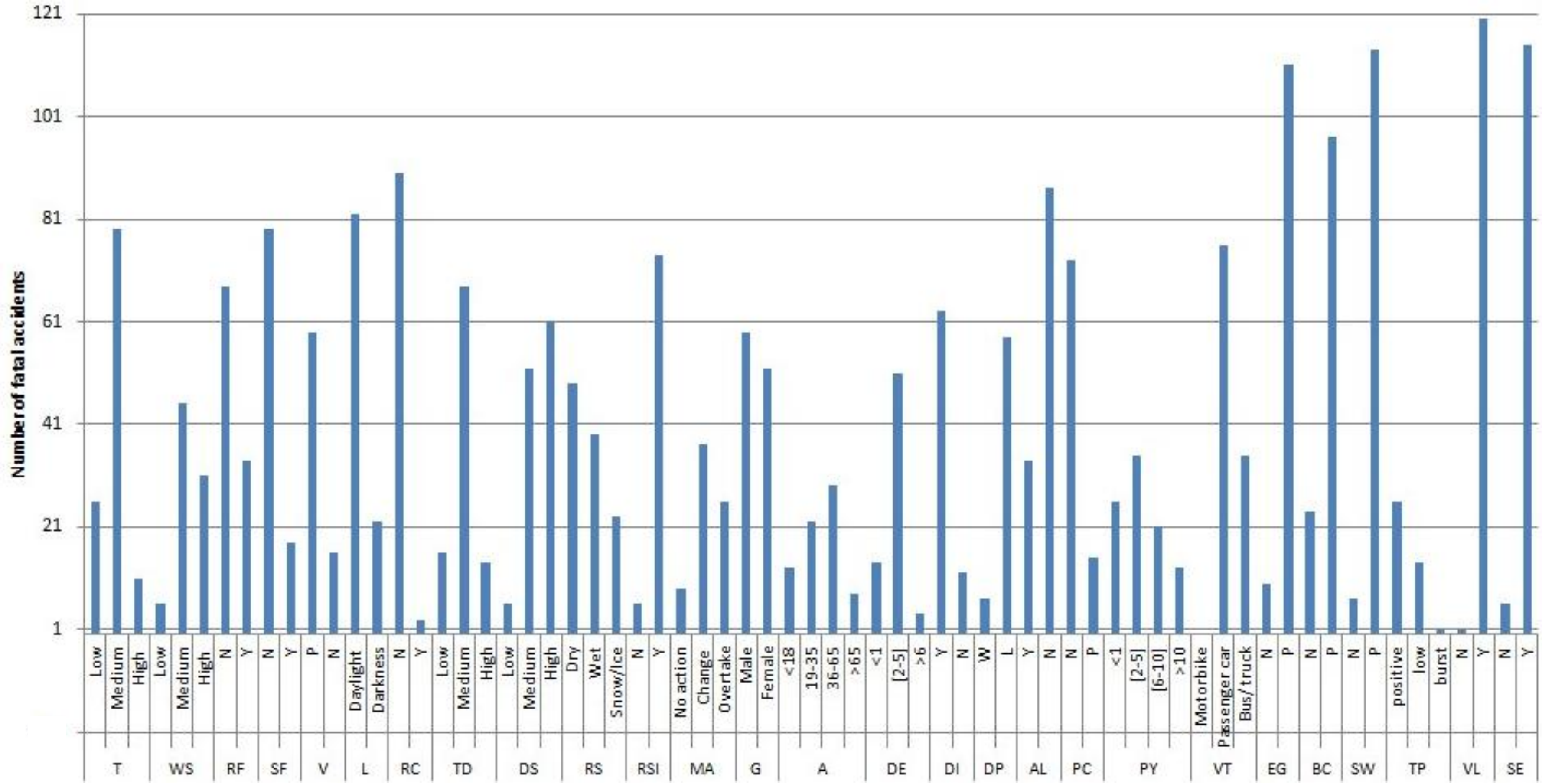


Figure 14 Statistical information of 121 highway fatal accidents on Highway #63 during 1990-2012

Figure 15 summarized the number of highway fatal accidents over the period of 1990-2012. The pattern of highway accidents remains relatively stable for the first few years and gradually increases since 1999. The trend declines to a lower point in 2004 and then on rise again reaching its peak in 2007. This historical fatal accident data in Figure 15 will be used as a baseline to compare with prediction results from BNs model.

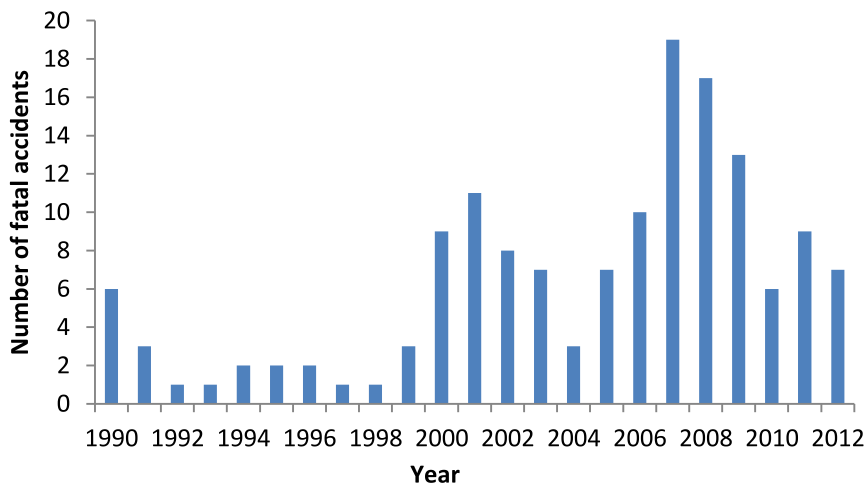


Figure 15 121 Highway fatal accidents distribution on highway #63 (1990-2010)

Figure 16 highlights the average daily traffic density on determined points on highway #63 with a trend line increasing steadily from 1990 to 2010. There are more statistical tables of daily traffic density for each determined point behind this figure. (Appendix D) The values of traffic density are used for simulation of accident scenarios in BNs model testing and also act as significant indexes for calculating the number of predictive fatal accidents.

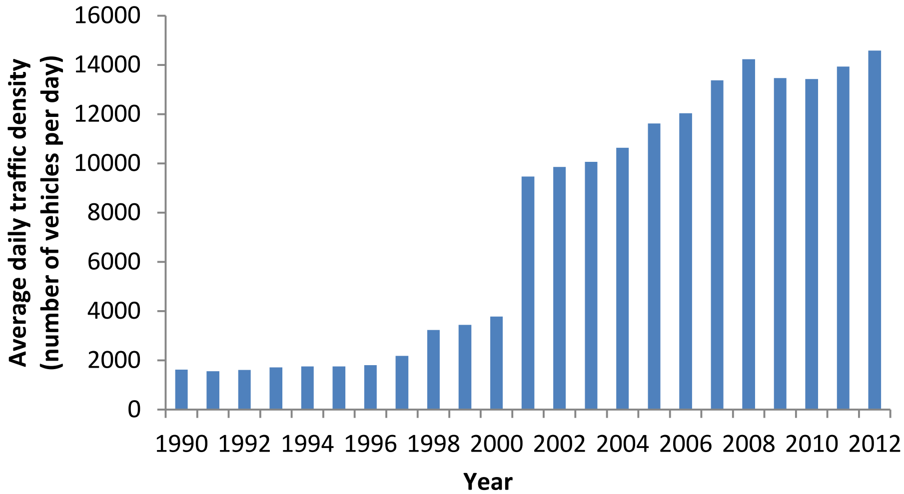


Figure 16 Average daily traffic density on determined points on highway #63 (1990-2010)

4.2 Model testing

The procedure of model testing is shown in Figure 17. The first two steps, model development and sensitivity analysis, have been discussed in chapter 3 eariler. All variables are redefined with updating CPTs after sensitivity analysis. The model testing aims to simulate the scenarios of detailed historical accidents being recorded and predict the probability of accident occurrence under these scenarios in BNs model. The validity of the BNs model is established by comparing prediction results with historical records. It is expected that prediction results are close to historical records, or both trend lines are similar. If so, this BNs model would be acceptable and considered as an effective tool for fatal accident prediction in this selected highway region. By contraries, if the prediction results can not match the historical records well by the value or the trend line, it would be tracked back to the step of model development for modifying the current BNs model.

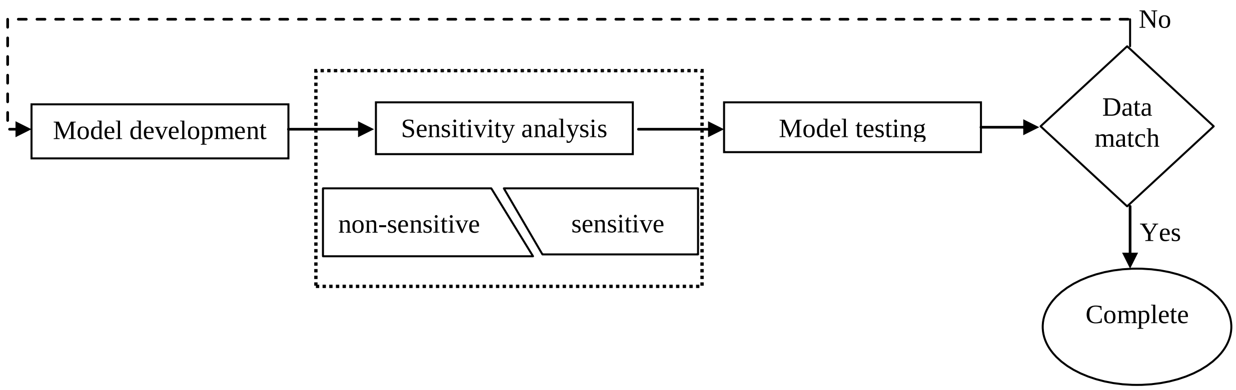


Figure 17 The procedure of model testing

Firstly, available accident data need to be converted to variables with specific states, which are able to be used in BNs model. The example presenting here is simulation of seven fatal accidents happened on Highway #63 in 2012. The major causes of these seven accidents from police reports are heavy fog, slippery road surface, alcohol intake (triple the legal alcohol limit), snow storm with icy road, darkness with low visibility, overtaking and driver error (fatigue), respectively. The convert of these accident information are summarized in Table 6 and other accident data are processed in identical way.

Table 6 Seven fatal accident information happened on Highway #63 in 2012

Item	Accident record	Variable	State description
1	heavy fog	VI, W	VI: low (0) W: negative (0)
2	slippery road surface	RS	RS: wet (1)
3	alcohol intake	AL	AL: yes (1)
4	snow storm with icy road	SF, W, RS	SF: yes (1) W: negative (0) RS: ice (2)
5	darkness with low visibility	L, VI	L: darkness (0) VI: low (0)
6	overtaking	MA	MA: overtaking (1)
7	driver error (fatigue)	PS	PS: negative (0)

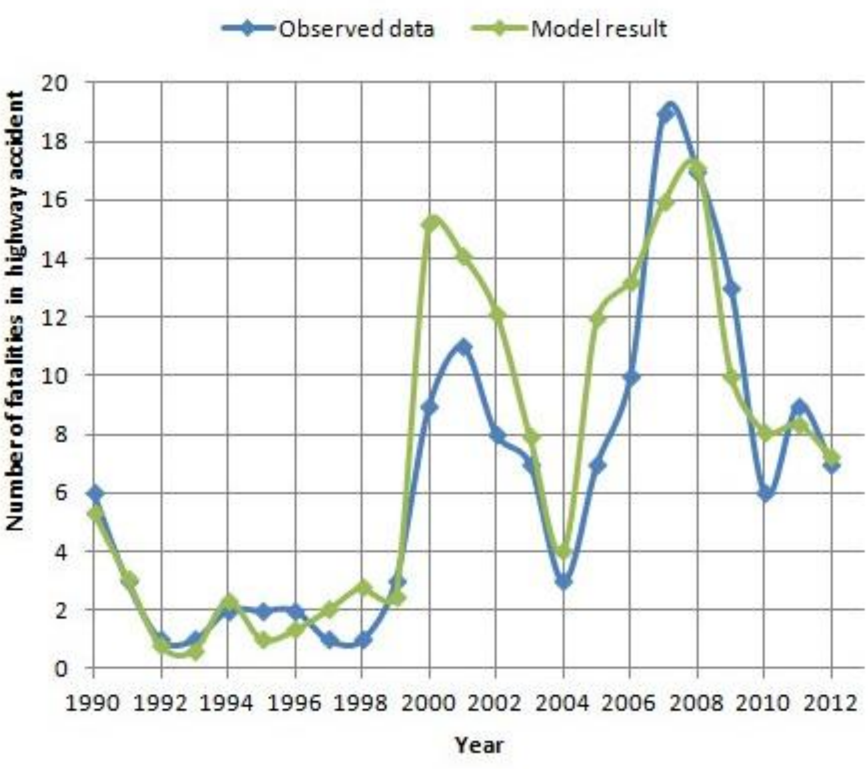
Secondly, the selected case study of 121 highway fatal accidents are simulated respectively in BNs model. For each scenario of accident, the state of variable using in the simulation is same as that when the accident happened and these specific variables are set as evidence in BNs model. It should be noted that some variables were not mentioned in accident record. For unavailable information of variable state, it is assumed to have a state which has minor contribution to the occurrence of accident. Most of variables have two states which are "positive" and "negative", or "yes" and "no". A few variables are continuous and all the states are available in historical accident data. Once the simulation of 121 accidents is completed, the annual fatal accident rate could be estimated eventually by the prediction results of probability of fatal accident occurrence from BNs model and relevant average daily density from database.

4.3 Testing results

The prediction result of annual fatal accident number is provided in Figure 18, along with the plot of observed accident data from historical record. From this figure, it is evident that these two curves are overlapping and they have similar inclination. As can be seen, a few points exactly have the same values, such as year 1991, 1992 and 1993. It is also indicated that most points of model results are higher than observed accident number. This may be considered as an over prediction, which is acceptable from safety predictive aspect.

Specifically, it is necessary to pay more attention on the point underestimating, which have observed data higher than prediction results. In Figure 18, there are only two points with under prediction which are year 2007 and 2009. The probable reason for these under prediction may be the incompleteness of accident data and human factors contributing to highway accidents. It should be noted that there are two accidents in 2007 and one accident in 2009 which have less available accident information in database. The assumption on the state of variables may cause the bias in model results. In addition, five accidents in 2007 and seven accidents in 2009 occurred due to driver error according to the accident records. As previously discussed, the main variable DR (driver condition) is composed of seven basic variables standing for different characteristics of DR. However, the measure of human behavior is hardly to be quantified and this issue would highly affect the simulation results. In consideration of these influence factors, it is recommended to use larger database with more detailed information to reduce the deviation error. As well, it is suggested to consider the complexity of human error when this risk factor appears in lots of testing cases.

From the quantitative comparison in Figure 18 and result analysis, it is fair to say this predictive BNs accident model is capable of predicting the occurrence of fatal accident in specific highway region reliably.



Year	Observed Data	Model Result
1990	6	5.359
1991	3	3.080
1992	1	0.797
1993	1	0.646
1994	2	2.328
1995	2	1.020
1996	2	1.338
1997	1	2.026
1998	1	2.787
1999	3	2.489
2000	9	15.204
2001	11	14.101
2002	8	12.130
2003	7	7.917
2004	3	4.021
2005	7	11.964
2006	10	13.226
2007	19	15.942
2008	17	17.121
2009	13	10.003
2010	6	8.105
2011	9	8.340
2012	7	7.232

Figure 18 Comparison of model results and observed data on highway #63 (1990-2012)

Chapter 5

5. Integration of SIS with BNs model

The proposed predictive BNs accident model can be integrated with Safety Instrumented System (SIS). This may be called as risk-inferred warning system. General SIS consists of input elements such as sensors or transmitters, logic solver, and output elements like safety valves or actuators. These three components of SIS can be precisely linked to the highway predictive BNs accident model. This system comprises four phases and the operating principle of risk-inferred warning system is illustrated in Figure 19.

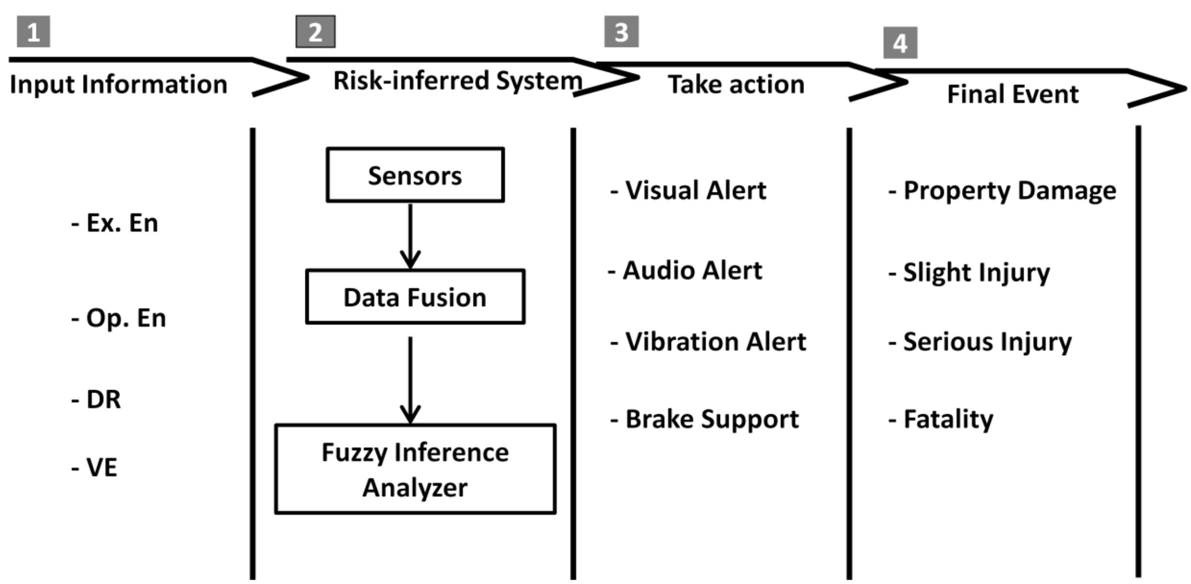


Figure 19 Risk -inferred warning system

The first phase of this system is input information. Sensors, both on board and remote, are used to collect real-time data which is categorized based on the type of background variable in BNs model. This is a procedure of data collection and processing.

The second phase of this system is risk inference. The predictive BNs accident model would be the part of data fusion and analyzer including inference, updating and probability estimation. It initially adopts the developed BNs model and keeps updating when any new evidence is observed. The uncertainty of prior beliefs in BNs can be reduced through probability updating, which can also make the current one more reliable and effective.

The next phase is system response. Once the simulation completing, there is a predictive result including the probability of accident occurrence and the severity of this accident. SILs with regard to highway transportation system are preset threshold values based on each warning level of highway accidents. If the predictive result exceeds any threshold value, the risk-inferred warning system would make an optimal response from four types of warning to prevent the highway accident.

The last phase of this system is accident prevention and severity mitigation. The indication of most significant risk factors can be provided through upward propagation in BNs model, which calculating the probabilities of each background variable contributing to accident. The variables with highest probability value is considered to be eliminated or changed state. It is helpful for preventing accident or at least mitigating the consequences of accidents that could not be prevented successfully.

In order to demonstrate this integration of the proposed BNs model with SIS, this research simulates 10 different scenarios that would result the probability of accident occurrence with a range from 0.0743% to 11.296%, as shown in Table 7.

Table 7 Simulation results of 10 scenarios of highway fatal accidents

Item	Node	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
1	T	2	2	2	0	0	0	0	0	0	0
2	WS	1	1	1	1	1	1	2	2	2	2
3	SF	0	0	0	0	0	0	1	1	1	1
4	RF	0	1	1	1	1	1	0	0	0	0
5	VI	1	1	0	0	0	0	0	0	0	0
6	L	1	1	1	1	1	1	1	0	0	0
7	RC	0	0	0	0	1	0	0	0	0	1
8	RS	0	1	1	1	1	1	2	2	2	2
9	TD	1	0	2	2	1	2	1	2	2	2
10	RSI	1	1	1	1	1	1	1	1	1	0
11	MA	0	0	1	2	2	2	2	2	1	2
12	DS	1	1	1	2	2	2	2	2	2	2
13	G	0	0	1	0	1	0	0	0	1	1
14	A	2	2	1	0	3	0	1	2	2	0
15	DP	0	0	0	0	1	0	0	1	0	0
16	PC	1	1	1	1	1	0	1	1	0	0
17	DI	0	0	1	0	1	1	0	1	1	1
18	AL	0	0	0	0	0	1	1	0	0	1
19	DE	2	1	2	1	0	1	3	0	1	0
20	PY	1	1	1	2	1	2	1	2	1	2
21	BC	1	1	1	1	1	1	1	0	1	0
22	VL	1	1	1	1	1	1	1	0	0	0
23	TP	0	0	0	1	0	1	0	0	2	1
24	VT	1	1	1	1	1	2	2	1	2	1
25	SE	1	1	1	1	0	1	0	1	1	1
26	EC	1	1	1	1	1	1	1	0	1	0
27	SW	1	1	1	1	1	0	1	0	0	0
Probability (%)		0.0743	0.3644	2.7514	3.6207	1.5903	4.7349	6.6150	7.4170	9.0802	11.296

The first scenario describes a common situation with values of normal states for all background variables. The predicted probability of accident would happen on highway is only 0.0743%. For scenario 2, the weather condition is changed to rainfall, along with wet road surface. The predicted value increases to 0.3644%, which explains the effect of rainfall as a risk factor in highway accident is detected. By comparing scenarios 4 and 6, the state of alcohol intake changes from "no (0)" to "yes (1)" and all other variables keep in the same states for both scenarios. It is obviously the probability of accident occurrence increases with approximate 1%. Specifically, in scenario 10, the states of all variables are set as adverse conditions such as snowfall with low visibility, male driver under 18 years with alcohol intake, distraction and problems with vehicle. The probability of accident occurrence is estimated as 11.296% that has much higher likelihood than scenario 1. It is implied that this reliable result presents great potential of the effectiveness of this predictive BNs accident model.

Assuming this prediction result can be used for defining the initial range of SILs. Therefore, SIL 1 is set as the highest probability 11.296% and SIL 4 is set as 0.0743%. The comparison table of probability values and system response can be roughly constructed in Table 8.

Table 8 SILs, probabilities and system reactions

SIL level	Probabilities Inference	System response
SIL 1	> 0.11296	Brake support
SIL 2	[0.01, 0.1]	Vibration Alert
SIL 3	[0.001,0.01]	Audio Alert
SIL4	[0.000743,0.001]	Visual Alert

As mentioned previously, if the predicted value is greater than 0.000743 which is the threshold value for SIL 1, the risk-inferred warning system would provide visual alert of the potential risk. As the predicted values increasing, the system would take more attractive way to alert driver and the extreme response is terminate the operating state through brake support. These threshold values for SILs can be changed according to various BNs models. It can also be modified if accident has occurred and being recorded in SIS, which is identical to the updating theory in BNs model if any evidence has been observed.

Chapter 6

6. Conclusion and further work

In this research, a predictive accident model is proposed for highway transportation system using BNs. This model would be useful to either prevent the occurrence of an accident and/or reduce the severity level of an accident. In this study, traditional regression models are also reviewed which have been commonly used in highway safety studies. The limitations of a pre-defined relationship among variables are discussed. It is observed that most regression models are based on assumptions which are not reasonable for practical applications. The method of BNs is introduced to resolve these issues. Unlike other regression approaches, the advantages of BNs model are that it is less dependent on the theoretical distribution of data and it has representative graphical structure to deal with variables and their relationships readily. The BNs makes the predictive accident model more suitable for real applications. The risk factors considered in this study are well-defined variables and the characteristics of each variable cover all the possible states which would appear during the highway accident.

The model testing is also conducted for the proposed predictive BNs accident model in this research. The positive result has testified that this BNs model is applicable to fatal accident prediction in highway region to prevent accident effectively. Besides, probability updating can reduce the uncertainty of prior beliefs in BNs model. As discussed earlier, this predictive BNs accident model is appropriate only for Canadian highway region due to the limitation of data collection and the test case study in this research is also selected within Canada. The variety of implementation need to be further improved. It is strongly required larger database with detailed accident information in order to enhance the reliability and the stability of this predictive BNs accident model.

Additionally, this BNs model can be integrated with SIS which acts as a risk-inferred warning system. The integral warning system is not only indicating the probability of highway accident occurrence, but also attaching safety functions, which helps creating an intelligent system to effectively prevent accidents and makes the driving environment on highway more safe and reliable. Although this integration is proposed as a conceptual work without entire system architecture, it is hoped that this predictive BNs accident model could be carried out for more practical applications.

With respect to the further work, it is suggested to extend the current model to general case by considering other indicated explanatory variables, updating the dependent relations. The BNs model is developed using the Transport Canada's NCDB and it is more applied to Canadian highways because variables and dependent relationships may vary due to the change in geographical conditions, the climate situation, drivers' habits and highway construction criteria. On the other hand, the BNs is an useful method for problem domains with a static state, which means every variable has a single and fixed value. Unfortunately, this assumption of a static state does not always hold, as many variables are dynamic and variation over time and space is necessary. Therefore, in subsistent attempts, the current predictive accident BNs model needs to be extended to consider a Dynamic Bayesian network (DBN) which is a directed, acyclic graphical model of a stochastic process and consists of time dependency. In summary, searching larger detailed historical accident data and constructing dynamic BNs would be great challenges for next step. These further works would help improve and optimize the current BNs model and solve highway safety problems more effectively and efficiently.

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APPENDIX A

Statistical accidents data in Canada from 1991 to 2010.

Year	Number of Accidents				
	Total	Fatal	Serious Injury	Slight Injury	Property Damage only
1991	278,480	3,228	26,035	144,658	104,559
1992	278,417	3,073	25,521	144,119	105,704
1993	274,616	3,121	23,902	144,204	103,389
1994	267,566	2,837	22,830	141,812	100,087
1995	262,769	2,817	21,494	140,456	98,002
1996	248,757	2,740	18,734	135,210	92,073
1997	237,355	2,660	17,294	130,255	87,146
1998	232,099	2,583	16,197	129,418	83,901
1999	237,276	2,632	16,187	132,496	85,961
2000	240,999	2,547	15,583	137,717	85,152
2001	234,187	2,413	15,285	133,711	82,778
2002	241,197	2,583	15,907	137,952	84,755
2003	233,824	2,489	15,125	135,420	80,790
2004	224,256	2,436	15,591	129,657	76,572
2005	223,129	2,551	15,814	129,789	74,975
2006	218,245	2,599	15,676	126,837	73,133
2007	209,441	2,462	14,235	124,377	68,367
2008	191,359	2,182	12,722	114,926	61,529
2009	185,255	2,011	11,829	111,687	59,728
2010	183,855	2,026	11226	111,915	58,714
Total	2,623,023	28,905	175,180	1,526,484	892,454

* Transport Canada's National Collision Database (NCDB)

APPENDIX B

Summary of CPTs for each variable(node) in BNs

T	WS	RF	SF	VI	W	
					Adverse	Normal
Low	Low	Y	Y	P	0.209225	0.790775
Low	Low	Y	Y	N	0.312265	0.687735
Low	Low	Y	N	P	0.151109	0.848891
Low	Low	Y	N	N	0.254149	0.745851
Low	Low	N	Y	P	0.0759	0.9241
Low	Low	N	Y	N	0.17894	0.82106
Low	Low	N	N	P	0.017784	0.982216
Low	Low	N	N	N	0.120824	0.879176
Low	Medium	Y	Y	P	0.224753	0.775247
Low	Medium	Y	Y	N	0.327793	0.672207
Low	Medium	Y	N	P	0.166637	0.833363
Low	Medium	Y	N	N	0.269677	0.730323
Low	Medium	N	Y	P	0.091428	0.908572
Low	Medium	N	Y	N	0.194468	0.805532
Low	Medium	N	N	P	0.033312	0.966688
Low	Medium	N	N	N	0.136352	0.863648
Low	High	Y	Y	P	0.224728	0.775272
Low	High	Y	Y	N	0.327768	0.672232
Low	High	Y	N	P	0.166612	0.833388
Low	High	Y	N	N	0.268859	0.731142
Low	High	N	Y	P	0.091403	0.908597
Low	High	N	Y	N	0.194443	0.805557
Low	High	N	N	P	0.033287	0.966713
Low	High	N	N	N	0.136327	0.863673
Medium	Low	Y	Y	P	0.2174	0.7826
Medium	Low	Y	Y	N	0.32044	0.67956
Medium	Low	Y	N	P	0.158491	0.84151
Medium	Low	Y	N	N	0.262324	0.737676
Medium	Low	N	Y	P	0.084075	0.915925

T	WS	RF	SF	VI	W	
					Adverse	Normal
Medium	Low	N	Y	N	0.187115	0.812885
Medium	Low	N	N	P	0.025959	0.974041
Medium	Low	N	N	N	0.128206	0.871795
Medium	Medium	Y	Y	P	0.232928	0.767072
Medium	Medium	Y	Y	N	0.335968	0.664032
Medium	Medium	Y	N	P	0.174812	0.825188
Medium	Medium	Y	N	N	0.277852	0.722148
Medium	Medium	N	Y	P	0.099603	0.900397
Medium	Medium	N	Y	N	0.202643	0.797357
Medium	Medium	N	N	P	0.041487	0.958513
Medium	Medium	N	N	N	0.144527	0.855473
Medium	High	Y	Y	P	0.232903	0.767097
Medium	High	Y	Y	N	0.335943	0.664057
Medium	High	Y	N	P	0.174787	0.825213
Medium	High	Y	N	N	0.277827	0.722173
Medium	High	N	Y	P	0.099578	0.900422
Medium	High	N	Y	N	0.202618	0.797382
Medium	High	N	N	P	0.041462	0.958538
Medium	High	N	N	N	0.144502	0.855498
High	Low	Y	Y	P	0.20571	0.79429
High	Low	Y	Y	N	0.30875	0.69125
High	Low	Y	N	P	0.147594	0.852406
High	Low	Y	N	N	0.250634	0.749366
High	Low	N	Y	P	0.072385	0.927615
High	Low	N	Y	N	0.175425	0.824575
High	Low	N	N	P	0.146801	0.8532
High	Low	N	N	N	0.117309	0.882691
High	Medium	Y	Y	P	0.221238	0.778762
High	Medium	Y	Y	N	0.324278	0.675722
High	Medium	Y	N	P	0.163122	0.836878
High	Medium	Y	N	N	0.266162	0.733838
High	Medium	N	Y	P	0.087913	0.912087
High	Medium	N	Y	N	0.190953	0.809047
High	Medium	N	N	P	0.029797	0.970203
High	Medium	N	N	N	0.132837	0.867163
High	High	Y	Y	P	0.221213	0.778787

T	WS	RF	SF	VI	W	
					Adverse	Normal
High	High	Y	Y	N	0.324253	0.675747
High	High	Y	N	P	0.163097	0.836903
High	High	Y	N	N	0.266137	0.733863
High	High	N	Y	P	0.087888	0.912112
High	High	N	Y	N	0.190928	0.809072
High	High	N	N	P	0.029772	0.970228
High	High	N	N	N	0.266137	0.733863

L	RC	W	EEC	
			N	P
Daylight	Y	Inverse	0.146584	0.853416
Daylight	Y	Normal	0.121242	0.878758
Daylight	N	Inverse	0.134734	0.865266
Daylight	N	Normal	0.109392	0.890608
Darkness	Y	Inverse	0.171959	0.828041
Darkness	Y	Normal	0.146617	0.853383
Darkness	N	Inverse	0.160109	0.839891
Darkness	N	Normal	0.134767	0.865233

RS	W	
	Adverse	Normal
Dry	0.2168	0.6842
Wet	0.5233	0.2273
Snow/Ice	0.2599	0.0885

RC	W	TD		
		Low	Medium	High
Y	Inverse	0.090586	0.866649	0.042765
Y	Normal	0.117378	0.660649	0.221973
N	Inverse	0.185086	0.637999	0.176915
N	Normal	0.211878	0.431999	0.356123

RC	RSI	
	N	Y
Y	0.15	0.85
N	0.05	0.95

RSI	TD	RS	RCU	R-side	
				N	P
Y	Low	Dry	Y	0.106838	0.893162
Y	Low	Dry	N	0.119878	0.880122
Y	Low	Wet	Y	0.112443	0.887557
Y	Low	Wet	N	0.125483	0.874517
Y	Low	Snow/Ice	Y	0.093842	0.906158
Y	Low	Snow/Ice	N	0.106882	0.893118
Y	Medium	Dry	Y	0.178425	0.821575
Y	Medium	Dry	N	0.191465	0.808535
Y	Medium	Wet	Y	0.18403	0.81597
Y	Medium	Wet	N	0.19707	0.80293
Y	Medium	Snow/Ice	Y	0.165429	0.834571
Y	Medium	Snow/Ice	N	0.178469	0.821531
Y	High	Dry	Y	0.15781	0.84219
Y	High	Dry	N	0.17085	0.82915
Y	High	Wet	Y	0.163415	0.836585
Y	High	Wet	N	0.176455	0.823545
Y	High	Snow/Ice	Y	0.144814	0.855186
Y	High	Snow/Ice	N	0.157854	0.842146
N	Low	Dry	Y	0.113488	0.886512
N	Low	Dry	N	0.126528	0.873472
N	Low	Wet	Y	0.119093	0.880907
N	Low	Wet	N	0.132133	0.867867
N	Low	Snow/Ice	Y	0.100492	0.899508
N	Low	Snow/Ice	N	0.113532	0.886468
N	Medium	Dry	Y	0.185075	0.814925
N	Medium	Dry	N	0.198115	0.801885
N	Medium	Wet	Y	0.19068	0.80932
N	Medium	Wet	N	0.20372	0.79628
N	Medium	Snow/Ice	Y	0.172079	0.827921
N	Medium	Snow/Ice	N	0.185119	0.814881

RSI	TD	RS	RCU	R-side	
				N	P
N	High	Dry	Y	0.16446	0.83554
N	High	Dry	N	0.1775	0.8225
N	High	Wet	Y	0.170065	0.829935
N	High	Wet	N	0.183105	0.816895
N	High	Snow/Ice	Y	0.151464	0.848536
N	High	Snow/Ice	N	0.164504	0.835496

A	G	PC	DP	DS		
				Low	Medium	High
<18	F	P	W	0.097867	0.801363	0.10077
<18	F	P	L	0.138027	0.736803	0.12517
<18	F	N	W	0.131135	0.709755	0.15911
<18	F	N	L	0.171295	0.645195	0.18351
<18	M	P	W	0.046507	0.796692	0.156801
<18	M	P	L	0.135826	0.682973	0.181201
<18	M	N	W	0.128934	0.655925	0.215141
<18	M	N	L	0.169094	0.591365	0.239541
[19,35]	F	P	W	0.102967	0.833078	0.063955
[19,35]	F	P	L	0.143127	0.768518	0.088355
[19,35]	F	N	W	0.136235	0.74147	0.122295
[19,35]	F	N	L	0.176395	0.67691	0.146695
[19,35]	M	P	W	0.100766	0.779248	0.119986
[19,35]	M	P	L	0.140926	0.714688	0.144386
[19,35]	M	N	W	0.134034	0.68764	0.178326
[19,35]	M	N	L	0.174194	0.62308	0.202726
[35,65]	F	P	W	0.104506	0.830571	0.064923
[35,65]	F	P	L	0.144666	0.766011	0.089323
[35,65]	F	N	W	0.137774	0.738963	0.123263
[35,65]	F	N	L	0.177934	0.674403	0.147663
[35,65]	M	P	W	0.102305	0.776741	0.120954
[35,65]	M	P	L	0.142465	0.712181	0.145354
[35,65]	M	N	W	0.135573	0.685133	0.179294
[35,65]	M	N	L	0.175733	0.620573	0.203694
>65	F	P	W	0.107757	0.828434	0.063809
>65	F	P	L	0.147917	0.763874	0.088209

A	G	PC	DP	DS		
				Low	Medium	High
>65	F	N	W	0.141025	0.736826	0.122149
>65	F	N	L	0.181185	0.672266	0.146549
>65	M	P	W	0.105556	0.774604	0.11984
>65	M	P	L	0.145716	0.710044	0.14424
>65	M	N	W	0.138824	0.682996	0.17818
>65	M	N	L	0.178984	0.618436	0.20258

MA	DS	V-side	
		N	P
N	Low	0.052274	0.947726
N	Medium	0.12779	0.87221
N	High	0.0843	0.9157
Change	Low	0.050188	0.949812
Change	Medium	0.125704	0.874296
Change	High	0.082214	0.917786
Overtake	Low	0.049136	0.950864
Overtake	Medium	0.124652	0.875348
Overtake	High	0.081162	0.918838

R-side	V-side	OEC	
		N	P
N	N	0.084905	0.915095
N	Y	0.127903	0.872097
Y	N	0.142978	0.857022
Y	Y	0.185977	0.814023

A	G	PC	
		N	P
<18	F	0.08723	0.91277
<18	M	0.093573	0.906427
[19,35]	F	0.108585	0.891415
[19,35]	M	0.114928	0.885072
[35,65]	F	0.0912	0.9088

A	G	PC	
		N	P
[35,65]	M	0.097543	0.902457
>65	F	0.073855	0.926145
>65	M	0.080198	0.919802

DE	DP	PC	DI	AL	DC	
					N	P
<1	W	P	Y	Y	0.302658	0.697342
<1	W	P	Y	N	0.229398	0.770602
<1	W	P	N	Y	0.163733	0.836267
<1	W	P	N	N	0.090473	0.909527
<1	W	N	Y	Y	0.360998	0.639002
<1	W	N	Y	N	0.287738	0.712262
<1	W	N	N	Y	0.222073	0.777927
<1	W	N	N	N	0.148813	0.851187
<1	L	P	Y	Y	0.327058	0.672942
<1	L	P	Y	N	0.253798	0.746202
<1	L	P	N	Y	0.188133	0.811867
<1	L	P	N	N	0.114873	0.885127
<1	L	N	Y	Y	0.385398	0.614602
<1	L	N	Y	N	0.312138	0.687862
<1	L	N	N	Y	0.246473	0.753527
<1	L	N	N	N	0.173213	0.826787
[2-5]	W	P	Y	Y	0.275205	0.724795
[2-5]	W	P	Y	N	0.201945	0.798055
[2-5]	W	P	N	Y	0.13628	0.86372
[2-5]	W	P	N	N	0.06302	0.93698
[2-5]	W	N	Y	Y	0.333545	0.666455
[2-5]	W	N	Y	N	0.260285	0.739715
[2-5]	W	N	N	Y	0.19462	0.80538
[2-5]	W	N	N	N	0.12136	0.87864
[2-5]	L	P	Y	Y	0.299605	0.700395
[2-5]	L	P	Y	N	0.226345	0.773655
[2-5]	L	P	N	Y	0.16068	0.83932
[2-5]	L	P	N	N	0.08742	0.91258
[2-5]	L	N	Y	Y	0.357945	0.642055

DE	DP	PC	DI	AL	DC	
					N	P
[2-5]	L	N	Y	N	0.284685	0.715315
[2-5]	L	N	N	Y	0.21902	0.78098
[2-5]	L	N	N	N	0.14576	0.85424
>6	W	P	Y	Y	0.255954	0.744046
>6	W	P	Y	N	0.182694	0.817306
>6	W	P	N	Y	0.117029	0.882971
>6	W	P	N	N	0.043769	0.956231
>6	W	N	Y	Y	0.314294	0.685706
>6	W	N	Y	N	0.241034	0.758966
>6	W	N	N	Y	0.175369	0.824631
>6	W	N	N	N	0.102109	0.897891
>6	L	P	Y	Y	0.280354	0.719646
>6	L	P	Y	N	0.207094	0.792906
>6	L	P	N	Y	0.141429	0.858571
>6	L	P	N	N	0.068169	0.931831
>6	L	N	Y	Y	0.338694	0.661306
>6	L	N	Y	N	0.265434	0.734566
>6	L	N	N	Y	0.199769	0.800231
>6	L	N	N	N	0.126509	0.873491

PY	VT	SE	
		N	Y
<1	Motorbike	0.037926	0.962074
<1	Passenger car	0.108756	0.891244
<1	Bus/ truck	0.018826	0.981174
[2-5]	Motorbike	0.093875	0.906125
[2-5]	Passenger car	0.164705	0.835295
[2-5]	Bus/ truck	0.074775	0.925225
[6-10]	Motorbike	0.082055	0.917945
[6-10]	Passenger car	0.152885	0.847115
[6-10]	Bus/ truck	0.062955	0.937045
>10	Motorbike	0.090846	0.909154
>10	Passenger car	0.161676	0.838324
>10	Bus/ truck	0.071746	0.928254

PY	EC	
	N	P
<1	0.001	0.999
[2-5]	0.015	0.985
[6-10]	0.189	0.811
>10	0.277	0.723

SE	VL	ES	
		N	P
N	N	0.11039	0.88961
N	Y	0.10039	0.89961
Y	N	0.15571	0.84429
Y	Y	0.14571	0.85429

TP	SW	BC	VCH	
			N	P
P	N	N	0.1294	0.8706
P	N	Y	0.1683	0.8317
P	Y	N	0.1739	0.8261
P	Y	Y	0.2128	0.7872
L	N	N	0.07587	0.92413
L	N	Y	0.11477	0.88523
L	Y	N	0.12037	0.87963
L	Y	Y	0.15927	0.84073
Burst	N	N	0.06905	0.93095
Burst	N	Y	0.10795	0.89205
Burst	Y	N	0.11355	0.88645
Burst	Y	Y	0.15245	0.84755

ES	PS	VCH	VC	
			N	P
N	N	N	0.13763	0.86237
N	N	P	0.12473	0.87527
N	P	N	0.1183	0.8817
N	P	P	0.1054	0.8946

ES	PS	VCH	VC	
			N	P
P	N	N	0.11919	0.88081
P	N	P	0.10629	0.89371
P	P	N	0.09986	0.90014
P	P	P	0.08696	0.91304

EEC	OEC	DC	VC	ACC	
				Y	N
N	N	N	N	0.1129605	0.88703953
N	N	N	P	0.0903622	0.90963782
N	N	P	N	0.0237276	0.97627245
N	N	P	P	0.0525356	0.94746442
N	P	N	N	0.0908025	0.90919751
N	P	N	P	0.0682042	0.9317958
N	P	P	N	0.0529759	0.9470241
N	P	P	P	0.0303776	0.9696224
P	N	N	N	0.0963286	0.90367141
P	N	N	P	0.0737303	0.92626971
P	N	P	N	0.058502	0.94149801
P	N	P	P	0.0359037	0.9640963
P	P	N	N	0.0741706	0.92582939
P	P	N	P	0.0515723	0.94842769
P	P	P	N	0.036344	0.96365599
P	P	P	P	0.0137457	0.98625428

APPENDIX C

Accident records from highway #63 from southwest of Radway to north of Fort Mackay in north Alberta, Canada.

Item	Date	Fatality	Accident type	Time	Conditions	Victim Sex	Victim Age
1	4/3/1990	1	Car vs. semi	1:30 a.m.	Heavy fog	Male	24
2	25/4/1990	1	Car vs. commercial vehicle	8:00 a.m.	Snowy road	Male	42
3	31/7/1990	1	Single-vehicle crash	3:45 a.m.		Male	20
4	12/8/1990	1	Car vs. car	12:30 a.m.		Male	31
5	1/9/1990	1	Single-vehicle crash			Male	32
6	3/9/1990	1	Wildlife	12 a.m.		Male	31
7	15/2/1991	1	Car vs. car	9:15 p.m.	Icy roads	Female	23
8	12/8/1991	1	Car vs. pedestrian			Female	27
9	23/8/1991	1	Motorcycle vs semi	1:30 a.m.		Male	19
10	20/1/1992	1	Single-vehicle crash			Male	23
11	16/7/1993	1	Car vs. semi			Male	27
12	1/11/1994	1	Single-vehicle crash			Male	57
13	26/4/1994	1	Semi vs commercial vehicle			Male	53
14	24/2/1995	2	Unknown		On a curve	Male	3
15	22/11/1995	1	Wildlife	Night		Male	36
16	22/3/1996	1	Car vs. pedestrian			Male	28
17	25/10/1996	1	Car vs. car			Female	37
18	17/6/1997	1	Unknown			Male	16
19	21/12/1998	1	Car vs. semi	6:00 p.m.	Bad weather	Male	33
20	4/10/1999	1	Car vs. commercial vehicle	8:30 a.m.		Male	49
21	26/3/1999	1	Car vs. semi	2:10 a.m.		Male	53
22	28/8/1999	1	Car vs. semi	12:30 p.m.		Male	32
23	2/6/2000	1	Car vs. car	6:45 p.m.		Male	58
24	7/12/2000	1	Car vs. car		Icy roads	Male	30
25	11/7/2000	1	Multiple (3+) vehicle			Male	22

Item	Date	Fatality	Accident type	Time	Conditions	Victim Sex	Victim Age
26	28/7/2000	2	Car vs. car			Male	52
27	12/10/2000	1	Single-vehicle crash	9:10 p.m.		Male	44
28	28/10/2000	1	Car vs. pedestrian			Female	42
29	14/11/2000	1	Car vs. car	7:00 a.m.	Icy roads	Female	26
30	19/12/2000	1	Car vs. commercial vehicle			Male	60
31	17/2/2001	2	Car vs. car			Female	39
32	22/4/2001	1	Single-vehicle crash			Male	23
33	7/8/2001	3	Car vs. commercial vehicle	4:30 p.m.		Female	39
34	13/9/2001	1	Multiple (3+) vehicle	11:00 p.m.		Unknown	Unknown
35	30/10/2001	3	Car vs. car	7:00 a.m.		Male	19
36	13/11/2001	1	Car vs. semi	2:40 a.m.		Male	22
37	3/2/2002	3	Car vs. car	After midnight		Male	27
38	14/5/2002	1	Unknown			Male	19
39	10/7/2002	1	Semi vs. pedestrian			Male	49
40	23/8/2002	1	Semi vs. pedestrian			Female	21
41	18/11/2002	1	Single-vehicle crash	12:21 p.m.		Unknown	27
42	10/12/2002	1	Single-vehicle crash			Male	49
43	13/2/2003	2	Car vs. car	2:10 p.m.		Male	44
44	21/3/2003	3	Car vs. semi			Male	19
45	10/10/2003	1	Car vs. semi	4:00 p.m.		Male	Unknown
46	/3/2003	1	Car vs. semi	10:00 p.m.		Male	38
47	26/2/2004	1	Car vs. semi			Male	Unknown
48	19/12/2004	2	Car vs. semi			Male	50
49	22/3/2005	1	Car vs. commercial vehicle	6:00 a.m.		Unknown	Unknown
50	30/6/2005	1	Single-vehicle crash			Male	25
51	27/7/2005	1	Unknown	10:30 p.m.		Male	60
52	6/8/2005	1	Car vs. car	9:30 p.m.		Male	77
53	19/11/2005	1	Single-vehicle crash	10:00 a.m.	Icy roads	Male	23
54	20/11/2005	1	Single-vehicle crash			Male	Unknown
55	27/12/2005	1	Car vs. car			Male	24
56	2/5/2006	1	Car vs. semi	5:00 a.m.	Icy and slushy	Male	26
57	3/1/2006	2	Car vs. debris	3:30 a.m.		Male	62
58	5/12/2006	1	Car vs. commercial vehicle	Morning		Male	23

Item	Date	Fatality	Accident type	Time	Conditions	Victim Sex	Victim Age
59	17/3/2006	1	Car vs. semi			Male	Unknown
60	27/6/2006	1	Wildlife	3:30 a.m.		Male	64
61	17/8/2006	2	Car vs. car	4:00 p.m.		Male	30
62	7/9/2006	1	Single-vehicle crash			Male	33
63	20/10/2006	1	Unknown			Female	78
64	6/11/2007	1	Single-vehicle crash	Morning	Icy roads	Male	46
65	8/11/2007	1	Car vs. semi	Afternoon	Icy roads	Male	41
66	19/1/2007	2	Car vs. car	10:00 p.m.		Male	20
67	25/1/2007	1	Car vs. semi	2:00 p.m.	Icy roads in a whiteout	Male	59
68	3/12/2007	1	Car vs. semi	3:00 p.m.		Female	45
69	10/4/2007	2	Car vs. car	5:00 p.m.		Male	21
70	10/4/2007	2	Car vs. car	Morning		Female	48
71	23/7/2007	1	Single-vehicle crash			Male	57
72	26/7/2007	1	Car vs. pedestrian	2:15 a.m.		Female	81
73	30/10/2007	1	Unknown			Male	Unknown
74	30/11/2007	1	Car vs. car		Poor driving conditions	Male	49
75	30/11/2007	2	Car vs. semi	Afternoon	Poor driving conditions	Male	38
76	12/12/2007	1	Commercial vehicle vs. semi	9:30 p.m.		Unknown	Unknown
77	19/12/2007	1	Car vs. car	5:30 p.m.		Male	49
78	27/12/2007	1	Car vs. car	3:30 p.m.		Male	Unknown
79	6/10/2008	1	Single-vehicle crash	6:00 p.m.		Female	51
80	7/12/2008	4	Car vs. semi			Male	47
81	8/2/2008	2	Car vs. car	7:15 a.m.	High winds, drifting snow and ice	Male	32
82	8/2/2008	2	Unknown	7:15 a.m.		Unknown	Unknown
83	21/3/2008	1	Car vs. semi	6:00 p.m.		Male	Unknown
84	28/3/2008	2	Multiple (3+) vehicle	11:15 a.m.		Unknown	Unknown
85	18/4/2008	1	Car vs. semi	1:15 a.m.	Good roads and weather	Male	23
86	19/6/2008	1	Car vs. commercial vehicle	1:00 p.m.		Male	31
87	27/10/2008	1	Car vs. car	3:30 p.m.		Unknown	23
88	23/11/2008	1	Single-vehicle crash		Icy roads	Male	70
89	31/12/2008	1	Car vs. semi	2:00 a.m.	Bad weather	Unknown	Unknown
90	13/1/2009	1	Car vs. semi	10:00 a.m.	Poor roads	Male	Unknown
91	28/1/2009	3	Car vs. commercial vehicle	3:00 p.m.		Male	80

Item	Date	Fatality	Accident type	Time	Conditions	Victim Sex	Victim Age
92	28/1/2009	1	Car vs. semi	11:45 a.m.		Female	Unknown
93	28/1/2009	2	Single-vehicle crash	2:00 a.m.		Male	36
94	9/4/2009	1	Multiple (3+) vehicle	9:15 p.m.		Unknown	Unknown
95	12/5/2009	1	Car vs. car	9:00 p.m.		Male	48
96	4/8/2009	1	Single-vehicle crash	9:00 p.m.		Female	50
97	28/9/2009	1	Car vs. car			Male	30
98	28/9/2009	1	Car vs. semi			Male	52
99	15/10/2009	1	Car vs. car	8:30 p.m.		Male	58
100	10/1/2010	2	Car vs. semi			Male	50
101	18/2/2010	1	Multiple (3+) vehicle	11:10 a.m.		Male	21
102	23/4/2010	1	Car vs. car	10:30 p.m.	severe snow storm and slushy roads	Male	21
103	13/12/2010	2	Car vs. car			Female	30
104	3/2/2011	1	Car vs. semi	9:00 a.m.	Slippery roads	Unknown	Unknown
105	14/3/2011	1	Car vs. semi			Male	62
106	2/5/2011	1	Car vs. car	Afternoon		Female	28
107	1/9/2011	2	Car vs. car			Male	54
108	11/10/2011	1	Single-vehicle crash			Male	Unknown
109	13/11/2011	1	Car vs. car		Poor weather	Male	42
110	14/12/2011	1	Car vs. car		Slippery roads	Male	65
111	31/12/2011	1	Unknown	3:00 p.m.	Snowfall	Male	22
112	27/4/2012	7	Car vs. car			Male	34
113							
114	6/1/2013	1	Car vs. car			Male	53
115	21/1/2013	1	Car vs. semi				
116	2/1/2013	1	Car vs Commercial Vehicle				
117	1/12/2012	1	Semi vs. Semi		Poor road	Male	38
118	17/11/2012	1	Single-vehicle crash		alcohol limit .	Male	43
119	17/11/2012	1	Single-vehicle crash			Male	68
120	13/11/2012	1	Car vs. Semi	10:15 a.m.	Slippery roads	Female	
121	9/9/2012	2	Car vs. Car	8:45 a.m.	Driver error	Female	52

APPENDIX D

Allocation of traffic volume determined points on Highway #63

Item	CS	TCS	Muni	Location Description
1	00	04	Thor	N OF 28 & 829 W OF RADWAY
2	00	04	Thor	3.0 KM N OF 28 & 63 EGREMONT
3	00	04	Thor	S OF 18 & 656 E OF THORHILD
4	00	08	Thor	N OF 18 & 656 E OF THORHILD
5	00	08	Thor	S OF TWP RD 610 (ABEE N ACC) 36-60-21-413800000
6	00	08	Thor	N OF TWP RD 610 (ABEE N ACC) 36-60-21-413800000
7	00	08	Thor	S OF 661 E OF NEWBROOK
8	00	12	Thor	N OF 661 E OF NEWBROOK
9	01	04	Atha	W OF 663 W OF BOYLE WJ
10	01	06	Atha	S OF TWP RD 654 21-65-19-400000000
11	01	06	Atha	N OF TWP RD 654 21-65-19-400000000
12	01	08	Atha	E OF 663 W OF BOYLE WJ
13	01	08	Atha	S OF 663 AT BOYLE EJ
14	01	12	Atha	N OF 663 AT BOYLE EJ
15	01	12	Atha	W OF 831 AT BOYLE NJ
16	01	16	Atha	N OF 831 AT BOYLE NJ
17	01	16	Atha	S OF 55 S OF DONATVILLE SJ
18	01	20	Atha	N OF 55 S OF DONATVILLE SJ
19	01	20	Atha	S OF SPRUCE VALLEY RD 10-67-19-400001300
20	01	20	Atha	N OF SPRUCE VALLEY RD 10-67-19-400001300
21	01	20	Atha	W OF ALPAC ACC 24-67-19-407000000

Item	CS	TCS	Muni	Location Description
22	01	20	Atha	E OF ALPAC ACC 24-67-19-407000000
23	01	20	Atha	W OF 1 ST W IN GRASSLAND 21-67-18-408050000
24	01	20	Atha	E OF 1 ST W IN GRASSLAND 21-67-18-408050000
25	01	20	Atha	5.4 KM W OF 55 & 63 GRASSLAND NJ
26	01	20	Atha	W OF 55 & 855 W OF ATMORE NJ
27	02	04	Atha	N OF 55 & 855 W OF ATMORE NJ
28	02	04	Atha	5.5 KM N OF 55 & 63 ATMORE NJ
29	02	04	Atha	S OF PLAMONDON TURNOFF 27-68-17-413600360
30	02	04	Atha	N OF PLAMONDON TURNOFF 27-68-17-413600360
31	02	04	Atha	4.0 KM N OF WANDERING RIVER
32	02	04	Wdbf	S OF TWP RD 730 35-72-17-400000000
33	04	04	Wdbf	N OF TWP RD 730 35-72-17-400000000
34	06	04	Wdbf	MARIANA LAKE
35	08	04	Wdbf	S OF LOCAL RD 4-81-13-404280780
36	08	04	Wdbf	N OF LOCAL RD 4-81-13-404280780
37	08	04	Wdbf	S OF JACOS HANGINGSTONE ACC RD 36-84-11-403550660
38	08	04	Wdbf	N OF JACOS HANGINGSTONE ACC RD 36-84-11-403550660
39	10	04	Wdbf	S OF 881 NW OF ANZAC
40	10	08	Wdbf	N OF 881 NW OF ANZAC
41	10	08	Wdbf	7.4 KM S OF 63 & 69 FORT MCMURRAY
42	11	04	Wdbf	S OF 69 AT FT MCMURRAY
43	11	08	Wdbf	S OF LANDFILL ACC IN FT MCMURRAY 22-88-9-404150790
44	11	08	Wdbf	N OF LANDFILL ACC IN FT MCMURRAY 22-88-9-404150790
45	11	08	CoFM	N OF 69 AT FT MCMURRAY
46	11	08	CoFM	S OF MACKENZIE BLVD IN FT MC 34-88-9-409601160
47	11	08	CoFM	N OF MACKENZIE BLVD IN FT MC 34-88-9-409601160

Item	CS	TCS	Muni	Location Description
48	11	08	CoFM	S OF PARENT WAY NJ IN FT MCMURRY 3-89-9-410701590
49	11	08	CoFM	N OF PARENT WAY NJ IN FT MCMURRY 3-89-9-410701590
50	11	08	CoFM	S OF GREGOIRE/BEACON DR IN FT MC 3-89-9-411401120
51	11	12	CoFM	N OF GREGOIRE/BEACON DR IN FT MC 3-89-9-411401120
52	11	12	CoFM	0.4 KM N OF 63 & BEACON HILL DRIVE, FORT MCMURRAY
53	11	12	CoFM	S OF KING ST IN FT MCMURRAY 10-89-9-413950645
54	11	16	CoFM	N OF KING ST IN FT MCMURRAY 10-89-9-413950645
55	11	16	CoFM	S OF HOSPITAL ST IN FT MCMURRAY 16-89-9-403201300
56	11	20	CoFM	N OF HOSPITAL ST IN FT MCMURRAY 16-89-9-403201300
57	11	20	CoFM	S OF HARDIN ST IN FT MC 16-89-9-413000260
58	11	24	CoFM	N OF HARDIN ST IN FT MC 16-89-9-413000260
59	11	24	CoFM	S OF MORRISON ST IN FT MC 21-89-9-415601520
60	11	28	CoFM	N OF MORRISON ST IN FT MC 21-89-9-415601520
61	11	28	CoFM	S OF THICKWOOD BLVD FT MC 29-89-9-409601290
62	11	36	CoFM	N OF THICKWOOD BLVD FT MC 29-89-9-409601290
63	11	36	CoFM	S OF CONFEDERATION WAY IN FT MC 29-89-9-413600000
64	11	40	CoFM	N OF CONFEDERATION WAY IN FT MC 29-89-9-413600000
65	11	40	CoFM	S OF BUS TRANSFER IN FT MC 6-90-9-406801460
66	11	40	CoFM	N OF BUS TRANSFER IN FT MC 6-90-9-406801460
67	11	40	Wdbf	15.4 KM N OF 63 & 69 FORT MCMURRAY
68	12	04	Wdbf	10.8 KM N 63 & CONFEDERATION WAY
69	12	04	Wdbf	S OF AOSTRA RD 25-91-10-408050150
70	12	04	Wdbf	N OF AOSTRA RD 25-91-10-408050150
71	12	04	Wdbf	S OF SUNCOR ACC 11-92-10-402900400
72	12	08	Wdbf	N OF SUNCOR ACC 11-92-10-402900400
73	12	12	Wdbf	S OF FT MACKAY ACC 1-94-11-407201040

Item	CS	TCS	Muni	Location Description
74	14	04	Wdbf	N OF FT MACKAY ACC 1-94-11-407201040
75	14	04	Wdbf	2.4 KM N OF PETER LOUGHEED BRIDGE
76	14	04	Wdbf	S OF SHELL ALBIAN ACC N OF FT MCMURRAY 31-94-10-404251240
77	14	04	Wdbf	N OF SHELL ALBIAN ACC N OF FT MCMURRAY 31-94-10-404251240
78	14	04	Wdbf	S OF SYNCRUDE AURORA RD 18-95-10-401300300
79	14	05	Wdbf	N OF SYNCRUDE AURORA RD 18-95-10-401300300

Annual traffic volume on 79 determined points from 1990 to 2012

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
1	1230	1220	1370	1300	1210	1190	1190	1260	1250	1270	1360
2	1230	1220	1370	1300	1210	1190	1190	1260	1250	1270	1360
3	1500	1400	1570	1490	1390	1440	1240	1320	1310	1340	1440
4	1680	1560	1750	1660	1550	1540	1360	1440	1430	1370	1470
5											
6											
7	1370	1270	1430	1360	1270	1020	1020	1080	1080	1100	1210
8	1200	1120	1260	1200	1120	1020	1020	1080	1080	1100	1130
9	1190	1200	1350	1280	1160	1180	1180	1240	1240	1260	1280
10											
11											
12	1650	1660	1900	1800	1710	1730	1730	1830	1830	1870	1970
13	2020	2030	2320	2150	2040	2120	2120	2240	2240	2290	3330
14	920	930	1060	1010	960	1000	1000	1070	1070	1000	1460
15	870	920	1090	1030	980	1020	1020	1090	1080	1020	1480
16	1730	1830	2170	2060	1960	2220	2220	2350	2360	2370	2650
17	1460	1550	1770	1780	1920	1980	1980	2090	1990	2080	2240

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
18	1700	1800	2320	2020	2180	2280	2280	2450	2350	2480	2720
19											
20											
21				1840	1980	1990	2010	2190	2170	2280	2550
22				2190	2360	2390	2410	2630	2490	2620	2930
23				2580	2870	2900	2940	3220	2750	2890	3220
24				2570	2860	2900	2940	3220	2790	2930	3270
25	1720	1770	1840	2050	2210	2240	2270	2490	2520	2640	2950
26	1730	1650	1700	1890	2090	2120	2150	2360	2350	2470	2760
27	1210	1280	1180	1260	1390	1420	1490	1680	1710	1900	2180
28	1240	1200	1170	1250	1380	1400	1470	1650	1680	1870	2140
29	1140	1100	1070	1170	1290	1310	1380	1540	1560	1720	1960
30	1190	1150	1120	1380	1380	1410	1800	2020	2040	2260	2600
31	1190	1150	1080	1150	1280	1310	1370	1560	1560	1750	2060
32											
33											
34											
35											
36											
37											
38											
39	1180	1140	1070	1140	1270	1210	1260	1330	1440	1600	1670
40	2010	1940	1760	1740	1940	1850	1940	2550	2430	2680	2810
41	2170	2100	1910	2030	2260	2160	2250	2580	2740	3010	3160
42	3520	3070	2790	2970	2990	2860	2980	3420	3630	4000	4320
43											

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
44											
45	4930	4200	3820	4070	3920	3750	3910	4570	4890	5270	6260
46											
47											
48											
49											
50											
51											
52											
53									22250	22650	23770
54									21070	21450	22510
55											
56											
57											
58											
59											
60											
61											
62											
63											
64											
65											
66											
67	3620	3440	3300	3570	3540	3550	4200	5110	5230	6410	7170
68											
69								4900	5000	6130	6850

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
70								4680	4780	5860	6560
71											
72											
73	220	210	180	190	190	190	190	590	610	670	750
74	60	60	50	50	50	50	60	190	190	210	230
75											
76											
77											
78											
79											
Average	1616.552	1557.586	1612.759	1713.03	1754.848	1755.758	1805.152	2179.429	3228.108	3434.865	3777.838

Annual traffic volume on 79 determined points from 1990 to 2012 (Cont.)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
1	1440	1400	1440	1490	1590	1730	1890	1860	1850	1960	2110	2330
2	1440	1400	1450	1500	1590	1760	1890	1860	1840	1980	2120	2340
3	1520	1490	1530	1570	1670	1810	1970	1940	1920	2040	2200	2420
4	1580	1550	1680	1740	1850	2010	2190	2170	2140	2260	2440	2660
5						1810	1970	1970	1970	2090	2200	2400
6						1790	1950	1950	1950	2070	2200	2400
7	1290	1260	1300	1340	1600	1730	1870	1870	1900	2000	2120	2300
8	1210	1180	1220	1260	1600	1730	1870	1870	1880	1980	2100	2280
9	1320	1280	1320	1360	1720	1880	2060	2060	2070	2190	2330	2510
10					3190	3330	3650	3750	3760	4000	4390	4610

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
11					3090	3230	3530	3630	3560	3780	4150	4350
12	2050	1990	2050	2120	2240	2400	2620	2620	2870	3050	3190	3370
13	3460	3360	3400	3020	3200	3420	3740	3740	3500	3720	3900	4080
14	1530	1490	1530	1520	1620	1740	1900	1920	1900	2020	2120	2240
15	1540	1490	1530	1520	1620	1740	1900	1920	1900	2020	2120	2240
16	2850	2760	2780	3150	3420	3640	3980	4020	4380	4640	5100	5360
17	2450	2410	2420	2620	2880	3020	3300	3580	3340	3540	3960	4160
18	2970	2910	2960	3040	3320	3500	3880	4360	4080	4320	4820	5020
19			3060	3140	3430	3580	3960	4170	3890	4300	4800	5000
20			3020	3100	3390	3540	3920	4110	3830	4240	4740	4940
21	2840	2780	3040	3120	3370	3510	3890	4050	3790	4390	4890	5090
22	3270	3210	3550	3640	3780	3940	4380	4560	4260	4740	5280	5500
23	3580	3510	3770	3850	4230	4410	4990	5180	4580	4990	5570	5790
24	3640	3570	3750	3830	4200	4380	4960	5150	4630	5050	5630	5850
25	3280	3210	3440	3540	3840	4070	4560	4720	4380	4830	5390	5550
26	3070	3000	3190	3270	3600	3760	4240	4780	4450	4840	5400	5620
27	2450	2420	2580	2630	3020	3140	3510	3760	3480	3870	4330	4570
28	2410	2420	2610	2730	3050	3210	3570	3640	3330	3770	4200	4410
29	2370	2360	2580	2630	3010	3300	3380	3440	3180	3540	4140	4360
30	2390	2380	2600	2650	3030	3700	3640	3700	3400	3800	4300	4520
31	2350	2370	2620	2780	3100	3240	3500	3630	3450	3870	4260	4540
32										3800	4220	4540
33										3800	4220	4540
34									3370	3700	4040	4330
35										3570	3930	4230
36										3570	3930	4230

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
37										3720	4100	4420
38										3740	4120	4440
39	2250	2310	2410	2620	2700	3440	4190	4430	4030	3910	4430	4690
40	3660	3760	3930	4280	5220	6750	7640	7600	6600	6890	7920	8890
41	3740	3870	4080	4580	5240	7190	7650	7580	6480	7000	8000	8950
42	5430	5570	5830	4950	5940	7680	8640	8580	7280	7620	9500	10540
43											8060	9050
44											9500	10540
45	7560	7820	8190	8500	9240	10870	10980	11270	11360	11800	14200	15120
46	5540	5730	6100	7570	8230	9670	10980	11270	11360	11800	14200	15120
47	13290	13750	14980	16130	17460	19340	21870	22510	21260	21920	24090	25140
48	13290	13750	14980	16130	17460	19340	21790	22430	21170	21820	23980	25000
49	13690	14380	15670	16740	18120	20070	22260	22910	21660	22320	24120	25090
50	13690	14380	15670	16740	18120	20070	22080	22740	21660	22330	23820	25090
51	26170	27610	27840	29150	31560	34220	37510	38620	36760	37900	39890	41310
52	26700	27530	28140	29540	31560	34840	37640	38650	36700	38070	39990	41310
53	26170	27610	27840	29150	31560	34220	37510	38620	36760	37900	39890	41310
54	24390	26200	27010	28290	30700	31960	34810	36350	34600	35720	37490	38830
55	24390	26200	27010	28290	30700	31960	34810	36350	34600	35720	37490	38830
56	28700	30760	29310	30740	33490	34860	37990	40420	38460	40050	41740	43220
57	28700	30760	29310	30740	33490	34860	37990	40420	38460	40050	41740	43220
58	28790	30850	30750	32370	35400	36650	39940	42850	41360	43470	45140	46640
59	28790	30850	30750	32370	35400	36650	39940	42850	41360	43470	45140	46640
60	34520	36700	38200	40210	44260	45740	49830	53330	52010	55350	57390	59290
61	34520	36650	38150	40210	44260	45740	49720	53210	51890	55220	57260	59160
62	14510	15380	19080	20970	26430	27110	29770	32860	31660	33790	35450	36570

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
63	14510	15380	19080	20970	26430	27110	29770	32860	31660	33790	35450	36570
64	10120	10030	10970	12350	15730	16070	20350	23070	21880	23620	24790	25540
65	10120	10030	10970	12350	15630	15980	19900	23070	21880	23620	24790	25540
66	9800	9630	10490	11060	14060	14360	17130	19690	18600	20850	21940	22600
67	9920	9650	10590	11520	14060	14310	17280	19940	18490	20960	22020	22610
68											21360	22320
69	9730	9450	10300	10850	13790	14040	17130	19690	18410	20630	20770	21870
70	9240	8980	9780	10310	13100	13930	16870	19390	18130	20330	20630	21730
71									18130	20330	20630	21730
72									12760	14030	14230	14970
73	2940	2860	3120	3280	4040	4910	6260	7200	8440	9120	9440	9800
74	2630	2550	2770	2910	3570	3450	4210	4840	7600	8250	7600	8580
75									7510	8210	7790	8840
76											6910	8010
77											3140	3640
78	2700	2640	2880	3040	2160	2200	2680	3020	3020	3070	3140	3640
79	640	640	690	730	180	180	220	220	220	310	310	350
Average	9467.931	9852.759	10054.83	10630	11621.61	12028.44	13375	14231.56	13456.47	13419.32	13929.49	14575.06