THE PREDICTION OF ACCIDENTS ON DIGITAL NETWORKS: CHARACTERISTICS AND ISSUES RELATED TO THE APPLICATION OF ACCIDENT PREDICTION MODELS

by

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ABSTRACT

Transportation planning models are used to estimate, as accurately as possible, future traffic patterns, peak periods, travel time, and various environmental or other related traffic flow by-products. Unfortunately, traffic safety is seldom, if ever, explicitly analyzed during the transportation planning process. The non-evaluation of safety is attributed to various factors, including the lack of available tools needed to estimate the number of accidents on digital networks or urban transportation networks. Thus, the primary objective of this work was to develop a series of models that would allow the estimation of traffic accidents on digital networks; that is, before a physical transportation facility is built or upgraded. The secondary objective consisted of describing all the issues surrounding their application on digital networks. To accomplish this goal, several accident prediction models that include trend were developed to predict accidents at nodes and on links. As part of this work, a new method to estimate the coefficients of models with trend is explained. A few illustrative applications of the models are also presented. The models were applied to three sample digital networks and the simulation of traffic was performed with either EMME/2 or Paramics. The results showed that it is possible to predict accidents on digital networks, but the accuracy is directly related to the precision of transportation planning software programs. Hence, inaccurate traffic flow prediction leads to incorrect accident prediction. Thus, efforts should be made in trying to find better flow estimates. Some proposed models are also sensitive to how the digital network is coded and the predicted number of accidents should be adjusted accordingly. Finally, several issues and limitations related to the application of accident prediction models to determine the safest paths on digital networks and evaluate the safety effects of dynamic route guidance systems are described in this thesis.

To Laurent, Diane, Sebastien, and Simmi

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GLOSSARY

NOTATION AND OPERATORS:

$E\{\ \}$	Expected value of the random variable inside { }.
$VAR\{\ \}$	Variance of random variable inside { }.

LATIN SYMBOLS:

F_1	Entering flow for the major approaches (in AADT) at the nodes. In this thesis, we speak of F_1 in year j and this is denoted by F_{1t}.
F_2	Entering flow for the minor approaches (in AADT) at the nodes. In this thesis, we speak of F_2 in year j and this is denoted by F_{2t}.
F	Entering flow for the flow (in AADT) on links. In this thesis, we speak of F in year t and this is denoted by F_t.
t	Year t, t=1 for 1990 to t=6 for 1995.
L	Length of links.

GREEK SYMBOLS:

$\alpha, \beta, \gamma, \ldots$	Coefficients of functions (e.g., $\alpha\,(flow)^{\beta}$). The coefficient α is a number between 0 and 1 which specifies what portion of $E\{\kappa\}$ to use in estimating κ.
κ	$E\{\kappa\}$, expected number of accidents of some kind occurring on a group of entities during a specified time period. In this thesis, we speak of κ in year t and this is denoted by κ_t.
K	K, the number of accidents that occurred on an entity.

ACRONYMS:

Acc/veh	Accidents per Vehicle
Acc/yr	Accidents per Year
AADT	Annual Average Daily Traffic
ADT	Average Daily Traffic
APMs	Accident Prediction Models
ATIS	Advanced Transportation Information Systems
CBD	Central Business District
DRG	Dynamic Route Guidance
EIF	Empirical Integral Function
GEE	Generalized Estimating Equations
GLM	Generalized Linear Models
ID	Integral-Differentiate
ITS	Intelligent Transportation Systems

JPINT	Joint Program in Transportation
LOS	Level of Service
MT	Metro Transportation
NB	Negative Binomial (distribution)
PDO	Property Damage Only (accidents)
SO	System-Optimum
TDC	Traffic Data Centre of Metro Transportation
TSCS	Traffic Signal Control Section of Metro Transportation
UE	User-Equilibrium
UTN	Urban Transportation Networks
Veh/hr	Vehicles per Hour

CHAPTER 1

INTRODUCTION

This chapter includes the problem statement, the objectives of the study, and a discussion of various issues relating to the urban transportation planning process and traffic safety.

1.1 STATEMENT OF PROBLEM

The losses to society caused by motor-vehicle collisions are considerable: on a global basis, traffic accidents on highways and urban roads kill 500,000 individuals and maim about 15 million people worldwide annually (Wilson and Burtch, 1992). In 1990, the estimated cost of such accidents for the U.S. was close to $137 billion dollars (Blincoe and Faigin, 1992). In Ontario, economic losses resulting from accidents amounted to $24 billion dollars between 1988 and 1993 alone (Nguyen, 1997). According to Rice *et al.* (1989), the cost of an injured person and a fatality are estimated at $9,062 ($US) and $352,042 ($US) respectively. The values for Ontario in 1994 dollars for a non-fatal and a fatal injury are $20,084 and $831,429 respectively (Vodden, *et al.* 1994). An average property damage only (PDO) collision in Ontario is estimated at $6,136 in 1994 dollars. These costs include both direct costs (such as damages to vehicles and property, emergency services, police, hospitalization) and indirect costs (such as loss of productivity).

The role of traffic safety specialists is to study and analyze the causes of traffic accidents in order to implement countermeasures for reducing the number and severity of collisions, thereby decreasing the personal and societal costs they generate. More specifically, traffic and safety engineers who are responsible for the efficient and safe movement of people and goods on highways employ accident data to evaluate troublesome locations, conduct before and after studies and develop accident prediction models (APMs). These models are useful tools in traffic safety studies.

The theories on how to estimate and apply APMs are generally well developed. Indeed, the latest development in this area is described in the literature review. However, APMs are usually applied or used in a reactive manner. Most typically, the facility or road network has already been built and is being used by motorists. Only after accidents occur are the models used to identify dangerous locations; some call such locations "black spots" or "hazardous locations" while others, perhaps more appropriately refer to them as, "sites with promises", that is to say, sites that once identified, can be improved (Hauer, 1996). Thus, by the time a location has been flagged as dangerous and treatable, many people have already either been killed or injured. Ideally, the number of predicted accidents should be estimated before a facility is either built or upgraded so that troublesome areas can be identified and corrected accordingly, even before the facility is used.

Before pursuing this discussion further, it is important to define the urban transportation planning process in a way that presents problems and their potential solutions to decision makers (e.g., policy makers, managers, etc.). The transportation planning process can be separated into four stages (Meyer and Miller, 1984). These include (a) fully understanding the extent of the problems, (b) identifying different solutions and alternatives, (c) evaluating long-term and short-term consequences of alternative choices, and (d) efficiently presenting the best alternatives to the decision makers. The stage that is the most relevant to this research, however, is (c) evaluating alternatives, since the product of this research is used to identify the consequences of alternative choices.

In this context, the three major impacts (other than travel delays) most commonly assessed in urban planning projects are the air quality, noise level, and fuel consumption. These three factors provide additional criteria for determining which proposed alternatives produce the least negative environmental repercussions. The assessment of these factors in urban transportation models is well established (see the work of the ILUTE Group at the University of Toronto). Unfortunately, safety impacts are rarely if ever estimated for urban transportation projects. Since the societal costs of collisions are very high, it is imperative that the impact of accidents be evaluated to the same extent as the other impacts.

The non-evaluation of safety can be attributed to three reasons. The first reason relates to the role of safety in the planning process. Although road safety is considered to be an important objective throughout the urban planning process, it is seldom, if ever, defined explicitly as such at the various levels of analysis. Indeed, many planning-for-safety principles already exist and have been applied, such as the design of street layouts in subdivisions. However, traffic safety is never computed quantitatively (i.e., compute the expected number of accidents). For instance, a transportation planner may choose specific road and intersection designs based on pre-established guidelines but still fail to provide numbers that would quantify the safety of the facilities. Furthermore, although design manuals might claim that one particular design is safer than another (e.g., traffic lights versus stop signs), that claim may not hold under all circumstances. For example, one facility could become more dangerous than another one as a result of different traffic flow volumes. In short, traffic safety should be quantified and used, along with the aforementioned criteria in the evaluation of designs and alternatives. A good discussion on safety in relation to planning issues is to be found in the work of Stogios (1988).

The second reason is linked indirectly to the first. It is a widely held misconception that following pre-established guidelines or standards automatically renders a facility safe. Thus, urban transportation planners generally tend to believe that their designs will be accident free. And, that there is therefore no need to estimate the future safety of a facility. This is far from true. As discussed in a document produced by the Association of

Professional Engineers of Ontario (PEO, 1997), there is no such thing as a safe road. Indeed, the document maintains that it is inappropriate to say that a road is safe insofar as collisions are bound to occur. The document also suggests that one should never claim that a road is safe, only that it is relatively more or less safe than another. The PEO document also argues that standards often are outdated and thus should not be used to validate that a facility is either safe or unsafe.

The third reason affecting the non-evaluation of safety is related to the lack of available tools needed to estimate the safety of a facility. As explained earlier, while the tools to identify the problematic locations are well developed, these tools cannot be used efficiently with current urban transportation models (see Chapter Four for issues related to the application of APMs on digital networks). This research project is an attempt to fill this gap by providing new tools for evaluating traffic safety at the planning stage.

Many different urban transportation models are used to predict travel patterns within a city or region and these models have advantages and disadvantages. However, it is not the role of this research to examine which model performs best. The most common travel demand model is the *Urban Transportation Modelling System* (UTMS). It features a four-stage sequential procedure (trip generation, trip distribution, modal split, and traffic assignment) that attempts to model the decision-making process of the driver. Another model, known as the *choice theory model*, employs the random utility approach. This model attempts to predict the decision-making process of individual trip makers in an attempt to determine the aggregated demand. More recent models include *simulation*, *disaggregated modelling procedures*, and an *interactive land use modelling approach*. These models attempt to predict how many vehicles will use different components (i.e, nodes and links) of a given transportation system or network.

In the context of this research, only the output of the urban transportation models (i.e., vehicle flow) is of interest. Therefore, the choice of the model is not important. The output is used to predict the number of accidents for the entire network. The tools developed in this research project would enable a transportation planner to quantify safety before a facility is either built or upgraded. In short, it would provide an additional criterion in the selection of the best alternatives for urban planning projects. Given the recent increase in awareness concerning traffic safety issues, both on the part of decision makers and the media, the findings of this research are likely to be of great benefit both to transportation planners and engineers. Similarly, the findings would also contribute to the reduction of traffic accidents in both future and existing projects.

In summary, traffic safety is only infrequently evaluated quantitatively in the current urban transportation planning process. Since traffic accidents cause tremendous financial, social, and emotional loss, it is important to estimate the number of accidents on a transportation facility that has to be either built or upgraded. The goal of such an exercise is to minimize, *a priori*, the number and severity of collisions by quantifying the safety of each alternative that is evaluated. Unfortunately, currently available tools such as APMs are inadequate for predicting the number of accidents during the urban planning process, more specifically, on urban transportation networks (UTN) or digital networks. In short, the goal of this research is to create a tool to help transportation analysts estimate more precisely the safety of different alternatives at the planning stage.

1.2 OBJECTIVES AND STRUCTURE OF RESEARCH

The objectives of this research are:

1. Create new a series of APMs to estimate the number of accidents at nodes and links with the output (i.e., traffic flow) of commercially available transportation planning software programs. Given this objective, introduce a new method to estimate the coefficients of models that include trend.

2. Describe all the issues surrounding the application of APMs for the following:

- Investigate and quantify the safety of digital networks for different scenarios. Given this objective, changes in the degree of safety are examined in a network that has been substantially modified. The degree of assessment of future safety impacts is also explored.

- Develop a safest path algorithm to determine the safest routes on digital networks. This application is likely be beneficial to companies that carry hazardous materials or for governmental transportation agencies.

- Explore the use of accident risk to find the safest routes on networks. The accident risk is defined as the inherent risk of a driver to be involved in a collision on a link or node that experiences *x* accidents and *y* vehicles per day. This definition does not include the consequences of a collision such as the probability for an unbelted driver to be seriously injured or the risk of a chemical spill for an accident involving a truck carrying hazardous materials.

- Investigate the use of accident risk in the context of dynamic route guidance (DRG) system. This system is a core component of intelligent transportation systems (ITS). The objective is to simulate changes in network safety when accident risk information is provided to road users.

This thesis is divided into seven chapters (including the Introduction). Chapter Two contains the literature review. The subject areas reviewed include: the digital coding process of physical networks; the characteristics of APMs; the description of relevant issues in network safety; and, finally, the application of optimization algorithms on transportation networks.

Chapter Three contains a description of the data used for this research. The data consisted of information on traffic accidents and traffic counts for the period 1985 to 1996. The procedure used to estimate missing traffic counts and the various steps taken for the data reduction process are presented in this chapter.

Chapter Four contains a description of the APMs. The methodology used to create the models is explained in the first section. Subsequent sections present the characteristics of models that could be used both for predicting the number of accidents on transportation networks and for other applications described in the objectives (e.g., DRG).

The application of the APMs on digital networks is illustrated in Chapter Five. This chapter undertakes to explain the mechanics of how the models are applied on a digital network; and, also how the models can be used within the urban transportation planning process. The models were applied on two digital networks. The first network digitally represents physical urban roads located in the non-central business district (CBD) of Toronto. The second network, which does not represent any physical network, was created solely to show the changes in safety for networks that are substantially modified.

Chapter Six includes a description of two useful applications of APMs on digital networks. The first application consists of utilizing a shortest path algorithm to find the safest routes on a network. The steps taken for the proposed safest path algorithm are presented in this application. The implementation of the APMs in the context of ITS is presented in the second application. The APMs are used to explore network safety issues for networks that have DRG-equipped road users.

Chapter Seven contains a summary of the analysis and a discussion about the results of the research. Also included is a set of recommendations for future research.

The subsequent appendices include: a sample of the various electronic databases, references to the theory not explained in the text, and, finally, a description of the computer codes created in this research.

CHAPTER 2

LITERATURE REVIEW

The objective of this chapter is to review the literature in several subject areas related both to urban transportation networks and traffic safety: the digital representations of physical urban transportation infrastructures, the characteristics of accident prediction models, accident prediction on transportation networks, and the least risk path models in networks.

2.1 DIGITAL REPRESENTATION OF PHYSICAL NETWORKS

The term *network* may refer either to physical structures (such as streets, railroads or airline paths) or conceptual constructions (such as the assignment of personnel inside an organization or affiliations between corporations). In either case, a network is characterized by a series of *nodes* (i.e., *vertices* or *points*) and *links* (i.e., *arcs* or *edges*) that connect these nodes. In digital networks, the nodes and links usually represent physical structures such as streets, intersections and interchanges.

The digital representation of physical urban transportation infrastructures is very important to transportation analysts. Digital networks, as used by transportation planning software programs characterize, in a mathematical form, the movement of goods and people within a physical network. As explained by Potts and Oliver (1972), a regularity exists in the habits of an urban population that establishes certain patterns of movements that can be described by mathematical models. Moreover, the goal of such models is to predict or estimate, as accurately as possible, future traffic patterns, peak periods, travel time, and various environmental or other related impacts. In the end, digital networks enable transportation analysts both to estimate the flow (vehicles, passengers, pedestrians) that travels through each component of the physical network and, given the flow pattern, evaluate several measures of interest such as travel costs operation characteristics (revenues, etc.), or flow by-products (e.g., pollution).

The coding of transportation infrastructures is dependent on the scale of the studied area. For someone interested in examining the macroscopic movement of traffic throughout an extensive region, it is preferable to divide the region into sub-areas. The network should be divided according to a set of predetermined districts or zones. The links should represent the major highways, main arterial roads, etc. The links do not include all physical intersections present on the actual road corridor. The nodes usually correspond to major intersections or highway interchanges. However, extra nodes often are used to connect the network with the centroids (discussed below), and thus may not necessarily represent a physical infrastructure. Traffic origins and destinations are assumed to concentrate to a point in the middle of the zone, represented by a *centroid*. Each centroid is connected to the network by one or more *centroid connectors*.

Figures 2.1a and 2.1b illustrate the digital representation of a physical urban transportation infrastructure. The actual physical network is shown in Figure 2.1a. The network consists of four major arterial roads and several local streets. The digital representation of the physical network of Figure 2.1a is illustrated in Figure 2.1b. This network has five nodes and four links. Four nodes (one in each corner) are used to represent the intersection of the four arterial roads. The fifth node (located to the left) is used to connect the centroid to the network through one of the three centroid connectors. This node does not represent an actual intersection. The four links represent the four arterial roads. The centroid and the centroid connectors are utilized to simulate the number of trips that occur on the local streets (i.e., within the zone). The intersection of local streets with the major arterial roads is not depicted in the digital representation.

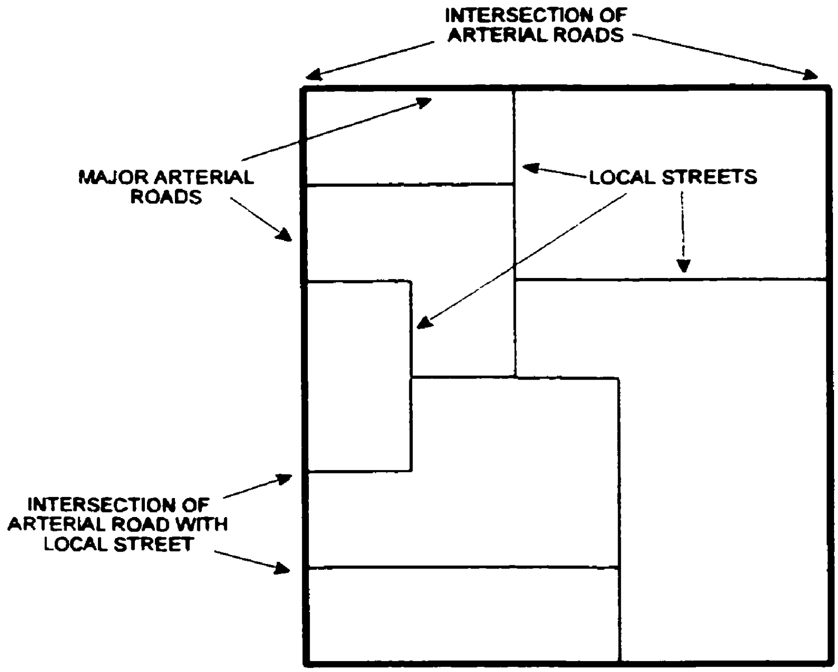


FIGURE 2.1a Physical network

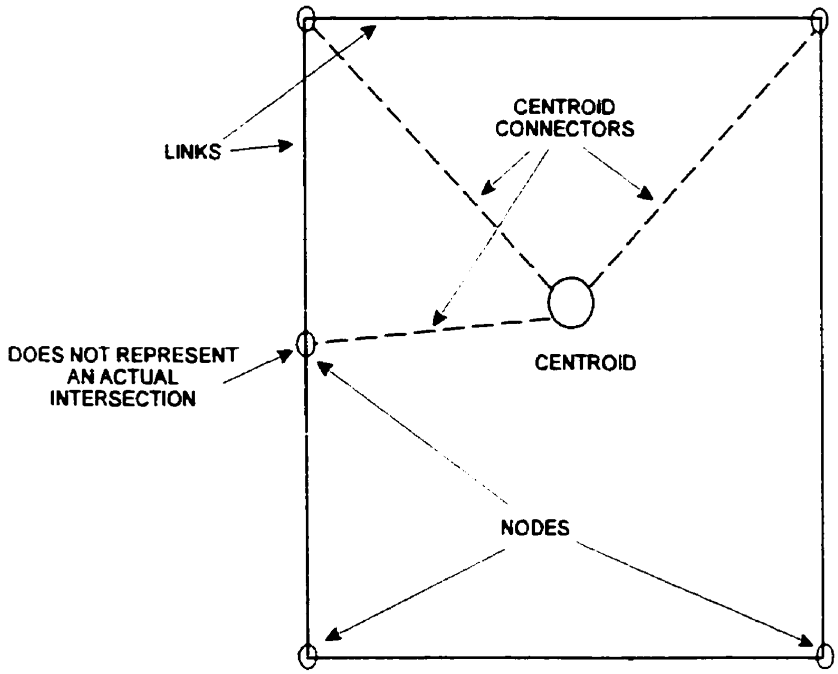


FIGURE 2.1b Digital representation of the physical network

For the study of very small regions or neighborhoods, it is possible to digitally represent every street and intersection. For this kind of representation, no districts or zones as defined above are used to simulate trip attractions and productions. Instead, centroids are placed at the outskirts of the network to simulate oncoming and outgoing traffic at specific gateways. As expected, this representation is very time-consuming and requires an enormous amount of information (e.g., turn prohibitions, traffic light phases, etc.). Consequently, this type of network representation is only infrequently used and is not the focus of this research. The reader is referred to Potts and Oliver (1972) and Sheffi (1985) for a more detailed discussion concerning the digital representation of urban physical transportation networks.

2.2 ACCIDENT PREDICTION MODELS

This section reviews literature pertaining to four areas: (1) the general characteristics of accident prediction models (APMs), (2) APMs used to estimate the number of accidents at intersections, (3) APMs that predict the number of collisions on arterial road sections, and, finally, (4) the application of APMs on transportation networks.

2.2.1 CHARACTERISTICS OF ACCIDENT PREDICTION MODELS

APMs are used to predict the number of collisions at intersections, on arterial roads, or on any other transportation related facility. Since traffic accidents are usually statistically independent random events, their use is essential. In short, accident counts alone cannot be used to predict the number of collisions on a given transportation facility (Hauer, 1997).

As with any statistical model, APMs are developed by drawing inferences about a relationship between a dependent variable and a series of covariates. In general, predictive models have the following form:

$$E\{\kappa\} = f\{\boldsymbol{x}, \beta\} \tag{2.1}$$

where,

$E\{\kappa\}$= expected number of accidents per unit of time;

$\mathbf{x}$ = a series of covariates, $x_1, x_2, \ldots, x_p$;

β = coefficients to be estimated, $\beta_0, \beta_1, \ldots, \beta_p$.

Equation (2.1) is used to predict the number of accidents per unit of time on a given transportation facility. Models can be used to predict accidents according to severity, impact type or their occurrence at different time periods. The main goal of equation (2.1) is to find the estimate of the coefficients, β, associated with the covariates (or explanatory variables). The techniques for finding these coefficients are very well developed, and many documents exist that are related to linear models (Myers, 1990; and, Bowerman and O'Connell, 1990), generalized linear models (GLM) (McCullagh and Nelder, 1989), and non-linear models (Saber and Wild, 1989). In general, the coefficients of APMs are usually estimated by GLM through regression or maximum likelihood methods.

The right-hand side of equation (2.1), $f\{\}$ can be comprised of several independent covariates: traffic flow, sight distance, turning lanes, speed limit, road lighting, traffic control, etc. The models proposed by Kulmala (1995), and Vogt and Bared (1998) incorporate such covariates. The most common models, however, ordinarily use traffic flow as the only input. Examples of these can be found in Hauer *et al.* (1988), Bonneson and McCoy (1993), Bélanger (1994), and Persaud and Nguyen (1998).

There are many different types of model forms. Some model forms for APMs used for intersections and arterial road sections are presented in the next two sections. These model forms range from very simple to extensively detailed. As an example, equations (2.2) and (2.3) illustrate two different types of models that predict accidents on highways:

$$E\{\kappa\} = \alpha L^{\beta_1} F^{\beta_2} \tag{2.2}$$

$$E\{\kappa\} = \alpha L^{\beta_1} F^{\beta_2} e^{\sum_{i=3}^{p} x_i/\beta_i} \tag{2.3}$$

where,

$E\{\kappa\}$ = expected number of accidents per unit of time;

L = length of highway section;

F = traffic flow on highway;

$\alpha, \beta_1, \beta_2, \beta_i$ = coefficients to be estimated;

$\sum_{i=3}^{p} x_i/\beta_i$ = a series independent variables, such as sight distance, shoulder width, warning signs, private entrances, etc., for $i = 3$ to p.

Equation (2.2) shows a very simple model form while equation (2.3) illustrates a very detailed model form with many covariates.

According to Hauer and Persaud (1996), given that enough data points exist, it is more favorable to separate the data in different categories and develop a model for each category rather than to create one model with many covariates. They argued that models with categorical variables are usually inflexible since the outcome depends on the covariates simultaneously. Hauer and Persaud proposed creating a string of models with traffic flow as the only input and separating them into a series of cell. To illustrate this approach, let us consider this APM for signalized intersections with many covariates:

$$E\{\kappa\} = \alpha F_1^{\beta_1} F_2^{\beta_2} e^{\beta_3 R + \beta_4 TC + \beta_5 ST} \tag{2.4}$$

where,

$E\{\kappa\}$ = expected number of accidents at signalized intersections per unit of time;

F_1, F_2 = traffic flow on each approach;

R = type of region, 1 for urban, 2 for rural;

TC= Traffic control, 1 for actuated, 2 for pretimed;

ST = signal type, 1 for isolated, 2 for coordinated;

$\alpha, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ = coefficients to be estimated.

With the approach proposed by Hauer and Persaud, the original reference population could be divided into 15 distinct cells as presented in Figure 2.2.

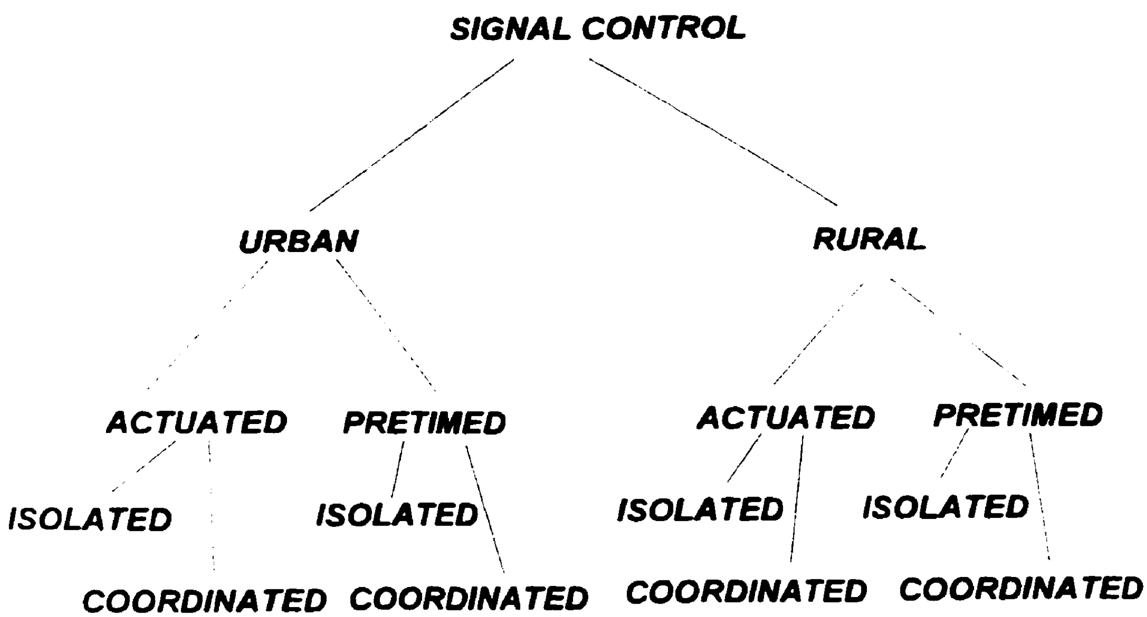


FIGURE 2.2 Variables and cells for intersections with traffic signals

For each cell shown in Figure 2.2, a simple model with the following relationship would be created:

$$E\{\kappa\} = \alpha F_1^{\beta_1} F_2^{\beta_2} \tag{2.5}$$

The only disadvantage of this approach is related to the number of data points required in each cell. As the number of cells grows, the number of data points available becomes smaller for each cell.

After choosing the proper approach, it is important to select the appropriate model form that links the accidents to the explanatory variables. Unfortunately, few tools exist to help an analyst choose the proper model form. The Integral-Differentiate (ID) method, proposed by Hauer and Bamfo (1997), is one tool that can assist the analyst. The ID method consists of creating a graph to investigate and select the proper function that links the dependent variable with the independent variables. Accordingly, the analyst has to create a graph of the Empirical Integral Function (EIF) where the independent variable (note that we can only evaluate one variable at a time) is separated into a series of bins placed in an increasing order. The EIF graph is then compared to a set of predetermined graphs. The appropriate model form is selected by choosing the predetermined graph that either matches or looks very similar to the EIF graph. The reader is referred to Hauer and Bamfo for a full description on the selection of model forms.

2.2.2 ACCIDENT PREDICTION MODELS FOR INTERSECTIONS

Extensive research has been conducted on the prediction of accidents at intersections. The majority of the models proposed in the literature are for signalized intersections (Hauer *et al.*, 1988, Kulmala, 1995; Persaud and Nguyen, 1998). Fewer models are for unsignalized intersections (Bélanger, 1994; Rodriguez and Sayed, 1999; Bared and Vogt, 1999). The models developed for this research do not include categorical variables. Thus, a description and review of these models have been omitted from this section. The APMs that use traffic flow as the only input can have many different forms. Some common model forms are shown in equations (2.6) to (2.8) (Maycock and Hall, 1984; Mountain and Fawaz, 1996; Brüde *et al.*, 1998):

$$E\{\kappa\} = \alpha(F_1 + F_2)^{\beta} \tag{2.6}$$

$$E\{\kappa\} = \alpha(F_1 F_2)^{\beta} \tag{2.7}$$

$$E\{\kappa\} = \alpha(F_1 + F_2)^{\beta_1}\left(\frac{F_2}{F_1}\right)^{\beta_2} \tag{2.8}$$

where,

$E\{\kappa\}$ = the expected number of accidents in a specified period of time;

F_1, F_2 = major and minor traffic flows (by approach or movement);

α, β_1, β_2 = coefficients to be estimated.

The model forms presented in equations (2.6) to (2.8) have various degrees of success in the prediction of accidents at intersections. The selection of the model form is often based on the analyst's judgement and on the characteristics of the data. According to Mountain and Fawaz (1996) and Nicholson and Turner (1996), the most suitable model form for intersection modelling is the following:

$$E\{\kappa\} = \alpha F_1^{\beta_1} F_2^{\beta_2} \tag{2.9}$$

The model form of equation (2.9) is the one most commonly found in the safety literature. Equation (2.9) also has two main advantages. First, the model follows the logic of "no traffic flows, no accidents" (Zegeer *et al.*, 1981; Satterhwaite, 1981; Hauer and Persaud, 1988). Indeed, one would reasonably expect that no accidents would occur if no traffic were present. Second, the model follows the logic that no linear relationship exists between accidents and traffic flow. This relationship has been thoroughly investigated and dates as far back as 1953 (Tanner, 1953).

Depending on the kind of outcome sought, equation (2.9) can be used either to predict the number of accidents for an entire intersection by using total approach flows, or for specific conflicting movement manoeuvres. To predict the total number of accidents at an intersection, the variables F_1 and F_2 are usually defined as the summation of both approach flows in any one direction (e.g., North-South or East-West) (Bonneson and McCoy, 1993; Rodriguez and Sayed, 1999). The estimate of the coefficients (β) for such models usually varies from 0.2 to 1.0. The value of these estimates depend on a variety of factors, such as the location of the intersection (rural vs urban) and the characteristics of the population located near these intersections.

To predict accidents for specific conflicting movements, APMs are built according to the type of impact that occurred at the intersection (Hauer *et al.*, 1988; Persaud and Nguyen, 1998), such as collisions between straight-through and left turning vehicles, or right-angled crashes. There are between 15 and 25 different categories of collisions at intersections (depending on the definition given by the researcher). In principle, the summation of the predicted accidents in the various categories for each leg of an intersection should be equal to the total number of accidents, as predicted in the model described in the previous paragraph. The main drawback of using this approach is related to enormous amount of information needed to develop these models. For example, the manoeuvre of each vehicle involved in every collision must be known. This may not be a problem when dealing with a few intersections, but may become problematic if the intersection and accident databases are very large. Sometimes, APMs cannot be created for categories that do not have enough accident counts.

2.2.3 ACCIDENT PREDICTION MODELS FOR ARTERIAL ROADS

Few APMs are used to predict accidents on urban arterial road sections. Available studies indicate that many models are utilized to assess the safety of various road characteristics, such as the presence of a median, two-way left-turns, speed limits, the number of intersections, and access density. Thus, researchers are trying to determine which geometric characteristic could explain the occurrence of accidents on urban road sections. These models obviously include many explanatory variables. Such models were proposed by Brown and Tarko (1999). They have the following form:

$$E\{\kappa\} = \alpha L Y F^{\beta_1} e^{\left(\sum_{i}^{m} (\beta_i X_i)\right)} \tag{2.10}$$

where,

$E\{\kappa\}$ = the expected number of accidents in a specified time period;

L = length of the road section;

Y = number of years;

F = flow on the road section (AADT);

X_i = a series of independent characteristics, for i = 2 to m;

α, β_1, β_i = coefficients to be estimated, for i = 2 to m.

Brown and Tarko created a different model for injury, property damage only (PDO), and all accidents combined. The final models selected on the basis of the best fit had eight explanatory variables each, including many dummy variables (e.g., 1 or 0). Some of the variables included access density, presence of a median, commercial area, and two-way left-turn lanes.

Vogt and Bared (1999) used a similar approach (e.g., models with many variables) to that proposed by Brown and Tarko, but for rural rather than urban roads. Instead of using one model to predict accidents for the entire road section (as suggested by Brown and Tarko), they created two different models: one for intersections and one for mid-block sections. Their model form was similar to that in equation (2.10).

Jackett (1993) examined the use of APMs for urban routes in New Zealand. He suggested separating accidents that happened at intersections from those that occurred between junctions. Thus, he proposed one APM for intersections and one for mid-block sections. The model predicting accidents for mid-block road sections had the following form:

$$E\{R\} = \alpha\, e^{\left(\sum_{i}^{5} (\beta_i X_i)\right)} \tag{2.11}$$

where,

$E\{R\}$ = the expected accident rate in 10^8 Vkms;

X_i = a series of independent characteristics, for i = 1 to 5;

X_1 = 1 for residential development, 0 otherwise,

X_2 = 1 for flush medians, 0 otherwise,

X_3 = 1 for solid medians, 0 other wise,

X_4 = 1 for 50 km/h, 0 otherwise,

X_5 = the number of intersections per km;

α, β_i = coefficients to be estimated, for i = 1 to 5.

Equation (2.11) includes neither the section length nor the exposure, as both are already contained in the accident rate.

The development of APMs for highway road sections with minor junctions, where traffic counts on minor approaches were not available, was investigated by Mountain *et al.* (1996) and Sawalha *et al.* (2000). Although the models proposed by Mountain *et al.* were created for rural highways, their application is still relevant for this research. Since traffic counts are not always performed at every intersection located along a highway corridor, traditional models cannot be used to predict accidents on such road sections. Thus, Mountain *et al.* and Sawalha *et al.* proposed a series of models to estimate the number of accidents for such highway sections. The suggested APMs had the following forms:

$$E\{\kappa\} = \alpha L^{\beta_1} F^{\beta_2} e^{(\beta_3 N)} \quad \mathit{and} \quad E\{\kappa\} = \alpha L^{\beta_1} F^{\beta_2} \tag{2.12}$$

where,

$E\{\kappa\}$ = the expected number of accidents on road section per unit of time;

L = length of the road section;

F = flow on the road section (AADT);

N = number of intersections on road section;

α, β_1, β_2, β_3 = coefficients to be estimated.

An important characteristic of equation (2.12) is related to the relationship between accidents and the length of the section. It is often assumed that accident counts are proportional to the length of a road section. However, this relationship may not be true in all circumstances. For instance, equation (2.12) shows that this relationship does not exist, since the variable L is allowed to be different than 1. Mountain *et al.* argued that the power of the coefficient in their models is below unity, which implies that shorter lengths have a higher accident count than longer lengths *ceteris paribus*. A similar relationship was also found by Brown and Tarko (1999) but was not deemed significant (they forced the length variable, *L*, to equal 1). Mountain *et al.* attributed the relationship between length and accidents to the difference in density of intersections at long versus short road sections. They stated that the influence of intersections on accidents is probably greater than what has been established to date. Unfortunately, Sawalha *et al.* did not provide any explanation for the non-linear relationship.

All model forms described in this section comply with the rule, "no flows, no accidents." They also follow the logic that no linear relationship exists between accidents and traffic flow.

2.2.4 PREDICTION OF ACCIDENTS ON DIGITAL NETWORKS

At the beginning of this research project, it was believed that issues related to network safety were seldom researched and that little interest was shown by the research community on this subject. Since then, a few researchers have examined the application of APMs on transportation networks, which has lead to the publication of few research documents. A thorough review of these documents is thus presented in this section.

The first attempt to use APMs for digital networks was performed by Al-Deek *et al.* (1993). The authors examined the potential impact of Advanced Traveler Information Systems (ATIS) on accident rates in an urban highway corridor located in Orlando, Florida. The study area consisted of a freeway and an adjacent arterial road. The goal of the study was to propose a method to assess the overall change in safety if traffic were to be rerouted from the congested freeway to the adjacent road. The method used two APMs—one for the freeway and one for the arterial road—and a risk matrix that used queuing and traffic density as input. Unfortunately, because the authors did not apply their method on the network, it is not known if the method works correctly in that context.

Since that study, the prediction of accidents on transportation networks has been investigated by very few researchers. Burrow and Taylor (1995) used different APMs to compute the expected number of accidents on two urban networks in England. The CONTRAM (Leonard *et al.*, 1989) software was used to simulate traffic on the networks and the number of accidents was calculated from APMs published elsewhere. Burrow and Taylor assessed the safety of the network for different scenarios (e.g., re-routing of traffic) and with different traffic calming measures. Overall, there was a reduction in the predicted accidents by up to 30% for some scenarios. Burrow and Taylor's paper provided a good initial assessment on the quantitative aspect of network safety. However, a better description of the models used in their work would have been more helpful to the reader.

Nicholson and Turner (1996) also tried to estimate the number of accidents on digital networks. In their research, several APMs were created from a sample of intersections located in Christchurch, New Zealand. No models were created or used either for links or arterial road sections. The models were applied on three networks and their output was compared with observed accident counts at intersections only. The authors found that the models under-estimated the observed counts for all three networks, and that the under-estimation varied from 13% to 34%. This article provides a thorough discussion on several modelling issues. What was unclear, however, was how the models were applied on the network, insofar as the article was almost entirely devoted to a discussion of modelling issues.

Turner and Nicholson (1998) used the same APMs proposed by Nicholson and Turner (1996) to study the effects of area-wide traffic management measures on traffic safety. These measures included the use of physical barriers to prevent vehicles from entering local streets from arterial roads, the banning of left-turning movements, and the realignment of arterial roads. For this study, mid-block accidents were estimated using Jackett's model (1993) reviewed in the previous section. The models were applied on the same three networks described above and were deemed appropriate for evaluating traffic management measures with digital networks. This paper is basically a follow up to their previous paper, except that it focuses more on the application of the models on urban networks than on a discussion of modelling issues *per se*.

The influence of Dynamic Route Guidance (DRG) on traffic accidents has been examined by Chatterjee and McDonald (1998). The goal of their research was to evaluate the changes in safety on UTN that have vehicle-equipped DRG systems. Several scenarios were evaluated with different levels of market penetration for vehicles equipped with ATIS. Chatterjee and McDonald also briefly examined the issue of least risk routes in networks. The simulation of traffic was performed with RGCONTRAM (McDonald *et al.*, 1995). The authors used APMs available from other sources in the literature. The results showed that the DRG has a negligible influence on the overall safety of the network; also, that the safest routes on a network are, as expected, the routes having the shortest distance. Chatterjee and McDonald applied the same definition of risk outlined in the objectives of Chapter One. This research document provides a good preliminary analysis on safety issues related to DRG systems.

The most exhaustive application of APMs on transportation networks is related to the work of Maher *et al.* (1993). The aim of their research was to develop a function that would optimize network flows and minimize thereby delays and accidents simultaneously. The objective function was as follows:

$$z(x,\theta) = T + kA \tag{2.13}$$

where,

$z(x,\theta)$ = the objective function to optimize; x represents the flows, and θ represents the signal settings of signalized intersections;

T = time measured in vehicles-hour per hour;

A = the total number of accidents in the network;

k = a weight factor for accidents; $k = 0$ for pure travel time minimization, and $k = \infty$ for pure accident minimization.

Maher *et al.* tried to optimize the objective function under the system-optimum (SO) assumption for several scenarios and for different k values. They concluded that traffic routing, which minimizes delay, often "contradicts" traffic routing, that minimize accidents. For instance, travel delay-minimization assignments usually tend to spread flows on as many links as possible, whereas accident-minimization assignments tend to concentrate flows on a minimum number of links. Furthermore, the final solution was found to be non-convex, which implies that many local minima exists. It was also discovered that the optimal solution is heavily dependent on the initial flow patterns.

The work of Maher *et al.* is the first to optimize network flows and accidents simultaneously. It contains a good discussion about issues related to initial assumptions, user-equilibrium (UE) and SO traffic assignments, and the appropriate value of *k*. It would have been worthwhile, however, had the authors provided a more comprehensive description of the various APMs used in their study.

In brief, the reviewed documents on network safety showed that few researchers examined the application of APMs on transportation networks. Moreover, many researchers used models developed from a reference population located outside the study area. Thus, it was not known what kind of models or model forms were used. A comparison between the predicted number of accidents and the observed counts was performed in only two documents (observed counts are often used to calibrate models). In those two studies, the APMs under-estimated observed accidents by up to 34%. Finally, it was unclear in some studies whether the digital network represented only the major roads and intersections, or whether they represented a detailed description of the physical network.

2.3 OPTIMUM ROUTING

The literature on minimum risk route models is briefly reviewed in this section. To date, these models have been applied only to the transportation of hazardous materials. As a result, their applicability to this research may be somewhat limited, since the models proposed in the literature usually focus on inter-urban settings. In addition, many of the proposed models are partially optimized for safety, and incorporate other factors, such as transport costs. It should be pointed out that the risk in these models is usually defined as the societal risk. In other words, the risk is defined as the accident likelihood (the number of accidents) given the volume of traffic on each link of the network.

Since hazardous materials can create serious harm both to the population and to the environment if an accident occurs, private carriers of such materials are always interested in the application of models that minimize the risk of such accidents. These models usually involves five components (Saccomanno *et al.*, 1993): (1) accident likelihood, (2) containment failure, given an accident, (3) volume of rate of material released, (4) the hazard area associated with each potential threat, for different releases and materials, and (5) the population affected by the hazard. In short, the models attempt to estimate both the risk of an accident on a given route and the potential damage to the environment and population, given this accident and its location. Obviously, the risk is also dependent on the type of product carried and the characteristics of the vehicle carrying the product. Also, most of these models are developed exclusively for inter-cities transportation networks. Thus, it is not uncommon to see studies that compare the risks of transporting dangerous goods in different kinds of transportation networks, such as road vs. rail systems (Kornhauser *et al.*, 1993, Purdy, 1993; Leeming and Saccomanno, 1994).

A wide variety of algorithms are available for determining the minimum risk route on a network. The proposed algorithms can be simple, such as the one put forward by Ashtakala and Eno (1996), based on the Moore algorithm. Alternately, they can be highly complex such as the algorithm proposed by Miller-Hooks and Mahmassani (1998), which predicts the optimal routing on a stochastic, time-dependent transportation network. These models are not described here since they fall outside the scope of this research. One should note that many of the proposed models also include a constraint imposed by the operating cost. In such cases, the optimal route is not optimized solely for safety.

From the literature identified for this section, moderate deficiencies were observed with respect to several issues. First, it was noted that the safety component of the proposed models tend to be simplistic. For instance, all of the least risk models still use the traditional accident rates as input (not based on APMs) despite the fact that they have been found to be an inaccurate estimation of safety (Hauer, 1997). Second, the accident risk is assumed to remain constant for different time periods during the day. Obviously, the risk of being involved in an accident is however very different for a truck traveling during the peak period than during the middle of the night. Third, few if any least risk models exist for urban areas, where the potential of harm to the population is more significant than in rural settings. Fourth, it was also noted that few models included the risk of accidents at conflict points, such as intersections or interchanges, despite the fact that many accidents occur at these locations (46%) (MTO, 1993). Sometimes however, the risk at conflict points is combined with the risk computed for links. While the conflict points may not be a major problem on inter-urban networks, they are probably more crucial in urban settings. In short, the models proposed in the literature should include the risk of accidents at nodes.

2.4 SUMMARY

This chapter contained a review of the literature on several subject areas related to digital networks and traffic safety. The issues related to the coding of urban networks and its digital representation were presented in the first section, where it was shown that the digital representation of networks can be performed in many different ways. An extensive review on accident prediction modelling issues was presented in the second section, where it was demonstrated that the relationship between accidents and explanatory variables can have various forms. Different model forms were presented for APMs used for intersections and those used for urban road sections. An enormous number of studies are available on intersections, but far fewer are available that concern urban road sections. The few research documents related to the application of APMs on digital networks were also reviewed in the second section, and showed that network safety is now becoming an increasing researched subject. The application of optimum routing models in networks was described in the last section. Hence, the studies showed that the safety component of the proposed models was somewhat deficient in some areas, and that more research is therefore needed. The data used for this research project are described in the next chapter.

CHAPTER 3

THE DATA

The objective of this chapter is to describe the data used for this research. The data included information on traffic accidents, traffic flow, and the physical characteristics of intersections and arterial roads located in the City of Toronto. The steps taken for the data reduction process and how the reference population for the nodes and links were created are also described in this chapter.

3.1 TRAFFIC ACCIDENT DATA

A list of all traffic accidents that occurred within the boundaries of Toronto between 1985 and 1995 inclusively was provided electronically by the Traffic Data Centre (TDC) of Metro Transportation (MT), the transportation agency of Toronto. The role of the TDC is to collect and validate accident data, maintain the electronic database and perform traffic safety studies. The database included accidents at intersection, non-intersection (i.e., mid-block), or other location, such as in private lots.

An initial appraisal of the accident database revealed a few interesting findings. For instance, between 47,000 and 52,000 traffic accidents per year were reported between 1985 and 1995, of which, 50 to 70 were fatal. The word "reported" is emphasized here since many accidents are not reported (Hauer and Hakkert, 1989). From the total number of reported accidents, the distribution between traffic accidents that occurred at intersections and those occurring at mid-block locations was about 45/55 respectively. Very few accidents were found to have happened on private property. The percentages of accidents with injuries and property damage only (PDO) were about 30% and 70% respectively, and remained fairly constant throughout the studied period. It is important to note that many variables could contribute toward the year-to-year variation in reportable accidents. They include the threshold of a reportable accident, weather patterns, improvement in the treatment of injuries by emergency personnel and hospital staff, and different applications of traffic laws, such as the RIDE program.

Entries in the database (i.e., each row) are defined by the person involved in a collision. For instance, if an accident involves two drivers and a pedestrian, each person is coded as a separate entry. Thus, three different entries would be recorded in the accident database for that collision. In addition, if a passenger of one of the vehicles is also injured, a fourth entry would be added to the original three entries, mainly to explain the type of injury.

The characteristics of each accident can be described by 43 fields (i.e., columns) and 831 codes. Of the 43 fields, only 31 fields were deemed useful for this research; some of the non usable fields are utilized by the Toronto Police Department (TPD) for legalistic purposes. The TDC separates the fields into two categories. The first category includes the so-called *incident* fields. The fields in this category are common for every person involved in the collision and describe the same characteristic for everyone. The second category includes the *involvement* fields. These fields show a specific characteristic for every person involved. Some of the most important fields for both categories are explained below. A sample of the accident database is presented in Appendix A.

INCIDENT FIELDS:

ACCIDENT NUMBER: Each accident is coded with a different number. The accidents are usually coded sequentially by date of occurrence.

DAY OF THE WEEK: Each day of the week is assigned a different number (1 for Sunday and 7 for Saturday).

STREET NAMES: These fields are used to describe the exact location of a collision. There are two fields for each road connected to an intersection: one field for the actual street name and the other for the street category (e.g., street, road, boulevard, etc.).

ACCIDENT TIME: This field is used to indicate the time of the accident. Before 1992, 24 codes were used to denote the time of the accident, with each code representing a different 1-hour period. For example, the code *00* implied that the accident occurred between 00:00 and 00:59 am. Since 1992, the actual accident time is used, e.g., 10:25 or 17:34.

LOCATION COORDINATE: This field explains the characteristic of the road on which the accident happened, such as, at an intersection or between intersections.

ACCIDENT CLASS: This file describes the severity of the accident according to four categories: fatal injury, non-fatal injury, PDO, and non-reportable. The category is defined by the most serious injury among all injured people. For example, if there are three injured people and one deceased person in a collision, the accident is categorized as fatal injury.

IMPACT TYPE: This field explains the type of accident, such as angle, rear-end, or turning.

INVOLVEMENT FIELDS:

INVOLVEMENT TYPE: This field explains the type of person involved in the collision such as driver, passenger, pedestrian, or cyclist.

INJURY: This field describes the type of injury for each person involved in the collision.

INITIAL DIRECTION: This field indicates the initial direction (north, south, east, west) each person was facing before the accident. This applies only for the driver, pedestrian and cyclist.

MANOEUVER: This field explains the actual manoeuver in which each person was engaged, such as turning left, stopped, or merging.

Collisions between vehicles and pedestrians or between vehicles and cyclists were not used in this research. Indeed, the proportion of pedestrian and cyclist accidents in this database is less than 5%. Since the output of transportation planning software programs does not provide traffic estimates for bicycles and pedestrians, it was decided not to include them in the analysis. Moreover, to estimate properly the number of accidents with pedestrians and cyclists, it would be necessary to know the actual exposure (i.e., recorded traffic counts). Such information was not always recorded on-site for these road users.

3.2 TRAFFIC FLOW DATA

The TDC maintains an electronic 8-hour traffic count database for 1,551 signalized and unsignalized intersections. The traffic flow data were available from 1985 to 1996. In general, observed traffic counts were conducted on at least 400 junctions every year. However, they were not conducted at every intersection, nor they were recorded for every year. The 8-hour database also included observed counts carried out for special events, and requested by citizens or city councillors.

Traffic counts normally are performed at intersections during the morning, mid-day, and afternoon peaks; also, during one off-peak period. Two-hour counts start at 7:30 a.m., 11:00 a.m., and 4:00 p.m. respectively for the peak periods. For the off-peak period, traffic counts are performed for 1 hour, both in the morning and afternoon, and usually beginning at 10:00 a.m. and 2:00 p.m. respectively. Traffic counts are divided into 15-minute periods and include all possible movements at an intersection (e.g., 12 movements for a 4-legged intersection). A sample of the 8-hour database is presented in Appendix A.

3.3 PHYSICAL CHARACTERISTICS

The TDC maintains an electronic physical characteristics database on the 1,551 intersections described in the previous section. Some of the characteristics contained in this database included the number of approaches for each intersection, the type of traffic control, the type of intersection (e.g., regular 4-legged, offset intersection), and the presence of left-turning lanes. A sample of the physical characteristics database is presented in Appendix A.

The physical characteristics database did not, unfortunately, contain enough information to conduct a proper analysis of the data. Important pieces of information were not available such as the installation date of signalized intersections, or the number of lanes on arterial road sections. Furthermore, it was discovered during the data collection process that the TDC database included many coding mistakes and other kind of errors. Therefore, additional information needed to be gathered to validate and complete the physical characteristics database.

The supplemental information was collected from three other sources. First, the Traffic Signal Control Section (TSCS) of MT provided additional information on the number of lanes per approach for each signalized intersection, turning lanes, signal phasing, the installation date of traffic controllers, and other special characteristics. The information was gathered electronically and from maps, construction drawings, and engineering reports.

Second, for the data that could not be provided by the TSCS, the information on the physical characteristic was collected from on-site visits. All unsignalized intersections, arterial road sections, and some signalized intersections were visited at least once. In total, 250 sites were visited. The data gathered included the number of lanes for arterial roads, street markings, location of stop signs, and other information deemed relevant for this research.

Third, a hired student assembled additional information about major intersection and road section modifications from the three local districts at MT. These districts are distinct from the TDC and the TSCS and may sometimes provide supplemental data not available in the former two. These modifications included the closure or addition of a leg, the widening of a road, and changes in street markings. Unfortunately, information on the modification of intersections and on construction upgrades was very difficult to obtain, especially before 1990. Intersections and road sections known to have been extensively modified were removed from the analysis.

3.4 DATA REDUCTION

The three steps used to perform the data reduction process are described in this section. The first step consisted of expanding the 8-hour traffic flow to an annual average daily traffic (AADT). The second step was related to the need of estimating traffic counts for the years that manual traffic counts were not performed. The third step consisted of selecting the reference population for the models used for predicting the number of accidents at nodes and links.

3.4.1 EXPANSION OF 8-HOUR COUNTS TO AADT

All the expansion factors were provided by the TDC. The factors were created from various permanent counting stations (24-hour counts) located throughout the city and were divided into five categories. The first category applied to roads classified as freeways or expressways. The second category pertained to roads located in the downtown core. The expansion factors used in this category were those created by the Market Investigation Services of the Traffic Division during the 1980's, as data from other sources were not readily available. More accurate expansion factors currently are being computed for this category. The third category applied to roads classified as suburban arterial roads. The fourth category pertained to roads categorized as industrial roads. Finally, the last category applied to roads classified as residential streets.

For each category, a different expansion factor existed for the day of the week and the month of the year. Thus, for each category, there were 84 different expansion factors (7 days x 12 months). The expansion factor values generally varied from about 1.50 to 2.20 and were applied manually to each available 8-hour manual traffic count recorded between 1985 and 1995.

3.4.2 ESTIMATION OF MISSING AADT COUNTS

The accident prediction models (APMs) developed in this research incorporated time trend (explained in Chapter Four). Thus, it was imperative that data on accidents and traffic flows be available for every year (Diggle *et al.*, 1994). Indeed, missing values may lead to biased models and inaccurate predictions. A procedure was therefore created to estimate traffic counts (expanded to AADT) that had not been recorded on-site between 1985 and 1995, and for every intersection contained in the TDC database (1,551). The procedure, briefly described below, is fully explained in Appendix B.

The proposed procedure was adapted from the work of Hauer (1993a) and modified for the current data set. Basically, it consisted of estimating the missing AADT counts (left, through, and right, for each leg) for a given year and for a particular intersection, by extrapolating from other traffic counts available in the database (i.e., counts from other intersections and/or from other years). The missing AADT counts were estimated with a series of linear regression equations. The final output contained the traffic flow in AADT for each movement at the intersection and for every year in the database. The procedure proved to be accurate as described in Appendix B.

3.4.3 REFERENCE POPULATION FOR NODES AND LINKS

The EMME/2 digital network, created by the Joint Program in Transportation (JPINT) at the University of Toronto, was used as the input network for creating the reference population for nodes and links. The digital network included all cities located within the Greater Toronto Area (GTA). However, only the section of the network representing the City of Toronto was utilized for this research. In this section, the links represented every major physical arterial road, while the nodes depicted the junction between different arterial roads and between arterial roads and centroid connectors. As indicated in Chapter Two, the minor intersections present on the physical network were not shown on the digital network. The EMME/2 digital network of the City of Toronto is illustrated in Figure 3.1.

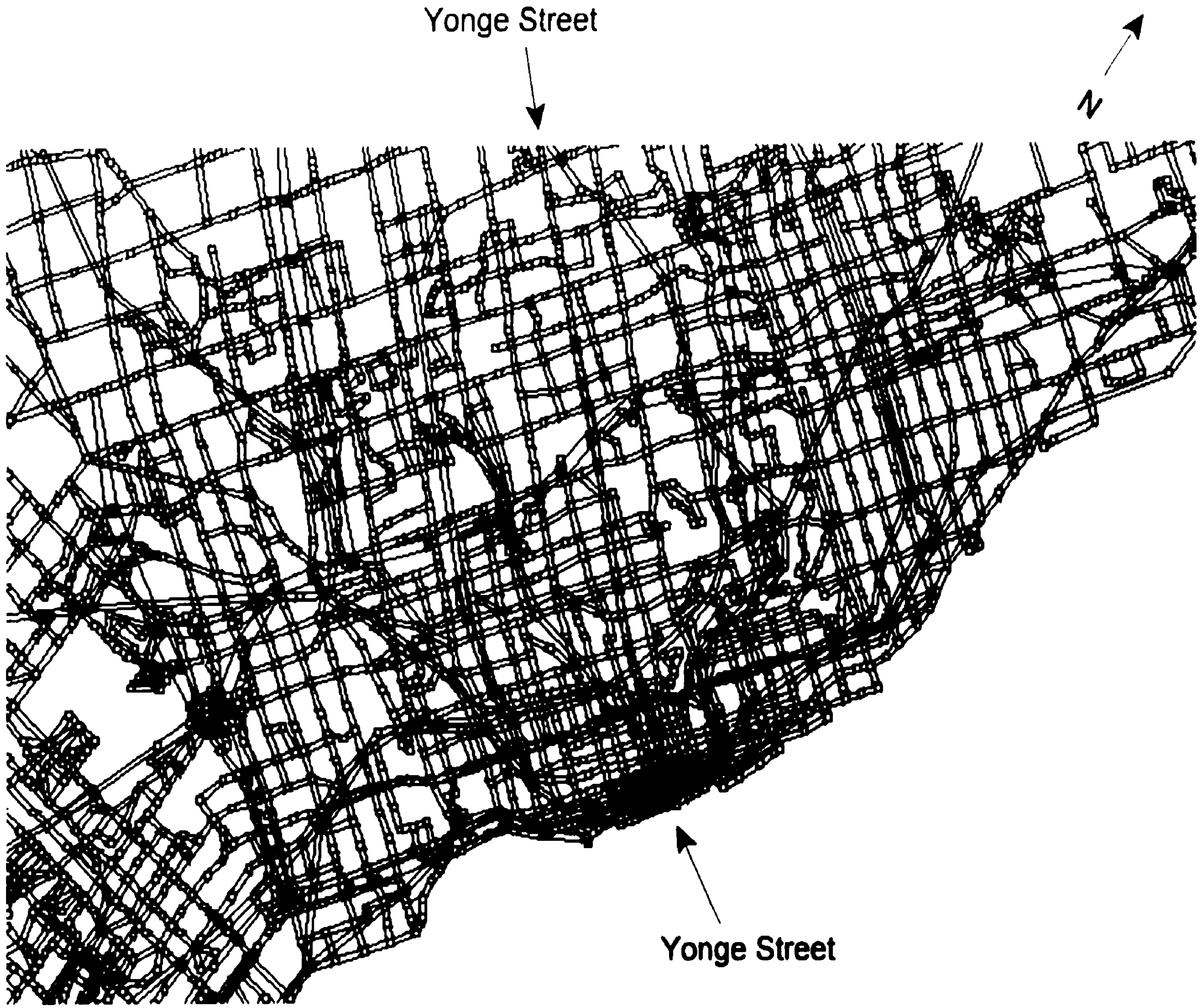


FIGURE 3.1 EMME/2 network of Toronto

The reference population for the nodes consisted of 1,354 signalized and unsignalized intersections; 197 intersections were removed from the original sample owing either to data inconsistences (e.g., problems with traffic counts) or to significant intersection upgrades (e.g., construction, signalization upgrades, etc.). The reference population contained 868 4-legged and 250 3-legged signalized intersections, and 59 4-legged and 177 3-legged unsignalized intersections. This reference population was taken directly from the list provided by the TDC. Thus, data on traffic accidents, traffic counts, and physical characteristics were readily available.

The reference population for the links consisted of 284 road sections. The sites were picked evenly across the different parts of Toronto and was based on the EMME/2 digital network. Further manipulations were required to obtain the number of accidents and the traffic flow for each link, since the selected road sections were not an integral part of any of the TDC databases. The link flows were estimated from traffic counts that had been recorded at different points on the link. The reference population contained 20 2-lane, 215 4-lane (59 in the central business district or CBD and 161 in non-CBD Toronto), and 49 6-lane roads. The length of links varied from 0.32 to 3.82 km, with an average of 1.40 km.

3.5 OUTPUT DATABASE

The final database was separated into three computer files. One computer file contained a description of the physical characteristics of intersections and arterial road sections in the sample. Another file contained data on traffic flow linked to the various intersections and arterial road sections in AADT. The last computer file contained traffic accident counts at 1,354 intersections and 284 road sections. This file included information on injury (fatal and non-fatal), PDO, and injury + PDO. The three files were linked together by street name and the specific year. Thus, different data sets could be created as input for the APMs by combining the three files and selecting the relevant attributes of each computer file.

The time period used for the final databases extended from 1990 to 1995 instead of from 1985 to 1995, as originally planned. The decision to utilize this time period was based on two factors. The first factor was related to the accuracy of the physical characteristics database. The staff at MT indicated that many examples of road rehabilitations (e.g., road widening or the addition of a leg) occurred in the late 1980s, especially in the northern part of the city. Moreover, even after taking extensive measures to verify the data, it was difficult to validate changes and major upgrades that had occurred at intersections and on arterial roads before 1990.

The second factor was related to the size of the three databases (1,354 intersections and 284 links over 11 years). During the exploratory data analysis and the preliminary accident modelling process, it was discovered that the current databases were too large to be handled by one person. In particular, many steps in the data reduction process would have required extensive manual manipulation. Since the databases were very large, to modify each one manually when specific corrections or modifications were required would have been extremely time-consuming. Similarly, validating the APMs promised to be extremely cumbersome, since each year had to be handled separately.

Based on these two factors, it was decided that the final databases would be created for the 6-year time period 1990 to 1995, a period of time judge sufficient for providing input for the APMs without compromising significantly their quality-of-fit. The final databases consisted of the following:

ACCIDENT DATABASE: the number of accidents, grouped according to their severity, occurring at intersections and on road sections between 1990 and 1995.

TRAFFIC FLOW DATABASE: the traffic flow counts in AADT, from 1990 to 1995, for each movement, and at every intersection and link.

PHYSICAL CHARACTERISTICS DATABASE: information on the physical characteristics of 1,354 intersections and 284 links.

3.6 SUMMARY

This chapter contained a description of the data used for this research. The data consisted of information on traffic accidents, traffic flows, and the physical characteristics of 1,354 intersections and 284 road sections located in Toronto between 1990 and 1995. Electronic databases for traffic accidents, traffic counts and the physical characteristics of the intersections were provided by the TDC. Data not available electronically were gathered from on-site visits or other sources. The data reduction process consisted of three steps: the expansion of 8-hour counts to AADT, the estimation of missing traffic counts (in AADT), and the selection of the reference population for nodes and links. The final database contained three different computer files (traffic flow, accidents, physical characteristics) linked together by the street name and year. The characteristics of the APMs utilized for predicting accidents on nodes and links are presented in the next chapter.

CHAPTER 4

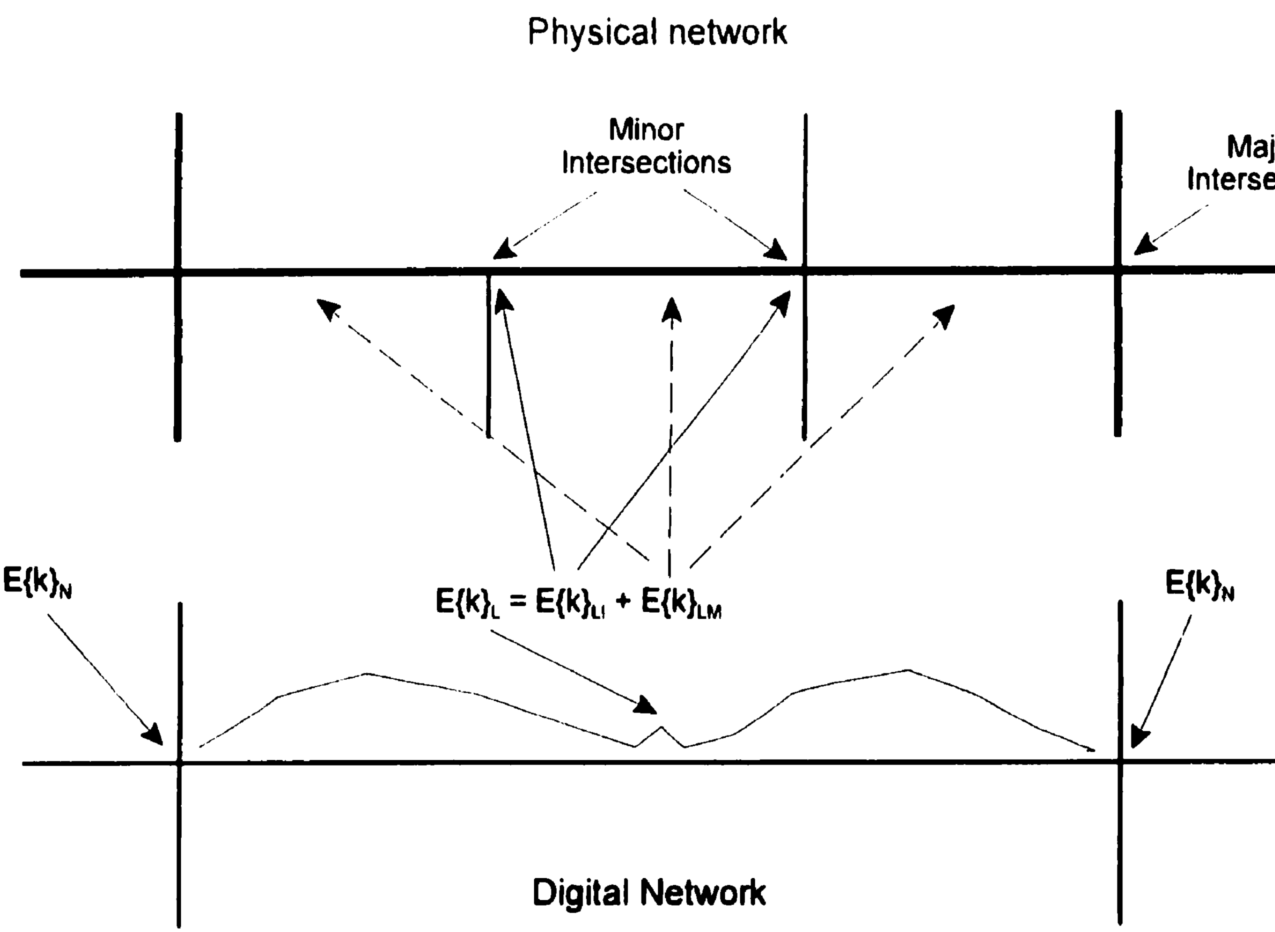
ACCIDENT PREDICTION MODELS

The purpose of this chapter is to describe the characteristics of the accident prediction models (APMs) used for predicting the number of accidents on links and nodes. The chapter is divided into three sections. The approach taken to create the various APMs is described in the first section. The regression results for the APMs used for nodes and links are summarized in the second and third sections respectively.

4.1 MODELLING APPROACH

The methodology used in this thesis was based on the approach proposed by Hauer and Persaud (1996). As described in Chapter Two, the authors suggested dividing the reference population, given a sufficient number of observations, into a series of cells, and creating a separate model for each cell. They argued that it is better to create many simple models rather than to create one single model with many covariates and categorical variables.

The number of accidents on networks was predicted with three different types of models. The first type was used for predicting accidents at nodes. The second and third types were utilized for predicting accidents on links. As suggested in the literature, the prediction of collisions on links could be separated into two components: *mid-block* and *intersection*. The mid-block component models predict the number of accidents between minor intersections located on the physical network but not encoded as nodes on the digital network. The intersection component models estimate the number of accidents at these minor intersections. Figure 4.1 illustrates the above description.



$E\{k\}_N$ = expected number of accidents at nodes

$E\{k\}_L = E\{k\}_{LM} + E\{k\}_{LI}$ = expected number of accidents on links

$E\{k\}_{LM}$ = expected number of accidents for mid-block component (f{link flow})
$E\{k\}_{LI}$ = expected number of accidents for intersection component (f{link flow})

FIGURE 4.1 Illustration of the three model types ($E\{\kappa\}_N$, $E\{\kappa\}_{LM}$, $E\{\kappa\}_{LI}$)

The predictive models were grouped into many different cells. For the first type of model, APMs were divided according to whether the node was signalized or not, and whether the node had three or four legs. Thus, four different APMs were created for this type. They are illustrated in Figure 4.2, in which the selected models are located inside the rectangles.

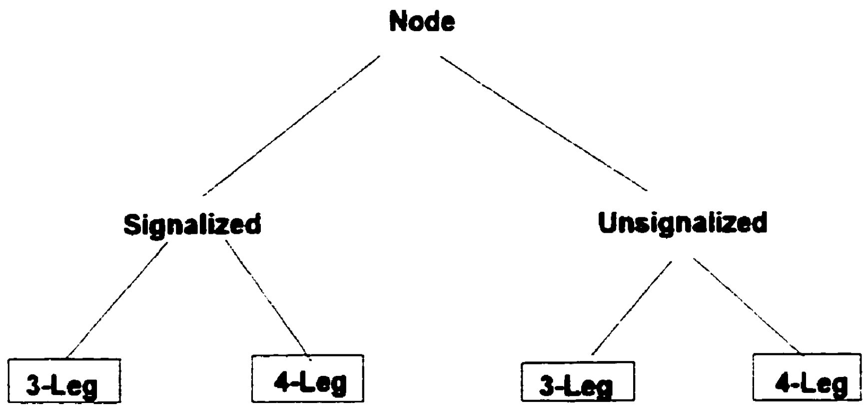


FIGURE 4.2 Variables and cells for nodes

The models categorized under the second type (mid-block component) were divided according to the number of lanes on the link (2-lane, 4-lane, or 6-lane) since the links on digital networks are characterized as such. The 4-lane category was further divided according to whether the link was located in a central business district (CBD) or in a non-CBD area. The road characteristics between CBD and non-CBD are very different (e.g., number of parking manoeuvres, bike lanes, etc.) and warrant to be grouped separately. However, there were not enough observations for 2-lane and 6-lane roads to further divide these cells as CBD or non-CBD. Thus, five different models were developed for the mid-block component. The models are shown in Figure 4.3 (inside the rectangles).

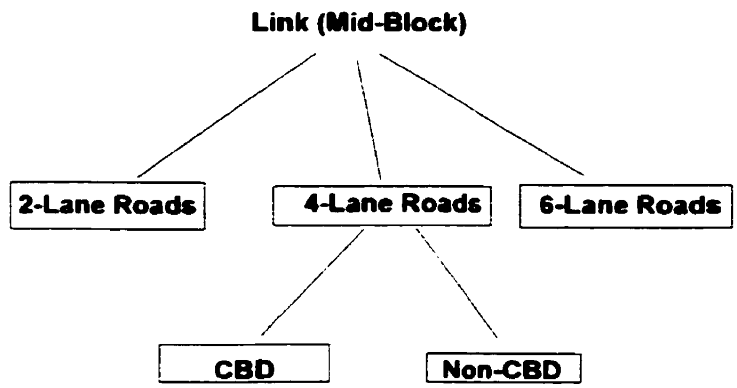


FIGURE 4.3 Variables and cells for the mid-block component of links

The models categorized under the third type (intersection component) were separated according to a pattern similar to that used for the first type, that is, on the basis whether or not the intersection was signalized or not, and whether it had three or four legs. Figure 4.4 illustrates the four different models (inside the rectangles).

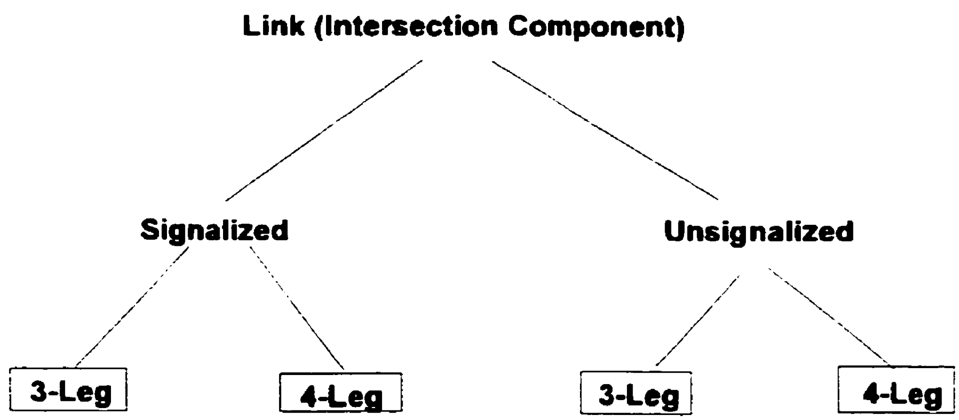


FIGURE 4.4 Variables and cells for the intersection component of links

The model forms for the three model types were selected after conducting several exploratory analyses on the data. The ID method proposed by Hauer and Bamfo (1997) was also utilized in the selection process. Basically, the method consists of separating each independent variable into a series of bins (e.g., one for each intersection or a road section) placed in increasing order to create an Empirical Integral Function (EIF). For each entity, the left boundary of the bin is located halfway between the current entity and the previous entity. The right boundary is located halfway between the current entity and the next entity. The bin height is the number of accidents that occurred at that entity. Hence, the vaiue of the EIF at the right boundary of the current bin is the sum of all bin areas, from the lowest value up to that boundary. For instance, take three sites that experience 5,000, 10,000, and 15,000 vehicles per day and 10, 12, and 15 accidents respectively. For the second bin, the left and right boundaries are equal to 7,500 and 12,500 respectively and the height of the EIF at the right boundary is equal to 22 (10+12). The goal of the method is to compare the EIF graph created above with pre-established graphs of well-known functions (power, gamma, polynomial, etc.) (Figure 4.5). The graph having a shape similar to one of the pre-established graphs should indicate the proper relationship between the dependent and independent variables being investigated. However, this method should only be used as a preliminary assessment of the relationship; additional tools should be used to confirm that relationship. The EIFs of the parameters F_1 and F_2 for the signalized 4-legged intersections are shown in Figures 4.6 and 4.7 respectively. The reader is referred to Hauer and Bamfo (1997) for a more detailed description of this method.

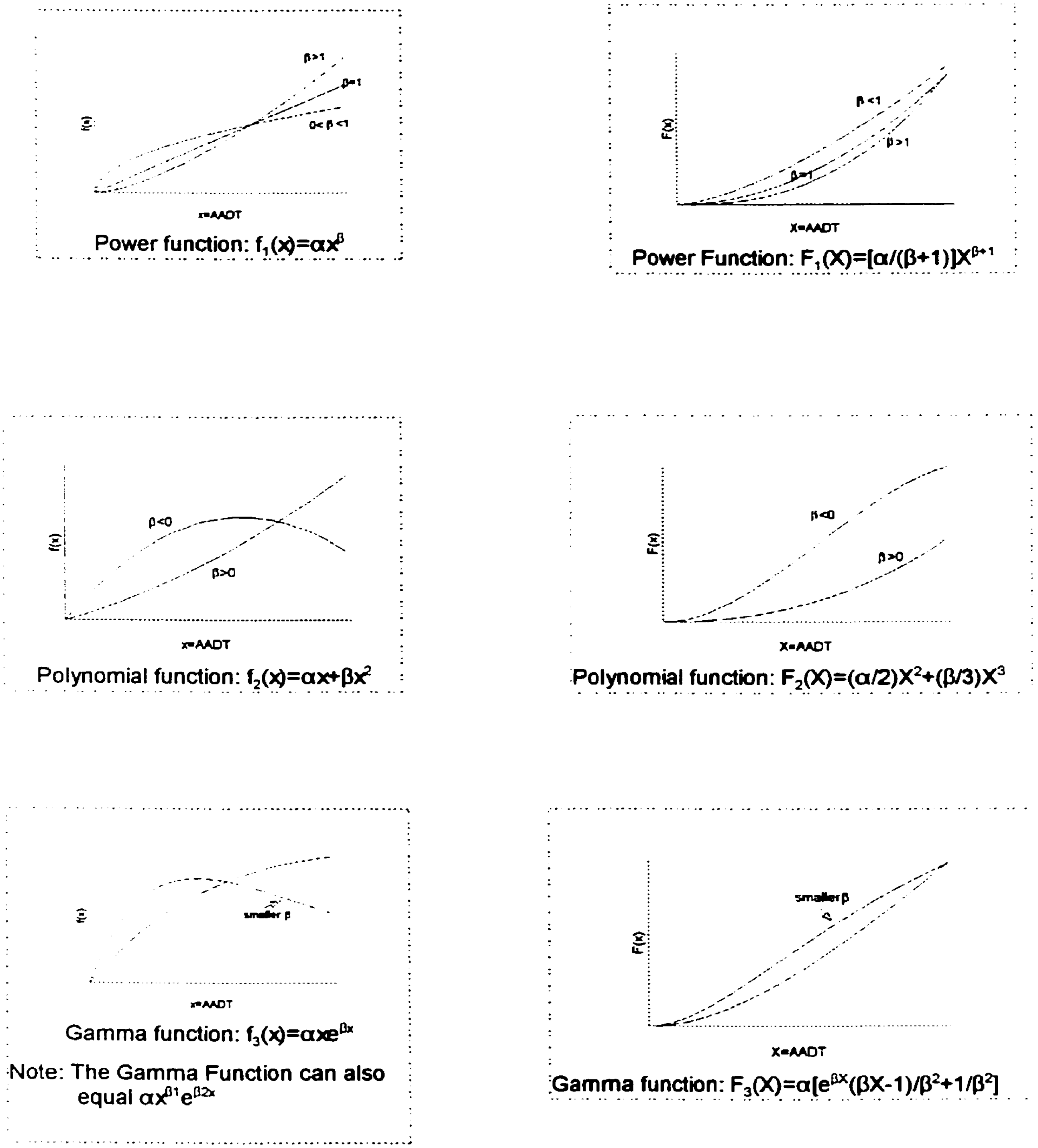


FIGURE 4.5 Corresponding f(x) and F(x) of well-known functions (power, polynomial, Gamma) (Hauer and Bamfo, 1997)

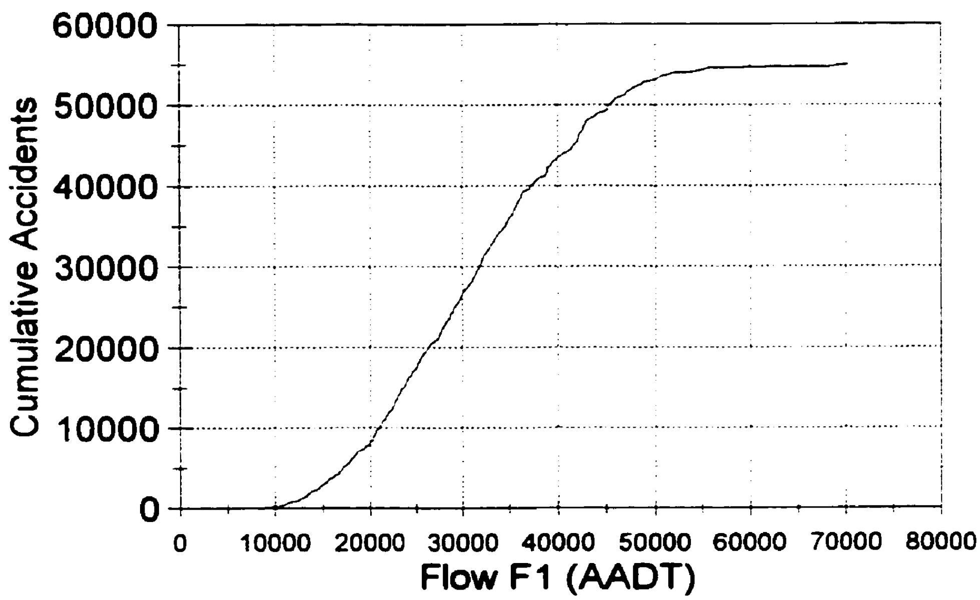


FIGURE 4.6 EIF for parameter F_1 for signalized 4-legged intersections

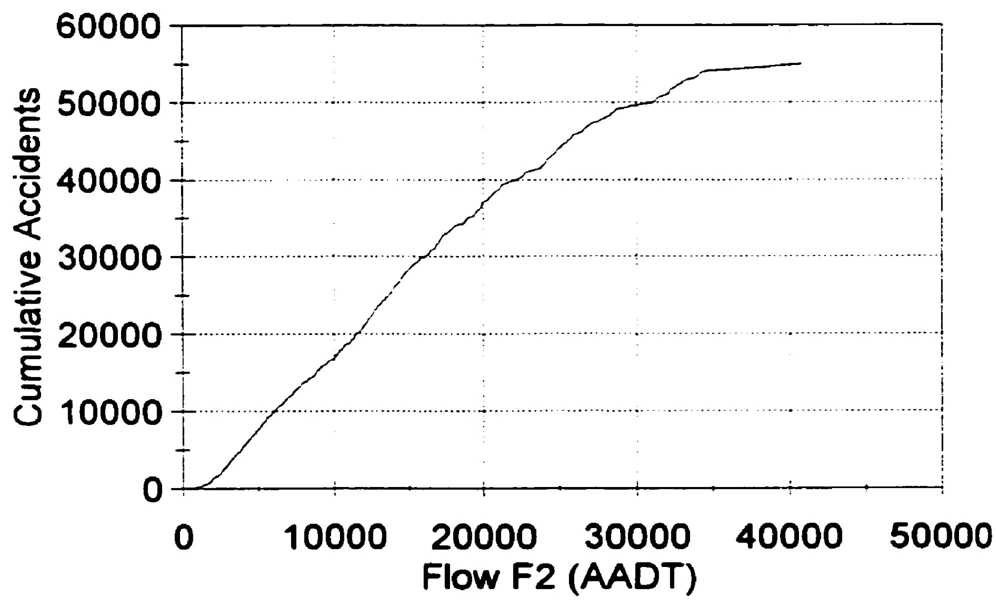


FIGURE 4.7 EIF for parameter F_2 for signalized 4-legged intersections

The results of the exploratory analysis showed that the relationship between accidents and each covariate of each model could be described either by the Power function or the Gamma function (see Figure 4.5). To determine whether the relationship between accidents and each covariate followed a Power or a Gamma function, each relationship was investigated in turn. Several model forms were also investigated, such as those proposed by Brüde *et al.* (1998), in which the ratio of the minor entering flows to the total entering flows is included in the model. Brüde *et al.*'s model form was shown to be not as adequate as the model forms proposed in the equations below, which depicted all possible types of relationships between the covariates and accidents.

The selected model forms for the APMs used to predict the number of accidents at nodes are shown in equations (4.1a) to (4.1d). The models can follow one of these four forms, depending on the relationship between each covariate and the accident count:

F_1 = Gamma, F_2 = Gamma

$$E\{\kappa_t\} = \alpha_t F_{1t}^{\beta_1} F_{2t}^{\beta_2} e^{(\beta_3 F_{1t} + \beta_4 F_{2t})} \tag{4.1a}$$

F_1 = Power, F_2 = Gamma ($\beta_3 = 0$)

$$E\{\kappa_t\} = \alpha_t F_{1t}^{\beta_1} F_{2t}^{\beta_2} e^{(\beta_4 F_{2t})} \tag{4.1b}$$

F_1 = Gamma, F_2 = Power ($\beta_4 = 0$)

$$E\{\kappa_t\} = \alpha_t F_{1t}^{\beta_1} F_{2t}^{\beta_2} e^{(\beta_3 F_{1t})} \tag{4.1c}$$

F_1 = Power, F_2 = Power ($\beta_3 = 0$, $\beta_4 = 0$)

$$E\{\kappa_t\} = \alpha_t F_{1t}^{\beta_1} F_{2t}^{\beta_2} \tag{4.1d}$$

where,

$E\{\kappa_t\}$ = the expected number of accidents for time period t, for t = year *1* (1990) to year *6* (1995);

F_{1t}, F_{2t} = entering flows of the major and minor roads in AADT;

α_t, β_1, β_2, β_3, β_4 = coefficients to be estimated.

The model forms for the APMs used to estimate the number of accidents for the mid-block component are shown in equations (4.2a) and (4.2b). The models can follow either one of these two forms:

F = Gamma

$$E\{\kappa_t\} = \alpha_t L^{\beta_1} F_t^{\beta_2} e^{(\beta_3 F_t)} \tag{4.2a}$$

F = Power (β_3 = 0)

$$E\{\kappa_t\} = \alpha_t L^{\beta_1} F_t^{\beta_2} \tag{4.2b}$$

where,

$E\{\kappa_t\}$ = the expected number of accidents for time period t, for t = year *1* (1990) to year *6* (1995);

F_t = link flow in AADT (both directions) for time period t;

L = length of section in kilometers (less 30 m per minor intersection on the physical network but not on the digital network);

α_t, β_1, β_2, β_3 = coefficients to be estimated; use β_t when warranted.

The measured distance used in equation (4.2) is the length of the road section between two nodes less the distance measured for each minor intersection in between. According to the Traffic Data Centre (TDC), crashes are coded as an intersection accident if they happen within 15 meters from the center of the junction. Based on this definition, the distance used for each minor intersection is equal to 30 meters. To illustrate: if a link measures 1000 meters and there are four minor intersections located on this link, the measured distance is equal to 850 m (1000 m - 4 x 30 m - 2 x 15 m (or half the width of the node at both ends if the nodes represent intersections) = 850 m.

The chosen model forms for the intersection component of links are shown in equations (4.3a) and (4.3b). The models can follow either one of these two forms:

F = Gamma

$$E\{\kappa_t\} = \alpha_t F_t^{\beta_1} e^{(\beta_2 F_t)} \tag{4.3a}$$

F = Power (β_2 = 0)

$$E\{\kappa_t\} = \alpha_t F_t^{\beta_1} \tag{4.3b}$$

where,

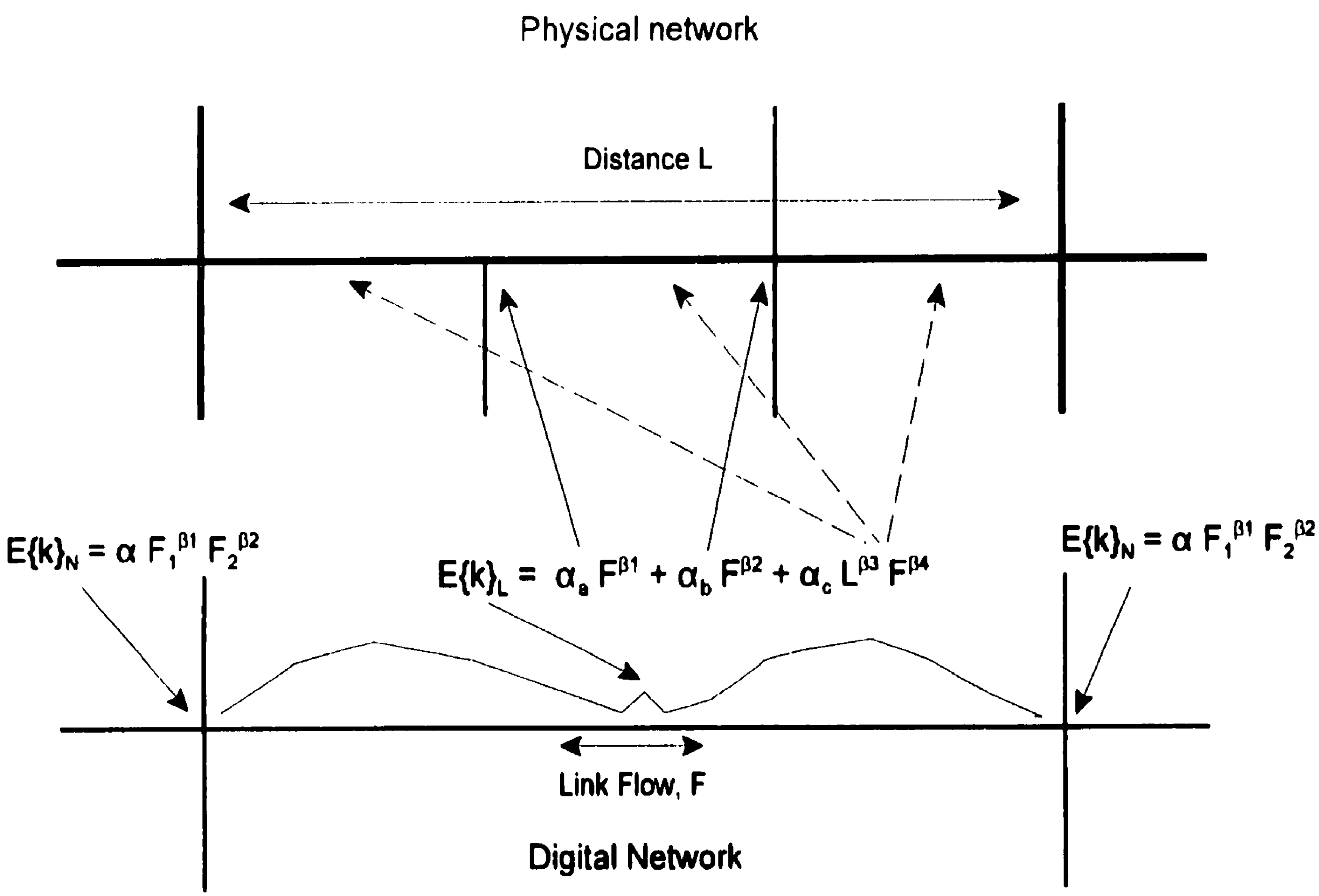
$E\{\kappa_t\}$ = the expected number of accidents for time period t, for t = year *1* (1990) to year *6* (1995);

F_t = link flow in AADT (both directions) for time period t;

α_t, β_1, β_2 = coefficients to be estimated.

The prediction model of equations (4.3a) and (4.3b) uses only one input flow. Thus, this model can only be used on link segments.

Figure 4.8 illustrates how the models are applied to digital networks. The same network shown in Figure 4.1 is used in the illustration. The model forms presented in this figure are for the model forms of equations (4.1d), (4.2b), and (4.3b) respectively.



$E\{k\}_N$ = expected number of accidents at nodes

$E\{k\}_L$ = expected number of accidents on links

α_a and α_b are for the intersection component models; α_c is for the mid-block component model

Note: the model forms illustrated are for a power relationship: equations (4.1d), (4.2b), and (4.3b)

FIGURE 4.8 Illustration and application of APMs on digital networks

The models described in the next two sections were estimated with Genstat 5, Version 4.1 (Payne *et al.*, 1993) and the error distribution was assumed to follow the Negative Binomial (NB) distribution. The NB has been shown to describe accurately the distribution of traffic accidents between sites (Hauer, 1993b; Kulmala, 1995; and Nicholson and Turner, 1996; Poch and Mannering, 1996). Since the APMs incorporated time trend (see Maher and Summersgill, 1996; and Mountain *et al.*, 1998), the built-in GEE procedure of Genstat was utilized (the theory is explained in detail in Appendix C). The procedure was modified and adapted to incorporate the NB distribution with the help of Dr. D.M. Smith of the University of New England in Australia since Genstat did not offer a built-in NB distribution. For each model type, APMs were created for injury, property damage only (PDO), and injury + PDO accidents.

The issue of how to select the best regression model has been addressed extensively in the literature. The coefficient of determination (R^2), the adjusted R^2, and other tools such as the PRESS and C_p statistics are very useful criteria for determining the best least-squared and weighted least-squared regression models (Myers, 1990). However, these criteria are shown to be less effecient for evaluating APMs estimated by GLMs (or GEE) since the error variance is not constant (Miaou, 1995). The best GLM can be selected based on Pearson χ^2 (Bélanger, 1994), deviance (McCullagh and Nelder, 1989), scaled deviance (Kulmala, 1995), Akaike Information Criteria (Miaou, 1996), and the dispersion parameter of the NB regression (Hauer, 1992; and, Nguyen, 1997). From the reviewed documents on the selection of the best APMs, it appears that no definitive criterion is superior to the other, so also, that the chosen criterion often is subject to the modeler's discretion. In addition, not all tests are appropriate for every circumstance and they often depend on the outcome sought, i.e., models used for prediction, significance of each variable, etc. Thus, selecting the best models for this research was based on the following average indicators: the deviance ratio (output of Genstat), the scaled deviance, the Pearson χ^2, the dispersion parameter of the NB, and the significance of each coefficient. The models in this thesis are used for predicting accidents.

Some of the models presented in the next sections include not statistically significant variables (5%). Since the models are used for predicting accidents, these variables were left in the models since they improved the prediction of accidents. It should be pointed out that, when the temporal correlation is not included, all the insignificant variables become significant. Thus, these variables can still be adequately included in the models proposed below.

The cumulative residuals (CURE) method, as proposed by Hauer and Bamfo (1997), was plotted for each covariate of each model to identify that the model having the best fit. This method consists of plotting the cumulative residuals (the difference between the actual and fitted values for each entity) in increasing order for each covariate separately. The graph shows how well the model fits the data. For a very good fit, the curve depicted in the graph should oscillate around the value of 0 and lie between the two standard deviation boundaries (see Hauer and Bamfo for a complete description of this method). A graph depicting the cumulative residuals for each covariate of every model is shown in Appendix E.

During the course of the accident modelling process, each APM was tested for outliers and influence points. It is important to note that an outlier is not necessarily an influence point, and vice-versa (Myers, 1990). The standardized residuals were tested with the R-Student statistic and examined graphically, while the influence points were verified with the Cook's D method (Myers, 1990). For observations flagged by the various tests, a thorough analysis was performed on a case by case basis and observations were removed only when warranted. Overall, very few outliers and influence points were removed.

The variance of the expected number of accidents for period t was computed with the following equation:

$$VAR\{\kappa_t\} = \frac{E\{\kappa_t\}^2}{\gamma} \tag{4.4}$$

where,

$VAR\{\kappa_t\}$ = the variance of the expected number of accidents for time period t;

$E\{\kappa_t\}$ = the expected number of accidents for time period t;

γ = dispersion parameter of the NB regression.

The technique for finding the dispersion parameter of a NB regression is well described in the work of Hauer *et al.* (1988), Hauer and Persaud (1988), and Hauer (1992). It has been successfully argued that

$$VAR\{K\} = E\{\kappa\} + \frac{E\{\kappa\}^2}{\gamma} \tag{4.5}$$

where,

$VAR\{K\}$ = the variance of the accident counts;

$E\{\kappa\}$ = the expected number of accidents;

γ = dispersion parameter of the NB regression.

The dispersion parameter is found through an iterative process. An initial value of γ is assumed and the coefficients are computed with any statistical software program. The output of the regression is saved into a computer file. The number of accidents (K) and the expected number of accidents ($E\{\kappa\}$) of every entity in the reference population are included in this file. The computer file is then fed into a maximum likelihood program (Persaud, 1997) and a new value of γ is calculated. The new γ is used again in the statistical software package for a second run. The iteration process goes on until γ and the likelihood program reach their maximum value. At that point, the values of γ and all of the coefficients are final.

The process described above was also used to find the dispersion parameter for the models developed in this research. Since the models have a different α for the time period t, the dispersion parameter had to be found with the following equation:

$$VAR\{K\} = \sum_{t=1}^{6} E\{\kappa_t\} + \frac{\left(\sum_{t=1}^{6} E\{\kappa_t\}\right)^2}{\gamma} = E\{\kappa\} + \frac{E\{\kappa\}^2}{\gamma} \qquad (4.6)$$

where,

$VAR\{K\}$ = the variance of the accident counts for t = year *1* to year *6*;

$E\{\kappa\}$ = the total expected number of accidents for t = year *1* to year *6*;

$E\{\kappa_t\}$ = the expected number of accidents for time period t;

γ = dispersion parameter of the NB regression.

Equation (4.6) is basically the same as equation (4.5) except that the expected number of accidents for each period is added together to obtain the total expected number of accidents for each site. The characteristic of equation (4.6) shows that it is the variability in accident counts between sites that are of interest and not the variability between years (which is already assumed to follow the Poisson distribution). Thus, the dispersion parameter is estimated by using both the total number and expected number of accidents of each site; where each site, in principle, is independent from others. The relationship shown in equation (4.6) is illustrated in Figure 4.9 for signalized 4-legged intersections.

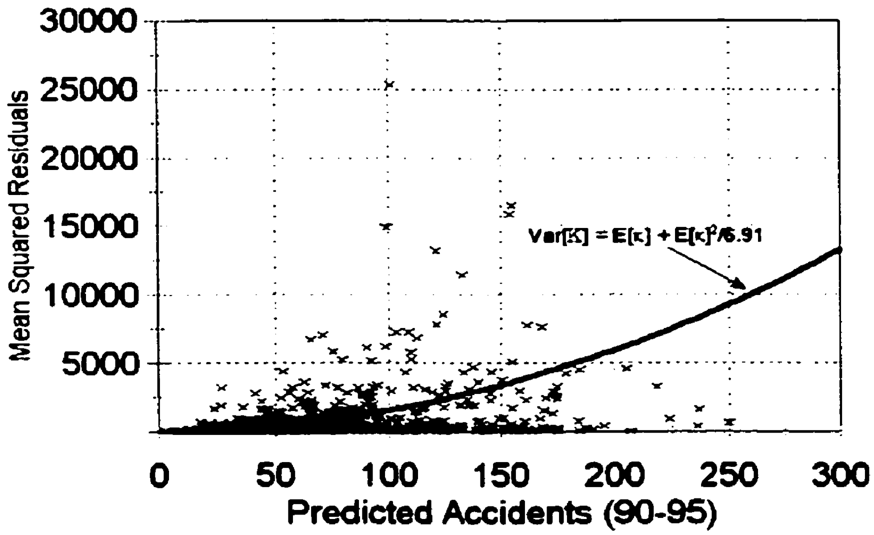


FIGURE 4.9 Relationship of equation (4.6) for signalized 4-legged intersections

4.2 ACCIDENT PREDICTION MODELS FOR NODES

The APMs used for predicting accidents at nodes are described in this section. The models developed for nodes representing signalized intersections are described in section 4.2.1. The models created for nodes representing unsignalized intersections are explained in section 4.2.2.

4.2.1 SIGNALIZED INTERSECTIONS

The characteristics of the intersections used as input for the models for signalized 4- and 3-legged intersections are summarized in Tables 4.1 and 4.2 respectively. There are, respectively, 868 and 250 signalized 4- and 3-legged junctions. It should be noted that the data included few intersections with low entering flows. The flows of these intersections were validated to ascertain that they were not coding mistakes. The intersections with very low flows were located either inside residential areas (where the ratio major/minor is usually equal to 50/50), at entrances of private and commercial properties, or at high pedestrian traffic corridors.

TABLE 4.1 Characteristics of signalized 4-legged intersections

Year	Severity	Accidents (min-max-total)	Major Road Flow (min-max)	Minor Road Flow (min-max)
1990	Total Injury PDO	0-10-8,276 0-21-2,696 0-34-5,580	5,305-71,798	51-41,306
1991	Total Injury PDO	0-53-8,141 0-17-2,332 0-45-5,809	5,294-71,527	52-41,003
1992	Total Injury PDO	0-58-8,714 0-16-2,380 0-42-6,334	5,342-71,498	52-41,150
1993	Total Injury PDO	0-63-9,818 0-19-2,641 0-52-7,177	5,369-71,450	52-41,131
1994	Total Injury PDO	0-54-10,010 0-19-2,879 0-45-7,130	5,464-72,310	53-42,012
1995	Total Injury PDO	0-54-10,030 0-23-3,411 0-38-6,619	5,469-72,178	53-42,644
1990-1995	Total Injury PDO	0-63-54,989 0-23-16,339 0-52-38,650	5,305-72,310	51-42,644

TABLE 4.2 Characteristics of signalized 3-legged intersections

Year	Severity	Accidents (min-max-total)	Major Road Flow (min-max)	Minor Road Flow (min-max)
1990	Total Injury PDO	0-30-1,124 0-14-362 0-18-762	1,663-73,607	155-17,125
1991	Total Injury PDO	0-34-1,094 0-12-275 0-22-819	1,660-73,460	155-17,076
1992	Total Injury PDO	0-31-1,185 0-9-322 0-22-863	1,674-74,122	156-17,215
1993	Total Injury PDO	0-28-1,213 0-11-330 0-17-883	1,683-74,469	157-17,340
1994	Total Injury PDO	0-28-1,301 0-13-362 0-23-939	1,713-75,813	160-17,777
1995	Total Injury PDO	0-37-1,297 0-15-423 0-22-874	1,714-75,887	160-17,923
1990-1995	Total Injury PDO	0-37-7,214 0-15-2,074 0-23-5,140	1,660-75,887	155-17,923

The regression results for the signalized intersection models are summarized in Table 4.3. The number of intersections and collisions for the 4- and 3-legged models are shown at the top of the table. Moreover, the number of collisions exhibited in this table is for the period 1990 to 1995 inclusively. The estimate of the coefficients is the actual estimate as computed by the GEE procedure. In other words, the estimate is not transformed back to the format of equations (4.1) to (4.3). The estimate is left as it is to simplify descriptions of the standard error associated with each coefficient. The dispersion parameter of the NB distribution and the deviance of the models are displayed at the bottom of the table. The characteristics of Table 4.3 are repeated in all subsequent tables that show the results of regression models.

TABLE 4.3 APMs for signalized 4- and 3-legged intersections

Parameters	Signalized 4-legged			Signalized 3-legged		
	*All	Injury	PDO	All	Injury	PDO
# of entities	868	868	868	250	250	250
Collisions	54,989	16,339	38,650	7,214	2,074	5,140
LN(α_1)	**-8.443** (0.599)	**-10.171** (0.676)	**-10.247** (1.364)	**-11.285** (0.809)	**-13.940** (0.976)	**-10.977** (0.863)
LN(α_2)	**-8.453** (0.598)	**-10.302** (0.675)	**-10.200** (1.365)	**-11.299** (0.805)	**-13.194** (0.981)	**-10.902** (0.859)
LN(α_3)	**-8.391** (0.598)	**-10.295** (0.676)	**-10.125** (1.365)	**-11.216** (0.807)	**-14.041** (0.981)	**-10.845** (0.859)
LN(α_4)	**-8.302** (0.597)	**-10.208** (0.676)	**-10.030** (1.364)	**-11.217** (0.805)	**-14.041** (0.979)	**-10.840** (0.855)
LN(α_5)	**-8.316** (0.598)	**-10.193** (0.676)	**-10.075** (1.364)	**-11.179** (0.808)	**-13.949** (0.984)	**-10.825** (0.857)
LN(α_6)	**-8.321** (0.600)	**-9.990** (0.675)	**-10.149** (1.363)	**-11.193** (0.803)	**-13.820** (0.977)	**-10.891** (0.858)
Average LN(α)	**-8.371**	**-10.186**	**-10.138**	**-11.232**	**-13.997**	**-10.880**
β_1 (LN_F$_1$)	**0.527** (0.041)	**0.622** (0.050)	**0.658** (.146)	**0.803** (0.079)	**0.984** (0.097)	**0.721** (0.084)
β_2 (LN_F$_2$)	**0.568** (0.043)	**0.530** (0.046)	**0.597** (0.0.47)	**0.568** (0.043)	**0.524** (0.064)	**0.586** (0.041)
β_3 (F$_1$)	**0.000**	**0.000**	**-6.48E-6** (5.52E-6)	**0.000**	**0.000**	**0.000**
β_4 (F$_2$)	**8.61E-6** (3.97E-6)	**6.94E-6** (4.21E-6)	**8.21E-6** (4.33E-6)	**0.000**	**0.000**	**0.000**
γ	6.91	5.64	6.87	4.51	4.35	4.33
Deviance	5471	5282	5639	1608	1597	1572

* All = (injury + PDO)

In Table 4.3, all the models provide a good fit as is illustrated in Figures 4.10 and 4.11 and in the figures in Appendix E. The figures show that the cumulative residuals stay between the two standard deviation boundaries for both parameters. It should be pointed out, however, that two separate models could be developed for signalized 4-legged intersections for entering flows on the minor road over and below 15,000 veh/day, as illustrated in Figure 4.11. The models seem to underestimate accidents below 15,000 veh/day and overestimate accidents above this value. Unfortunately, the development of such models is outside the scope of this work. Table 4.3 also shows that the parameter F_2 follows a Gamma relationship for the three 4-legged models, while the parameters F_1 and F_2 follow a power function relationship for the 3-legged models.

Based on the standard errors of $\ln(\alpha_t)$ in Table 4.3 (and in all subsequent tables), it would be tempting for a modeller to conclude that the year-to-year differences are not statistically significant and therefore one would select a model with a common α for each year. However, note that the values of α_t for years 4 and 5 are approximately 15% higher than for years 1 and 2 for the 4-legged signalized intersections (all accidents). Thus, a model with a common α for each year would overestimate accidents in years 1 and 2 and underestimate accidents in years 4, 5, 6. This would create some difficulty in longitudinal studies. To see this, imagine that intersections were treated in Year 3 and, for a proper before and after study (see Hauer, 1997), a model with common α is used in the estimation of the number of accidents that would have occurred in Years 4, 5, 6 without the treatment. Since this value is underestimated, the treatment effectiveness obtained by comparing it to the actual number of accidents in years 4, 5 and 6 would be underestimated. This difficulty would be avoided by using a model with trend since this model captures the increased accident experience in the "after" period that would have materialized without the treatment. Another benefit of using the time trend is that it allows the jurisdiction to identify and investigate potentially dangerous trends such as the 15% increase in accidents noted above. AMPs with trend have also been shown to perform better than traditional models since they incorporate additional information (year-to-year changes in weather, economic conditions, etc.) that models with a common α cannot. Thus, on balance, it seems beneficial to incorporate trend in developing APMs since trends that are insignificant in the statistical sense, such as the one in our application, still require consideration.

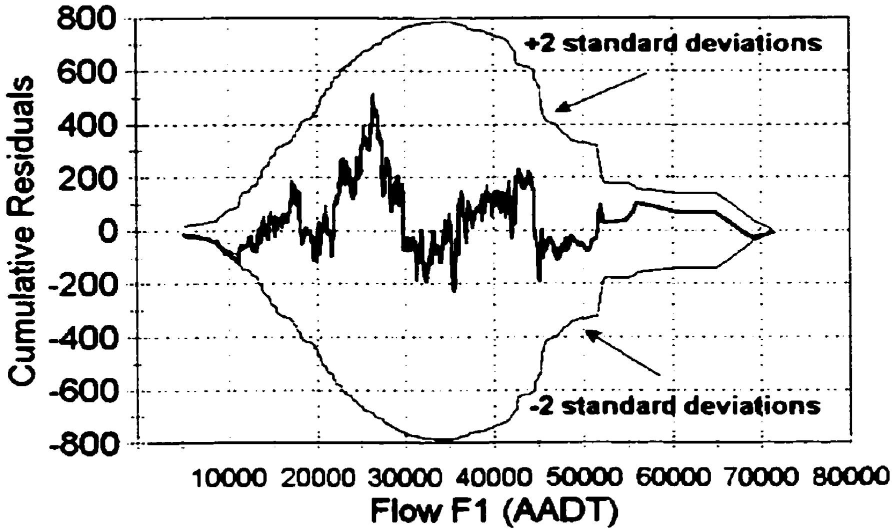


FIGURE 4.10 Cumulative residuals for signalized 4-legged intersections (parameter F_1)

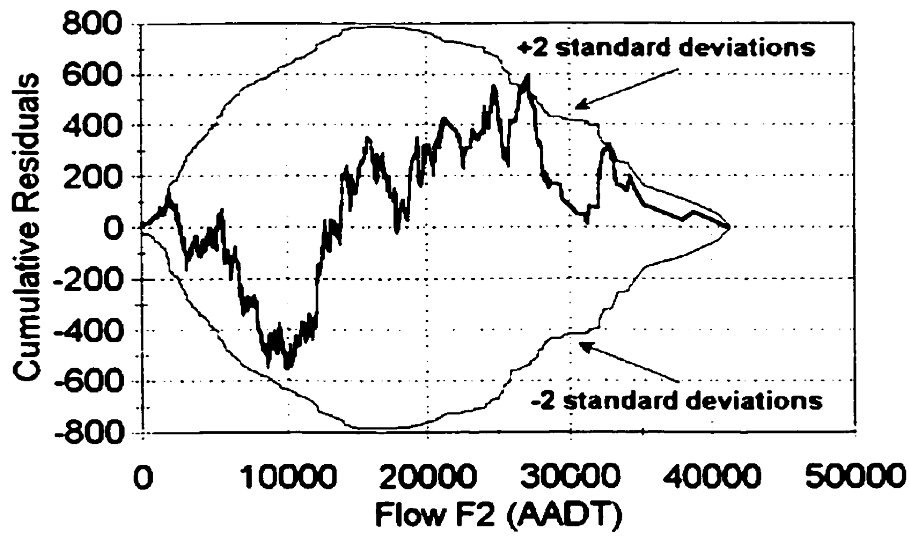


FIGURE 4.11 Cumulative residuals for signalized 4-legged intersections (parameter F_2)

The relationship between accidents (injury + PDO) and the parameter F_1 is graphically shown in Figures 4.12 and 4.13 for 4- and 3-legged intersections respectively. The parameter F_1 is shown on the ordinate and the expected number of accidents per year is illustrated on the abscissa. In these (and subsequent figures), the average coefficient α is used. Figure 4.12 shows the relationship for three values of F_2:1,000, 15,000, and 30,000 veh/day. Figure 4.13 also shows the relationship for three values of F_2: 1,000, 7,500, and 15,000 veh/day. Figures 4.12 and 4.13 reveal that accidents increase at a decreasing rate for the entire traffic flow range of F_1.

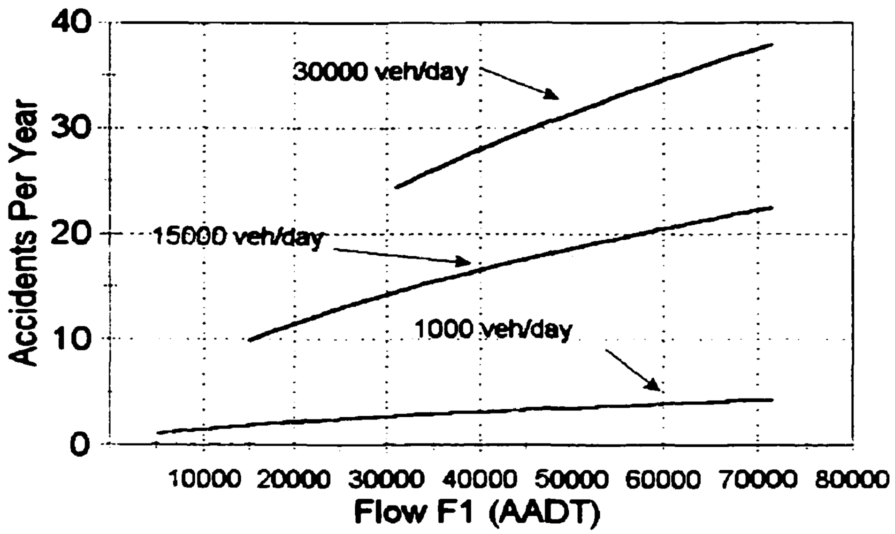


FIGURE 4.12 Relationship between accidents (injury + PDO) and the parameter F_1 for signalized 4-legged with F_2 = 1,000, 15,000, and 30,000 veh/day

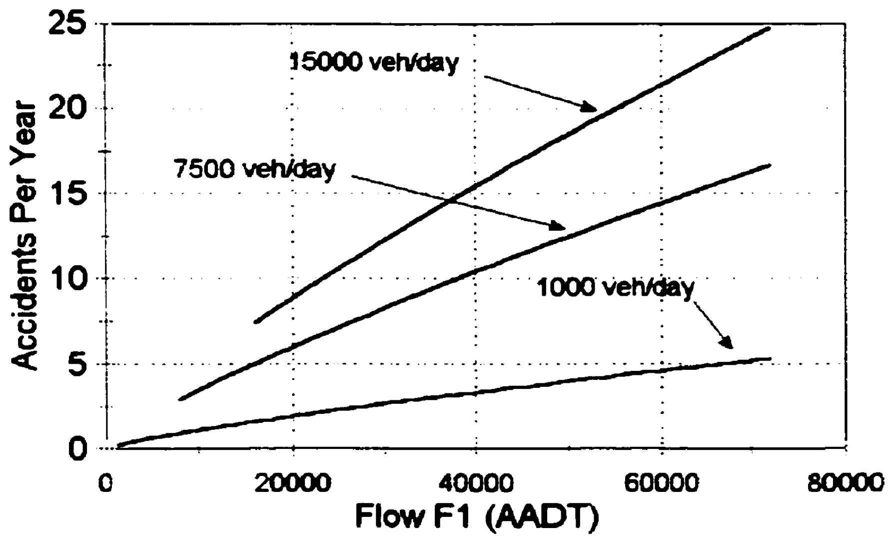


FIGURE 4.13 Relationship between accidents (injury + PDO) and the parameter F_1 for signalized 3-legged intersections with F_2 = 1,000, 7,500, and 15,000

4.2.2 UNSIGNALIZED INTERSECTIONS

The characteristics of the intersections used as input for the models for unsignalized 4- and 3-legged intersections are summarized in Tables 4.4 and 4.5 respectively. There are 59 and 277 unsignalized 4- and 3-legged junctions.

TABLE 4.4 Characteristics of unsignalized 4-legged intersections

Year	Severity	Accidents (min-max-total)	Major Road Flow (min-max)	Minor Road Flow (min-max)
	Total	0-11-210		
1990	Injury	0-4-52	5,681-51,924	379-8,378
	PDO	0-10-158		
	Total	0-12-216		
1991	Injury	0-4-57	5,669-51,820	378-8,361
	PDO	0-9-159		
	Total	0-14-194		
1992	Injury	0-5-55	5,721-52,286	382-8,437
	PDO	0-10-139		
	Total	0-13-244		
1993	Injury	0-4-62	5,750-52,546	383-8,479
	PDO	0-11-182		
	Total	0-14-241		
1994	Injury	0-4-64	5,851-53,479	390-8,629
	PDO	0-14-177		
	Total	0-11-212		
1995	Injury	0-4-67	5,857-53,531	391-8,638
	PDO	0-9-145		
	Total	0-14-1,317		
1990-1995	Injury	0-5-357	5,857-53,531	379-8,638
	PDO	0-14-960		

TABLE 4.5 Characteristics of unsignalized 3-legged intersections

Year	Severity	Accidents (min-max-total)	Major Road Flow (min-max)	Minor Road Flow (min-max)
1990	Total Injury PDO	0-10-288 0-4-86 0-9-202	8,689-51,062	104-7,671
1991	Total Injury PDO	0-13-272 0-3-65 0-12-207	8,966-50,959	104-7,656
1992	Total Injury PDO	0-12-313 0-4-87 0-9-232	9,047-51,419	105-7,725
1993	Total Injury PDO	0-12-282 0-3-71 0-9-211	9,092-51,674	105-7,763
1994	Total Injury PDO	0-13-278 0-5-84 0-8-194	9,254-52,592	107-7,901
1995	Total Injury PDO	0-10-257 0-4-85 0-9-172	9,263-52,643	107-7,909
1990-1995	Total Injury PDO	0-13-1,690 0-5-472 0-12-1,218	8,869-52,643	104-7,909

Regression results for the unsignalized intersection models are summarized in Table 4.6. The selected models for unsignalized intersections all provide a good fit, as illustrated by the cumulative residuals graphs shown in Appendix E. Interestingly, the coefficient β_1 (in combination with β_3) for the 3-legged injury models is much higher than the 3-legged PDO, and injury + PDO models. The relationship between accidents and the major approach flows implies that the expected number of accidents increases, peaks and then decreases over the flow range of the parameter F_1. The same relationship can also be found with the parameter F_2 for the 4-legged PDO and for the 4-legged injury + PDO models. A possible explanation regarding this relationship is described below.

TABLE 4.6 APMs for unsignalized 4- and 3-legged intersections

Parameters	Unsignalized 4-legged			Unsignalized 3-legged		
	All	Injury	PDO	All	Injury	PDO
# of entities	59	59	59	177	177	177
Collisions	1,317	357	960	1,690	472	1,218
$LN(\alpha_1)$	**-11.061** (2.338)	**-7.705** (2.553)	**-13.195** (2.287)	**-7.526** (1.534)	**-34.990** (10.580)	**-6.730** (1.585)
$LN(\alpha_2)$	**-11.031** (2.323)	**-7.614** (2.523)	**-13.185** (2.284)	**-7.591** (1.542)	**-35.270** (10.561)	**-6.719** (1.596)
$LN(\alpha_3)$	**-11.151** (2.324)	**-7.658** (2.582)	**-13.354** (2.261)	**-7.441** (1.533)	**-35.060** (10.541)	**-6.596** (1.582)
$LN(\alpha_4)$	**-10.904** (2.324)	**-7.540** (2.536)	**-13.051** (2.278)	**-7.555** (1.541)	**-35.190** (10.567)	**-6.697** (1.592)
$LN(\alpha_5)$	**-10.952** (2.331)	**-7.519** (2.558)	**-13.124** (2.276)	**-7.610** (1.538)	**-35.050** (10.582)	**-6.813** (1.589)
$LN(\alpha_6)$	**-11.051** (2.334)	**-7.468** (2.567)	**-13.296** (2.285)	**-7.670** (1.547)	**-35.030** (10.550)	**-6.924** (1.600)
Average $LN(\alpha)$	**-11.025**	**-7.584**	**-13.201**	**-7.566**	**-35.098**	**-6.746**
β_1 (LN_F_1)	**0.607** (0.167)	**0.602** (0.182)	**0.657** (0.184)	**0.440** (0.145)	**3.320** (1.150)	**0.306** (0.154)
β_2 (LN_F_2)	**0.903** (0.294)	**0.205** (0.144)	**1.094** (0.308)	**0.565** (0.055)	**0.478** (0.061)	**0.596** (0.064)
β_3 (F_1)	**0.000**	**0.000**	**0.000**	**0.000**	**-8.90E-5** (4.14E-5)	**0.000**
β_4 (F_2)	**-2.29E-4** (1.12E-4)	**0.000**	**-2.56E-4** (1.21E-4)	**0.000**	**0.000**	**0.000**
γ	3.52	4.08	3.20	4.75	7.00	4.39
Deviance	355	352	360	748	688	748

Figures 4.14 and 4.15 illustrate the relationship between accidents (injury + PDO) and the parameter F_1 for unsignalized 4- and 3-legged intersections. Figure 4.14 shows the relationship for three values of F_2: 500, 4,000, and 7,000 veh/day. Figure 4.15 shows the relationship for three values of F_2: 500, 2,500, and 4,000 veh/day.

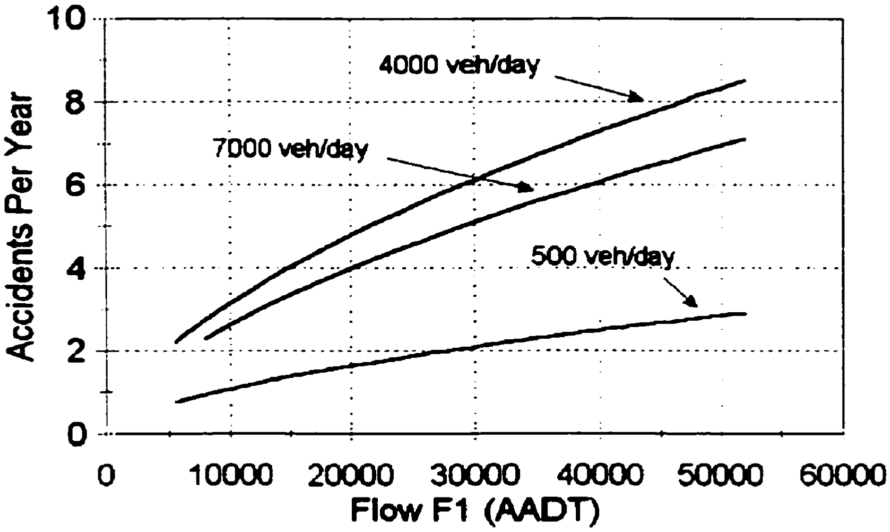


FIGURE 4.14 Relationship between accidents (injury + PDO) and the parameter F_1 for unsignalized 4-legged intersections with F_2 = 500, 4,000, and 7,000 veh/day

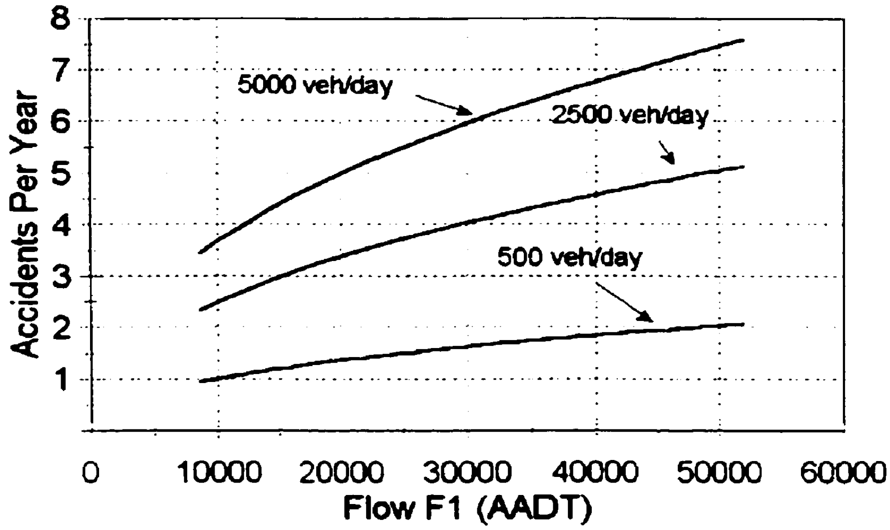


FIGURE 4.15 Relationship between accidents (injury + PDO) and the parameter F_1 for unsignalized 3-legged intersections with F_2 = 500, 2,500, and 5,000 veh/day

Figure 4.14 reveals that the predicted number of accidents increases, peaks, and decreases over the flow range of the parameter F_2 for the 4-legged model (injury + PDO). Exploratory analyses conducted on the data showed that more traffic accidents occur at the medium traffic flows than at high or low traffic flows on minor approaches; hence, the shape of the curves illustrated in Figure 4.14. This relationship may be explained by the characteristics of unsignalized intersections with medium entering flows that could be different from intersections with high entering flows. The same argument can also be made for the 3-legged models described above. It is important to point out that one should be careful on how to interpret this relationship. Indeed, one should not interpret the results to mean that by redirecting and increasing traffic to minor approaches, there will be a reduction in the number of traffic accidents.

4.3 ACCIDENT PREDICTION MODELS FOR LINKS

The APMs developed for links are described in this section. The models are distinguished on the basis of the two components previously described. The models used for the mid-block component are presented in section 4.3.1. The APMs used for the intersection component are described in section 4.3.2.

4.3.1 MID-BLOCK COMPONENT

The characteristics of the intersections used as input for the models for 2-lane, 4-lane (CBD and non-CBD), and 6-lane roads are summarized in Tables 4.7 and 4.8 respectively. The data include 20 2-lane, 215 4-lane, and 49 6-lane road sections. For the 4-lane data, 54 road sections are located in the CBD area while 161 are located in a non-CBD location.

TABLE 4.7 Characteristics of 2-, 4- and 6-lane road sections

	2-Lane Road			4-Lane Road			6-Lane Road		
Year	Severity	Accidents (min-max-total)	Link Flow (min-max)	Severity	Accidents (min-max-total)	Link Flow (min-max)	Severity	Accidents (min-max-total)	Link Flow (min-max)
	Total	0-28-226		Total	0-76-4,975		Total	5-78-1,291	
1990	Injury	0-10-61	5,226-21,433	Injury	0-33-1,245	1,425-45,002	Injury	1-28-386	20,820-54,409
	PDO	0-18-165		PDO	0-59-3,730		PDO	3-50-905	
	Total	2-27-223		Total	0-78-4,727		Total	5-100-1,288	
1991	Injury	0-6-46	5,238-21,306	Injury	0-23-1,012	1,460-44,950	Injury	0-22-296	20,970-54,109
	PDO	2-22-177		PDO	0-66-3,715		PDO	4-78-992	
	Total	2-30-258		Total	0-96-5,104		Total	3-109-1,361	
1992	Injury	0-7-49	5,308-21,422	Injury	0-28-1,023	1,512-45,395	Injury	0-24-327	21,354-54,406
	PDO	1-27-209		PDO	0-77-4,061		PDO	2-85-1,034	
	Total	1-24-232		Total	0-109-5,444		Total	6-104-1,486	
1993	Injury	0-8-51	5,358-21,453	Injury	0-33-1,171	1,559-45,659	Injury	0-29-345	21,654-54,482
	PDO	1-20-161		PDO	0-78-4,273		PDO	4-75-1,141	
	Total	1-29-221		Total	0-118-5,666		Total	7-123-1,580	
1994	Injury	0-8-51	5,476-21,757	Injury	0-27-1,561	1,626-46,510	Injury	0-30-381	22,237-55,253
	PDO	1-20-161		PDO	0-93-4,105		PDO	3-93-1,199	
	Total	0-42-242		Total	0-123-5,125		Total	6-134-1,543	
1995	Injury	0-13-73	5,505-21,702	Injury	0-44-1,479	1,668-46,595	Injury	0-43-464	22,458-55,110
	PDO	0-29-166		PDO	0-84-3,656		PDO	4-91-1,079	
	Total	0-42-1,402		Total	0-123-31,041		Total	3-134-8,549	
1990-1995	Injury	0-13-346	5,226-21,757	Injury	0-44-7,481	1,425-46,595	Injury	0-43-2,549	20,820-55,253
	PDO	0-29-1,056		PDO	0-84-23,560		PDO	2-93-6,350	
length (km)	0.44-1.36-6.62 (min-average-max)			0.24-1.20-3.97 (min-average-max)			0.65-1.39-3.82 (min-average-max)		

TABLE 4.8 Characteristics of CBD and non-CBD 4-lane road sections

	CBD			Non-CBD		
Year	Severity	Accidents (min-max-total)	Link Flow (min-max)	Severity	Accidents (min-max-total)	Link Flow (min-max)
	Total	3-70-1220		Total	0-76-3,686	
1990	Injury	0-11-226	8,300-28,531	Injury	0-33-1,007	1,425-45,002
	PDO	2-59-994		PDO	0-58-2,679	
	Total	2-65-1215		Total	0-78-3,420	
1991	Injury	0-13-202	8,292-28,064	Injury	0-23-792	1,460-44,950
	PDO	2-54-1013		PDO	0-66-2,628	
	Total	3-71-1292		Total	0-96-3,704	
1992	Injury	0-13-192	8,371-27,904	Injury	0-28-813	1,512-45,395
	PDO	2-58-1100		PDO	0-77-2,891	
	Total	1-89-1274		Total	0-109-4,032	
1993	Injury	0-14-186	8,420-27,803	Injury	0-33-953	1,559-45,659
	PDO	0-78-1088		PDO	0-77-3,079	
	Total	4-90-1244		Total	0-118-4,311	
1994	Injury	0-26-371	8,576-28,324	Injury	0-27-1,166	1,626-46,510
	PDO	2-64-873		PDO	0-93-3,145	
	Total	2-66-1060		Total	0-123-3.956	
1995	Injury	0-14-224	8,590-28,400	Injury	0-44-1,216	1,668-46,595
	PDO	2-57-836		PDO	0-84-2,740	
	Total	2-90-7,305		Total	0-123-23,109	
1990-1995	Injury	0-26-1,401	8,292-28,531	Injury	0-44-5,947	1,425-46,595
	PDO	0-78-5,904		PDO	0-84-17,162	
length (km)	0.24-0.69-1.69 (min-average-max)			0.44-1.37-3.97 (min-average-max)		

Regression results for the mid-block component models are summarized in Tables 4.9 and 4.10. Models for the 2-lane, 4-lane, and 6-lane roads are shown in Table 4.9. Models for the CBD and non-CBD 4-lane roads are presented in Table 4.10.

TABLE 4.9 APMs for the mid-block component

Parameters	2-Lane Road			4-Lane Road			6-Lane Road		
	All	Injury	PDO	All	Injury	PDO	All	Injury	PDO
# of entities	20	20	20	215	215	215	49	49	49
Collisions	1,402	346	1,056	31,041	7,481	23,560	8,549	2,199	6,350
$LN(\alpha_1)$	**-2.186** (4.994)	**-3.701** (6.091)	**-2.223** (4.651)	**-4.567** (1.284)	**-6.834** (1.242)	**-4.596** (1.323)	**-13.891** (3.685)	**-14.521** (4.310)	**-14.077** (3.663)
$LN(\alpha_2)$	**-2.209** (4.973)	**-4.025** (6.010)	**-2.143** (4.645)	**-4.610** (1.285)	**-7.030** (1.242)	**-4.596** (1.323)	**-13.933** (3.692)	**-14.826** (4.317)	**-14.016** (3.669)
$LN(\alpha_3)$	**-2.060** (4.990)	**-3.924** (5.972)	**-1.923** (4.678)	**-4.554** (1.286)	**-7.040** (1.242)	**-4.522** (1.324)	**-13.876** (3.694)	**-14.739** (4.320)	**-13.971** (3.670)
$LN(\alpha_4)$	**-2.190** (4.972)	**-3.952** (5.993)	**-2.133** (4.656)	**-4.503** (1.283)	**-6.928** (1.234)	**-4.483** (1.323)	**-13.816** (3.703)	**-14.695** (4.313)	**-13.907** (3.684)
$LN(\alpha_5)$	**-2.251** (4.988)	**-3.725** (6.045)	**-2.283** (4.652)	**-4.482** (1.283)	**-6.953** (1.251)	**-4.560** (1.319)	**-13.771** (3.699)	**-14.605** (4.328)	**-13.3.68** (3.678)
$LN(\alpha_6)$	**-2.201** (4.962)	**-3.558** (6.015)	**-2.277** (4.625)	**-4.595** (1.284)	**-6.735** (1.238)	**-4.663** (1.323)	**-13.828** (3.700)	**-14.452** (4.338)	**-14.007** (3.675)
Average $LN(\alpha)$	**-2.183**	**-3.814**	**-2.174**	**-4.552**	**-6.860**	**-4.570**	**-13.852**	**-14.640**	**-13.976**
β_1 (LN_Length)	**0.696** (0.183)	**0.749** (0.209)	**0.646** (0.183)	**0.321** (0.068)	**0.556** (0.074)	**0.257** (0.069)	**0.665** (0.142)	**0.722** (0.156)	**0.644** (0.142)
β_2 (LN_Flow)	**0.479** (0.522)	**0.499** (0.632)	**0.449** (0.487)	**0.764** (0.127)	**0.845** (0.123)	**0.739** (0.131)	**1.616** (0.351)	**1.560** (0.411)	**1.601** (0.349)
β_3 (Flow)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
γ	4.05	2.80	4.64	3.06	3.61	2.86	4.86	4.65	4.78
Deviance	120	112	117	1421	1456	1400	310	297	305

Table 4.9 reveals four interesting findings. First, most of the models in this table provide a relatively good fit, with the exception of the 2-lane models. Cumulative residual plots are shown in Appendix E. In fact, the cumulative residuals for 2-lane models do not oscillate randomly around the value of 0, as they should. In addition, the coefficients α_t and β_2 all have very high standard errors. The low quality-of-fit of the 2-lane models is attributed to the very small number of observations and to differences in the characteristics of 2-lane road sections. Despite the low quality-of-fit, these models could still be useful in some circumstances, hence their inclusion in the table. Second, the traffic flow for each model follows a power function relationship, as indicated by the coefficient $\beta_3 = 0$ for every model.

Third, the estimate of the coefficient β_2 for the 6-lane models is greater than 1. This implies that the number of accidents rises at an increasing rate as the link flow becomes higher. Persaud (1992) found a similar relationship for 6-lane urban freeways. This author argues that 6-lane freeways have a greater likelihood of accident occurrences as traffic flow increases since lane changes happen more frequently on 6 lanes than on freeways having fewer lanes. It is possible that the same phenomenon occurs on 6-lane urban roads.

Fourth, the number of accidents is not proportional to the distance L (in equation 4.2). In fact, the estimate of the coefficient β_1 varies from 0.257 for PDO accidents to 0.722 for collisions with injuries. This result is not unique and this kind of relationship has been also found in the literature. As described in Chapter Two, Mountain and Fawaz (1996) found a similar relationship for 4-lane rural road sections. They attributed this phenomenon to the difference in intersection density on links of different lengths, and suggested that the influence of intersections on mid-block accidents is probably greater than one might expect.

Other possible explanations could account for the non-linear relationship between length and accidents. The results of an exploratory analysis provided useful insights into this relationship. For instance, it was discovered that the location of major intersections at both ends of the link has an important effect on the number of accidents. In Toronto, land that is located near the intersection of major arterial roads is often the site of major commercial establishments, such as shopping malls, restaurants, or gas stations. The vehicular activity generated by these establishments creates more collisions than with non-commercial establishments. The exploratory analysis showed that between 30% and 70% of all mid-block accidents at a given link occur near the intersection of two major arterial roads. Since an important proportion of accidents occurs near the link's ends, shorter road sections, proportionally, would tend to have a greater number of accidents than longer road sections (the number of accidents per kilometer). For example, let us compare two links with similar traffic flow but having no intersections: link 1 is 1000 meters long and has 50 accidents, with 25 accidents near both ends; link 2 is 1500 meters long and has 60 accidents, also with 25 accidents near both ends. When the two links are compared, link 1 has 50 accidents per kilometer while link 2 has 40 accidents per kilometer. If the number of accidents were proportional to the length of the link, one would expect link 2 to have 75 accidents.

The non-linear relationship could further be explained by such unknown factors as the number of private and commercial entrances located along the link, as well as the number of available parking spots and parking manoeuvres. The staff at the TDC indicated that all accidents on public roads not classified by police officers as intersection collisions are usually classified as mid-block accidents. In short, the classification of accidents as mid-block is dependent on the person investigating the collision. During the course of the exploratory data analysis, the staff also specified that many accidents coded as mid-block collisions happen either at or near private entrances of commercial establishments, which sometimes, resemble the characteristic of an unsignalized intersection. Therefore, accidents classified as mid-block should, in principle, be coded as intersection crashes. Unfortunately, it was not possible to examine every mid-block accident and evaluate the validity of its classification. An investigation into the physical characteristics of the links and the disadvantages of coding accidents as mid-block are beyond the scope of this work. Further research is needed in this area to understand more fully the non-linear relationship.

Because of the limitations described above, it is necessary to warn the reader that the models for mid-block accidents can be used only for this research, specifically, to predict the number of accidents on a digitalized link. These models can be applied only within the City of Toronto boundaries and should not be used in other contexts that attempt to identify a cause-effect relationship between geometric features of road sections and the number of accidents. As indicated earlier, better models could probably be developed given more detailed information about the physical characteristics of mid-block road sections.

Figures 4.16 to 4.18 illustrate the relationship between accidents (injury + PDO) and the parameter F (link flow) for 2-lane, 4-lane and 6-lane roads. Figure 4.16 shows the relation for three values of the parameter L: 0.5, 1.0, and 1.5 kilometers. Figures 4.17 and 4.18 also show the relationship for three values of the parameter L: 0.5, 1.0, and 2.0 kilometers.

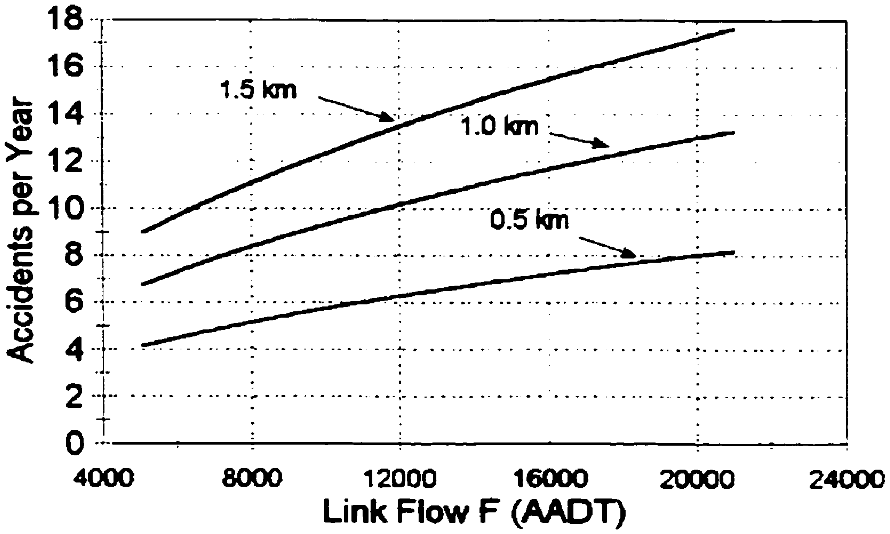


FIGURE 4.16 Relationship between accidents (injury + PDO) and the parameter F for 2-lane roads with L = 0.5, 1.0, and 1.5 km

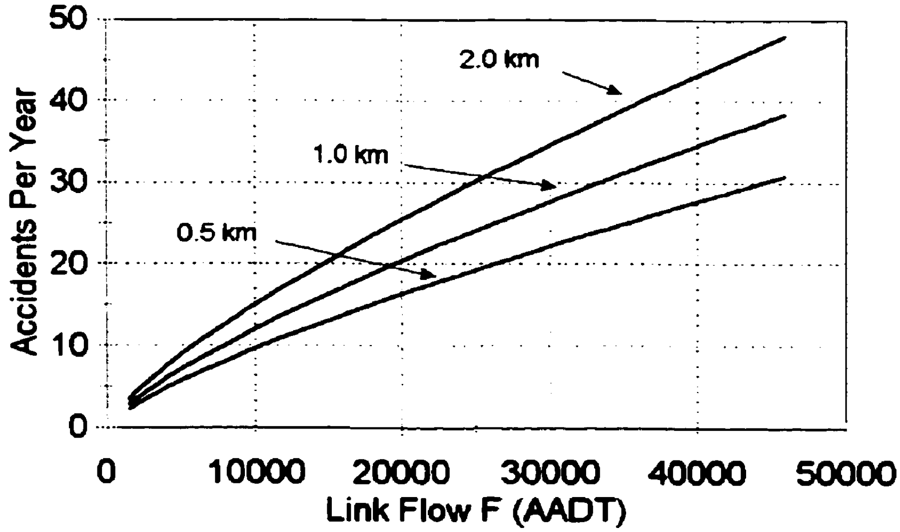


FIGURE 4.17 Relationship between accidents (injury + PDO) and the parameter F for 4-lane roads with L = 0.5, 1.0, and 2.0 km

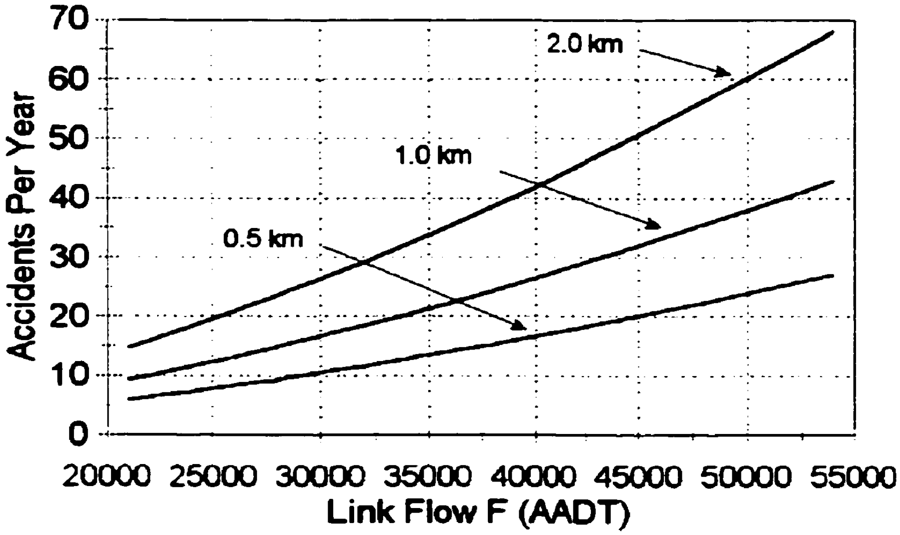


FIGURE 4.18 Relationship between accidents (injury + PDO) and the parameter F for 6-lane roads with L = 0.5, 1.0, and 2.0 km

TABLE 4.10 APMs for the mid-block component (downtown and suburban)

Parameters	4-Lane CBD Road			4-Lane non-CBD Road		
	All	Injury	PDO	All	Injury	PDO
# of entities	54	54	54	161	161	161
Collisions	7,305	1,401	5,904	23,109	5,947	17,162
$LN(\alpha_1)$	**-1.334** (2.277)	**-2.196** (2.011)	**-1.616** (2.386)	**-9.197** (1.219)	**-10.852** (1.366)	**-9.423** (1.257)
$LN(\alpha_2)$	**-1.339** (2.280)	**-2.309** (2.014)	**-1.600** (2.386)	**-9.266** (1.219)	**-11.084** (1.364)	**-9.439** (1.256)
$LN(\alpha_3)$	**-1.282** (2.289)	**-2.326** (2.013)	**-1.535** (2.400)	**-9.227** (1.215)	**-11.095** (1.363)	**-9.380** (1.252)
$LN(\alpha_4)$	**-1.303** (2.277)	**-2.395** (1.999)	**-1.541** (2.388)	**-9.143** (1.214)	**-10.941** (1.358)	**-9.315** (1.254)
$LN(\alpha_5)$	**-1.333** (2.275)	**-1.673** (2.000)	**-1.780** (2.384)	**-9.097** (2.219)	**-10.730** (1.374)	**-9.328** (1.255)
$LN(\alpha_6)$	**-1.509** (2.287)	**-2.228** (2.035)	**-1.822** (2.393)	**-9.193** (2.219)	**-10.737** (1.364)	**-9.456** (1.257)
Average $LN(\alpha)$	**-1.350**	**-2.188**	**-1.649**	**-9.187**	**-10.907**	**-9.390**
β_1 (LN_L)	**0.864** (0.102)	**0.959** (0.112)	**0.829** (0.100)	**0.498** (0.093)	**0.679** (.0096)	**0.451** (0.096)
β_2 (LN_F_i)	**0.491** (0.234)	**0.408** (0.206)	**0.499** (0.245)	**1.205** (0.121)	**1.233** (0.134)	**1.197** (0.124)
β_3 (F_i)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
γ	5.19	5.96	4.89	3.60	3.90	3.42
Deviance	319	312	316	1067	1097	1036

The models in Table 4.10 provide a relatively good fit, as is illustrated by the cumulative residual plots. Despite the good fit, the coefficients α_1 to α_6 for the CBD models have very high standard errors. The high standard errors are attributed to the models which are forced to go through the origin (i.e., zero flow and no accidents). The exploratory analysis revealed that no data points were found to be near the origin. In addition, the number of accidents is relatively uniform (but increases slightly) for flows varying from 10,000 to 30,000 veh/day. Despite this drawback, and since CBD arterial roads always have relatively high traffic flows, the models were deemed adequate to predict the number of accidents on CBD 4-lane links for the range of 10,000 to 30,000 veh/day. Table 4.10 also shows that the number of accidents for the CBD 4-lane road sections is proportional to the length as seen with the coefficient β_1. Finally, the coefficient β_2 for the road sections located in the suburbs is slightly above unity.

The relationship between accidents (injury + PDO) and the parameter F for the CBD 4-legged models and non-CBD 4-legged models is illustrated in Figures 4.19 and 4.20 respectively. Figure 4.19 shows the relationship for three values of L: 0.5, 1.0, and 1.5 kilometers. Figure 4.20 also shows the relationship for three values of L: 0.5, 1.0, and 2.0 kilometers.

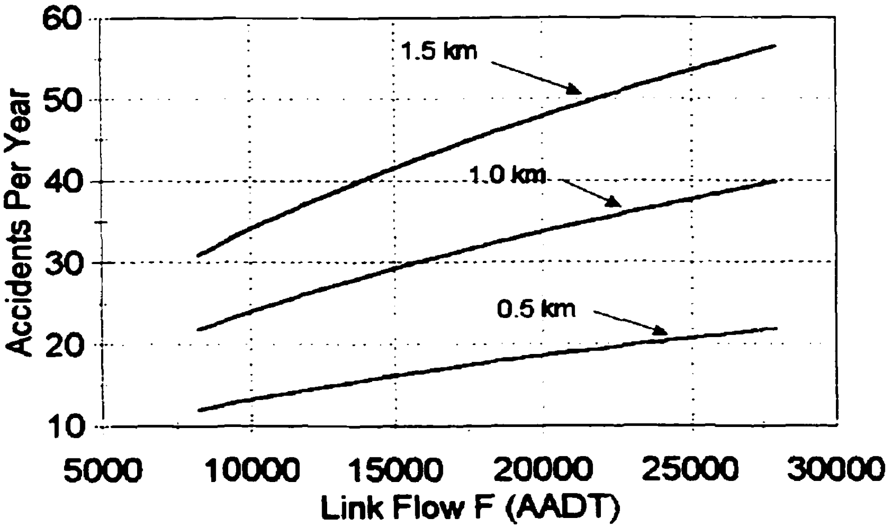


FIGURE 4.19 Relationship between accidents (injury + PDO) and the parameter F for CBD 4-lane roads with L = 0.5, 1.0, and 1.5 km

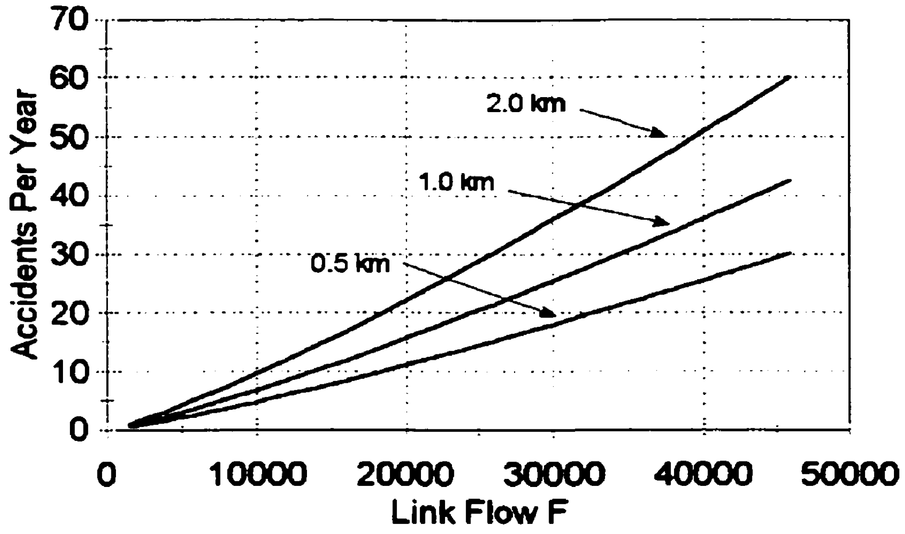


FIGURE 4.20 Relationship between accidents (injury + PDO) and the parameter F for non-CBD 4-lane roads with L = 0.5, 1.0, and 2.0 km

Figures 4.19 and 4.20 reveal that CBD roads have a higher expected number of accidents than non-CBD roads for similar flows. Indeed, it is believed that CBD roads have more accidents because many more conflicting situations occur on CBD than on the non-CBD roads. For instance, conflict situations arise in relation to on-street parking manoeuvres and lane restrictions, such as bike lanes or street car lines. In addition, the sight distances at downtown intersections are usually lower than the sight distances found in the suburbs.

4.3.2 INTERSECTION COMPONENT

The characteristics of the signalized intersections used as input for the intersection component models are presented in Tables 4.11 and 4.12. A new sample of signalized intersections was selected from the original list of signalized intersections described in section 4.2.1. This new list of intersections was needed in order to include signalized intersections connecting a major arterial road to a local connector road. Thus, each intersection of two major arterial roads was removed from the sample; the major intersections usually represented nodes on digital networks. Signalized intersections located between two major signalized intersections along arterial roads normally have moderate to low entering traffic flows coming from the local road. In fact, they often are installed to allow traffic coming from the local road to turn onto the arterial road; also to allow pedestrians to cross the arterial road. These minor signalized intersections are not used as nodes on digital networks.

TABLE 4.11 Characteristics of signalized 4-legged intersections (intersection component)

Year	Severity	Accidents (min-max-total)	Major Road Flow (min-max)
1990	Total Injury PDO	0-15-1,198 0-8-404 0-12-794	5,305-54,058
1991	Total Injury PDO	0-18-1,197 0-9-361 0-12-836	5,294-53,951
1992	Total Injury PDO	0-16-1,285 0-7-367 0-12-918	5,342-54,437
1993	Total Injury PDO	0-21-1,447 0-7-441 0-15-1,006	5,369-54,707
1994	Total Injury PDO	0-25-1,400 0-9-460 0-16-940	5,464-55,679
1995	Total Injury PDO	0-19-1,377 0-11-522 0-14-855	5,469-55,733
1990-1995	Total Injury PDO	0-25-7,904 0-11-2,555 0-16-5,349	5,305-55,733

TABLE 4.12 Characteristics of signalized 3-legged intersections (intersection component)

Year	Severity	Accidents (min-max-total)	Major Road Flow (min-max)
1990	Total Injury PDO	0-10-298 0-6-99 0-8-199	1,663-50,954
1991	Total Injury PDO	0-13-290 0-4-74 0-11-216	1,660-51,209
1992	Total Injury PDO	0-18-345 0-5-100 0-13-245	1,674-52,030
1993	Total Injury PDO	0-16-339 0-4-94 0-14-245	1,683-52,650
1994	Total Injury PDO	0-16-355 0-5-114 0-12-241	1,703-53,954
1995	Total Injury PDO	0-20-319 0-7-103 0-13-216	1,714-54,374
1990-1995	Total Injury PDO	0-20-1,948 0-7-584 0-14-1,364	1,660-54,374

The regression results for the signalized intersection models (intersection component) are summarized in Table 4.13. The models in Table 4.13 perform well, despite the use of only one flow as input, as is illustrated in the cumulative residual plots in Appendix E. As expected, the variance is much greater with these models than with those of Table 4.3. Table 4.13 also shows that the parameter F can be described with a Power function relationship for all 3- and 4-legged models. In addition, the coefficient β_1 is below unity for the 4-legged models and oscillates between 1.031 and 1.351 for the 3-legged models; this is very similar to the coefficient β_1 found in all 4 and 3-legged models of Table 4.3.

TABLE 4.13 APMs for the intersection component (signalized intersections)

Parameters	4-legged signalized			3-legged signalized		
	All	Injury	PDO	All	Injury	PDO
# of entitites	288	288	288	115	115	115
Collisions	7,904	2,555	5,349	1,948	584	1,364
$LN(\alpha_1)$	**-4.786** (0.721)	**-6.547** (0.894)	**-4.951** (0.788)	**-10.268** (2.164)	**-13.964** (2.469)	**-9.978** (2.217)
$LN(\alpha_2)$	**-4.787** (0.721)	**-6.662** (0.895)	**-4.931** (0.789)	**-10.287** (2.166)	**-14.248** (2.475)	**-9.891** (2.218)
$LN(\alpha_3)$	**-4.717** (0.723)	**-6.645** (0.900)	**-4.080** (0.789)	**-10.116** (2.172)	**-13.957** (2.482)	**-9.767** (2.222)
$LN(\alpha_4)$	**-4.617** (0.716)	**-6.473** (0.897)	**-4.796** (0.782)	**-10.137** (2.167)	**-14.019** (2.486)	**-9.776** (2.210)
$LN(\alpha_5)$	**-4.657** (0.720)	**-6.437** (0.901)	**-4.856** (0.784)	**-10.124** (2.174)	**-13.854** (2.484)	**-9.823** (2.217)
$LN(\alpha_6)$	**-4.677** (0.721)	**-6.317** (0.898)	**-5.020** (0.787)	**-10.230** (2.157)	**-13.964** (2.456)	**-9.921** (2.209)
Average	**-4.707**	**-6.513**	**-4.939**	**-10.194**	**-14.001**	**-9.859**
β_1 (LN_F_i)	**0.617** (0.071)	**0.680** (0.088)	**0.589** (0.077)	**1.098** (0.212)	**1.351** (0.241)	**1.031** (0.217)
β_2 (F_i)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
γ	4.83	4.00	4.92	3.42	3.96	3.37
Deviance	1897	1752	1929	809	742	783

The relationship between accidents (injury + PDO) and the parameter F for signalized 4- and 3-legged intersections is shown in Figure 4.21. This figure shows that the 4-legged model indeed predicts more accidents than the 3-legged model.

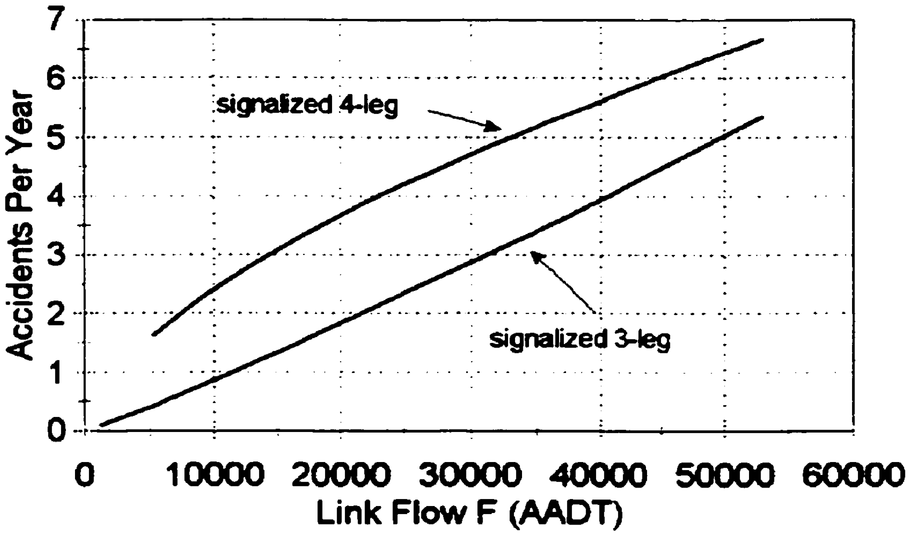


FIGURE 4.21 Relationship between accidents (injury + PDO) and the parameter F for signalized 4- and 3-legged intersections (intersection component)

Regression results for the unsignalized intersection models (intersection component) are summarized in Table 4.14. The models in Table 4.14 provide a good fit, as shown by the cumulative plots. This table shows that the parameter F follows a Power relationship for the 4-legged models and a Gamma function relationship for the 3-legged models. The relationship between accidents and the parameter F of the models in Table 4.14 is very similar to the relationship between accidents and the parameter F_1 (coefficients β_1 and β_3) of Table 4.6.

TABLE 4.14 APMs for the intersection component (unsignalized intersections)

Parameters	4-legged unsignalized			3-legged unsignalized		
	All	Injury	PDO	All	Injury	PDO
# of entities	59	59	59	177	177	177
Collisions	1,317	357	960	1,690	472	1,218
$LN(\alpha_1)$	**-4.549** (1.323)	**-5.419** (1.589)	**-4.943** (1.498)	**-14.804** (8.285)	**-30.330** (11.155)	**-10.850** (8.186)
$LN(\alpha_2)$	**-4.511** (1.327)	**-5.328** (1.578)	**-4.889** (1.505)	**-14.865** (8.281)	**-30.610** (11.135)	**-10.829** (8.188)
$LN(\alpha_3)$	**-4.639** (1.322)	**-5.378** (1.595)	**-4.800** (1.505)	**-14.737** (8.274)	**-30.400** (11.119)	**-10.721** (8.184)
$LN(\alpha_4)$	**-4.395** (1.322)	**-5.257** (1.558)	**-4.724** (1.508)	**-14.834** (8.277)	**-30.530** (11.142)	**-10.813** (8.181)
$LN(\alpha_5)$	**-4.430** (1.312)	**-5.229** (1.560)	**-4.810** (1.498)	**-14.851** (8.292)	**-30.370** (11.161)	**-10.898** (8.192)
$LN(\alpha_6)$	**-4.524** (1.332)	**-5.175** (1.590)	**-4.897** (1.517)	**-14.927** (8.273)	**-30.350** (11.125)	**-11.016** (8.184)
Average	**-4.508**	**-5.298**	**-4.842**	**-14.837**	**-30.432**	**-10.854**
β_1 (LN_F_i)	**0.575** (0.130)	**0.524** (0.153)	**0.589** (0.148)	**1.675** (0.909)	**3.184** (1.214)	**1.222** (0.900)
β_2 (F_i)	**0.000**	**0.000**	**0.000**	**-4.84E-5** (3.55E-5)	**-8.75E-5** (4.47E-5)	**-3.73E-5** (3.55E-5)
γ	2.66	3.77	2.21	2.51	5.54	2.33
Deviance	350	341	355	760	720	767

The relationship between accidents (injury + PDO) and the parameter F for unsignalized 3- and 4-legged intersections is presented in Figure 4.22. As in Figure 4.21, the 4-legged model indeed predicts more accidents than the 3-legged model.

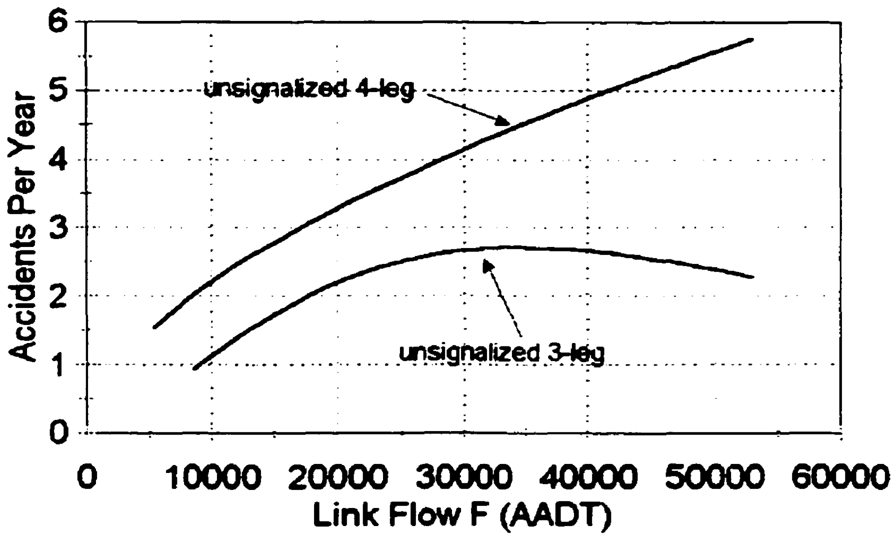


FIGURE 4.22 Relationship between accidents (injury + PDO) and the parameter F for unsignalized 4- and 3-legged intersections (intersection component)

A series of models that combined all the signalized and unsignalized junctions together was created for the intersection component of links. It is not always possible to know at the planning stage the characteristics of every minor intersection on the link. Thus, these models were created to predict the number of accidents for the intersection component in those cases in which it is not known whether or not a minor intersection is signalized, or whether the junction has 3 or 4 legs. The application of these models is evaluated and compared to applications of the disaggregated models (described previously in this section) in the next chapter.

Regression results for the general models are summarized in Table 4.15. The models provide a good statistical fit, with the exception of the PDO model, and the cumulative residual plots can be found in Appendix E. Interestingly, the PDO model seems to consistently overestimate accidents for high link flows. This may be explained by the different characteristics (e.g., signalized and unsignalized mixed together) of intersections used as input for these models. These characteristics may influence PDO accidents differently. Table 4.15 shows that the parameter F for every model is described by a power function.

TABLE 4.15 General models for the intersection component

Parameters	General model		
	All	Injury	PDO
# of entities	579	579	579
Collisions	12,859	3,968	8,891
LN(α_1)	**-4.399** (0.654)	**-6.392** (0.823)	**-4.443** (0.685)
LN(α_2)	**-4.406** (0.654)	**-6.533** (0.824)	**-4.393** (0.686)
LN(α_3)	**-4.333** (0.655)	**-6.468** (0.827)	**-4.320** (0.686)
LN(α_4)	**-4.263** (0.650)	**-6.362** (0.823)	**-4.259** (0.681)
LN(α_5)	**-4.289** (0.653)	**-6.291** (0.827)	**-4.329** (0.682)
LN(α_6)	**-4.337** (0.654)	**-6.220** (0.825)	**-4.437** (0.685)
Average	**-4.338**	**-6.376**	**-4.369**
β_1 (LN_Flow)	**0.555** (0.064)	**0.640** (0.081)	**0.522** (0.067)
β_2 (Flow)	**0.000**	**0.000**	**0.000**
γ	2.77	2.55	2.77
Deviance	3660	3523	3718

The relationship between accidents (injury + PDO) and the parameter F for the general model is illustrated in Figure 4.23.

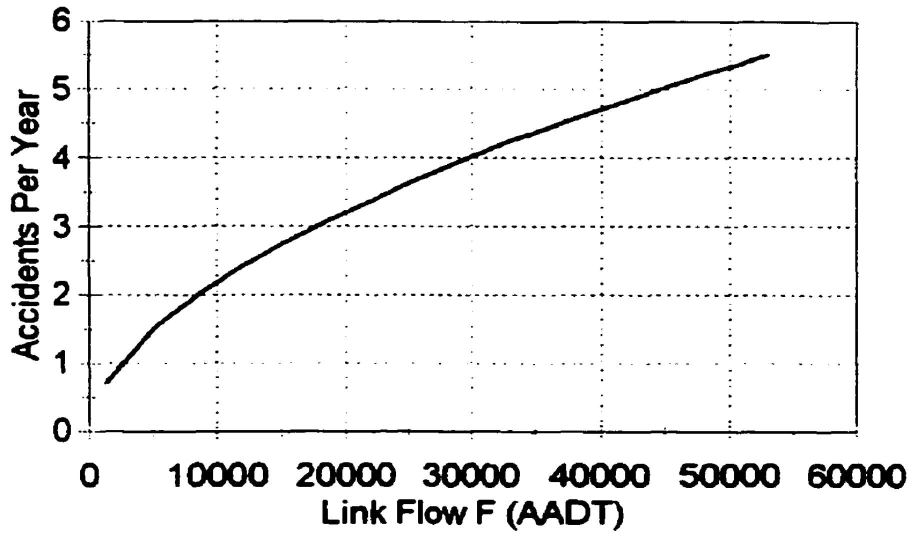


FIGURE 4.23 Relationship between accidents (injury + PDO) and the parameter F for the general model (intersection component)

4.4 SUMMARY

This chapter contained a description of the regression models with trend developed for predicting accidents on different components of transportation networks. Three different types of models were proposed. The first type of model was related to the prediction of accidents at nodes. The second and third types were associated with the prediction of accidents on links: the mid-block and intersection components respectively. Models for the mid-block component predict accidents between minor intersections, which are located on the physical network but are not coded as a node on the digital network. Models for the intersection component predict accidents at these minor intersections. All the coefficients of models were estimated with the GEE method in order to handle the temporal correlation.

The regression results revealed a few interesting findings. First, models for the nodes provided, in general, a good statistical fit. Second, the majority of the models for the mid-block component offered a satisfactory fit, with only a few exceptions. Third, models for the mid-block component showed that a non-linear relationship existed between accidents and the length of sections. In addition, the relationship between accidents and traffic flow was found to be above unity for non-CBD road sections. Fourth, models for the intersection component all provided a good statistical fit, with the exception of one model, despite the use of one input flow. Overall, the results showed that the APMs reflected the actual relationship between accidents and the covariates, and were deemed sufficiently accurate for predicting the number of accidents on links and nodes. The next chapter describes how the models in this chapter are applied on transportation networks and within the urban transportation planning process.

CHAPTER 5

APPLICATION OF MODELS ON DIGITAL NETWORKS

The application of accident prediction models (APMs) on digital networks is described in this chapter. The chapter is divided into two sections. The mechanics of how the models are applied to a digital network are explained in the first section. The application of APMs within the urban transportation planning process to estimate the number of accidents for different scenarios is described in the second section. All the issues surrounding the application of models are also explained in this chapter.

5.1 APPLICATION OF MODELS

This section shows how the three different types of models, described in the previous chapter, are applied on a digital network. The sample network is described in section 5.1.1. The characteristics of the traffic flow simulation are explained section 5.1.2. The steps required to compute the predicted number of accidents on the sample network are described in section 5.1.3.

5.1.1 DESCRIPTION OF SAMPLE NETWORK

Three types of models were applied on a sample network selected from a digital representation of a street system located in the eastern part of Toronto. This network has six links, six nodes, one centroid (400), four centroid connectors (or dummy links) connecting centroid 400 to four nodes (Figure 5.1). The network represents the street system bounded by Warden Avenue to the West, Birchmount Avenue to the East, St. Clair Avenue to the South, and Eglinton Avenue to the North. Four nodes are used to represent the intersections of Eglinton/Warden (10655), St. Clair/Warden (10548), St.

Clair/Birchmount (10663), and Eglinton/Birchmount (10660). Two nodes (10566, 10661) are utilized to connect the links to adjacent centroids and do not represent a physical intersection. The street system in Figure 5.1 is laid out in a shape of a rectangle and is about one kilometer wide by two kilometers long. The digital representation was taken from the original EMME/2 (INRO, 1996) network created by the Joint Program in Transportation (JPINT) at the University of Toronto.

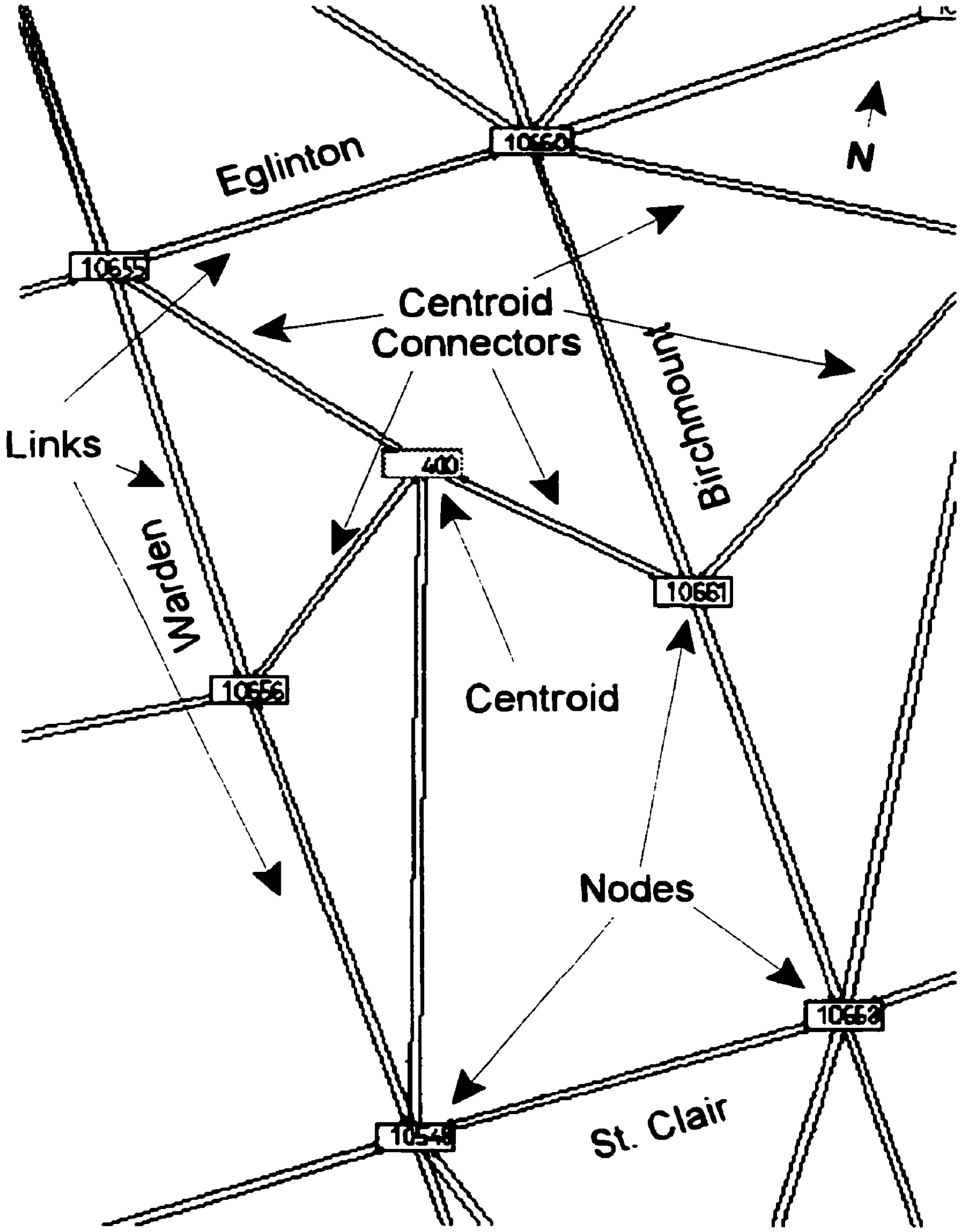


FIGURE 5.1 Sample network

The characteristics of the links are presented in Table 5.1. This table includes a description of the attributes of minor intersections not coded as nodes, the number of lanes, and the measured distances of links.

TABLE 5.1 Characteristics of links in the sample network

Link	lanes	[1]Sig4L	[1]Sig3L	[1]Unsig4L	[1]Unsig3L	length (km)	[2]length - intersections (km)
10660-10661	2	0	1	0	2	0.950	0.845
10661-10663	2	0	0	0	3	0.910	0.805
10655-10660	3	0	1	0	2	0.870	0.750
10548-10663	2	0	0	0	2	0.870	0.780
10556-10655	2	1	0	0	3	0.960	0.825
10656-10548	2	1	0	1	1	0.910	0.805

1 Sig=signalized, Unsig=unsignalized, 4L=4 legs, 3L=3 legs

2 length less 0.030 km for each minor intersection on link + 0.015 for the node at each end, if it represents an intersection

The characteristics of the four nodes representing physical intersections are presented in Table 5.2. The table shows that all the nodes are signalized 4-legged intersections.

TABLE 5.2 Characteristics of nodes in the sample network

Node	Sig4L	Sig3L	Unsig4L	Unsig3L
10660 (Birchmount/Eglinton)	1	0	0	0
10663 (Birchmount/St. Clair)	1	0	0	0
10655 (Eglinton/Warden)	1	0	0	0
10548 (St. Clair/Warden)	1	0	0	0

5.1.2 ESTIMATION OF TRAFFIC FLOW

The traffic flow simulation was performed with EMME/2. This software is a transportation planning computer program that often is used to assess traffic flows at a regional level. It is based on the traditional 4-stage transportation modelling process (trip generation, trip distribution, modal split, and traffic assignment). EMME/2 employs a static optimization algorithm (i.e., not time-dependent) and provides flows in vehicles per hour. Since the mid-70's, it has been used extensively throughout the world by various local and governmental agencies.

The EMME/2 traffic flow output in vehicles per hour for the selected sample network is presented in Figure 5.2. The output flows were provided by the JPINT, which performed a traffic assignment for the entire Greater Toronto Area (GTA), using the 1996 Transportation Tomorrow Survey as the input origin-destination (O-D) matrix. It is important to note that the direction of the link flow in this figure (and in all subsequent figures) is the same as that used in North America (where drivers travel on the right side of the road).

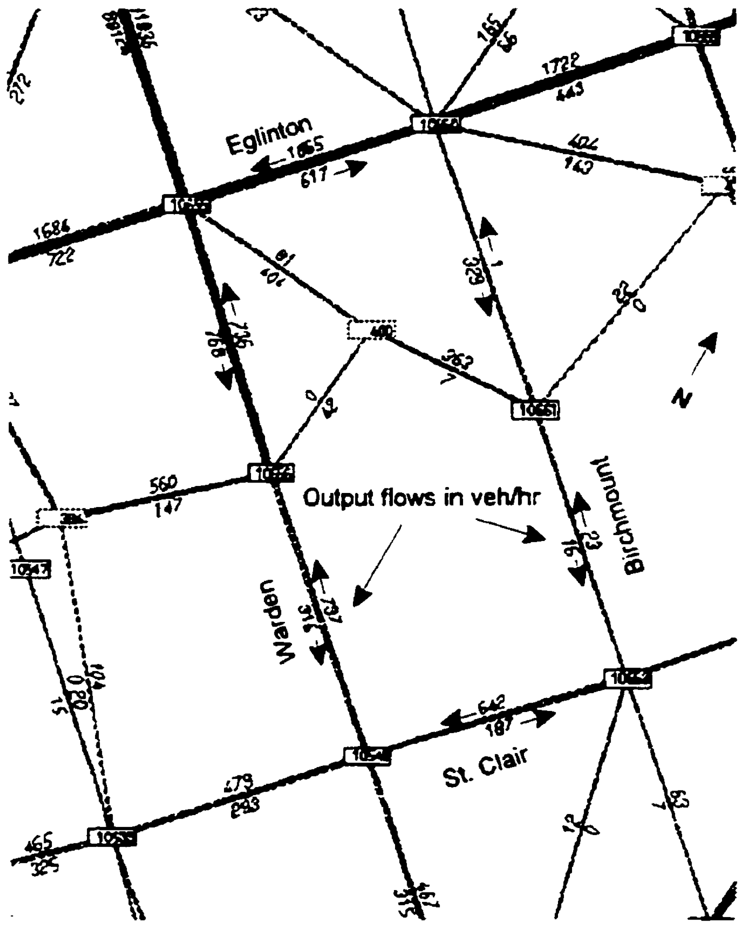


FIGURE 5.2 EMME/2 traffic flow output flow (veh/hr) for the sample network

Figure 5.2 shows that the morning peak hour flows are much higher on Eglinton (between nodes 10655 and 10660) than anywhere else on the network. This is not surprising, since Eglinton is a 6-lane arterial road. On the other hand, the traffic flow on Birchmount (represented by the links connecting nodes 10660, 10661 and 10663) is extremely low. At first glance, the results of the simulation hardly seem credible.

These predicted flows were compared with actual traffic counts recorded within the vicinity of this network between 1985 and 1995. These traffic counts are illustrated in Figure 5.3, in which the average value was used whenever there was more than one count that was recorded at the same location during this period.

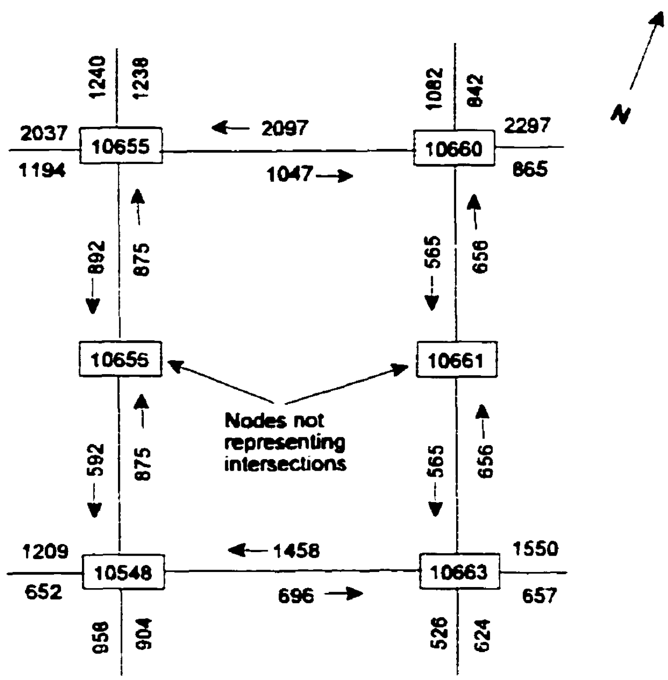


FIGURE 5.3 Morning peak hour flows (veh/hr) taken from traffic counts on the physical network

By comparing the flows of Figure 5.3 with those of Figure 5.2, one notes that the predicted flows of EMME/2 are grossly inaccurate. Moreover, the predicted flows are underestimated for the entire network. This inaccurate prediction may be caused by a variety of factors, such as problems associated, respectively, with the O-D matrix, volume-delay functions, and traffic assignment procedures. The goal of this research, however, is not to explain the causes of such inaccuracies. This subject is left for other researchers to explore.

Based on the outcome of the traffic flow analysis, it can be easily argued that the EMME/2 output flow cannot be used to estimate the number of accidents in the sample network. Indeed, it is only reasonable to expect that an inaccurate estimation of the traffic flow automatically leads to an incorrect prediction of accidents. In order to pursue the description in this section, the EMME/2 output flows were substituted with the actual traffic counts appearing in Figure 5.3. The recorded flows were therefore used as the input flow in the APMs.

5.1.3 PREDICTION OF ACCIDENTS

Before explaining how the APMs were applied on a digital network, it is necessary to describe how the hourly flows were expanded into daily flows. The output flows of many transportation planning programs typically are expressed in vehicles per hour. Thus, the flows cannot be used directly in models that incorporate the annual average daily traffic (AADT) as input. The description of how the hourly flows were expanded into AADT flows is presented in the next two paragraphs.

Several expansion factors were used to transform the morning peak hour flows to AADT. These factors were computed from actual traffic counts recorded on Eglinton, Birchmount, St. Clair, and Warden between 1985 and 1995 (Figure 5.4). Factors were developed according to whether the arterial road was located in the east-west or north-south axis. The exploratory analyses showed that the factors were very similar for the two roads located on the same axis. A different factor was utilized depending on the direction of traffic for each link.

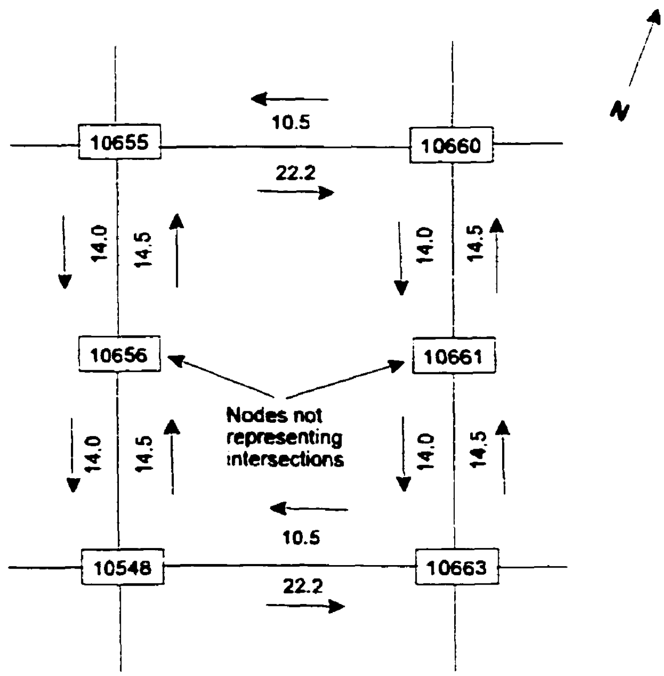


FIGURE 5.4 Expansion factors to transform morning peak hour flows to AADT for the sample network

The factors used in this research were computed from the actual area on which the digital network was based. However, it may not always be possible to create expansion factors as performed here. Consequently, it is suggested to potential users of this approach that they apply expansion factors available from other sources. For instance, many traffic engineering textbooks (see McShane and Roess, 1990; and ITE, 1992) already have expansion factors that can be used to enlarge morning peak hour counts to average daily traffic (ADT) and AADT. Nonetheless, the chosen factors preferably should be created from the immediate vicinity in which the analysis is performed.

The AADT flows expanded from the recorded traffic counts are shown in Figure 5.6. The traffic hourly counts were expanded with the factors of Figure 5.4. It should be pointed out that the majority of links in Figure 5.6 flows have balanced flows (i.e., similar flow volumes in opposite directions on the same link).

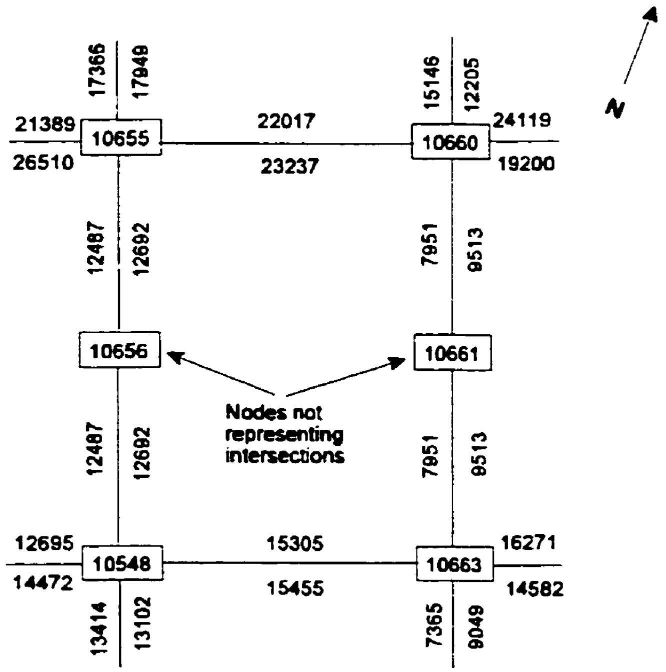


FIGURE 5.5 Expanded AADT flows from traffic counts on the physical network

The expanded AADT output flows of Figure 5.5 were used as input in the three types of APMs. The number of accidents at nodes was estimated with the signalized 4-legged intersection model, since all the nodes are signalized with four approaches. The predicted accidents were estimated at nodes 10655, 10680, 10663, and 10658, all of which represent actual physical intersections, as opposed to the nodes 10656 and 10661, neither of which represent a physical intersection. The number of accidents on the links connecting nodes 10655, 10658, 10680, and 10663 was calculated by the link models. Moreover, the number of accidents for the mid-block sections was estimated with the 4-lane non-central business district (CBD) and 6-lane link models. Finally, the coefficient α_6 (1995) was used for each model.

The predicted mid-block accidents on Warden and Birchmount were multiplied by the adjustment factors indicated in Table 5.3. The mid-block models were originally estimated from a sample of road sections located between nodes representing major physical intersections. The mid-block models cannot be used directly on Warden and Birchmount since nodes 10656 (on Warden) and 10661 (on Birchmount) do not represent physical intersections. Since a non-linear relationship exists between the distance and the number of mid-block collisions, the models predict more accidents at each section individually, than when applied on the entire link, as they purportedly are supposed to be. Thus, adjustment factors are used to make the addition of both sections equal to the prediction of the entire link. The factors presented in Table 5.3 were computed for different values of β, the power coefficient of L (i.e., L^{β}). The factors shown in this table should only be used if both sections are split evenly. The predicted accidents at each section is therefore multiplied by one of these factors. In short, the mid-block models are used on each section separately, but are multiplied by an adjustment factor.

TABLE 5.3 Adjustment factors for the mid-block component

coefficient β	0.40	0.50	0.60	0.70	0.80	0.90	1.0
Adjustment factors	0.66	0.71	0.76	0.81	0.87	0.93	1.0

For uneven split sections or for digital networks that include all minor physical intersections (the original link may divided into more than two sections), the predicted accidents for each section has to be multiplied by the following equation:

$$AF = \frac{P}{P^{\beta}} = P^{(1-\beta)} \tag{5.1}$$

where,

AF = adjustment factor;

P = proportion of original link ($0 < P \leq 1$), where P = length of section divided by the total length of original link (as described above);

β = power coefficient of L.

An illustration on how the models were applied on the sample network is presented below. The illustration is shown for node 10655, which represents the intersection of Eglinton and Warden and the link between nodes 10655 and 10656 on Warden Avenue. The application is illustrated for 1995 (t=6).

Node 10655 (Eglinton/Warden):

As seen in Figure 5.5, the flows F_1 and F_2 are:

F_1 = 26510 + 22017 = 48527 *veh/day*

F_2 = 17366 + 12692 = 30058 *veh/day*

Given the information above, the expected number of accidents becomes (equation 4.1c)

$$E\{\kappa_6\}_N = 0.0002132 \times (48527)^{0.527} \times (30058)^{0.568} \times e^{(8.61E-6 \times 30058)} = 31.4 \ acc/year$$

Link 10655-10656:

As seen in Figure 5.5 and Table 5.1, the link flow F and the length L are respectively:

F = 12487 + 12692 = 25179 *veh/day*
L = 0.825 *km*

The estimation of accidents on links is divided into two components (see Chapter Four): *intersection and mid-block components.*

1. INTERSECTION COMPONENT

On this link, there are four intersections: one signalized 4-legged intersection (Comstock Road) and three unsignalized 3-legged intersections (Civic Road, Sherry Road, and Malley Road). Thus, two models (IS4L= signalized 4-legged and IU3L= unsignalized 3-legged) are used to predict accidents for the intersection component. They are:

$$E\{\kappa_6\}_{IS4L} = 1 \times 0.008339 \times (25179)^{0.614} = 4.7 \textit{ acc/year}$$
$$E\{\kappa_6\}_{IU3L} = 3 \times 3.50E-7 \times (25179)^{1.675} \times e^{(4.84E-6 \times 25179)} = 6.9 \textit{ acc/year}$$

The total expected number of accidents for the intersection component becomes:

$$E\{\kappa_6\}_U = E\{\kappa_6\}_{IS4L} + E\{\kappa_6\}_{IU3L}$$
$$= 4.7 + 6.9 = 11.6 \textit{ acc/year}$$

2. MID-BLOCK COMPONENT

The link 10655-10656 has four lanes and is located in a non-CBD area. Therefore, the estimation of accidents is computed with equation (4.2a) in Chapter Four. The predicted number of accidents can be computed with the following equation:

$E\{\kappa_6\}_{LM}$ = 0.00009457 x $(0.825)^{0.498}$ x $(25179)^{0.614}$ = 18.6 *acc/year*

Since the coefficient β is below unity and since the link is not bounded by nodes representing a physical intersection, the result of the equation immediately above has to be multiplied by 0.71 (as indicated in Table 5.3). The new value then becomes:

$E\{\kappa_6\}_{LM}$ = 18.6 x 0.71 = 13.2 *acc/year*

The total expected number of accidents in 1995 for the link 10655-10656 now equals:

$E\{\kappa_6\}_L = E\{\kappa_6\}_U + E\{\kappa_6\}_{LM}$ = 11.6 + 13.2 = 24.8 *acc/year*

The proportion of predicted mid-block accidents (53%) is very similar to the proportion calculated from the City of Toronto accident database (55%).

The application results of the models on the sample network are presented in Table 5.4. The standard deviation and the actual number of accidents are included in this table. The graphical representation of the results in Table 5.4 is illustrated in Figure 5.6. The number inside the parentheses in this figure is the actual number of accidents that occurred on the physical network for 1995.

TABLE 5.4 Expected and actual number of accidents on the sample network for expanded network traffic counts

	S4L		S3L		U4L		U3L		Intersection Component		Mid-block Component		Total	
Link/Node	$\hat{E}\{\kappa\}$	K	$\hat{E}\{\kappa\}$	K	$\hat{E}\{\kappa\}$	K	$\hat{E}\{\kappa\}$	K	$\hat{E}\{\kappa\}$	K	$\hat{E}\{\kappa\}$	K	$\hat{E}\{\kappa\}$	K
10660-10661			**1.6** (0.89)	**4**			**3.6** (2.27)	**3**	**5.2** (2.44)	**11**	**8.6** (4.53)	**5**	**13.8** (7.84)	**12**
10661-10663							**5.4** (3.41)	**4**	**5.4** (3.41)	**4**	**8.4** (4.42)	**15**	**13.8** (8.48)	**19**
10655-10660							**6.9** (4.38)	**17**	**6.9** (4.38)	**17**	**27.2** (12.6)	**15**	**34.2** (16.6)	**32**
10548-10663							**4.9** (3.08)	**0**	**4.9** (3.08)	**0**	**23.0** (12.1)	**12**	**27.9** (13.8)	**12**
10655-10656	**4.7** (2.43)	**8**					**6.9** (4.33)	**6**	**11.6** (4.83)	**12**	**13.2** (6.96)	**14**	**24.8** (13.1)	**26**
10656-10548	**4.7** (2.43)	**2**			**3.7** (2.26)	**0**	**2.3** (1.44)	**1**	**10.7** (3.43)	**3**	**13.0** (6.87)	**10**	**23.7** (10.7)	**13**
10660													**27.4** (10.4)	**17**
10663													**16.8** (6.39)	**15**
10655													**32.5** (12.4)	**28**
10548													**22.1** (8.39)	**12**
Total on network													**236.9** (35.5)	**186**

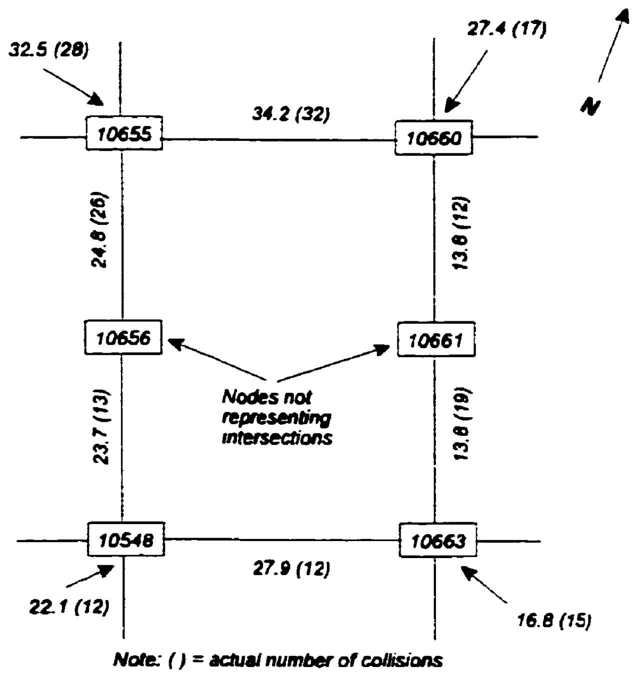


FIGURE 5.6 Predicted accidents (acc/yr) on the sample network with expanded traffic flow counts (1995)

Table 5.4 and Figure 5.6 reveal that Eglinton (link 10655-10660) has the highest number of predicted accidents, while both sections of Birchmount have the lowest number of predicted accidents. In general, the models predict values that are very similar to the true accident counts that occurred on the physical network.

In summary, this section has shown how to apply the three types of models on a digital network. It was demonstrated that the output flows of transportation planning software programs may not always be adequate to predict accidents on urban networks. In fact, bad traffic estimates necessarily lead to an inaccurate appraisal of network safety. Thus, it is imperative that the predicted flows truly reflect the traffic conditions on the physical network. It has also been shown that the application of models is dependent on how the network is coded. The predicted accidents on links have to be adjusted since the non-linear relationship exists between accidents and length. The application of APMs within the urban transportation planning process is presented in the next section.

5.2 APPLICATION OF MODELS WITHIN THE URBAN TRANSPORTATION PLANNING PROCESS

The APMs can be used efficiently to evaluate several scenarios during the urban transportation planning process. Thus, this section shows how the models can be used to compare the safety of networks quantitatively for different scenarios. However, the limitations regarding the application of the models for comparison purposes are also explained. It should be pointed out that the sample network used in this section is not based on any specific physical network.

The hypothetical network was built arbitrarily with EMME/2. Under the assumption that the estimated flows were predicted accurately by the program, the expected number of accidents was initially computed for the original layout. Next, the network was modified according to two scenarios. In the first scenario, two links were transformed from a 2-lane to a 4-lane road. This transformation was undertaken to represent a road widening process. In the second scenario, a centroid was added somewhere inside the network to assess the effects on traffic flow patterns and on the number of predicted accidents when a major traffic generator (e.g., supermarket, casino) is added to a network. No changes in the physical characteristics of the network were performed for this scenario. For both scenarios, the traffic flows and number of accidents were then re-estimated and the results compared with the output of the original network. Finally, the analysis also included the prediction of accidents for traffic flows forecasted within the next ten years.

5.2.1 DESCRIPTION OF SAMPLE NETWORK

The hypothetical sample network has 15 nodes, 6 centroids, 18 links, and 6 centroid connectors. Nine nodes are used to represent intersections, while the other six nodes are employed as gateway nodes located between the centroids at the outskirts of the network and the street system. The hypothetical physical network is illustrated in Figure 5.7a and its digital representation appears in Figure 5.7b.

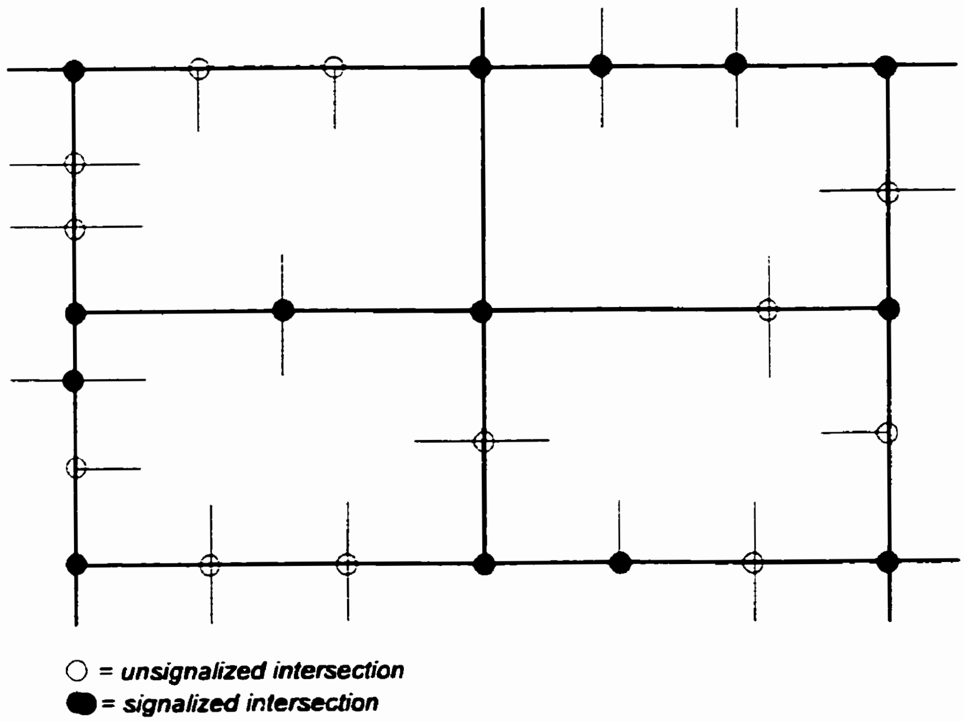


FIGURE 5.7a Hypothetical physical network

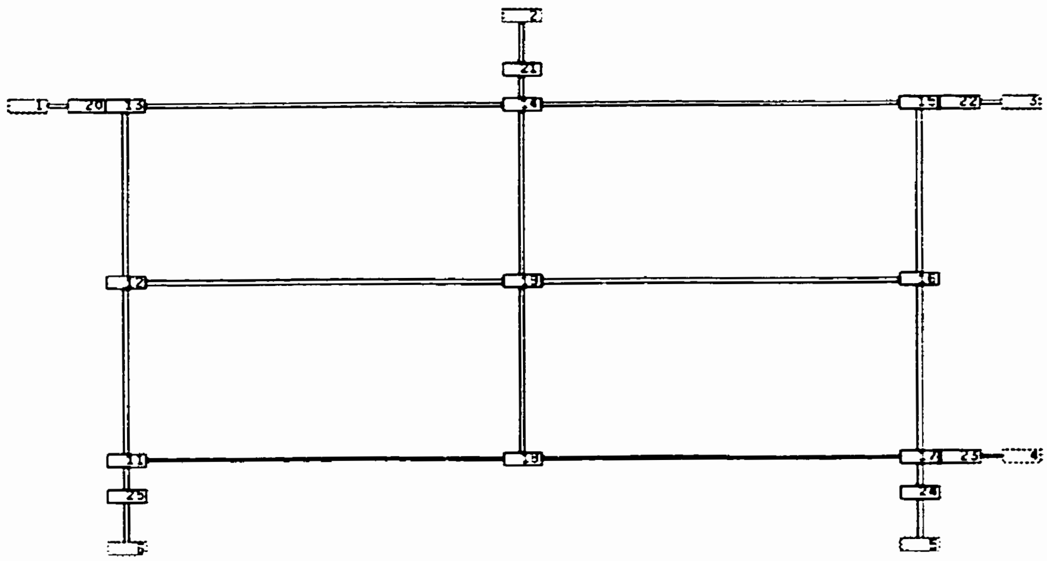


FIGURE 5.7b EMME/2 digital representation

The sample network is four kilometers wide by two kilometers long. The attributes of the links and nodes are presented in Tables 5.5 and 5.6 respectively. It should be noted that only the links and nodes located inside the rectangle bounded by nodes 11, 13, 15, and 17 are presented in the two tables. The prediction of accidents was performed on these links and nodes exclusively. The other links were used only to connect the centroids with the rectangular network. The application of the models to the sample network is presented in the next section.

TABLE 5.5 Characteristics of links in the sample network

Link (node to node)	lanes	Sig4L	Sig3L	Unsig4L	Unsig3L	length (km)	length - intersections
11-12	1	1	0	0	1	1.00	0.94
12-13	1	0	0	2	0	1.00	0.94
13-14	2	0	0	0	2	2.00	1.94
14-15	2	2	0	0	0	2.00	1.94
15-16	1	0	0	1	0	1.00	0.97
16-17	1	0	0	0	1	1.00	0.97
17-18	2	0	1	1	0	2.00	1.94
18-11	2	0	0	2	0	2.00	1.94
12-19	3	1	0	0	0	2.00	1.97
14-19	2	0	0	1	0	1.00	0.97
16-19	3	0	0	1	0	2.00	1.97
18-19	2	0	0	1	0	1.00	0.97

TABLE 5.6 Characteristics of nodes in the sample network

Node	Sig4L	Sig3L	Unsig4L	Unsig3L
11	0	1	0	0
12	0	1	0	0
13	0	1	0	0
14	1	0	0	0
15	0	1	0	0
16	0	1	0	0
17	1	0	0	0
18	0	1	0	0
19	1	0	0	0

5.2.2 PREDICTION OF ACCIDENTS FOR THE ORIGINAL LAYOUT

The O-D input matrix used for the sample network is presented in Table 5.7. This matrix has a total of 9800 vehicle-trips. The traffic assignment output is presented in Figure 5.8.

TABLE 5.7 Origin-destination input matrix in veh/hr for the sample network

O/D	1	2	3	4	5	6	Total
1	0	300	500	200	400	300	1700
2	400	0	200	300	300	400	1600
3	200	400	0	500	300	200	1600
4	300	300	200	0	300	500	1600
5	500	200	400	300	0	200	1600
6	300	400	300	300	400	0	1700
Total	1700	1600	1600	1600	1700	1600	9800

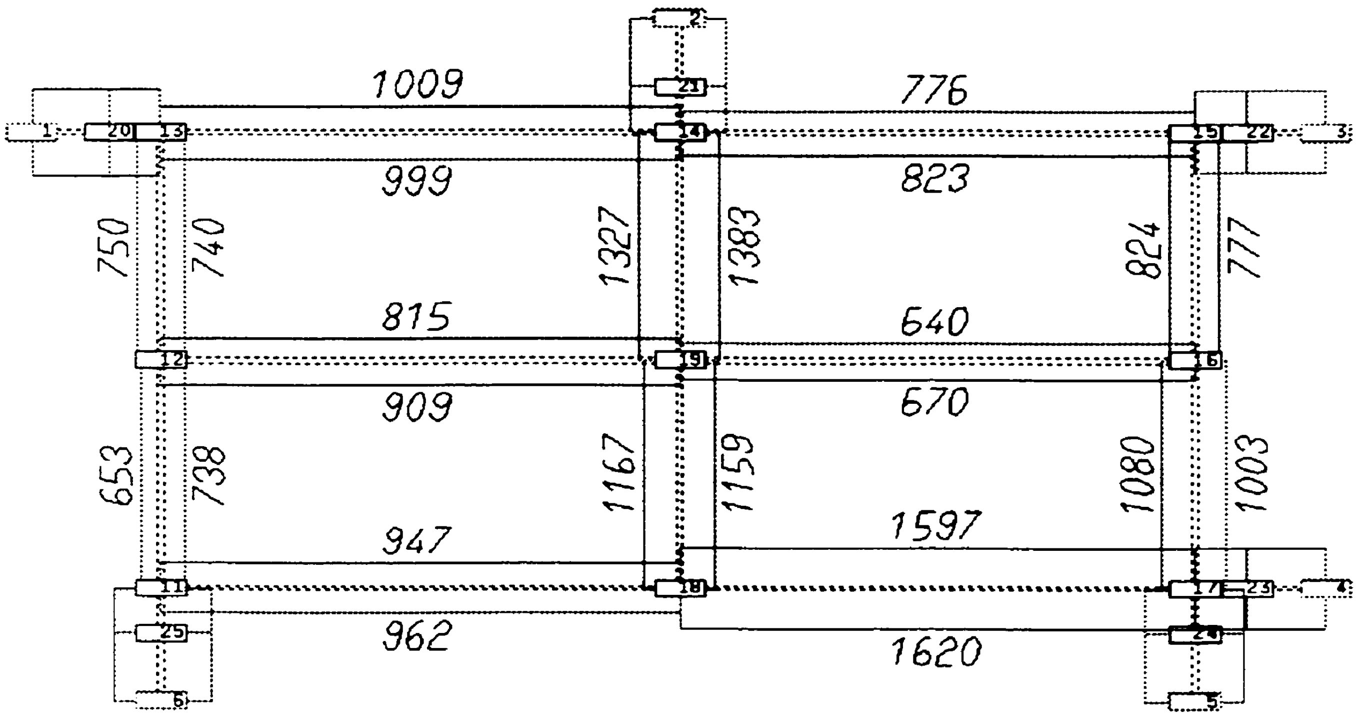


FIGURE 5.8 EMME/2 traffic flow output (veh/hr) for the sample network

The output flows were expanded to AADT with an average factor computed from the Toronto data. The flows were then used as input in the three types of APMs. The models used for each element of the network included those for 2-lane, 4-lane, 6-lane roads and signalized 3- and 4-legged intersections. They also included both specific (3-legged, 4-legged, signalized, unsignalized) and general models (no distinction between the attributes of non-node intersections) for the intersection component. The accidents were predicted for injury, PDO and injury + PDO, and with the average coefficient α.

The application results of the APMs on the sample network are presented in Table 5.8. The graphical representation of the results is shown in Figure 5.9. To improve the clarity of the tables and graphs, the standard deviation of the expected number of accidents is not shown.

TABLE 5.8 Expected number of accidents on the sample network

Link/Node	Mid-Block Component			Intersection Component (Specific models)			Intersection Component (General model)			Total Columns 1 + 2		
	0	P	I+P	I	P	I+P	I	P	I+P	I	P	I+P
11-12	3.1	9.4	12.4	1.8	4.4	6.1	1.9	4.5	6.4	4.9	13.7	18.5
12-13	3.3	9.7	12.8	1.9	4.9	6.8	2.0	4.6	6.6	5.1	14.6	19.6
13-14	9.0	24.2	33.3	1.5	3.7	5.3	2.4	5.4	7.8	10.5	27.9	38.5
14-15	7.4	20.5	28.0	1.3	3.3	4.6	2.1	4.8	6.9	8.7	23.7	32.5
15-16	3.5	10.2	13.5	1.0	2.6	3.5	1.0	2.4	3.4	4.4	12.8	17.1
16-17	3.9	11.4	15.4	0.8	1.9	2.7	1.2	2.8	4.0	4.7	13.3	18.0
17-18	13.3	34.2	47.6	3.1	7.2	10.2	3.3	6.9	10.1	16.4	41.5	57.8
18-11	8.6	23.3	32.0	2.1	5.7	7.8	2.3	5.3	7.6	10.7	29.1	39.8
12-19	5.4	18.1	23.7	1.5	3.1	4.5	1.1	2.5	3.6	6.8	21.2	28.2
14-19	10.4	29.3	39.4	1.3	3.5	4.8	1.5	3.2	4.6	11.6	32.8	44.2
16-19	3.3	9.1	12.2	0.9	2.3	3.2	0.9	2.2	3.1	4.2	11.4	15.3
18-19	6.9	22.6	29.8	1.2	3.2	4.4	1.3	2.9	4.2	8.1	25.8	34.2
11										3.5	9.1	12.7
12										2.1	6.0	8.0
13										3.5	8.7	12.3
14										7.4	17.6	25.2
15										3.3	8.3	11.6
16										2.3	6.2	8.5
17										10.6	25.7	37.1
18										4.2	10.9	15.2
19										6.0	14.6	20.6
Total										139.3	375.0	515.0

*Note: I = injury, P=PDO, I+P = injury + PDO

The results in Table 5.8 show two interesting findings. First, the addition of the output of the injury and PDO models is equal to the output of the models that combine both injury and PDO collisions (within ±1 accident). The proportion of accidents with injuries (27%)

is also similar to the proportion computed from the City of Toronto accident database (30%). Second, the general model used for the intersection component of links predicts values quite similar to the specific models for most links. Thus, the use of the general model seems to be appropriate for analysts who do not know the exact characteristics of non-node intersections. Finally, the link accidents account for about 70% of all accidents on the network (the ratio of accidents predicted on the mid-block and intersection components respectively is 82/12).

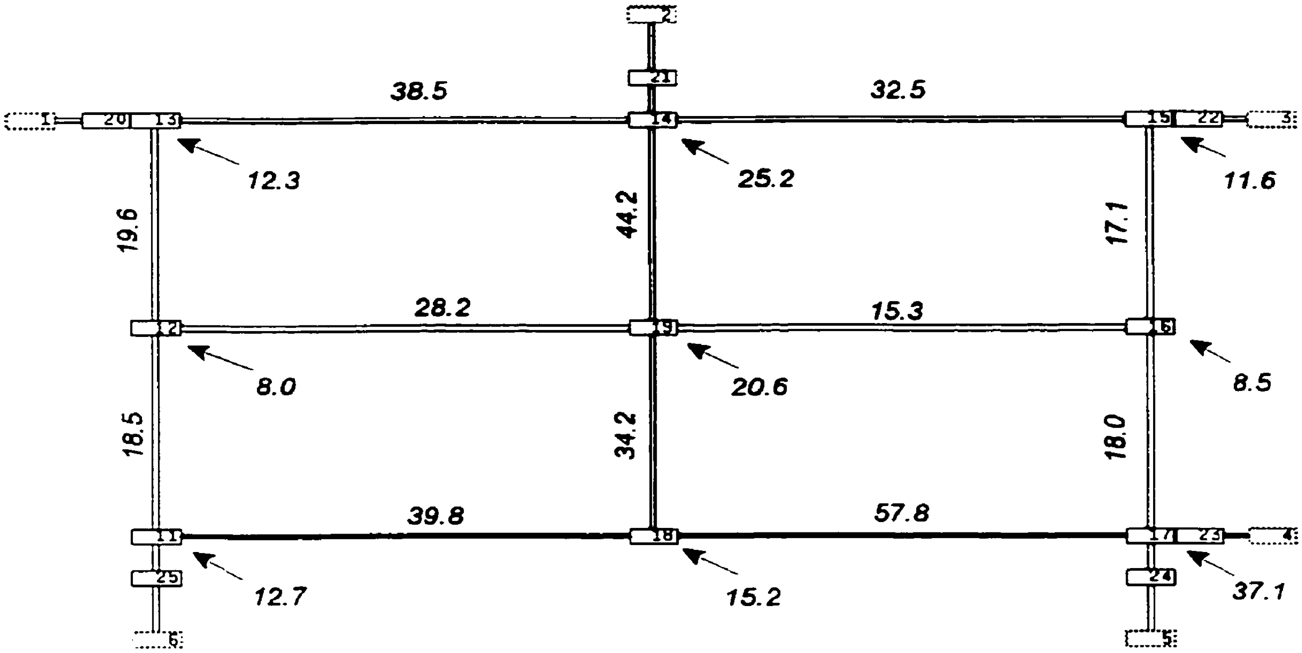


FIGURE 5.9 Predicted accidents (acc/yr) on sample network

5.2.3 PREDICTION OF ACCIDENTS FOR THE MODIFIED NETWORKS

In scenario 1, the sample network was modified by altering the characteristics of two links. Links 15-16 and 16-17, located in the right-hand side of the network, were upgraded from a 2-lane to a 4-lane arterial road. A traffic assignment was then performed with the same

O-D matrix presented in Table 5.7. The traffic flow output in vehicles per hour is presented in Figure 5.10.

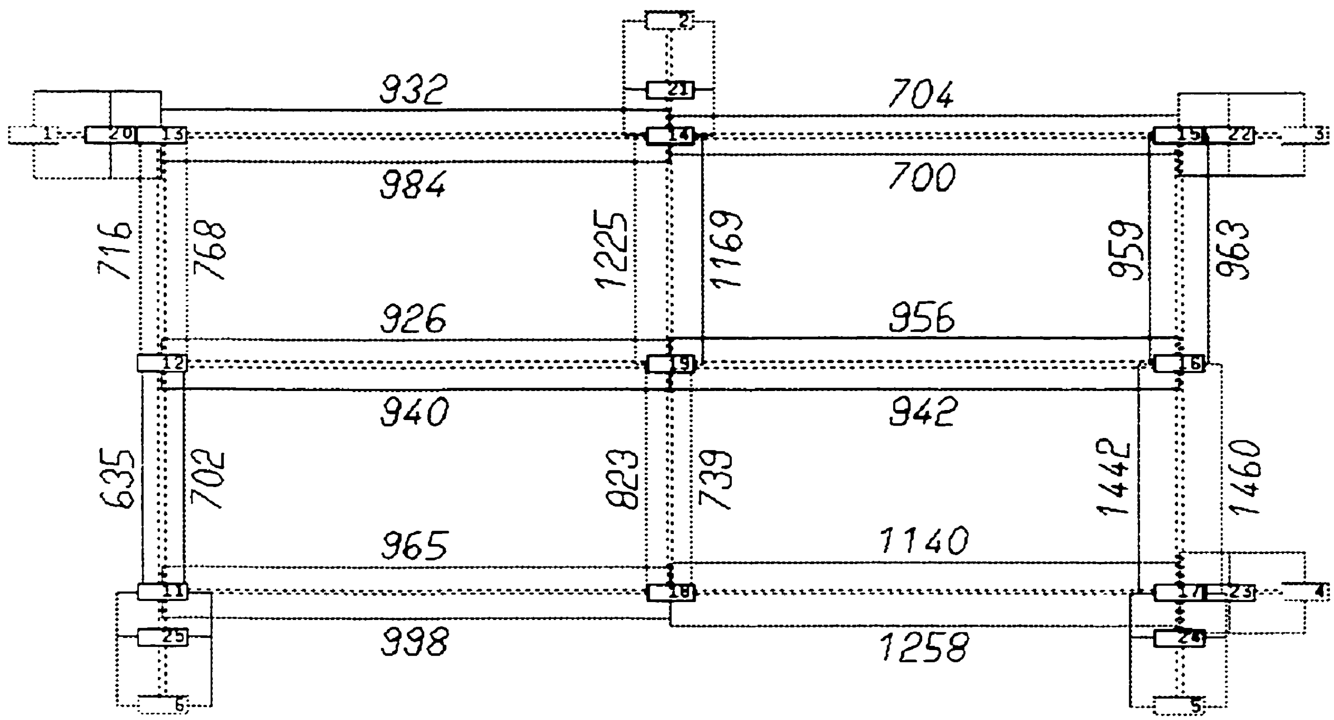


FIGURE 5.10 EMME/2 traffic flow output (veh/hr) for scenario 1

With the addition of a second lane on the links located between the nodes 15 and 17, an important shift in the traffic pattern occurred on the right side of the network. Indeed, links 16-17, 16-19, and 15-16 had an increase of about 800, 600, and 300 veh/hr respectively. On the other hand, the biggest losses occurred on links 17-18, 18-19, and 14-19, with a reduction in traffic flow of about 800, 750, and 300 veh/hr respectively. As expected, the left side of the sample network was less affected, with flows oscillating below 200 veh/hr.

In scenario 2, a seventh centroid was placed in the middle of the network to simulate the impacts of a new important traffic generator (Figure 5.11). This centroid is connected to the network halfway between nodes 16 and 19 with a signalized 3-legged intersection. To keep things simple, a trip-attraction of 150 veh/hr and a trip-destination of 150 veh/hr between the new centroid and each of the other centroids were added to the O-D matrix described in Table 5.7. As a result, an additional 1,800 vehicle-trips were generated on the network. The EMME/2 traffic flow output for scenario 2 is presented in Figure 5.12.

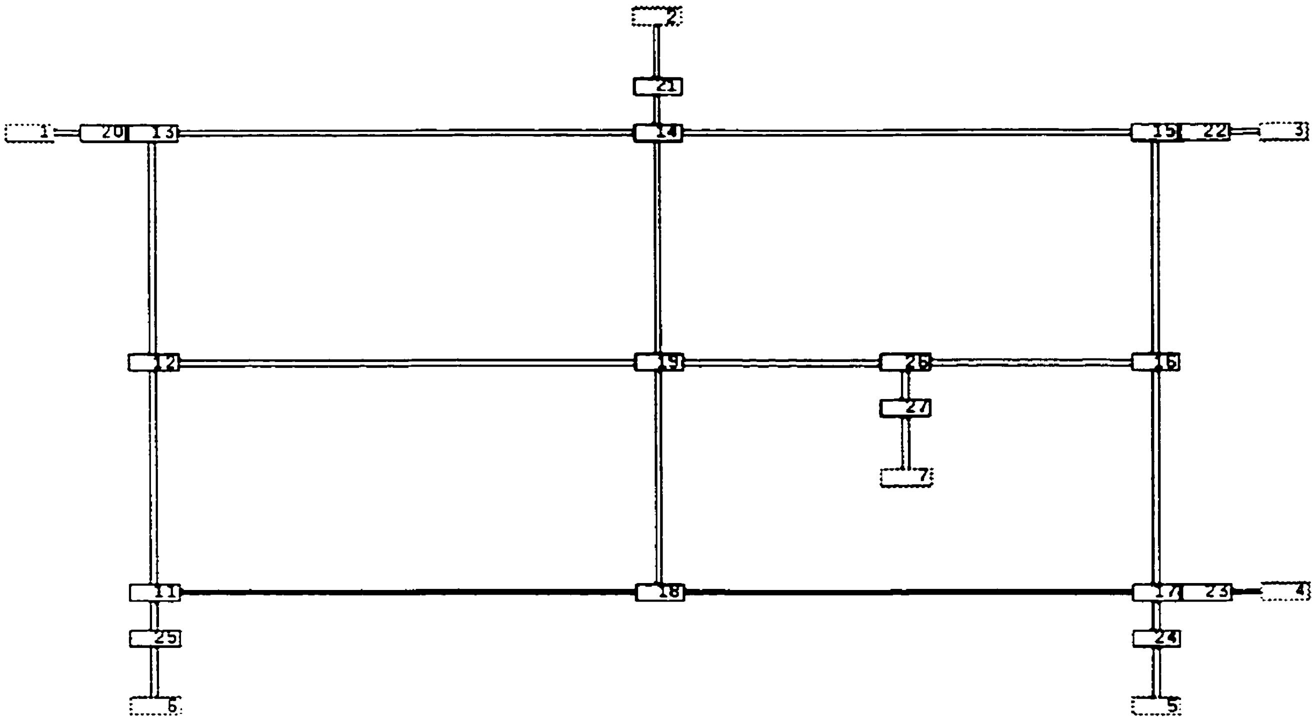


FIGURE 5.11 Network for scenario 2

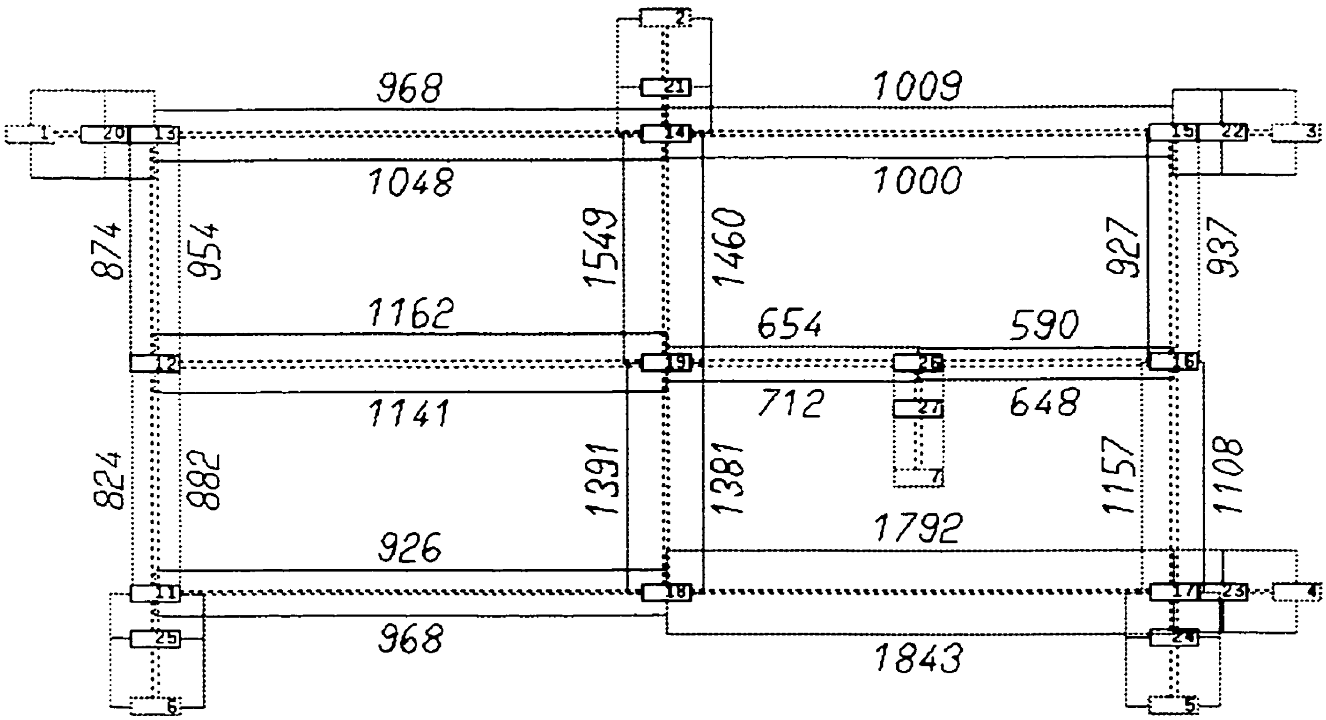


FIGURE 5.12 EMME/2 traffic flow output (veh/hr) for scenario 2

Figure 5.12 shows that the bulk of the traffic can be found on links 17-18, 18-19, 14-19, and 12-19. The output shows that the addition of centroid 7 leads to an important shift in the traffic pattern on the network. Indeed, about 60% of the vehicles using link 16-19 in the original network shifted routes to the aforementioned links.

The predicted accidents were computed for the two modified network with the output of Figures 5.10 and 5.12 respectively. The 4-lane model was used for links located between nodes 15 and 17 for scenario 1. The difference in predicted accidents between the network of scenarios 1 and 2 and the original network is presented in Tables 5.9 and 5.10 respectively. The results are also illustrated in Figures 5.13 and 5.14 respectively, in which the number inside the parentheses represents the difference in predicted accidents.

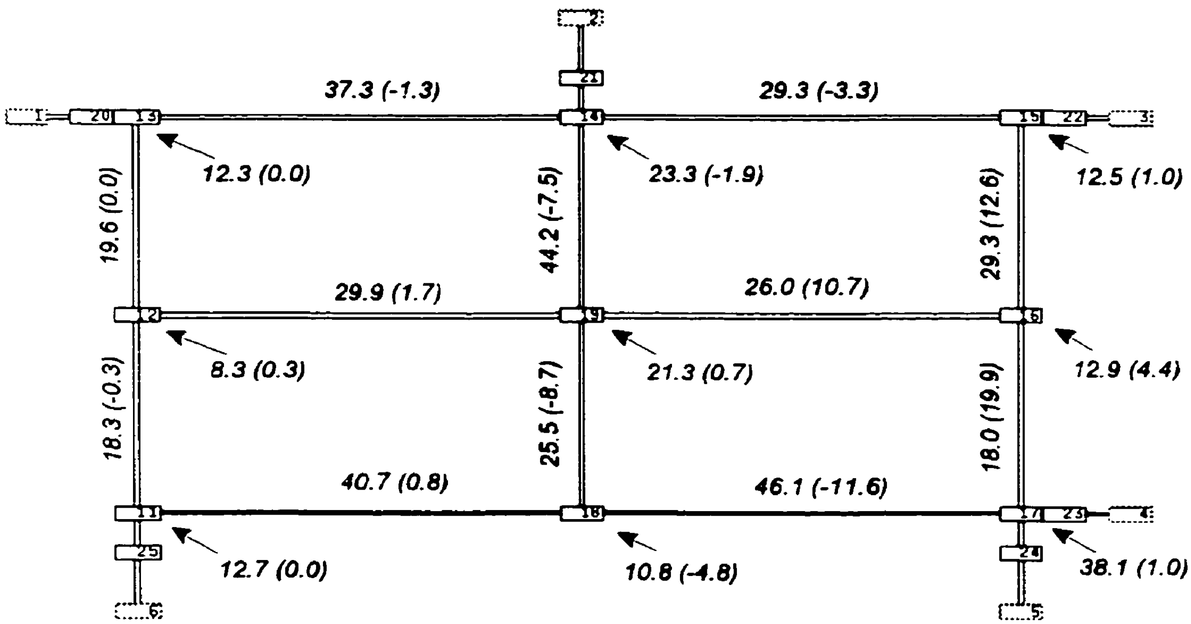
TABLE 5.9 Difference in the expected number of accidents (scenario 1 - original layout)

Link/Node	Mid-Block Component			Intersection Component (Specific models)			Total Columns 1 + 2		
	I	P	I+P	I	P	I+P	I	P	I+P
11-12	*-0.04	-0.11	-0.15	-0.04	-0.06	-0.10	-0.08	-0.17	-0.26
12-13	-0.01	-0.02	-0.02	-0.00	-0.01	-0.02	-0.01	-0.03	-0.04
13-14	-0.35	-0.83	-1.17	-0.05	-0.03	-0.08	-0.40	-0.86	-1.25
14-15	-0.77	-1.88	-2.64	-0.21	-0.41	-0.61	-0.98	-2.29	-3.25
15-16	2.44	9.45	12.21	0.10	0.29	0.39	2.53	9.75	12.60
16-17	4.40	15.16	19.92	0.03	-0.06	-0.03	4.43	15.11	19.89
17-18	-2.91	-6.62	-9.47	-0.74	-1.48	-2.16	-3.64	-8.09	-11.63
18-11	0.21	0.49	0.69	0.03	0.09	0.13	0.24	0.58	0.82
12-19	0.37	1.09	1.48	0.08	0.15	0.23	0.45	1.24	1.70
14-19	-1.82	-5.27	-7.15	-0.08	-0.25	-0.33	-1.90	-5.52	-7.48
16-19	2.61	7.41	9.98	0.19	0.56	0.75	2.80	7.97	10.73
18-19	-1.98	-5.76	-7.81	-0.22	-0.67	-0.90	-2.20	-6.43	-8.71
11							0.01	0.05	0.06
12							0.04	0.25	0.28
13							-0.03	-0.01	-0.03
14							-0.58	-1.18	-1.90
15							0.21	0.77	0.96
16							1.31	3.07	4.41
17							0.17	1.00	1.07
18							-1.27	-3.08	-4.37
19							-0.03	0.82	0.70
Total							1.06	12.97	14.29

* a positive number indicates an increase in the expected number of accidents.

Underline: change in predicted accidents significant (5%)

Table 5.9 shows that the total number of accidents increased by about 14 acc/year. Similar to the trend shown in Figure 5.10, accident counts increased significantly on links 15-16, 16-19 and 16-17, while a reduction in the accident counts occurred on links 17-18, 18-19, and 14-19 respectively. Interestingly, the intersection component of links does not significantly influence the changes in the expected number of accidents, despite an increase of 10,000 veh/day on some links. Here, the change in accident counts is attributed primarily to the mid-block component. Similarly, the expected number of accidents at nodes does not change drastically. The greatest increase in accidents occurred at node 16 with a gain of 4.41 acc/year, while the largest decrease happened at node 18, with a reduction of 4.37 acc/year. Based on the results in Table 5.9, it can be concluded that the addition of a second lane on the right side of the sample network leads to a decrease in safety.



Note: the number inside the parentheses represents the difference between modified and original networks

FIGURE 5.13 Predicted accidents (acc/yr) for scenario 1

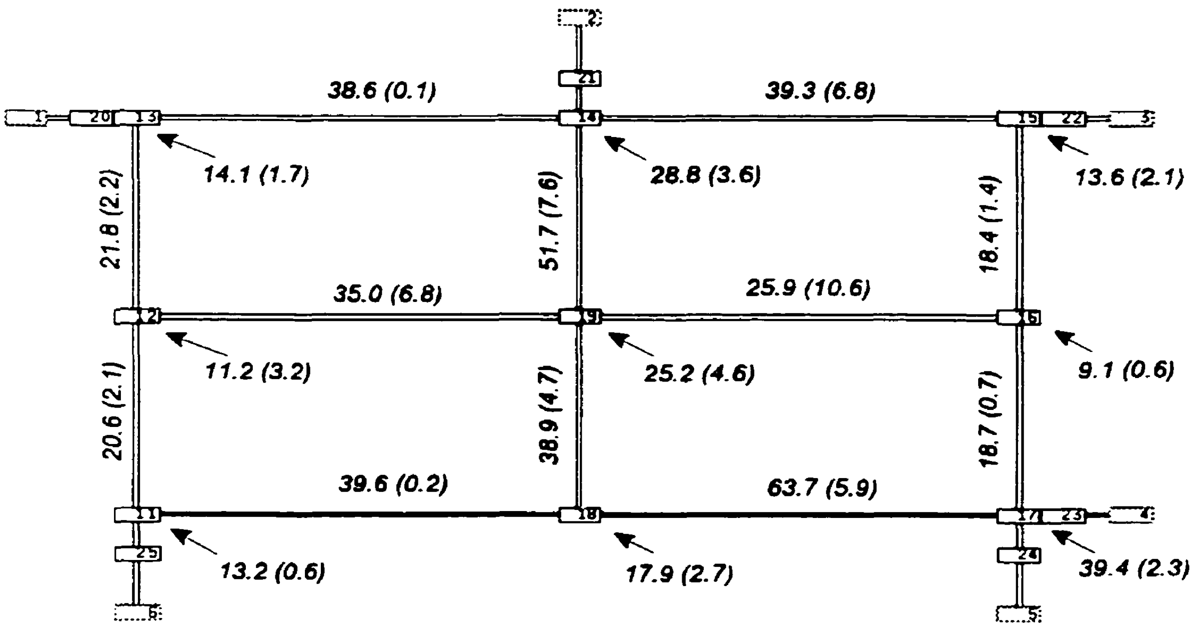
TABLE 5.10 Difference in the expected number of accidents (scenario 2 - original layout)

Link	Mid-Block Component			Intersection Component (Specific models)			Total Columns 1 + 2		
	I	P	I+P	I	P	I+P	I	P	I+P
11-12	0.34	0.90	1.27	0.34	0.49	0.82	0.68	1.38	2.09
12-13	0.35	0.93	1.32	0.21	0.63	0.85	0.56	1.56	2.17
13-14	0.03	0.07	0.10	0.00	0.00	0.01	0.03	0.07	0.11
14-15	1.61	3.84	5.44	0.48	0.89	1.33	2.09	4.73	6.77
15-16	0.27	0.72	1.02	0.08	0.24	0.32	0.35	0.96	1.35
16-17	0.17	0.44	0.63	0.03	0.01	0.04	0.20	0.45	0.67
17-18	1.49	3.32	4.78	0.40	0.76	1.12	1.89	4.08	5.90
18-11	0.06	0.14	0.19	0.01	0.03	0.04	0.07	0.16	0.23
12-19	1.49	4.32	5.87	0.32	0.57	0.88	1.81	4.89	<u>6.75</u>
14-19	1.84	5.34	7.25	0.07	0.22	0.30	1.91	5.57	<u>7.55</u>
16-19	0.68	2.47	3.06	0.03	0.07	0.10	<u>2.56</u>	<u>8.18</u>	<u>10.60</u>
18-19	1.11	3.13	4.27	0.11	0.35	0.47	1.22	3.48	4.74
11							0.21	0.35	0.56
12							0.86	2.33	<u>3.19</u>
13							0.44	1.29	1.74
14							0.96	2.45	3.55
15							0.59	1.45	2.05
16							0.21	0.37	0.59
17							0.70	1.30	2.33
18							0.79	1.90	2.70
19							1.37	2.95	<u>4.58</u>
Total							<u>19.37</u>	<u>49.57</u>	<u>69.75</u>

* a positive number indicates an increase in the expected number of accidents.

Underline: change in predicted accidents significant (5%)

Table 5.10 reveals that an increase of 1,800 vehicle-trips (~16%) leads to an increase of about 13% in the predicted accidents on the entire network. The biggest increases occur on every link that connects to node 19. For link 16-19, the increase in accidents is attributed primarily to the new node 26.



Note: the number inside the parentheses irepresents the difference between modified and original networks

FIGURE 5.14 Predicted accidents (acc/yr) for scenario 2

Based on the results shown in Tables 5.9 and 5.10, it would be possible to implement additional measures to minimize the increase in accidents for links and nodes plagued by a high decrease in safety. One could, for example, implement procedures that would redistribute the flow of traffic within the network. Alternately, one could attempt various localized interventions (site specific) to improve safety, such as at nodes 19 and 26 for scenario 2.

The application of APMs for comparison purposes can be problematic however. The models were applied with the assumption that all the characteristics with the exception of the selected modified ones remained unchanged. Obviously, it is unreasonable to expect that a modification for one road characteristic will not affect other factors that influence traffic accidents. For instance, increasing the capacity of a road may influence the land-use located along the modified links or nodes (private entrances, parking, etc.). In other instances, transportation agencies may automatically conduct minor road improvements within the vicinity of an added traffic generator. Unfortunately, the models proposed in this thesis may not be able to capture such changes. Thus, they may not be adequate to evaluate changes in safety for highly detailed networks nor for minor road upgrades such as the addition of a raised median on road sections.

More detailed models could be used to capture minor changes such as the ones described above. However, the main issue here is the availability of information about the physical characteristics of the network. It may be difficult to know, at the planning stage, the exact physical characteristics of roads and intersections or the type of land-use located within different sections of the network. Consequently, it may be difficult to use detailed models when the analyst has incomplete information about the network. Nonetheless, the models proposed in this thesis provide a good base of comparison since traffic flow is the one of the most important exploratory variables that is associated with accidents.

5.2.4 FORECASTED ESTIMATES

The APMs can also be used to quantify safety at the planning stage for traffic flows forecasted for the future. For instance, transportation agencies are always interested in estimating future traffic and its various impacts (delay, congestion, air pollution, etc.) within a 5-, 10- or 20-year span. With the models developed in Chapter Four, the safety benefits or drawbacks of different scenarios can also be estimated for the same time span. For instance, the coefficients α_t of APMs can be used to establish a possible trend (through regression or otherwise) in the expected number of accidents. For example, in this work, it was decided to employ the average α_t for the last three years for each model and to predict the number of accidents for the original network and scenario 1. The average of the last three years was shown to predict more accidents than did the average over six years. With the assumption that both the trend and all of the other variables (such as the definition to report an accident, etc.) would remain constant, a 1% yearly increase was applied to the traffic flow. The predicted accidents were estimated for the next 10 years for the two networks. The application results of the APMs on the two networks are presented in Table 5.11.

TABLE 5.11 Forecasting of predicted accidents for the original network and scenario 1

Year	Original	Layout 1	Difference
0	**526.9** *(56.3)	**543.3** (57.2)	**16.4**
1	**532.1** (56.9)	**548.7** (57.7)	**16.6**
2	**537.3** (57.4)	**554.2** (58.3)	**16.9**
3	**542.6** (57.9)	**559.7** (58.8)	**17.1**
4	**548.0** (58.5)	**565.3** (59.4)	**17.3**
5	**553.4** (59.0)	**571.0** (60.0)	**17.6**
6	**558.9** (59.6)	**576.7** (60.5)	**17.8**
7	**564.5** (60.2)	**582.5** (61.1)	**18.0**
8	**570.1** (60.7)	**588.4** (61.7)	**18.3**
9	**575.7** (61.3)	**594.4** (62.3)	**18.7**
10	**581.5** (61.9)	**600.4** (62.9)	**18.9**
Total	**5564.1**	**5741.3**	**177.2**

* standard deviation

Table 5.11 shows that, over 11 years (including year 0), there are approximately 177 more accidents on the network of scenario 1 than on the original network. For each year, the change in the number of predicted accidents was significant at the 5% level of accuracy. With a yearly increase of 1% in traffic flow, the expected number of accidents also increased by about 1% annually. It is interesting to note that the gap widened over the 10 year periods, as is shown in the last column of the table.

The main issue regarding the application of models for this purpose resides in the availability of information for long term studies. As explained above, it may be difficult to know how many intersections will be built on a physical network that has yet to be built or upgraded, especially in within a 10 or 20-year span. In addition, many characteristics that influence accidents (economic conditions, introduction of new laws and city by-laws, etc.) may change over time. Thus, the models may not be able to predict accurately the number of accidents when used for forecasting accidents in long-term analysis.

5.3 SUMMARY

This chapter contained a demonstration of the application of APMs on digital networks. The mechanics of how the models are applied on a digital network and how the models can be used within the urban transportation planning process were explained in the first and second sections respectively. Two networks were used to illustrate the application of the models on digital networks. The first digital network represented a system of arterial roads located in eastern Toronto. The second digital network, which was not based on any physical network, was created solely to show the changes in network safety when that network is substantially modified. Two scenarios were evaluated for the latter network.

The steps needed to apply the models and to predict accidents on a digital network were methodically described in the first section. Several issues were raised concerning the application of models on digital networks. First, inaccurate predicted flows will automatically lead to an incorrect number of predicted accidents. Thus, the predicted flows must be estimated as accurately as possible. Second, the application of models is dependant on how the network is coded. Indeed, adjustment factors must be employed for link (mid-block) models since a non-linear relationship exists between accidents and length.

The results described in the second section showed that an important change in accident counts occurs if a network is substantially modified. Accident counts increased for both scenarios. The results showed that it would be possible to pin-point problem areas before a facility is built or upgraded; moreover, that it would be possible to implement localized or area-wide safety measures that would minimize, *a priori*, the increase in number of predicted accidents. However, the models showed various limitations when applied for this purpose. For instance, they may not capture minor changes in the physical characteristics of the network. Furthermore, availability in information may be problematic, especially for long-term studies. Thus, APMs should be used with care when applied on digital networks. Two other useful applications of APMs on digital networks are presented in the next chapter.

CHAPTER 6

NETWORK SAFETY

The aim of this chapter is to describe two useful applications of accident prediction models (APMs) on digital networks. In the first application, the APMs are used to find the safest paths between any pair of centroids on a sample network. In the second application, the models are used to examine the safety effects of dynamic route guidance (DRG) systems on digital networks, when accident risk information is communicated to road users. The DRG system is a core component of intelligent transportation systems (ITS). All the issues and limitations related to the application of models for network safety analysis are described in great detail.

6.1 COMPUTATION OF ACCIDENT RISK ON NETWORKS

This section shows how to compute the accident risk on transportation networks. The steps needed to modify the network are explained in section 6.1.1. These steps are required to apply the proposed algorithm described in the next section. The computation of accident risk is described in section 6.1.2. The application of accident risk on a network is demonstrated in section 6.1.3.

6.1.1 MODIFICATION OF NETWORK

The safest path in this analysis was found by locating the route between each pair of centroids for which a driver has the lowest probability of being involved in an accident. The computation of accident risk is explained in the next section. Since the risk of a collision depended on the type of manoeuvre at a node (e.g., turning right, left or travelling through), it was necessary to modify the nodes the sample network used for this demonstration since very few commercially available transportation planning software programs can handle external cost factors for optimization purposes. For instance, EMME/2 (INRO, 1996) cannot assign external cost factors for different turning manoeuvres at nodes. The modification of transportation networks was performed by transforming each node and creating a new series of additional nodes and links that reflected the various turning manoeuvres at the intersection. Note that it would not have been required to modify the network if the same risk was assigned for all turning flows at nodes.

The modification process had to be performed in such way that unusual paths on the digital network were not created. Indeed, the safest path algorithm depended on the direction assigned to a link and unusual paths were created if the network was not re-coded properly. For instance, during the initial recoding of the network, the safest path indicated that a driver, who wanted to turn left, made a right turn, followed by a u-turn, and then travelled straight through the node. Obviously, this kind of travelling behaviour was highly unlikely in a real traffic situation. Thus, a proper modification procedure was developed that eliminated unusual paths. This procedure was separated into five different steps. Each node in a network had to be modified with this five-step procedure (the steps are illustrated in Figures 6.1a and b):

1) Create two extra nodes for each leg connected to the original node (node 5 in Figure 6.1a); one node is used to represent outgoing flows at the intersection and one node is used as the receiving node (Figure 6.1b).

2) Label each new node according to whether the node is an outgoing or an incoming node. It is suggested to use a simple but concise labelling system, as illustrated in Figure 6.1b. For instance, the label 5WO indicates that it is an outgoing node located West of node 5. It is important to label the nodes accurately since the simplest coding mistake automatically leads to a wrong estimate of the safest route.

3) Create a new series of links that connect the outgoing and incoming nodes for each leg (Figure 6.1b). Thus, there is a possibility of 12 new links for a 4-legged intersection.

4) Assign the proper accident risk to each new link. This is explained in the next two sections.

5) Repeat steps 1 to 4 above for all other original nodes.

The new set of nodes and links is used only to find the safest path on a network and is not intended to evaluate flows. In addition, the five-step procedure is only required if the algorithm is used outside a commercially available transportation planning software program.

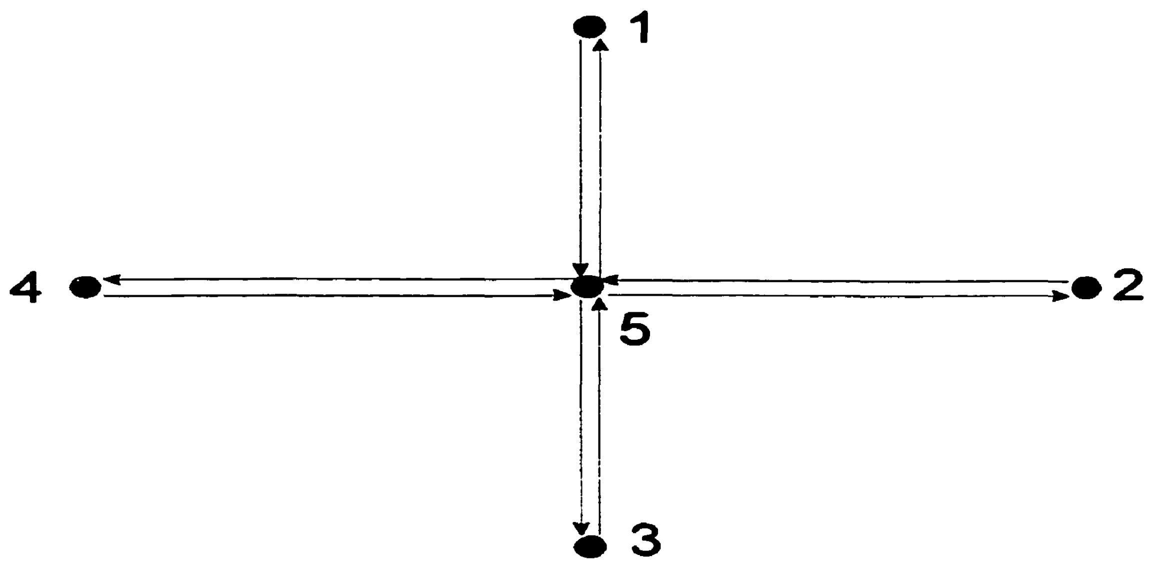


FIGURE 6.1a Original layout

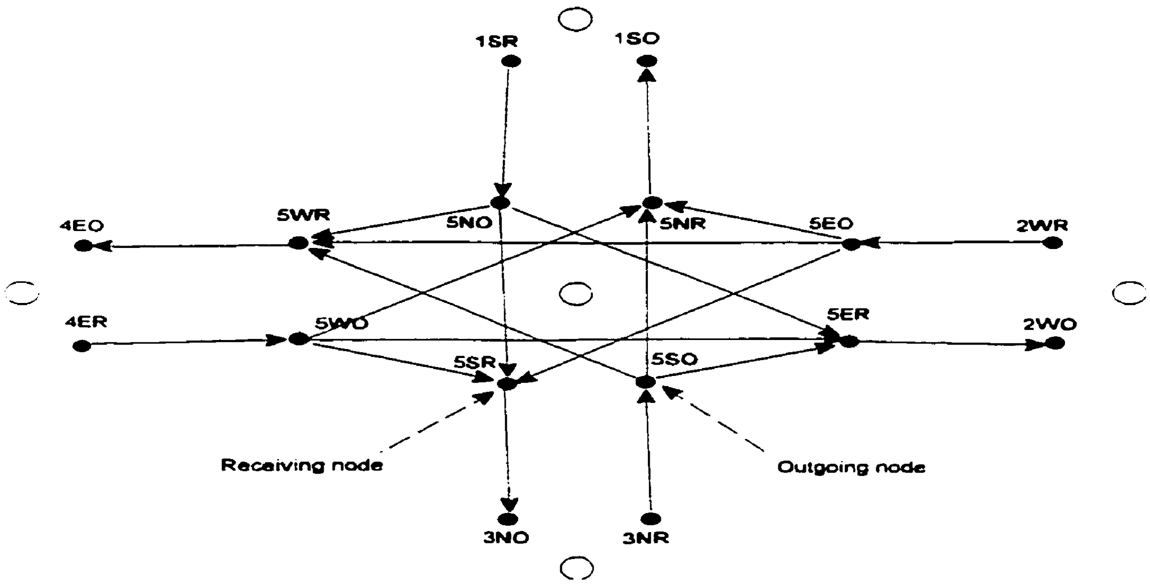


FIGURE 6.1b Modified layout for node 5

6.1.2 ACCIDENT RISK

The risk was estimated with equation (6.1) for each link and node on the sample network. The definition based on this equation is a widely used measure of individual risk; it is extensively applied in epidemiological studies. This definition has also been applied in various traffic safety studies (see Gårder, 1989; Davis *et al.*, 1989; and, Chatterjee and MacDonald, 1998). Equation (6.1) can be defined as the driver's risk of being involved in a collision given a certain level of exposure, that is, the probability that a driver would be involved in an accident on a link or node that has x accidents per day (or year) and y vehicles per day. The equation is as follows:

$$accident\ risk = \frac{expected\ number\ of\ accidents}{exposure} \tag{6.1}$$

The accident risk in equation (6.1) is estimated by dividing the expected number of accidents per unit of time with the traffic flow in vehicles per unit of time for any given link or node, as applied by Chatterjee and MacDonald (1998). By computing the expected number of accidents with an APM, equation (6.1) becomes:

$$AR = \frac{E\{\kappa\}}{flow \times 365} \tag{6.2}$$

where,

AR = the accident risk defined as the number of accidents per vehicle per link or per passing intersection;

$E\{\kappa\}$ = the expected number of accidents per year;

$flow$ = the traffic flow (in AADT) on the link or for the manoeuvre at a node (right, through, left) in vehicles per day;

365 = the number of days in one year.

The relationship of equation (6.2) can also be written as follows:

$$AR = \frac{E\{\kappa\}}{flow \times 365} = \frac{\alpha F^{\beta}}{F \times 365} = \frac{\alpha F^{\beta - 1}}{365} \tag{6.3}$$

Equation (6.3) exhibits a special characteristic for $\beta < 1$. Most models in this research contain a coefficient β below 1. When the power coefficient of the parameter F ($\beta - 1$) is negative, equation (6.3) indicates that the individual risk decreases as the flow increases. In fact, the relationship implies that it is less dangerous for a driver to travel under heavy flow conditions than under light flow conditions. For example, let us assume that an APM has the following form $0.01 \times Flow^{0.5}$ (single vehicle accident). When the model is applied on links with traffic flows equal to 100 veh/unit of time and 10 veh/unit of time, one gets 0.10 acc/unit of time and 0.03 acc/unit of time respectively. In principle, 10 vehicles out of the 100 vehicles and 0.3 vehicle out of the 10 vehicles should be involved in a collision respectively. Consequently, the probability for a driver to be involved in a collision becomes 0.01 and 0.03. This result shows that a driver has a greater likelihood of being involved in an accident if he or she travels on the link with 10 veh/unit of time. The special characteristic of equation (6.3) merits a thorough analysis.

The characteristic exhibited in equation (6.3) appears to be counterintuitive. Common sense would dictate that the individual risk of being involved in a an accident should increase as more road users share the same limited space on the road. Similarly, when one looks at human factors, the driving task should become more complicated as traffic increases. The driver should have greater difficulty absorbing information. Thus, the probability for a driver to make errors should be larger leading to a the greater likelihood of being involved in an accident. Recent work on traffic safety and capacity also showed that as the level of service (LOS) decreases, the risk becomes higher. Persaud and Look (2000), and Persaud and Nguyen (2000) developed APMs in relation to the LOS for freeway sections and signalized intersections. The results showed that, for similar flows, more accidents were predicted when the LOS decreased.

Despite what intuition and the preliminary empirical work on this subject might indicate, the relationship of equation (6.3) shows that it is safer to travel on roads with higher flows than with lower flows when the coefficient $\beta < 1$. The issue about the diminishing risk is directly related to the coefficient β. As explained in Chapter Two, studies have shown since 1953 that the number of accidents usually increases at a decreasing rate when the flow increases. Thus, the individual risk indeed becomes less as traffic flow increases. Even the models proposed by Persaud and Look (2000), and Persaud and Nguyen (2000) contain a $\beta < 1$ for the parameter F. Consequently, for a given LOS, it is safer to travel on a road or through an intersection that has more vehicles than less vehicles, everything else being equal (i.e., same road characteristics).

So far, there has been no explanation in the literature to interpret the relationship of $\beta < 1$. This relationship may be explained by various factors. It is possible that drivers may change or adapt their driving behaviour according to the level of traffic present on the road. They may become more alert as traffic increases. They may undertake less risky manoeuvres knowing that space on the road is limited. Another explanation might be related to speed. As traffic flow increases, the vehicles travel at a lower speed. The speed usually slightly decreases until near capacity conditions where, at that point, it sharply goes down. The damage caused by an accident to both the vehicle and its occupants is less severe at lower speed. Thus, perhaps accidents that were once serious may become less serious; that slight accidents may become PDOs (they are less likely to be reported), etc. The speed distribution may also play an important role. The variance in speed is probably higher for lower traffic flow than for higher traffic flow conditions. The speed may become more uniform when traffic density increases. Consequently, the likelihood for a conflicting situation to arise between vehicles is higher at a lower density. In short, the issue of diminishing risk should be explored in much greater detail since it may have important consequences on transportation policies and ITS strategies.

In other instances, it may be of interest to look at the societal risk. The goal, in this case, is to compute the accident likelihood for a given level of exposure. In other words, the predicted number of accidents per unit of time is computed for a given flow. Carriers of dangerous chemical materials usually apply this definition of risk, as discussed in Chapter Two. The accident likelihood is usually estimated from accident rates rather than from APMs. For this definition, the relationship of equation (6.2) becomes:

$$\textit{Accident likelihood} = E\{\kappa\} = \alpha F^{\beta} \tag{6.4}$$

Equation (6.4) may be estimated for different categories of road users such as for heavy vehicles or trucks.

Equation (6.4) shares the same characteristic as in equation (6.3) for $\beta < 1$ when used for the optimization of network safety. When one is interested in minimizing societal risk, the flows on networks will tend to concentrate on few links rather than disperse on many links since risk decreases with flow.

6.1.3 APPLICATION OF ACCIDENT RISK ON LINKS AND NODES

The computation of accident risk for the links (those found in the original network) was performed by applying equation (6.2) for each link in the network. In the analysis, the same risk was assigned to drivers travelling in opposite directions on each link. The disaggregation of accident risk by direction was not possible with the models developed in Chapter Four.

The computation of the accident risk for the nodes was a little more complicated and required further manipulation. As explained above, the risk of a collision at intersections depended upon the respective manoeuvre or movement (left, through, right). Since the models developed for the nodes in this research were not separated by collision type, few steps were necessary to separate the predicted accidents by type. It should be mentioned that the best approach would be to develop specific APMs for each accident type. In the first step, the proportion of accidents by type was examined for signalized 3- and 4-legged intersections in the accident database. Based on this exploratory analysis, it was possible to compute the proportion of accidents for drivers who turn left, right, or travel straight through the intersection. In the second step, the total expected number of accidents computed for each intersection was multiplied by the proportions calculated above. This resulted in finding the predicted number of accidents for each turning movement at the intersection. In the third step, the risk was computed with equation (6.2) for each manoeuvre at the node. In the end, a different accident risk value was used, depending on whether a driver turns left, right, or travels through a node.

After the accident risk was computed, it was then assigned to the modified network. The risk computed from the original link had to be allocated to all the modified links (between the receiving and outgoing nodes each leg) located between any adjacent nodes. For every node in the network, the risk was assigned to all additional links that represent the various turning movements at the intersection. The description can be better understood with the help of an example. With the network described in Figure 6.1, let us assume that the risk between node 5 and each of the other adjacent nodes is equal to 0.0500 acc/veh; that a left-turn is equal to 0.0045 acc/veh; that travelling through an intersection is equal to 0.0035 acc/veh; and that turning right is equal to 0.0020 acc/veh. The assignment of the various risk factors is presented in Figure 6.2. The application of the algorithm is presented in the next section.

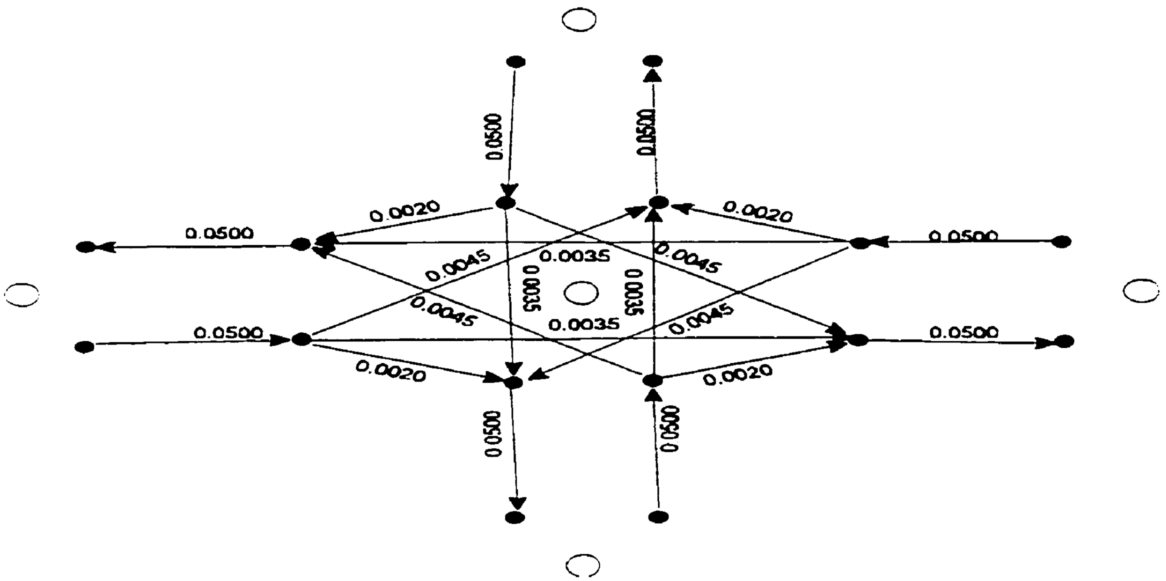


FIGURE 6.2 Assignment of risk on the network of Figure 6.1

6.2 APPLICATION OF SAFEST PATH ALGORITHM ON THE SAMPLE NETWORK

Different accident risk values, as computed by equation (6.3), were applied on the sample network of section two in Chapter Five. This sample network was modified according to the procedure described in the previous section. The number of nodes increased from 15 to 66 in the new modified network.

Figure 6.3 shows the accident risk on the sample network. The number in parentheses in this figure is the expected number of accidents per year. The different values of accident risk at nodes are presented in Table 6.2. Note that the high risk values in this table are due to extremely low flows on the network (to be discussed below). The blank cells indicate that this particular turning manoeuvre is not possible for that node.

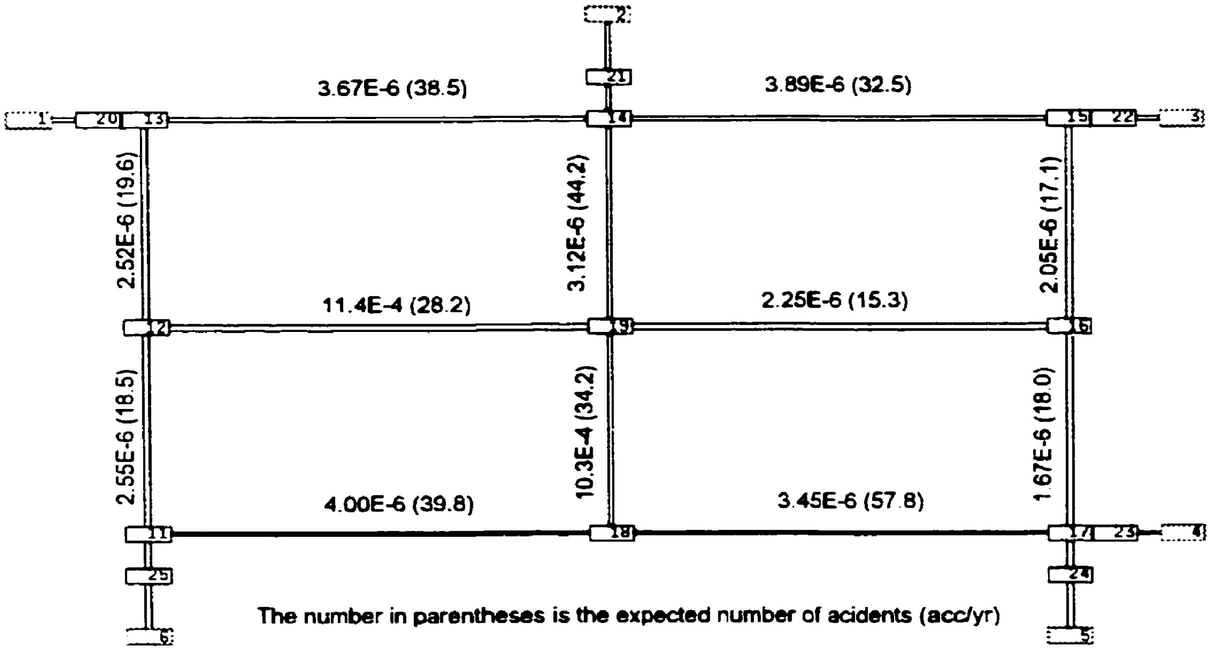


FIGURE 6.3 Assignment of risk (acc/veh) on the sample network

TABLE 6.1 Accident risk (acc/veh) at nodes

Node	Acc/yr	NB_L	NB_T	NB_R	SB_L	SB_T	SB_R	EB_L	EB_T	EB_R	WB_L	WB_T	WB_R
11	12.7		1.2E-6	6.3E-8	1.0E-6	1.3E-6					8.3E-8		8.3E-8
12	8.0		1.9E-6	8.6E-8	6.5E-7	1.9E-6					1.4E-7		5.8E-8
13	12.3	1.0E-7		2.7E-6					1.2E-6	7.9E-8	1.9E-5	8.6E-7	
14	25.2	1.0E-6	8.3E-7	7.1E-7	1.9E-5	7.5E-7	2.0E-7	1.2E-6	1.5E-6	5.0E-7	2.2E-6	3.6E-6	2.7E-7
15	11.6	2.2E-7		7.9E-8					9.7E-7	2.2E-7	5.3E-7	1.0E-6	
16	8.5	6.7E-7	1.1E-6			8.9E-7	2.5E-7	2.1E-7		1.1E-7			
17	37.1	8.3E-7	1.8E-6	4.3E-7	9.8E-7	2.2E-6	1.6E-7	8.2E-7	1.5E-6	1.4E-7	1.9E-6	1.2E-6	3.3E-7
18	15.2				1.0E-7		3.3E-7	2.2E-6	1.5E-6			1.5E-6	8.1E-8
19	20.6	1.2E-6	7.2E-7	1.2E-6	1.1E-6	7.4E-7	1.2E-6	1.2E-6	1.8E-6	2.3E-7	6.5E-6	2.0E-6	2.4E-7

A computer program written in QuickBASIC (Nameroff, 1989) was created to facilitate the search of the safest paths in the sample network. The Dantzig algorithm was coded in the computer program according to the method proposed by Yen (1977). The details about this algorithm can be found in Appendix D. The codes for the computer program are shown in Appendix F. Another computer program was also written with the Floyd algorithm to validate the results of the first program's output.

The total risk for the safest path between each pair of centroids is presented in Table 6.2. The graphical representations of the safest paths between centroids 1 and 5, and between centroids 3 and 4 are shown in Figures 6.4 and 6.5 respectively.

TABLE 6.2 Total risk (acc/veh) for the safest path between each pair of centroids

Centroids	1	2	3	4	5	6
1	0	6.05E-6	1.12E-5	13.2E-6	13.2E-6	8.41E-6
2	4.74E-6	0	9.62E-6	10.0E-6	11.1E-6	11.3E-6
3	9.95E-6	5.21E-6	0	6.14E-6	7.32E-6	1.42E-6
4	12.7E-6	9.10E-6	5.23E-6	0	1.92E-6	10.2E-6
5	1.32E-5	9.53E-6	5.67E-6	0.44E-6	0	9.86E-6
6	8.27E-3	1.21E-6	13.3E-6	9.59E-6	9.15E-6	0

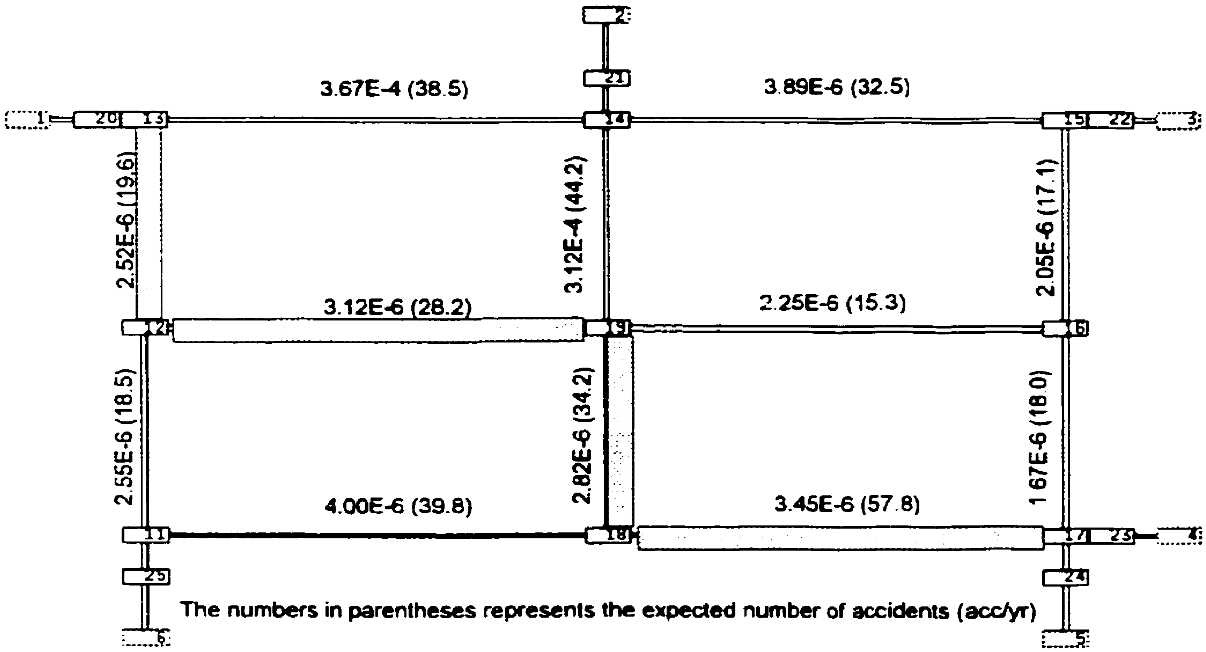


FIGURE 6.4 Safest path between centroids 1 and 5

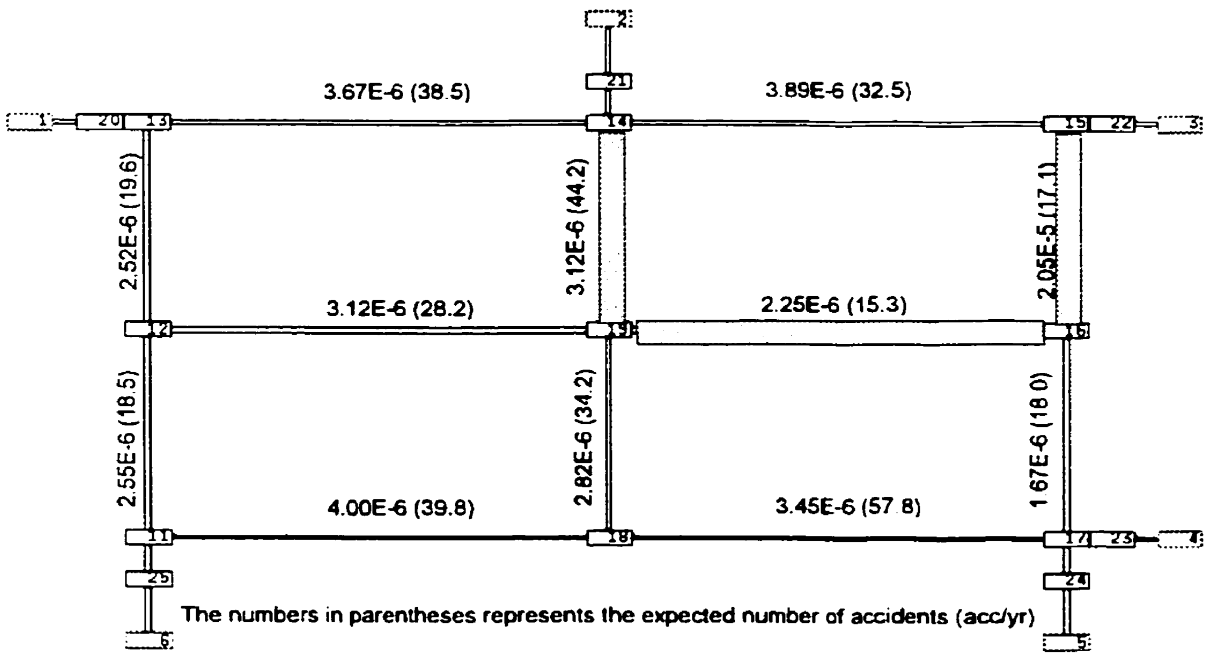


FIGURE 6.5 Safest path between centroids 2 and 3

Figure 6.4 reveals that the safest route is laid out in a stepwise fashion, with three right turns and two left turns. This path initially may appear inappropriate, since the addition of the risk factors associated respectively with links 16-19, and 16-17 (without including the risk at the nodes) is less than those associated with links 18-19 and 17-18. Since the accident risk for a right-turn is 8 to 16 times safer than travelling through at nodes 19 and 17, the sum of the risk factors on route 19-18-17 (7.5E-6 acc/veh) becomes less than that on route 19-16-17 (8.0E-6 acc/veh).

Figure 6.5 shows that it is safer to perform a detour through nodes 19-16-15 than to make a left turn at node 14 and travel on link 14-15. In real traffic conditions, it would be unlikely that a driver would take such a path. In fact, the shortest path is often the path with the lowest risk (Chatterjee and MacDonald, 1998). Since the left-turning traffic flow at node 14 is very low, the accident risk is very high. The risk for that particular left turn is about 20 to 30 times higher than the risk of turning left at other nodes in the network. Thus, it is safer to perform a detour than to use the most direct route, as unrealistic as this may seem. It is important to mention that this hypothetical digital network did not represent an actual physical network and that all the variables were set arbitrarily. Furthermore, the expected number of accidents for turning manoeuvres was not estimated from APMs but from an average value that was extracted from accident data. Therefore, it is not surprising that unusual routes could be selected in this network.

The main purpose of this section was to explain how the safest path algorithm could be implemented for digital networks. The safest path was found by incorporating the exposure and then computing the individual risk of a collision for a driver who travels on links and nodes that have x accidents and y vehicles per day. An algorithm was developed to find the path between any pair of centroids with the lowest probability of a collision. To find this path, it was necessary to substantially modify the network so as to include the various turning manoeuvres at nodes. Unfortunately, the computation of accident risk and modification process had a few drawbacks.

The first disadvantage was related to the number of additional links required to apply the algorithm properly. In fact, eight additional nodes were required for each original node. Thus, for an extended network, a very large number of additional links would be required which could be very difficult for a single user to handle (for a 20,000-node network, it may go well above 80,000 additional links). In addition, the network could even be too large for a single personal computer to handle. For instance, the algorithm took few minutes to converge to find all of the paths in this small network with a Pentium II, 400 MHz. Unless the turning flows are already coded in the transportation planning software program, it may be preferable to compute one risk for the overall node.

The second disadvantage was related to the computation of accident risk on links or nodes with extremely low flows (this is in addition to the issues explained in the previous section). The risk applied in this situation may sometimes be disproportionally large, owing to the low denominator. This result was illustrated in Figure 6.5. To avoid this problem, Chatterjee and McDonald (1998) suggested setting the links or nodes with minimum flow. They proposed to set the minimum flow equal to the lowest flow in the sample of sites producing the APMs.

The third disadvantage was associated with the APMs. In the analysis, the AADT flow was used as the input variable into the various models. These models, unfortunately, were not adequate when the true accident risk is sought for a particular time period (other than 24 hours). In that case, it would be preferable to use APMs that predict the number of accidents for the time period for which the traffic was simulated. Similarly, models should be used to predict accidents by type at nodes, rather than estimate the type of accident by other methods. Several safety issues related to the application of DRG systems on networks are described in the next section.

6.3 SAFETY ISSUES IN DYNAMIC ROUTE GUIDANCE

This part of the analysis was performed in cooperation with the Intelligent Transportation Systems (ITS) Group at the University of Toronto. This work was only a demonstration of the application of accident risk to networks provided with a DRG system. At the time of the analysis, the ITS Group was still in the process of fully integrating Paramics to ITS applications. Thus, the scope of this analysis was fairly limited, since many components of Paramics were not yet readily available. For instance, it was not possible to assign accident risk for the various turning manoeuvres at intersections. Nonetheless, the analysis provided useful insights about how to improve network safety by communicating relevant information to drivers.

Three issues must be addressed before pursuing the description of the methodology and the results. First, the analysis was a theoretical exercise, and it relied on the assumption that drivers completely optimize their route choice based on delay and the applied cost factors (i.e., accident risk). Several issues related to this assumption are discussed at the end of this section.

Second, the aim of the current analysis was related to the prediction of accidents based on the aggregate change in traffic over a fixed time interval. Paramics is a microscopic simulation software that simulates traffic on a given network in a real-time setting. Thus, each car on the network is simulated individually and the various measurements such as traffic flow or delay are computed at the end of each simulation run. The APMs were applied with the final output of each simulation run, once the measurements were calculated. Since the models employ a static average annual flow as input, they cannot be used to evaluate the actual effects of DRG systems on traffic safety (e.g., changes in headway, improvements in human factors, driver behaviour, etc.). But, they can be used to evaluate the effects on safety for changes in aggregated traffic flow on networks.

Third, APMs that employ traffic flow as input may not be adequate for estimating accidents on congested networks since traffic flow is highly unstable near capacity conditions. For a given flow, two possible traffic conditions can occur: high speed and low density or low speed and high density. Under free-flow condition, the use of models that incorporate flow is adequate. It is when the flow reaches capacity that the use of these models becomes problematic. Thus, it may perhaps be better to utilize density as the independent variable rather than flow for this situation. Unfortunately, information on density is not easily obtainable since it is measured infrequently. With new ITS technologies, it may be possible to record information on density very easily and in a real-time manner. Therefore, further work on the use of density for safety applications should be explored. Potential suggestions related to the microscopic evaluation of traffic safety for congested networks are proposed in the next chapter.

Advanced Traveler Information Systems (ATIS) and related dynamic route guidance are core components of ITS. ATIS provide traffic management and control centers the ability to communicate with suitably equipped road users in real time, and supply them with route guidance instructions. The objective of communicating guidance and routing instructions is to reroute traffic around congested portions of the network, either to minimize user costs or optimize system performance. Guidance is usually formulated on the basis of travel time as the sole cost element, with little attention given to other costs such as environmental impact (pollution) or traffic safety on the selected routes. Safety considerations are particularly important both for user-optimal and system-optimal routing. For instance, a route guidance system should avoid sending traffic to less safe routes in order to save time. The purpose of this section is, then, to investigate the integration of the models of Chapter Four with the DRG system.

The sample network used for the case study was located in the same vicinity as the first sample network presented in Chapter Five (the sample network of Chapter Five is a subset of this network). It covered a larger area and contains a total of 44 links and 18 nodes. Its boundaries were defined by Victoria Park Ave to the west, Kennedy Ave to the east, St. Clair Ave to the south, and Lawrence Ave to the north (Figure 6.6). In each direction, an additional link beyond the boundary node was included to simulate the traffic flow entering and exiting the study area by the various arterial roads. No centroids were used inside this network. All of the links are either 4- or 6-lane road sections, and all but one of the intersections were signalized.

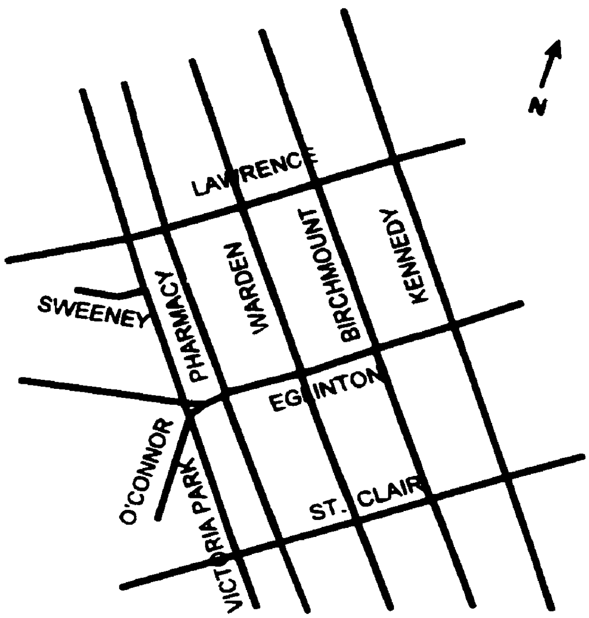


FIGURE 6.6 Sample network for the dynamic route guidance application

The characteristics of the simulation are briefly explained below. The traffic flow on the network was simulated for the morning peak hour, initially without taking any safety factors into consideration. The flows were expanded and adjusted with the factors described in Chapter Five. The simulation was performed five times and the average value was used to estimate the network safety and link costs (e.g., accident risk). In the first simulation sequence, it was specified that 50% of drivers would be informed of updated link costs throughout the simulation. This condition represented regular commuters who know the morning traffic conditions very well. The simulation provided reasonable delay and queue lengths. In the second set of simulations, 85% of drivers received these updates to study the network performance of improved DRG and increased market penetration. The difference in link flows between the first and second simulation runs is presented in Figure 6.7.

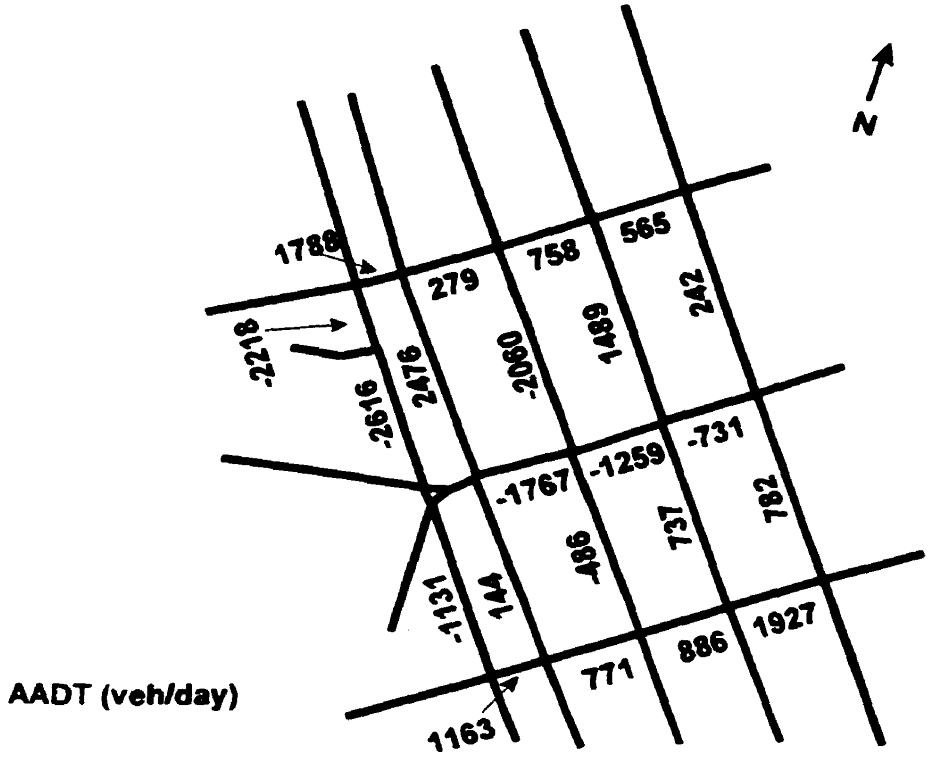


FIGURE 6.7 Difference in link flows (AADT) between simulation runs 1 (50% familiarity) and 2 (85% familiarity)

With the output of these first two simulation sequences, the expected number of accidents was estimated for the entire network with the models of Chapter Four. The difference in the expected number of accidents between first and second simulation runs is shown in Figure 6.8. The numerical difference at the nodes is not shown in this figure (nor in all subsequent figures) to improve the clarity of the graphic. Instead, a shaded circle is used to show a decrease in the predicted number of accidents at nodes, while the unshaded circle is used to a show an increase.

to show a decrease in the predicted number of accidents at nodes, while the unshaded circle is used to a show an increase.

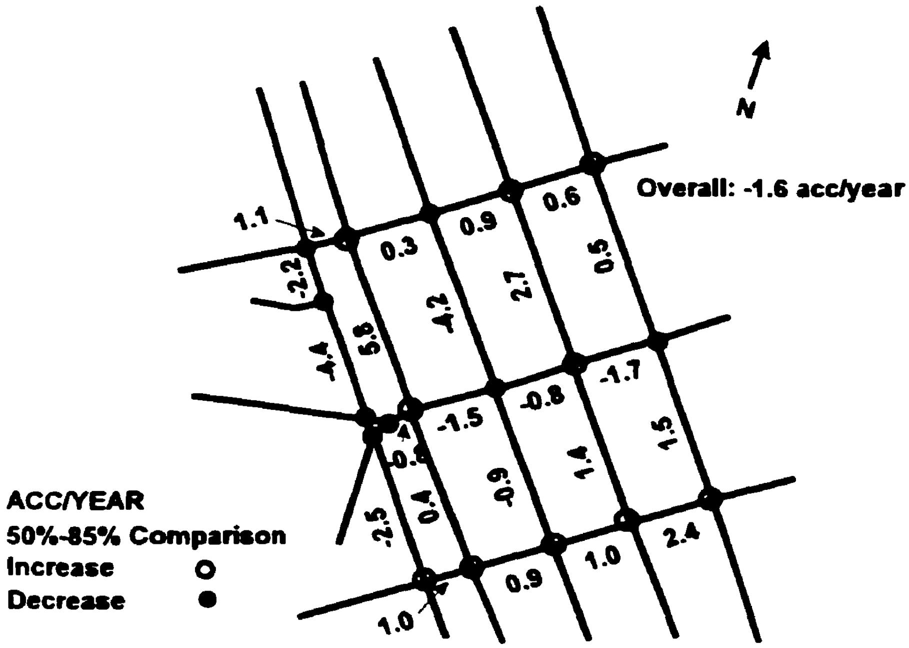


FIGURE 6.8 Difference in the expected number of accidents (acc/yr) between simulation runs 1 (50% familiarity) and 2 (85% familiarity)

The accident risk as defined in the previous section was estimated for the all the links and nodes with the output of second simulation (Figure 6.9). For the third simulation, the accident risk calculated from the second simulation set was applied as cost factors on the links and nodes in the network. This led to a shifting of traffic from links with a relatively high accident risk to links those having a lower risk. The difference in link flows between second and third simulation runs is illustrated in Figure 6.10. This figure shows that an important change in traffic flow can be seen on Pharmacy.

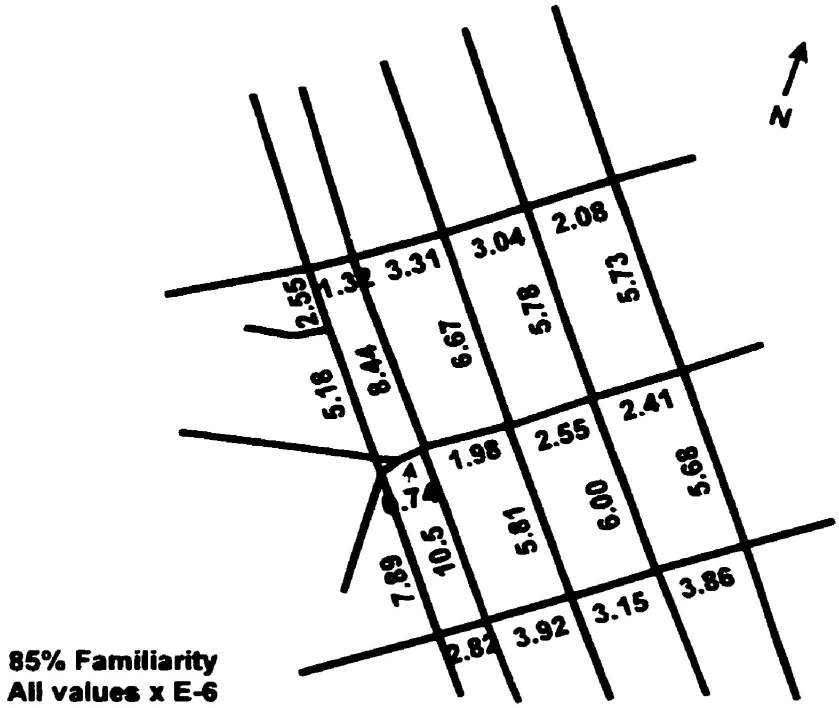


FIGURE 6.9 Accident risk on links based on simulation run 2

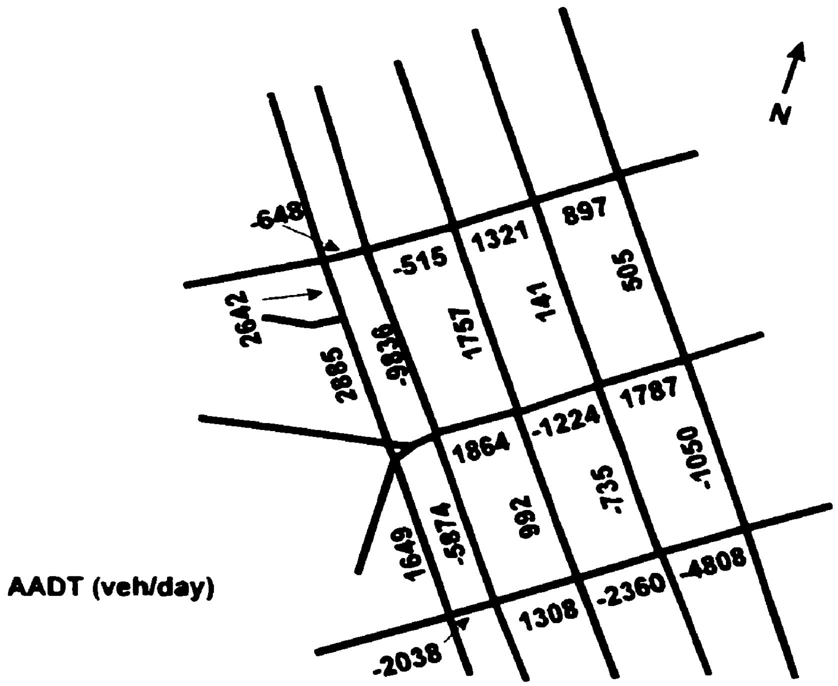


FIGURE 6.10 Difference in link flows (AADT) between simulation runs 2 (without cost factors) and 3 (with cost factors)

The difference in the predicted number of accidents on links between the second and third simulation runs is illustrated in Figure 6.11. It should be pointed out that the changes at nodes, both positive and negative, are usually below two accidents per year. Figure 6.11 shows that the overall reduction in network accidents is concentrated along Pharmacy. On the other hand, very slight increases or decreases can be seen in other parts of the network.

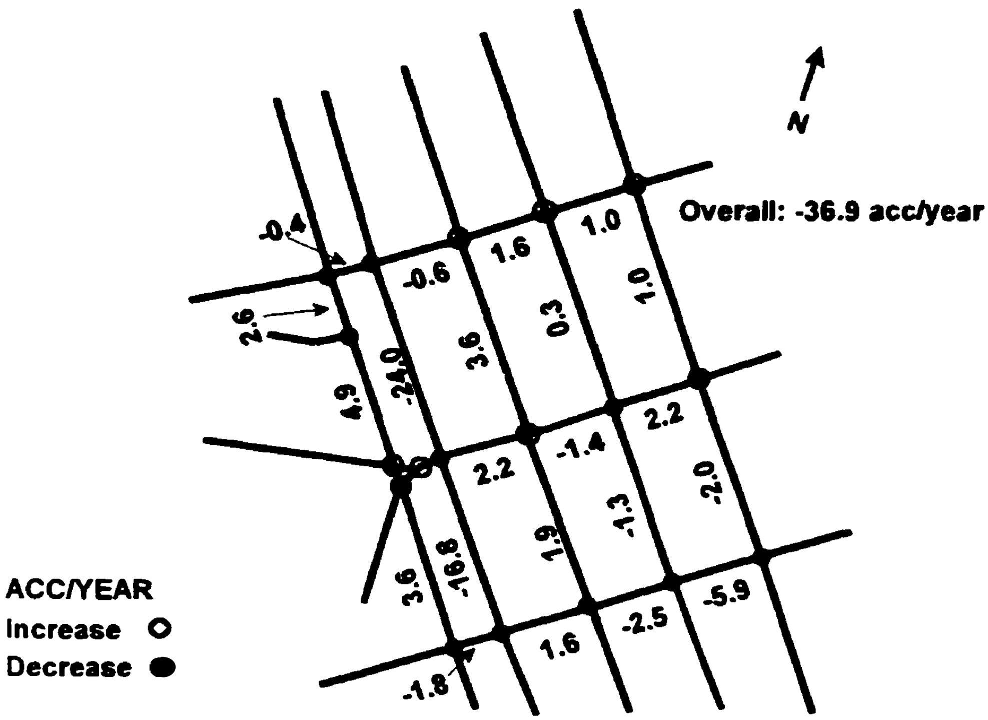


FIGURE 6.11 Difference in the predicted accidents (acc/yr) on links between simulation runs 2 (without cost factors) and 3 (with cost factors)

The summary results for all three simulation sequences are presented in Table 6.3. The table also presents the overall average trip time on the network. The number in parentheses shows the actual difference between the second and third simulation runs, for 85% familiarity.

TABLE 6.3 Results of the simulation with and without cost safety factors

Simulation	Characteristics	Familiarity	Average trip time (sec)	E{κ} (acc/year)
1	No cost factor	50%	362.2	1556
2	No cost factor	85%	350.5	1554
3	Cost factor applied	85%	*(+55.8) 406.3	*(-37) 1519

* difference between the second and third simulation runs

Table 6.3 reveals two interesting findings. First, the table shows that an increase in the percentage of drivers who are familiar with the network decreases the average trip time, as expected, yet has almost no effect on the expected number of accidents. This result is very similar to the conclusions of Chatterjee and McDonald (1998). Safety is inelastic relative to flow at high volumes, since the expected number of accidents increases at a decreasing rate. Therefore, a slight change in the flow on the various links will not substantially change the number of accidents, as is the case here. This result does not imply that DRG systems by themselves cannot not improve traffic safety. As explained at the beginning of this section, the application of ITS technology to networks may reduce the number of accidents by improving human factors conditions.

Second, the table further illustrates that when the accident risk is used as a cost factor, the safety of the network as a whole improves by about 2.5%, and 37 accidents are prevented. Based on the unit accident cost in MicroBENCOST (TTI, 1993), this would lead to annual savings of approximately US $260,000 (1990) for this small network. On the other hand, the average trip time for the network increases substantially. This result is expected as the flows are no longer optimized solely to reduce delay. As discussed by Maher *et al.* (1993), the optimization of flows on networks based on accidents and delay always produces contradictory results.

The results also demonstrate that the inclusion of the safety cost factors greatly influenced the route choice of drivers. The influence is more significant for drivers who have greater choice in the selection of routes, and they will more likely choose a safer route. The outcome of the analysis shows that some link flows increased or decreased by up to 60%. The biggest changes occurred on links with low flows.

In conclusion, the results in this section demonstrated that communicating information about the risk of collisions to drivers could improve, in principle, the overall safety of a network. However, a substantial increase in the average trip time occurred, since the network no longer was solely optimized for delay. It was worth noting that the safety gains may not always compensate for other system costs such as increased delay and air pollution. Furthermore, it was unrealistic to assume that everyone in the system will be influenced by accident risk in the same manner. In fact, some drivers may not even consider safety at all in their route choice. To attain the same safety benefits, it would be possible to transform the system cost factors in monetary value (road pricing) which would have a more direct impact on the route choice of drivers. Different values for the cost factors could also be applied to obtain greater safety gains. In the end, the ultimate goal for future ITS applications would be to find an appropriate balance between safety costs and other system costs, and to incorporate the varying perceptions of risk among road users within the applications.

6.4 SUMMARY

This chapter contained a demonstration of two applications of APMs on digital networks. The first application consisted of using the APMs to find the safest routes on a transportation network. A five-step procedure was proposed, namely to apply the Dantzig algorithm on a sample network to find the safest paths in the network. The procedure should be used only if external cost factors cannot be used within a commercially available transportation software program. In fact, very few computer programs allow the complete use of external cost factors. The accident risk was computed for every link and node in the network by dividing the predicted number of accidents with the link and node flows. Since the coefficient β is below unity for most APMs, the individual risk of being involved in an accident was shown to be decreasing as the number of vehicles increases on links and nodes. It has been hypothesized that speed and changes in driver behaviour may explain the diminishing risk. The results showed that the algorithm works very well. However, the algorithm may be difficult to implement on a very large network, particularly in the event that transportation planning software programs do not have turning flows at nodes. It was suggested that such flows should be no less than the minimum flow in the original sample of site producing the APMs.

The second application consisted of examining the safety of transportation networks by communicating accident risk information to road users through the use of DRG systems. The aim of this application was to assess the (theoretical) route choice of drivers who are provided with accident risk information and the impact of this route choice on the number of accidents on links and nodes. The simulation was performed with Paramics, an ITS oriented simulation software. The results showed that, by communicating to drivers the risk of being involved in a collision, the overall safety of a network could be improved, albeit with a significant loss in the optimization of delays. It was believed that drivers, in real traffic conditions, may not optimize their choices based on this information. Other system costs (road pricing) that simulate the same effect on the route choice of road users could be used. A summary of this research and a discussion on network safety issues are presented in the next chapter.

CHAPTER 7

SUMMARY AND CONCLUSIONS

The objectives of this thesis were to develop a series of accident prediction models (APMs) with trend to estimate the number of accidents on digital networks and describe all the issues related to their application on the networks. The summary of the work performed in this thesis is described in section 7.1. The results and issues related to the application of the APMs on digital networks are discussed in section 7.2. Recommendations for further research are explained in section 7.3.

7.1 SUMMARY OF WORK

Several subject areas related both to traffic safety and digital networks–the graphical representation of physical networks–were extensively reviewed for this research project. This review showed that digital networks, as used by commercially available transportation planning software programs, are very important to transportation analysts in that they can be used to predict future traffic patterns, peak periods, travel time, and various environmental or other flow by-products. Unfortunately, the programs seldom if ever are used to predict the number of accidents, despite the fact that traffic accidents cause tremendous financial, social, and emotional losses. The non-application of safety was attributed to three reasons: 1) the fact that traffic safety is not explicitly defined within the urban planning process; 2) the belief that following established guidelines will automatically render a design as safe; and, 3) the lack of available tools to predict the number of accidents on digital networks. The reviewed documents also showed that the digital representation of physical networks can be performed in many different ways. For instance, a network could be created in a very detailed manner, such that each street and intersection is coded on the network. More often than not, digital networks only represented important arterial roads and intersections. Minor roads and intersections were therefore not shown on the digital network.

The literature review showed that APMs are used to estimate the number of accidents at intersections, on arterial road sections, or on any other transportation facility. The models were built by drawing inferences between traffic accidents and a series of covariates (e.g. traffic flow, traffic control, road geometry, etc.). Furthermore, the relationship between accidents and the covariates could have many various forms. The emphasis of the review was placed on models used to predict the number of accidents at intersections and on arterial road sections. It was proposed in the literature to use a large number of simple models rather than to use a few models with many categorical variables to describe the relationship between the accidents and the covariates. Thus, the data should be separated into a series of cells and a different model created for each cell, given that enough data points exist in each cell.

The application of APMs on digital networks has been researched only infrequently. In fact, a total of six documents were reviewed and briefly criticized. The identified documents showed that researchers frequently used APMs that were published elsewhere. Thus, the information related to their use was often inadequate or incomplete. It was found that the application of models on digital networks varied from one study to the next. In one study, for example, the number of accidents was predicted only for intersections and not for mid-block sections. In other studies, accidents were estimated for the entire network, including non-intersection sections. A comparison between the predicted and observed number of accidents was found in only two documents. Finally, in many of the reviewed documents, it was unclear whether the digital network represented actual major roads and intersections, or whether it was simply a more detailed description of the physical network.

The characteristics of the data were explained in Chapter Three. Electronic databases for traffic accidents, traffic counts, and the physical characteristics of signalized and unsignalized intersections were provided by the Data Traffic Centre of Metro Transportation, which is the transportation agency of the City of Toronto. Data not available electronically were gathered from on-site visits or other sources. The data reduction process consisted of three steps: the expansion of 8-hour counts to average annual daily traffic (AADT); the estimation of missing traffic counts (in AADT); and, the selection of the reference population for nodes and links used in the creation of the APMs. The reference population consisted of 1,354 intersections and 284 road sections respectively. The data on traffic counts and traffic accidents were available between 1990 and 1995 inclusively. The final database consisted of three different computer files (traffic flow, accidents, physical characteristics), linked together by the street name and year.

The characteristics of APMs were presented in Chapter Four. Three different types of model were created in this research. The first type was used to predict the number of collisions at nodes. The second and third types were used to predict the number of accidents on links: one for the mid-block component and one for the intersection component. The models for the mid-block component were used to predict accidents between minor intersections; these intersections were located on the physical network but were not coded as nodes on the digital network. The models for the intersection component were used to predict accidents at these minor intersections. This type of model only used the link flow as input. Models were estimated for injury, PDO, and injury + PDO for each type of model. The coefficients of the models were estimated with the generalized estimating equations (GEE) procedure, since each model included time trend. Genstat (Payne *et al.*, 1993) was used for this purpose.

The application of the APMs on digital networks was described in Chapter Five. The mechanics of how the models are applied on a digital network and how the models can be used within the urban transportation planning process were explained in this chapter. The models were applied on two sample networks. The first sample network represented a street system located in Toronto. The second sample network did not represent any actual physical network. The simulation of traffic for the morning peak hour was performed with EMME/2 (INRO, 1996) for both networks. Two scenarios were evaluated for second sample network. The first scenario consisted of analyzing changes in the predicted number of accidents on the network, when one of the 2-lane roads was expanded to a 4-lane road. The second scenario assessed the overall safety impacts when an important traffic generator, such as a casino or major grocery store, was added to the network. The output of the two scenarios was compared with the results of the unmodified sample network.

Two other useful applications of APMs on digital networks were presented in Chapter Six. The first application was related to the implementation of the Dantzig algorithm to find the safest routes on one of the sample networks of Chapter Five. A five-step procedure was proposed to apply the algorithm properly since most commercially available transportation planning software programs cannot handle external cost factors. The process included a modification of the digital network. The safest paths were found by computing the individual risk of collision on every link and node. The accident risk was computed by dividing the number of accidents by the traffic flow ($E\{\kappa\}/(flow \times 365)$). The computation of risk showed an unusual characteristic for $\beta < 1$ (the coefficient of the parameter F in APMs). When the coefficient β is below unity, the risk of collision was shown to be decreasing as traffic flow increases. It has been hypothesized that speed and changes in driver behaviour may explain the diminishing risk.

In the second application, the models were used to examine the safety of transportation networks by providing accident risk information to road users through the use of dynamic route guidance (DRG) systems. This analysis was a theoretical exercise, since it was assumed that every driver optimizes his or her road choice based on the risk of a collision. The accident risk for this application was computed the same way as in the first application. The analysis was performed on a sample network representing a neighbourhood in located in eastern Toronto. The traffic flow was simulated with Paramics (Quadstone, 1998). The next section presents the results of this research.

7.2 DISCUSSION

The results and issues related to the data collection process, the estimation of APMs, and the application of the models on digital networks are presented in this section.

7.2.1 DATA COLLECTION AND REDUCTION PROCESSES

The models created in this thesis required an extensive amount of information. Thus, several problems were encountered during the data collection process. For instance, the information needed to build the reference population had to be gathered from many different sources. Since these sources were very different from one another (e.g, electronic database, hard copy, etc..), it was quite difficult to combine each source into a common database. Some of the difficulties encountered included street names at intersections that varied from one database to the next or unusual traffic counts recorded for special studies. During the data collection process, it was also found that some of the information was either incomplete or inaccurate, which added to the difficulty of creating one common database. Consequently, an important amount of time had to be performed to validate and reformat each source of data into a common configuration.

More problems were also encountered during the data reduction process. Since the reference population for the nodes and links consisted of 1,354 intersections and 284 road sections respectively, the resulting database was too unwieldy to be handled by one person. In particular, almost all the steps required for the data reduction process had to be done manually. As a result, the original scope of the research had to be reduced to complete the project within a reasonable amount of time.

Based on the issues mentioned above, it is suggested that transportation agencies maintain a highly detailed and up-to-date electronic database on traffic counts, traffic accidents, and physical characteristics. The databases should include information on important physical changes or improvements of the transportation facilities. Special attention should be given to the common identifier at intersections (such as street names) to facilitate the connection between databases. In fact, a specific number should be assigned for each intersection and road section to help the location of accidents and traffic counts during the data reduction process. The best approach would be to code intersections, road sections, and accidents in a geographical information system (GIS) format, an upcoming and promising new technology. It would also be very useful to automate the steps that were performed for the reduction process.

7.2.2 ESTIMATION OF ACCIDENT PREDICTION MODELS

The models of Chapter Four revealed interesting results. First, the models that estimate accidents for nodes provided, with a few exceptions, a good statistical fit. Second, most models that predict accidents on mid-block sections also provided a relatively good statistical fit and showed that a non-linear relationship exists between accidents and length. Third, the models for the intersection component of links all provided a good statistical fit, despite the use of one input flow. Overall, the APMs reflected the actual relationship between accidents and the covariates, and were deemed accurate to predict the number of accidents on links and at nodes.

The models used to predict accidents on mid-block sections provided a relatively good statistical fit, except for one model (i.e., 2-lane road sections). The results also revealed that a non-linear relationship exists between the length of a section and the number of accidents. This kind of relationship was also found by other researchers (Mountain *et al.*, 1996). Since very little research has been performed on the development of APMs for urban corridors (particularly for mid-block sections), it was difficult to pin point the reasons for such a relationship. Obviously, this relationship implied that some factors are not homogenous for the entire length of the section. It was discussed in Chapter Four that the influence of end points on links, i.e. the intersection of two major arterial roads, could greatly influence the occurrence of accidents on a given link. However, the relationship could be also explained by other contributing factors. For example, the density of driveways and minor intersections, or the number of street parking manoeuvres, may further contribute to this relationship. As a result, additional research is required on this topic.

Another relevant issue that relates to the models developed in this research is the transferability of models. Transferability implies that the APMs should be able to predict accidents within a reasonable level of accuracy (i.e., re-calibration may be necessary) on networks other than that upon which the models were built. However, the models proposed in this research project were not tested on other networks because the limited resources available such an activity. Moreover, to apply the models appropriately, an extensive amount of information on traffic counts, the number of collisions, and the physical characteristics of networks would be required. As discussed in the previous section, the information requested for this research proved to be very difficult to obtain and one would expect the same level of difficulty with a data set provided from another jurisdiction. Finally, digital networks may not always be readily available.

7.2.3 APPLICATION OF MODELS ON DIGITAL NETWORKS

The application results of the models on digital networks, illustrated in Chapter Five, showed that the accuracy of the prediction of accidents is directly linked to the output flows of transportation planning software programs. In fact, bad flow estimates lead to an inaccurate appraisal of network safety. The simulation results demonstrated that EMME/2 greatly under-predicts link flows. Hence, the models could not be used as input into the three types of model. Nonetheless, the recorded morning counts were substituted for the EMME/2 output flows and used as input into the models. The results showed that the models can be used to predict the number of accidents on links and nodes, as long as the flow predicted by the software is adequate.

The estimated flows of transportation programs must be validated whenever the APMs are applied on transportation networks. If not, the analyst may select the wrong scenario. For instance, if several alternative scenarios are being evaluated, based on the number of predicted collisions, it would be possible to select the alternative with the least number of predicted accidents. In this hypothetical situation, the safest alternative would be deemed safer than all other alternatives because of the poorly predicted flows. Thus, once the alternative is implemented, the physical network may be plagued by a higher number of collisions than that which initially was estimated. As a result, it is suggested that sensitivity analyses be conducted with different values of predicted flows. Obviously, it would be necessary to re-evaluate the prediction of accidents for each alternative accordingly.

The best way to improve the prediction of accidents is to ameliorate the estimation of flows within the simulation process. These improvements may include upgrading the characteristics of the O-D matrix, the delay-volume function of links or the parameters of the microsimulation. More often than not, however, it is not possible to improve or change the flow output of transportation programs. In such a case, it is proposed that one incorporate the actual traffic conditions taken from the physical networks to create adjustment factors in order to improve traffic flow estimates. This, however, is left for others to attempt.

The models developed for this research were not used directly within the transportation software programs. Instead, the traffic flow output of these programs were used in another computer program (e.g., spreadsheet) to calculate the predicted accidents on the digital network. Unfortunately, this computation process turned out to be very long and cumbersome to perform, thereby, making the process very inefficient. It would be possible, however, to include the models directly inside the software, as performed in MicroBENCOST (TTI, 1993). An additional module could be added to transportation planning computer programs that would use the output flows directly without any further manipulations from the analyst (that is, if the predicted flows are adequate). This topic is currently being investigated at the University of Toronto.

One critical aspect of the models developed in this thesis is related to the amount of information required to perform the analysis. For instance, the location and the characteristics of each minor intersection on links must be known before the link models for mid-block component can be applied on digital networks. Obviously, it may not be always possible to know the exact location of these minor intersections on networks that are yet to be built. Thus, additional models requiring less information should be created and evaluated. This topic is addressed in the next section.

Another topic relevant to traffic impact studies is the cost associated with accidents. The decision to upgrade or improve a transportation facility is often based on cost-benefit analyses (or other kind of measurements) that include various cost factors. Thus, for analyses that include the prediction of accidents, the direct and indirect societal cost of collisions probably should be evaluated. Since the purpose of this work was related to the actual prediction of accidents on urban networks, it was decided that issues related to accident costs would not be explored in great depth (they were briefly touched upon in Chapter Six). These issues are left to the analyst who will apply the models developed in this work. The main reason for not exploring this topic at this time has to do with the problems associated with the proper estimation of accident costs. Indeed, many methods for estimating accident costs currently exist. However, none has proved itself to be superior to the others. In fact, all have important drawbacks. Therefore, it would be easy to dispute why a particular cost was selected for analysis over another. The reader is referred to Lawson (1989), Miller *et al.* (1991), and Hauer (1994) for additional information regarding the estimation of accident costs.

The initial aim of the two applications illustrated in Chapter Six was to investigate areas of research that could be of interest to transportation agencies, private companies and specific road users (e.g., truckers, regular commuters). This research has also included a preliminary demonstration of the assessment of the safest routes and safety issues related to DRG systems. Accordingly, the applications were relatively simple and more sophisticated analyses most certainly could be performed. Other areas of research regarding these two applications are presented in the next section.

The application results for the least risk paths algorithm showed that the algorithm can be used effectively on digital networks. However, unusual routes were established when specific turning manoeuvres had a high risk of collision. Thus, APMs used to predict accidents for these manoeuvres should be utilized whenever possible (instead of estimating the type of accidents from the sample population average). The proposed five-step coding process for networks was found to be problematic for substantially large networks. For instance, eight additional nodes were needed for each original node. Therefore, for a 20,000-node network, over 80,000 new nodes may be required.

The application results of accident risk to DRG networks showed that, by communicating to drivers the risk of being involved in a collision, the overall safety of a network could be improved. The assumption was that every driver optimizes his or her route based on safety. Drivers, in real traffic conditions, however, may not always consider safety in their route choices. Thus, road pricing strategies could be used to attain the same safety benefits. The results also demonstrated that important increases in delay occurred, since traffic flows no longer were optimized solely for delay. Furthermore, the safety gains were not very substantial. It is possible that they may not even compensate for increases in other system costs. Thus, a thorough cost-benefit analysis that would include safety and other variables should be performed before implementing a DRG system on a network.

The APMs used in this research were developed with the number of vehicles per day (in AADT) as input. For more accurate results regarding the evaluation of different scenarios and the application of accident risk, it is suggested either to use or create models developed for specific time periods; also, to use the number of vehicles per hour as input. In addition, it would be preferable to use models disaggregated by collision type at intersections. With these models, small area-wide traffic impact studies (e.g., no left-turn signs, traffic calming, etc.) could be performed adequately and could be useful to many governmental agencies and private engineering firms. Similarly, the risk should reflect the actual time at which the vehicle travels on the network. Models that use the number of vehicles per hour as input would be more appropriate for this application.

The objectives of this research were related to the prediction of accidents at intersections and arterial road sections. In short, the models were not created (or used) for freeways and freeway interchanges (which are also components of urban networks). It would be possible to estimate the number of collisions on these two transportation facilities on the basis of models available in the literature. The research on the prediction of accidents for freeways is well developed and many models are readily available (Persaud and Dzbik, 1993; Persaud *et al.*, 1996). Unfortunately, there exist few models to predict accidents at interchanges. Moreover, the available models are often inadequate for predicting the number of accidents. Accident prediction models for interchanges can be especially difficult to create because many variables (e.g., type of interchange, number of ramps, curvature, elevation, etc..) can influence the occurrence of collisions. Additional research is needed in this area. Nonetheless, the reader is referred to Harwood *et al.* (1994), Janusz and Hauer (1995), and Bauer and Harwood (1998) for additional information on models for ramps or interchanges.

In summary, this thesis has demonstrated that:

1. Important issues related to network safety, such as the application of APMs on digital networks have seldom been researched and investigated. Although, few documents, articles or papers are available in the literature on this topic, an

accrued interest in the analysis of network safety has been noticed, nonetheless, within the past few years.

2. APMs cen be used efficiently to predict the number of accidents on digital networks. However, not all models available in the literature are adequate for predicting accidents on networks. In addition, no models exist that are able to predict the number of collisions for particular components of networks. Thus, new models were developed to predict the number of accidents on urban roads. The proposed models also included trend which improves the accuracy of the prediction.

3. A non-linear relationship exists between mid-block accidents and the length of links. This relationship can possibly be explained by a variety of factors, including the density of intersections on road sections and the influence of major intersections located at both ends of the road section on mid-block accidents.

4. The prediction of accidents is directly linked to the traffic flow output of transportation planning programs. Thus, grossly incorrect predicted flows lead to inaccurate predictions of accidents. It is therefore imperative that the traffic flow estimate be as accurate as possible. The application of models is also dependent on how the network is coded and the predicted number of accidents should be adjusted accordingly.

5. The safest paths on urban networks can be found efficiently with the algorithm proposed in this thesis. However, it is necessary to substantially modify the network to properly apply the algorithm, which may not always be easy to undertake especially in the case of a very large network. Furthermore, several issues must be examined and evaluated when APMs are used to compute accident risk and applied on digital networks.

6. Communicating the risk of collisions to motorists who are equipped with ATIS can improve, in principle, the overall safety of digital networks. The safety benefits may not always be substantial however. In fact, the safety benefits may not even compensate for increases in other system costs. Thus, the ultimate goal for future ITS applications would be to find an appropriate balance between safety and other system costs.

7. Whenever possible, the prediction of accidents should be estimated by APMs developed specifically for the time period for which the traffic flow is simulated. Similarly, models that predict the number of collisions by accident type at nodes are preferable to models that use approach flow as input.

The next section presents recommendations for further research.

7.3 RECOMMENDATIONS FOR FURTHER RESEARCH

The scope of this research was limited to a few topics on network safety, and there are many other areas of research that could be fruitfully explored. These areas include the development of APMs, their application on urban networks, the creation of more sophisticated algorithms that would incorporate simultaneously the costs of other variables (such as delay, pollution, etc.), and the incorporation of APMs with the ITS technology.

In the future, it may be worthwhile to investigate the non-linear relationship between mid-block accidents and street length. In fact, such variables as the density of minor intersections, the presence of private and commercial driveways, and the number of on-street parking manoeuvres should be examined more closely and included in the modelling process.

Additional models for nodes should be developed. The models should be separated by accident type. Moreover, models should also be built for different time periods (e.g., peak periods, nighttime, etc.). With better models, the assignment of risk to links or nodes would reflect more accurately the true risk for specific manoeuvres at intersections and different time periods. The new models could also be used to evaluate traffic calming measures such as prohibiting left-turns at key intersections on small scaled networks.

In this research, the models used to predict accidents on links were separated into two components. To simplify computation of accidents, APMs that combine both components should be investigated. As it stands now, the analyst has to use three series of models which may be cumbersome to handle if the analysis is conducted manually (i.e., when the models are used outside the computer program). The output of the suggested models (both components together) should be compared with the output of models proposed in this research to evaluate how the models fare with the ones proposed in this research. Simpler models that require less input information (e.g., non-coded minor intersections) should be evaluated.

The APMs should be directly incorporated as a separate module inside transportation planning software programs. By including the models in the program, it would be easier to assess visually the predicted accidents on the network with the graphical tool of the software. In additional, the extra module would greatly simplify the work of the analyst. However, care should be taken regarding the accuracy of the estimated flows, if they are used without being validated and adjusted accordingly, as discussed above.

Additional work is needed regarding the estimation of traffic flows by transportation planning software programs. Despite the fact that this issue is outside the scope of this work, it is important to argue for improvements in the prediction of flows. Fortunately, research is still ongoing with respect to this issue, but there is still a long path that must be pursued before we are able to obtain better traffic flow estimates.

The next area of research is related to the estimation of safety for other components of digital networks. For instance, it would be of great benefit to predict the number of accidents at centroids. They usually represent subdivisions bounded by major highways or roads. Thus, the goal would be to predict the number of accidents on the streets located inside this subdivision. This area of research has been seldom investigated, but may have great potential in an attempt to reduce the number of collisions (Henning-Hager, 1986). However, it is anticipated that the prediction of accidents at centroids may be difficult to model since many factors (e.g., the design of streets, number of intersections, parking density, or characteristics of the population) can influence the number of accidents in a subdivision. Furthermore, the large amount of information required to perform such a task may be difficult to gather.

With the advent of ITS technology, it would be possible to implement useful safety applications on urban networks. In that respect, more detailed algorithms that optimize for safety and vehicle delay should be developed, similar to that proposed by Maher *et al.* (1993). Factors that influence risk should also be examined such as the speed of vehicles on links (Davis, 1998). In addition, different road pricing strategies should be evaluated to improve vehicle delay and minimize the number of accidents. In the near future, specific models should be developed that would predict accidents both for AITS-equipped and non-equipped vehicles. This would allow their benefits and drawbacks to be evaluated properly.

It would also be important to investigate models that predict the number of accidents (or the risk of a collision) in real-time settings and for congested networks. Since the DRG technology is a time-dependent system, there is a need to develop tools that would evaluate safety in a time-dependent manner. Similarly, further research should be performed for predicting accidents for unstable traffic conditions. Preliminary work on this subject has already been performed by Hughes and Council (1999). Although the work of Hughes and Council is not related to DRG systems, they examine the relationship between safety and "traffic flow changes" during peak periods. One may also want to look at exploring the use of density as an input variable for the prediction of accidents. Other measures of safety could also be assessed, as proposed by Minderhoud and Bovy (2000), who use an extended time-to-collision method to evaluate the safety of Autonomous Intelligent Cruise Control systems (an ITS application). This area of research promises to become increasingly important in the coming years.

In conclusion, this thesis has shown that it is very important to estimate the safety of transportation facilities at the planning stage, insofar as specific designs or alternatives may turn out to be more hazardous than others, would not be noticed until the facility is built or upgraded, and would be only identified after accidents had occurred and people got injured, all of which increase the cost to society. The tools developed in this research would allow analysts to add a very useful criterion to the evaluation of different alternatives and to identify future potential unsafe locations before drivers use the facility. Moreover, given the increased liability of transportation agencies regarding traffic safety issues, it is important that they take action at the planning stage, which will allow them to show that proper steps were taken to reduce the number and severity of accidents. As stated by a speaker at a recent seminar on road safety audits: "*...an organization that audits, that recognizes that audits are a process intended to help road safety, that gets an audit done and then follows through and reports and documents what it will and will not do with respect to the audit report, suffers a better chance in a court of law than an organization that buries it's head in the sand and says, 'We don't want to find out about these things, we're better off to be blind to them*" (MTO, 1998, pg. 40). Although additional work needs to be done regarding the integration of traffic safety models into the urban transportation planning process, the product of this thesis should help other researchers pursue interesting and useful areas of research that would help reduce the number and the severity of collisions on urban roads.

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APPENDIX A

SAMPLES OF METRO TRANSPORTATION DATABASE

ACCIDENT DATABASE

ACCNB	ACCDATE	DAY_NO	ACCTIME	STNAME1	STREETYPE1	STNAME2	STREETYPE2
000002	950104	3	0802	GLADSTONE	AV	PEEL	AV
000002	950104	3	0802	GLADSTONE	AV	PEEL	AV
000002	950104	3	0802	GLADSTONE	AV	PEEL	AV
000002	950104	3	0802	GLADSTONE	AV	PEEL	AV
000004	950102	1	0148	ADELAIDE	ST	SHEPPARD	ST
000004	950102	1	0148	ADELAIDE	ST	SHEPPARD	ST
000004	950102	1	0148	ADELAIDE	ST	SHEPPARD	ST
000007	950104	3	2058	GOULD	ST	YONGE	ST
000007	950104	3	2058	GOULD	ST	YONGE	ST
000007	950104	3	2058	GOULD	ST	YONGE	ST
000009	950109	1	1110	CHURCH	ST	GERRARD	ST
000009	950109	1	1110	CHURCH	ST	GERRARD	ST
000009	950109	1	1110	CHURCH	ST	GERRARD	ST
000009	950109	1	1110	CHURCH	ST	GERRARD	ST
000009	950109	1	1110	CHURCH	ST	GERRARD	ST
000009	950109	1	1110	CHURCH	ST	GERRARD	ST
000016	950107	6	0238	PALMERSTON	AV	QUEEN	ST
000016	950107	6	0238	PALMERSTON	AV	QUEEN	ST
000016	950107	6	0238	PALMERSTON	AV	QUEEN	ST
000016	950107	6	0238	PALMERSTON	AV	QUEEN	ST
000016	950107	6	0238	PALMERSTON	AV	QUEEN	ST
000016	950107	6	0238	PALMERSTON	AV	QUEEN	ST
000016	950107	6	0238	PALMERSTON	AV	QUEEN	ST
000016	950107	6	0238	PALMERSTON	AV	QUEEN	ST

STNAME3	STREETYPE3	MUNICIPAL	LOCCOORD	IMPCTAREA	ACCLASS	ACCLOC	TRAFFICTL
		01	01	01	02	03	10
		01	01	01	02	03	10
		01	01	01	02	03	10
		01	01	01	02	03	10
		01	01	02	03	03	01
		01	01	02	03	03	01
		01	01	02	03	03	01
		01	01	08	03	02	10
		01	01	08	03	02	10
		01	01	08	03	02	10
		01	01	05	02	02	01
		01	01	05	02	02	01
		01	01	05	02	02	01
		01	01	05	02	02	01
		01	01	05	02	02	01
		01	01	05	02	02	01
TECUMSETH	ST	01	01	04	02	03	02
TECUMSETH	ST	01	01	04	02	03	02
TECUMSETH	ST	01	01	04	02	03	02
TECUMSETH	ST	01	01	04	02	03	02
TECUMSETH	ST	01	01	04	02	03	02
TECUMSETH	ST	01	01	04	02	03	02
TECUMSETH	ST	01	01	04	02	03	02
TECUMSETH	ST	01	01	04	02	03	02

VEHTYPE	INITDIR	IMPACTYPE	EVENT1	EVENT2	EVENT3	INVTYPE	INJURY
34	03	02	01			01	2
34	03	02	01			10	
14	01	02	01			01	0
14	01	02	01			10	
34	02	02	01			01	
34	02	02	01			10	
01	03	02	01			01	
		02				99	
01	03	02	01			10	
01	03	02	01			01	
01	01	03	01			01	0
01	01	03	01			02	0
34	01	03	01			01	2
34	01	03	01			02	2
34	01	03	01			02	2
34	01	03	01			10	
01	02	02	01			01	0
01	02	02	01			01	
01	02	02	01			10	
01	02	02	01			02	1
01	02	02	01			02	0
34	03	02	01			01	0
34	03	02	01			10	
34	03	02	01			02	0

DRIVACT	DRIVCOND	PEDCOND	PEDACT	VEHIMPTYPE	MANOEUVER	ENTRY
01	01			11	02	1
				11	02	
01	01			09	10	
				09	10	
08	01			01	04	1
				01	04	
01	01			07	01	
						1
				10	11	
01	01			05	01	
10	01			12	01	1
				12	01	
01	01			06	10	
				06	10	
				06	10	
				06	10	
08	03				01	1
08	03				01	3
					01	
					01	
					01	
01	01				01	
					01	
					01	

8-HOUR COUNT DATABASE

RD1	RD1TYPE	RD1SHORT	RD1DIR	RD2	RD2TYPE	RD2SHORT	RD2DIR	RD3	RD3TYPE	RD3SHORT	RD3DIR
NORTHCLIFFE		BV		ST. CLAIR		AV					
OAKWOOD		AV		ST. CLAIR		AV					
ALBION		ROAD		ELMHURST		DR					
BAYVIEW		AV		MCRAE		DR		MERTON		ST	
DAVENPORT		ROAD		UXBRIDGE		AV					
DUFFERIN		ST		WALLACE		AV					
KINGSTON		ROAD		MASON		ROAD		WHITECAP		BV	
FINCH		AV		LESLIE		ST					
BEVERLEY		ST		QUEEN		ST					

COUNT_DATE	INTER_CODE	COUNT_TYPE	COMMENT	AM_PK_HR	PM_PK_HR
950109	4000641502	R	W/B TRAFFIC, NORTH & EAST PEDESTRIANS COUNTED ON JANUARY 11 (WEDNESDAY	0800	1700
950111	4000643311	R		0815	1700
950104	0310102901	R	ELMHURST DR EAST - WESTBOUND.	0745	1645
950104	7010148613	R		0800	1645
950105	0200133711	R		0745	1630
950105	4010232814	P		0800	1615
950109	0130146706	R		0745	1645
950103	8010987001	R		0800	1645
950105	2000555101	P		0830	1600

AM_PK_HR	PM_PK_HR	AM_NB_X	AM_NB_T	AM_NB_R	AM_NB_L	AM_NS_P	AM_NB_B	AM_NB_O
0800	1700	185	44	35	31	139	0	0
0815	1700	465	335	48	39	92	0	0
0745	1645	530	502	0	73	10	0	0
0800	1645	735	692	16	98	1	0	0
0745	1630	10	1	10	14	21	0	0
0800	1615	438	353	0	27	0	0	0
0745	1645	95	2	13	10	20	0	0
0800	1645	680	558	154	161	24	0	0
0830	1600	378	0	0	0	74	0	0

AM_SB_X	AM_SB_T	AM_SB_R	AM_SB_L	AM_SS_P	AM_SB_B	AM_SB_O
0	0	0	0	45	0	0
452	399	74	72	38	0	0
1286	1107	56	0	6	0	0
1615	1432	93	4	13	0	0
13	1	1	5	24	0	0
683	607	45	0	2	0	0
13	2	20	7	19	0	0
1263	1001	173	130	33	0	0
0	0	139	70	0	0	0

AM_WB_X	AM_WB_T	AM_WB_R	AM_WB_L	AM_WS_P	AM_WB_B	AM_WB_O
549	518	81	0	113	0	0
616	503	89	1	66	0	0
129	0	0	0	8	0	0
426	235	11	118	38	0	0
379	364	3	4	3	0	0
72	0	0	0	56	0	0
2762	2732	36	8	7	0	0
1500	1166	7	90	32	0	0
475	336	115	0	14	0	0

AM_EB_X	AM_EB_T	AM_EB_R	AM_EB_L	AM_ES_P	AM_EB_B	AM_EB_O
994	959	0	60	57	0	0
806	686	52	41	126	0	0
0	0	179	28	0	0	0
170	150	65	32	11	0	0
661	646	8	6	5	0	0
0	0	76	85	0	1	0
1006	986	3	57	14	0	0
1319	1035	172	115	24	0	0
522	452	0	263	13	0	0

PM_NB_X	PM_NB_T	PM_NB_R	PM_NB_L	PM_NS_P	PM_NB_B	PM_NB_O
230	75	61	45	123	0	0
822	570	52	52	226	0	0
1284	1218	0	244	5	0	0
1179	1097	88	99	13	11	0
32	5	34	10	14	0	0
979	891	0	77	4	0	0
89	5	10	9	16	0	0
1182	1014	170	221	28	0	0
363	0	0	0	205	0	0

PM_SB_X	PM_SB_T	PM_SB_R	PM_SB_L	PM_SS_P	PM_SB_B	PM_SB_O
0	0	0	0	123	0	0
449	392	85	151	108	0	0
1008	883	52	0	7	0	0
971	801	56	19	13	0	0
57	1	3	2	62	0	0
795	730	90	0	2	0	0
50	5	24	7	26	0	0
855	547	82	83	34	0	0
0	0	165	108	0	0	0

PM_WB_X	PM_WB_T	PM_WB_R	PM_WB_L	PM_WS_P	PM_WB_B	PM_WB_O
860	815	81	0	53	0	0
973	836	214	2	199	0	0
296	0	0	0	8	0	0
319	164	22	61	22	0	0
670	657	6	15	9	0	0
167	0	0	0	74	0	0
1171	1138	23	17	6	0	0
1281	978	5	136	24	0	0
718	553	154	0	28	0	0

PM_EB_X	PM_EB_T	PM_EB_R	PM_EB_L	PM_ES_P	PM_EB_B	PM_EB_O
686	625	0	74	103	0	0
938	735	55	38	127	0	0
0	0	125	66	0	0	0
403	296	109	60	18	0	0
699	663	41	21	7	0	0
0	0	65	88	0	0	0
2348	2331	28	61	14	0	0
1316	1063	172	163	33	0	0
606	498	0	209	35	0	0

OF_NB_X	OF_NB_T	OF_NB_R	OF_NB_L	OF_NS_P	OF_NB_B	OF_NB_O
120	35	40	41	165	0	0
448	264	35	50	131	0	0
577	538	0	94	2	0	0
548	473	38	44	6	0	0
16	2	18	9	16	0	0
596	525	0	55	1	1	0
63	4	10	9	15	0	0
468	364	113	136	24	0	0
315	0	0	0	146	0	0

OF_SB_X	OF_SB_T	OF_SB_R	OF_SB_L	OF_SS_P	OF_SB_B	OF_SB_O
0	0	0	0	102	0	0
339	277	77	95	106	0	0
671	571	39	0	5	0	0
717	605	45	14	20	0	0
24	1	3	1	40	0	0
666	623	47	0	2	0	0
28	5	28	8	12	0	0
683	418	48	86	24	0	0
0	0	139	86	0	0	0

OF_WB_X	OF_WB_T	OF_WB_R	OF_WB_L	OF_WS_P	OF_WB_B	OF_WB_O
574	533	49	0	39	0	0
643	516	143	2	232	0	0
133	0	0	0	5	0	0
213	124	19	51	26	0	0
439	427	6	12	4	0	0
102	0	0	0	39	0	0
912	875	28	15	6	0	0
791	607	7	139	26	0	0
560	421	128	0	24	0	0

OF_EB_X	OF_EB_T	OF_EB_R	OF_EB_L	OF_ES_P	OF_EB_B	OF_EB_O
584	544	0	36	37	0	0
574	444	60	41	79	0	0
0	0	100	39	0	0	0
140	88	61	56	9	0	0
521	502	11	8	6	0	0
0	0	43	71	0	0	0
677	659	8	31	15	0	0
941	742	126	97	29	0	0
484	398	0	187	22	0	0

TL_NB_X	TL_NB_T	TL_NB_R	TL_NB_L	TL_NS_P	TL_NB_B	TL_NB_O
1246	362	329	328	1146	0	0
4336	2887	343	370	1112	0	0
5832	5443	0	1013	33	0	0
5763	5221	352	523	50	12	0
142	20	149	83	164	0	0
5002	4417	0	380	9	8	0
573	32	84	65	115	1	0
5278	4337	1031	1268	176	0	0
2544	0	0	0	1029	0	0

TL_SB_X	TL_SB_T	TL_SB_R	TL_SB_L	TL_SS_P	TL_SB_B	TL_SB_O
0	0	0	0	743	0	0
3165	2710	644	815	711	0	0
6916	5913	366	0	47	0	0
7632	6542	476	89	131	0	0
214	6	21	14	352	0	0
5479	5086	445	0	15	0	0
236	34	218	72	142	0	0
6836	4640	647	718	212	0	0
0	0	1137	708	0	0	0

TL_WB_X	TL_WB_T	TL_WB_R	TL_WB_L	TL_WS_P	TL_WB_B	TL_WB_O
4992	4664	486	0	422	0	0
5532	4518	1136	12	1483	0	0
1379	0	0	0	53	0	0
2222	1223	145	521	219	0	0
3794	3690	45	86	34	0	0
825	0	0	0	345	0	0
10504	10221	224	117	44	0	0
8301	6386	56	1017	199	0	0
4623	3486	999	0	170	0	0

TL_EB_X	TL_EB_T	TL_EB_R	TL_EB_L	TL_ES_P	TL_EB_B	TL_EB_O
5426	5097	0	398	413	0	0
5788	4630	443	313	752	0	0
0	0	1003	389	0	0	0
1569	1128	569	397	93	1	0
4708	4545	122	77	41	0	0
0	0	393	585	0	1	0
9020	8864	85	317	108	0	0
8740	6991	1179	885	220	0	0
3997	3289	0	1545	198	0	0

INTERSECTION DATABASE

STREET1	SHORT1	STREET2	SHORT2	STREET3	SHORT3
ABERFOYLE	CR	BLOOR	ST	GARDENVALE	ROAD
ADELAIDE	ST	BATHURST	ST		
ADELAIDE	ST	BAY	ST		
ADELAIDE	ST	CHURCH	ST		
ADELAIDE	ST	DUNCAN	ST		
ADELAIDE	ST	JOHN	ST		
ADELAIDE	ST	PARLIAMENT	ST		
ADELAIDE	ST	PETER	ST		
ADELAIDE	ST	SHERBOURNE	ST		
ADELAIDE	ST	SPADINA	AV		
ADELAIDE	ST	UNIVERSITY	AV		
ADELAIDE	ST	VICTORIA	ST		
ADELAIDE	ST	YONGE	ST		
ADELAIDE	ST	YORK	ST		
ADESSO	DR	PETER KAISER	GATE	STEELES	AV
ADIRONDACK	GATE	FINCH	AV	WAYSIDE	AV
ALAMOSA	DR	FINCH	AV	PINEWAY	BV
ALBERT	ST	BAY	ST		
ALBERTA	AV	ST. CLAIR	AV		
ALBION	ROAD	ARCOT	BV	IRWIN	ROAD
ALBION	ROAD	ARMEL	CT		
ALBION	ROAD	BENSTROW	AV	SANAGAN	ROAD
ALBION	ROAD	CARRIER	DR		
ALBION	ROAD	CLAIREPORT	CR	CODLIN	CR
ALBION	ROAD	ELMHURST	DR		
ALBION	ROAD	FINCH	AV		
ALBION	ROAD	HUMBERLINE	DR		
ALBION	ROAD	HWY 27			
ALBION	ROAD	INDIAN	LINE		
ALBION	ROAD	ISLINGTON	AV		
ALBION	ROAD	KIPLING	AV		
ALBION	ROAD	MARTIN GROVE	ROAD		
ALBION	ROAD	RIVERDALE	DR	THISTLE DOWN	BV
ALBION	ROAD	SHENDALE	DR		
ALBION	ROAD	SILVERSTONE	DR		
ALBION	ROAD	STEELES	AV		
ALBION	ROAD	WESTMORE	DR		
ALCORN	AV	SHAFTESBURY	AV	YONGE	ST
ALEXDON	ROAD	FINCH	AV		
ALEXMUIR	BV	BRIMLEY	ROAD	BRIMWOOD	BV
ALLANFORD	ROAD	BIRCHMOUNT	ROAD	SCARDEN	AV
ALLANFORD	ROAD	SHEPPARD	AV		
ALLIANCE	AV	JANE	ST		
ALNESS	ST	CHAMPAGNE	DR	FINCH	AV
ALNESS	ST	STEELES	AV		
AMBROSE	ROAD	PROVOST	DR	SHEPPARD	AV
ANCASTER	ROAD	WILSON	AV		
ANGLESEY	BV	ISLINGTON	AV		

ANNABELLE	DR	KIPLING	AV	ROWNTREE	ROAD
ANNETTE	ST	BABY POINT	ROAD	JANE	ST
ANNETTE	ST	CLENDENAN	AV		
ANNETTE	ST	EVELYN	AV		
ANNETTE	ST	INDIAN RD	CR		
ANNETTE	ST	KEELE	ST		
ANNETTE	ST	RUNNYMEDE	ROAD		
ANTIBES	DR	BATHURST	ST	DREWRY	AV
ANTRIM	CR	KENNEDY	ROAD		
APEX	ROAD	DUFFERIN	ST		
APEX	ROAD	GOOD SHEPPARD	CT	LAWRENCE	AV
ARAGON	AV	BAY MILLS	BV	SHEPPARD	AV
ARCHER	ROAD	SILVERWOOD	AV	SPADINA	ROAD
ARDAGH	ST	JANE	ST		
ARJAY	CR	BAYVIEW	AV		
ARKONA	DR	CLOVERLEAF	GATE	WARDEN	AV
ARLETA	AV	NORTHOVER	ST	SHEPPARD	AV
ARLINGTON	AV	ST. CLAIR	AV		
ARMADALE	AV	BLOOR	ST		
ARMOURY	ST	UNIVERSITY	AV		
ARNCLIFFE	CR	VICTORIA PARK	AV		
ARROW	ROAD	FINCH	AV	SIGNET	DR
ARROW	ROAD	SHEPPARD	AV		
ARROWSMITH	AV	KEELE	ST	MILFORD	AV
ASCOT	AV	DUFFERIN	ST		
ASHCOTT	ST	FENTON	ROAD	STEELES	AV
ASHTONBEE	ROAD	PHARMACY	AV		
ASHTONBEE	ROAD	WARDEN	AV		
ASPENWOOD	DR	STEELES	AV		
ATHABASKA	AV	YONGE	ST		
ATLAS	AV	ST. CLAIR	AV		
ATOMIC	AV	THE QUEENSWAY			
ATRIUM	LANE	DURNFORD	ROAD	SHEPPARD	AV
ATTWELL	DR	BELFIELD	ROAD		
AU LARGE	BV	FINCH	AV	SENECA HILL	DR
AUBURN	AV	DUFFERIN	ST		
AUGUSTA	AV	COLLEGE	ST		
AUKLAND	ROAD	BLOOR	ST		
AUKLAND	ROAD	DUNDAS	ST		
AVA	ROAD	BATHURST	ST		
AVENUE	ROAD	BALMORAL	AV		
AVENUE	ROAD	BLOOR	ST	QUEENS PARK	ROAD
AVENUE	ROAD	BRIAR HILL	AV		
AVENUE	ROAD	BROOKE	AV		
AVENUE	ROAD	CASTLEFIELD	AV		
AVENUE	ROAD	CHAPLIN	CR		
AVENUE	ROAD	COLLEGE VIEW	AV		
AVENUE	ROAD	COTTINGHAM	ST		
AVENUE	ROAD	CUMBERLAND	ST		
AVENUE	ROAD	DAVENPORT	ROAD		
AVENUE	ROAD	DUNBLAINE	AV		

AVENUE	ROAD	DUPONT	ST		
AVENUE	ROAD	EDMUND	AV		
AVENUE	ROAD	EGLINTON	AV		
AVENUE	ROAD	FAIRLAWN	AV		
AVENUE	ROAD	GLENCAIRN	AV		
AVENUE	ROAD	GLENGROVE	AV		
AVENUE	ROAD	HEATH	ST		
AVENUE	ROAD	HILLHURST	BV		
AVENUE	ROAD	LAWRENCE	AV		
AVENUE	ROAD	LONSDALE	ROAD		
AVENUE	ROAD	LYTTON	BV		
AVENUE	ROAD	MELROSE	AV		
AVENUE	ROAD	OLD ORCHARD	GROV		
AVENUE	ROAD	OXTON	AV		
AVENUE	ROAD	ROSELAWN	AV		
AVENUE	ROAD	ST. CLAIR	AV		
AVENUE	ROAD	ST. CLEMENTS	AV		
AVENUE	ROAD	WILSON	AV		
AVENUE	ROAD	WOBURN	AV		
AVENUE	ROAD	YORKVILLE	AV		
AVOCA	AV	ST. CLAIR	AV		
AVONDALE	AV	FLORENCE	AV	YONGE	ST
AYLMER	AV	BELMONT	ST	YONGE	ST
BAINBRIDGE	AV	BATHURST	ST	RAOUL WALLENBERG	ROAD
BALA	AV	EMMETT	AV	JANE	ST
BALLYRONAN	ROAD	LESLIE	ST	LONGWOOD	DR
BALMORAL	AV	ROSEHILL	AV	YONGE	ST
BANBURY	ROAD	CHIPSTEAD	ROAD	YORK MILLS	ROAD
BANFF	ROAD	EGLINTON	AV		
BANNATYNE	DR	LESLIE	ST		
BARBER GREENE	ROAD	DON MILLS	ROAD	GREEN BELT	DR
BARKER	AV	ISLINGTON	AV		
BARMAC	DR	SCHOLES	ROAD	STEELES	AV
BARRYMORE	ROAD	LAWRENCE	AV		
BARTLEY	DR	BERMONDSEY	ROAD		
BARTON	AV	BATHURST	ST		
BARTON	AV	CHRISTIE	ST		
BASSETT	AV	VICTORIA PARK	AV	YARDLEY	AV
BATHURST	ST	BAYCREST	AV		
BATHURST	ST	BLOOR	ST		
BATHURST	ST	BLUE FLAG	GATE	HORSHAM	AV
BATHURST	ST	BRIAR HILL	AV		
BATHURST	ST	BURTON	ROAD	STRATHEARN	ROAD
BATHURST	ST	CARIBOU	ROAD	DELLPARK	AV
BATHURST	ST	CARSCADDEN	DR	ELLERSLIE	AV
BATHURST	ST	CEDARCROFT	BV	PATRICIA	AV
BATHURST	ST	CLAXTON	BV	LONSDALE	ROAD
BATHURST	ST	CODSELL	AV		
BATHURST	ST	COLLEGE	ST		
BATHURST	ST	DAVENPORT	ROAD		
BATHURST	ST	DEWLANE	DR	ROCKFORD	ROAD

BATHURST	ST	DUNDAS	ST		
BATHURST	ST	DUPONT	ST		
BATHURST	ST	EDINBURGH	DR		
BATHURST	ST	EGLINTON	AV		
BATHURST	ST	ELM RIDGE	DR	ROSELAWN	AV
BATHURST	ST	FAIRLAWN	AV	PRINCE CHARLES	DR
BATHURST	ST	FINCH	AV		
BATHURST	ST	FISHERVILLE	ROAD		
BATHURST	ST	FLEET	ST	LAKESHORE	BV
BATHURST	ST	FRONT	ST		
BATHURST	ST	GLENCAIRN	AV		
BATHURST	ST	GLENGROVE	AV		
BATHURST	ST	GREENWIN VILLAGE	ROAD		
BATHURST	ST	HARBORD	ST		
BATHURST	ST	INVERMAY	AV		
BATHURST	ST	JOICEY	BV	MARQUETTE	AV
BATHURST	ST	KING	ST		
BATHURST	ST	LAURELCREST	AV	RAEBURN	AV
BATHURST	ST	LAWRENCE	AV		
BATHURST	ST	LENNOX	ST		
BATHURST	ST	MASCOT	PL	STAFFORD	ROAD
BATHURST	ST	MCALLISTER	ROAD		
BATHURST	ST	NASSAU	ST		
BATHURST	ST	NEPTUNE	DR		
BATHURST	ST	NINA	ST		
BATHURST	ST	OLD ORCHARD	GROV		
BATHURST	ST	QUEEN	ST		
BATHURST	ST	QUEENS	QUAY		
BATHURST	ST	RANEE	AV		
BATHURST	ST	REINER	ROAD		
BATHURST	ST	RICHMOND	ST		
BATHURST	ST	RIDGE HILL	DR	VESTA	DR
BATHURST	ST	SARANAC	BV		
BATHURST	ST	SHELBORNE	AV		
BATHURST	ST	SHEPPARD	AV		
BATHURST	ST	ST. CLAIR	AV		
BATHURST	ST	STEELES	AV		
BATHURST	ST	TICHESTER	ROAD		
BATHURST	ST	ULSTER	ST		
BATHURST	ST	VIEWMOUNT	AV		
BATHURST	ST	WARWICK	AV		
BATHURST	ST	WELLS	ST		
BATHURST	ST	WILSON	AV		
BATHURST	ST	YORK DOWNS	DR		
BAY	ST	BLOOR	ST		
BAY	ST	CHARLES	ST		
BAY	ST	DAVENPORT	ROAD		
BAY	ST	DUNDAS	ST		
BAY	ST	EDWARD	ST		
BAY	ST	HARBOUR	ST		
BAY	ST	LAKESHORE	BV		

BAY	ST	QUEEN	ST		
BAY	ST	RICHMOND	ST		
BAY	ST	WELLESLEY	ST		
BAY	ST	WELLINGTON	ST		
BAY MILLS	BV	BIRCHMOUNT	ROAD	BONIS	AV
BAYLAWN	DR	FINCH	AV		
BAYVIEW	AV	BAYVIEW MEWS	LANE		
BAYVIEW	AV	BLYTHWOOD	ROAD		
BAYVIEW	AV	BROADWAY	AV		
BAYVIEW	AV	CITATION	DR	EMPRESS	AV
BAYVIEW	AV	CUMMER	AV		
BAYVIEW	AV	DAVISVILLE	AV		
BAYVIEW	AV	EGLINTON	AV		
BAYVIEW	AV	FINCH	AV		
BAYVIEW	AV	FLEMING	CR	MANOR	ROAD
BAYVIEW	AV	FOREST HEIGHTS	BV		
BAYVIEW	AV	GARNIER	CT	NEWTON	DR
BAYVIEW	AV	HEATHCOTE	AV		
BAYVIEW	AV	LAWRENCE	AV		
BAYVIEW	AV	MCKEE	AV		
BAYVIEW	AV	MCRAE	DR	MERTON	ST
BAYVIEW	AV	MILLWOOD	ROAD		
BAYVIEW	AV	MOORE	AV		
BAYVIEW	AV	NESBITT	DR		
BAYVIEW	AV	OLD COLONY	ROAD		
BAYVIEW	AV	PARKHURST	BV	SOUDAN	AV
BAYVIEW	AV	POST	ROAD		
BAYVIEW	AV	POTTERY	ROAD		
BAYVIEW	AV	ROSEDALE VALLEY	ROAD		
BAYVIEW	AV	RUDDINGTON	DR		
BAYVIEW	AV	SCENIC	MLWY		
BAYVIEW	AV	SHEPPARD	AV		
BAYVIEW	AV	STEELES	AV		
BAYVIEW	AV	SUNNYDENE	CR		
BAYVIEW	AV	WIMPOLE	DR		
BAYVIEW	AV	YORK MILLS	ROAD		
BEACHELL	ST	EGLINTON	AV		
BEACONHILL	ROAD	KIPLING	AV		
BEARE	ROAD	STEELES	AV		
BEAUMONDE HEIGHTS	DR	ISLINGTON	AV		
BEDFORD	ROAD	BLOOR	ST		
BEDFORD	ROAD	DAVENPORT	ROAD		
BEECH	AV	KINGSTON	ROAD		
BEECH	AV	QUEEN	ST		
BEECHBOROUGH	AV	KEELE	ST		
BEECHGROVE	DR	KINGSTON	ROAD		
BEECHGROVE	DR	LAWRENCE	AV		
BEECROFT	ROAD	NORTH YORK	BV		
BEECROFT	ROAD	PARK HOME	AV		
BEECROFT	ROAD	SHEPPARD	AV		
BELFIELD	ROAD	HWY 27			

BELFIELD	ROAD	HWY 409		KIPLING	AV
BELFIELD	ROAD	MARTIN GROVE	ROAD		
BELLAMY	ROAD	BRIMORTON	DR		
BELLAMY	ROAD	EGLINTON	AV		
BELLAMY	ROAD	ELLESMERE	ROAD		
BELLAMY	ROAD	KINGSTON	ROAD	RAVINE	DR
BELLAMY	ROAD	LAWRENCE	AV		
BELLEFAIR	AV	QUEEN	ST		
BELMONT	ST	DAVENPORT	ROAD	NEW	ST
BELSIZE	DR	YONGE	ST		
BEMERSYDE	DR	EGLINTON	AV	WINCOTT	DR
BENTON	ROAD	LAWRENCE	AV		
BENTWORTH	AV	DUFFERIN	ST	RANEE	AV
BERGAMOT	AV	ISLINGTON	AV		
BERGAMOT	AV	REXDALE	BV		
BERKELEY	ST	FRONT	ST		
BERMONDSEY	ROAD	EGLINTON	AV	SLOANE	AV
BERMONDSEY	ROAD	O'CONNOR	DR	YARDLEY	AV
BERMONDSEY	ROAD	SUNRISE	AV		
BERTRAND	AV	BIRCHMOUNT	ROAD		
BERTRAND	AV	KENNEDY	ROAD		
BERTRAND	AV	WARDEN	AV		
BERWICK	AV	SOUDAN	AV	YONGE	ST
BESSARION	ROAD	BURBANK	DR	SHEPPARD	AV
BESTVIEW	DR	STEELES	AV		
BETHRIDGE	ROAD	MARTIN GROVE	ROAD		
BEVERLEY	ST	COLLEGE	ST	ST. GEORGE	ST
BEVERLEY	ST	DUNDAS	ST		
BEVERLEY	ST	QUEEN	ST		
BEVERLY GLEN	BV	CHESTER LE	BV	PHARMACY	AV
BEVERLY HILLS	DR	JANE	ST		
BICKNELL	AV	EGLINTON	AV	MUNICIPAL	DR
BIRCH	AV	YONGE	ST		
BIRCHCLIFF	AV	KINGSTON	ROAD		
BIRCHMOUNT	ROAD	COMSTOCK	ROAD		
BIRCHMOUNT	ROAD	DANFORTH	AV		
BIRCHMOUNT	ROAD	DANFORTH	ROAD		
BIRCHMOUNT	ROAD	EGLINTON	AV		
BIRCHMOUNT	ROAD	ELLESMERE	ROAD		
BIRCHMOUNT	ROAD	FINCH	AV		
BIRCHMOUNT	ROAD	FUNDY BAY	BV	IVY BUSH	AV
BIRCHMOUNT	ROAD	GLENDOWER	CRCT	TIMBERBANK	BV
BIRCHMOUNT	ROAD	HUNTINGWOOD	DR		
BIRCHMOUNT	ROAD	KINGSTON	ROAD		
BIRCHMOUNT	ROAD	L'AMOREAUX	DR	SILVER SPRINGS	BV
BIRCHMOUNT	ROAD	LAURA SECORD	WALK		
BIRCHMOUNT	ROAD	LAWRENCE	AV		
BIRCHMOUNT	ROAD	MCNICOLL	AV		
BIRCHMOUNT	ROAD	SAN WOOD	BV	WINTERMUTE	BV
BIRCHMOUNT	ROAD	SHEPPARD	AV		
BIRCHMOUNT	ROAD	ST. CLAIR	AV		

BIRCHMOUNT	ROAD	STEELES	AV		
BIRCHWOOD	AV	YORK MILLS	ROAD		
BIRKDALE	ROAD	ELLESMERE	ROAD		
BIRMINGHAM	ST	ISLINGTON	AV		
BISHOP	AV	HENDON	AV	YONGE	ST
BLACK CREEK	DR	EGLINTON	AV		
BLACK CREEK	DR	HUMBER	BV	WESTON	ROAD
BLACK CREEK	DR	JANE	ST		
BLACK CREEK	DR	KEELESDALE	DR		
BLACK CREEK	DR	LAWRENCE	AV		
BLACK CREEK	DR	PHOTOGRAPHY	DR		
BLACK CREEK	DR	TRETHEWEY	DR		
BLACKTHORN	AV	EGLINTON	AV		
BLAKEMANOR	BV	MARKHAM	ROAD		
BLANTYRE	AV	KINGSTON	ROAD		
BLOOR	ST	BROCK	AV		
BLOOR	ST	BRUNSWICK	AV		
BLOOR	ST	CASTLE FRANK	ROAD		
BLOOR	ST	CHRISTIE	ST	GRACE	ST
BLOOR	ST	CHURCH	ST		
BLOOR	ST	CLENDENAN	AV		
BLOOR	ST	COLBOURNE LODGE	DR	HIGH PARK	AV
BLOOR	ST	CRAWFORD	ST		
BLOOR	ST	DOVERCOURT	ROAD		
BLOOR	ST	DUFFERIN	ST		
BLOOR	ST	GLENDONWYNNE	ROAD		
BLOOR	ST	GREEN	LANS		
BLOOR	ST	HAVELOCK	ST		
BLOOR	ST	HURON	ST		
BLOOR	ST	INDIAN	ROAD		
BLOOR	ST	ISLINGTON	AV		
BLOOR	ST	JANE	ST		
BLOOR	ST	JARVIS	ST		
BLOOR	ST	KEELE	ST	PARKSIDE	DR
BLOOR	ST	KIPLING	AV		
BLOOR	ST	LANSDOWNE	AV		
BLOOR	ST	MANNING	AV		
BLOOR	ST	MARGUERETTA	ST		
BLOOR	ST	MILL	ROAD		
BLOOR	ST	OLD MILL	ROAD	THE KINGSWAY	
BLOOR	ST	OSSINGTON	AV		
BLOOR	ST	PALMERSTON	AV		
BLOOR	ST	PARK	ROAD		
BLOOR	ST	PARLIAMENT	ST		
BLOOR	ST	PRINCE EDWARD	DR		
BLOOR	ST	RIVERVIEW	GDNS		
BLOOR	ST	ROYAL YORK	ROAD		
BLOOR	ST	RUNNYMEDE	ROAD		
BLOOR	ST	SHAVER	AV		
BLOOR	ST	SHAW	ST		
BLOOR	ST	SHERBOURNE	ST		

BLOOR	ST	SOUTH KINGSWAY			
BLOOR	ST	SPADINA	AV	SPADINA	ROAD
BLOOR	ST	ST. GEORGE	ST		
BLOOR	ST	THE EAST	MALL		
BLOOR	ST	THE WEST	MALL		
BLOOR	ST	WINDERMERE	AV		
BLUE JAYS	WAY	KING	ST	PETER	ST
BLUFFWOOD	DR	FAIRWAY HTS	DR	STEELES	AV
BLYTHWOOD	ROAD	LYTTON	BV	YONGE	ST
BLYTHWOOD	ROAD	MOUNT PLEASANT	ROAD		
BOLINGBROKE	ROAD	LAWRENCE	AV		
BOND	AV	DON MILLS	ROAD	LEGATO	CT
BONIS	AV	CARDWELL	AV	KENNEDY	ROAD
BONNINGTON	PL	SHEPPARD	AV		
BORDEN	ST	COLLEGE	ST		
BOULTON	AV	DUNDAS	ST		
BOWIE	AV	DUFFERIN	ST	WHITMORE	AV
BOWMORE	ROAD	GERRARD	ST		
BRADSTOCK	ROAD	WESTON	ROAD		
BRAHMS	AV	FINCH	AV	LINUS	ROAD
BRANDON	AV	DUFFERIN	ST		
BRECKON	GATE	BRENYON	WAY	SHEPPARD	AV
BREMNER	BV	SPADINA	AV		
BRENTCLIFFE	ROAD	EGLINTON	AV		
BRENTWOOD	AV	EASTON	ROAD	SHEPPARD	AV
BRIAN	DR	CONSUMERS	ROAD	SHEPPARD	AV
BRIAN	AV	PHARMACY	AV		
BRIAR HILL	AV	DUFFERIN	ST		
BRIAR HILL	AV	SHERWOOD	AV	YONGE	ST
BRIDGELAND	AV	DUFFERIN	ST	YORKDALE	ROAD
BRIMLEY	ROAD	BRIMORTON	DR	WATERFIELD	DR
BRIMLEY	ROAD	CHARTLAND	BV		
BRIMLEY	ROAD	CHILLERY	AV		
BRIMLEY	ROAD	CITADEL	DR	GRAYLEE	AV
BRIMLEY	ROAD	DANFORTH	ROAD		
BRIMLEY	ROAD	DEERFIELD	ROAD		
BRIMLEY	ROAD	DORCOT	AV		
BRIMLEY	ROAD	EGLINTON	AV		
BRIMLEY	ROAD	ELLESMERE	ROAD		
BRIMLEY	ROAD	FINCH	AV		
BRIMLEY	ROAD	FRASERTON	CR	SHEDIAC	ROAD
BRIMLEY	ROAD	HEATHER	ROAD		
BRIMLEY	ROAD	HUNTINGWOOD	DR		
BRIMLEY	ROAD	KINGSTON	ROAD		
BRIMLEY	ROAD	LAWRENCE	AV		
BRIMLEY	ROAD	MCNICOLL	AV		
BRIMLEY	ROAD	PITFIELD	ROAD		
BRIMLEY	ROAD	PROGRESS	AV		
BRIMLEY	ROAD	SHEPPARD	AV		
BRIMLEY	ROAD	ST. CLAIR	AV		
BRIMLEY	ROAD	STEELES	AV		

BRIMLEY	ROAD	TRITON	ROAD		
BRIMORTON	DR	MARKHAM	ROAD		
BRIMORTON	DR	MCCOWAN	ROAD		
BRITISH COLUMBIA	ROAD	LAKESHORE	BV		
BROADBENT	AV	MIDLAND	AV	WAINFLEET	ROAD
BROADOAKS	DR	KEELE	ST		
BROADVIEW	AV	CHESTER HILL	ROAD		
BROADVIEW	AV	COSBURN	AV		
BROADVIEW	AV	DANFORTH	AV		
BROADVIEW	AV	DUNDAS	ST		
BROADVIEW	AV	EASTERN	AV		
BROADVIEW	AV	GERRARD	ST		
BROADVIEW	AV	HOGARTH	AV	MONTCREST	BV
BROADVIEW	AV	MORTIMER	AV	POTTERY	ROAD
BROADVIEW	AV	PRETORIA	AV		
BROADVIEW	AV	QUEEN	ST		
BROADWAY	AV	MONTGOMERY	AV	YONGE	ST
BROADWAY	AV	MOUNT PLEASANT	ROAD		
BROCK	AV	COLLEGE	ST		
BROCK	AV	DUNDAS	ST		
BROCK	AV	QUEEN	ST		
BROCKLEY	DR	LAWRENCE	AV		
BROOKBANKS	DR	PARKWOODS VILLAGE	DR		
BROOKLAWN	AV	KINGSTON	ROAD	ST. CLAIR	AV
BROOKSIDE	DR	KINGSTON	ROAD	WAVERLEY	ROAD
BROOKVIEW	DR	LAWRENCE	AV		
BROW	DR	FORTY-FIRST	ST	LAKESHORE	BV
BROWN'S	LINE	COULES	CT		
BROWN'S	LINE	HORNER	AV		
BROWN'S	LINE	JELLICOE	AV		
BROWN'S	LINE	LAKESHORE	BV		
BROWN'S	LINE	VALERMO	DR		
BROWN'S	LINE	WOODBURY	ROAD		
BRUCEWOOD	CR	GLENMOUNT	AV	LAWRENCE	AV
BRUNSWICK	AV	COLLEGE	ST		
BRUNSWICK	AV	DUPONT	ST		
BRUNSWICK	AV	HARBORD	ST		
BRYANT	ST	SHEPPARD	AV	YEOMANS	ROAD
BUCHAN	CT	SHEPPARD	AV		
BURNHAMTHORPE	ROAD	CORDOVA	AV	DUNDAS	ST
BURNHAMTHORPE	ROAD	KIPLING	AV		
BURNHAMTHORPE	ROAD	MARTIN GROVE	ROAD		
BURNHAMTHORPE	ROAD	MILL	ROAD		
BURNHAMTHORPE	ROAD	THE EAST	MALL		
BURNHAMTHORPE	ROAD	THE WEST	MALL		
BURNVIEW	CR	LAWRENCE	AV		
BUSHBY	DR	MCCOWAN	ROAD	TOWN CENTRE	CT
BYNG	AV	DANFORTH	AV		
BYNG	AV	YONGE	ST		
CABERNET	CIR	GIHON SPRING	DR	MARTIN GROVE	ROAD
CACTUS	AV	STEELES	AV		

CAITHNESS	AV	DANFORTH	AV		
CALEDONIA	ROAD	CALEDONIA PARK	ROAD	ST. CLAIR	AV
CALEDONIA	ROAD	CASTLEFIELD	AV		
CALEDONIA	ROAD	EGLINTON	AV		
CALEDONIA	ROAD	KITCHENER	AV		
CALEDONIA	ROAD	LAWRENCE	AV		
CALEDONIA	ROAD	NORMAN	AV		
CALEDONIA	ROAD	RAITHERM	ROAD		
CALEDONIA	ROAD	ROGERS	ROAD		
CALVINGTON	DR	KEELE	ST		
CAMBRIDGE	AV	PRETORIA	AV		
CANARCTIC	DR	KEELE	ST	YORK	BV
CANMOTOR	AV	LADY BANK	ROAD	THE QUEENSWAY	
CANNON JACKSON	DR	KEELE	ST		
CAPSTAN	GATE	SHALE	GATE	STEELES	AV
CARLAW	AV	DANFORTH	AV		
CARLAW	AV	DUNDAS	ST		
CARLAW	AV	EASTERN	AV		
CARLAW	AV	GERRARD	ST		
CARLAW	AV	LAKESHORE	BV		
CARLAW	AV	QUEEN	ST		
CARLINGVIEW	DR	DIXON	ROAD		
CARLINGVIEW	DR	FASKEN	DR		
CARLINGVIEW	DR	INTERNATIONAL	BV	RENFORTH	DR
CARLTON	ST	CHURCH	ST		
CARLTON	ST	JARVIS	ST		
CARLTON	ST	SHERBOURNE	ST		
CARNFORTH	ROAD	LAWRENCE	AV		
CARPENTER	ROAD	STEELES	AV		
CARSON	CR	WILLIAM CARSON	CR	YONGE	ST
CASEBRIDGE	CT	MCLEVIN	AV	MORNINGSIDE	AV
CASS	AV	PALMDALE	DR	WARDEN	AV
CASSANDRA	BV	VICTORIA PARK	AV		
CASTLE KNOCK	ROAD	EGLINTON	AV		
CASTLEFIELD	AV	DUFFERIN	ST		
CASTLEFIELD	AV	KINCORT	ST		
CASTLEFIELD	AV	RONALD	AV		
CASTLEFIELD	AV	YONGE	ST		
CATHEDRAL BLUFFS	DR	KINGSTON	ROAD	MCCOWAN	ROAD
CAVAN	AV	WESTON	ROAD		
CEDAR	DR	EGLINTON	AV		
CELESTE	DR	KINGSTON	ROAD		
CENTENNIAL	ROAD	LAWRENCE	AV		
CHANNEL NINE	CT	MCCOWAN	ROAD	MILNER	AV
CHAPLIN	CR	DAVISVILLE	AV	YONGE	ST
CHAPLIN	CR	EGLINTON	AV		
CHAPLIN	CR	ORIOLE	PKY		
CHAPLIN	CR	ROSELAWN	AV		
CHAPMAN	ROAD	SCARLETT	ROAD		
CHARLES	ST	JARVIS	ST	MOUNT PLEASANT	ROAD
CHATSWORTH	DR	LAWRENCE	AV		

CHATSWORTH	DR	ST. EDMUNDS	DR	YONGE	ST
CHEROKEE	BV	FINCH	AV		
CHESSWOOD	DR	FINCH	AV		
CHESSWOOD	DR	SHEPPARD	AV		
CHESTER	AV	DANFORTH	AV		
CHETTA	PL	DIXON	ROAD	WINCOTT	DR
CHINE	DR	KINGSTON	ROAD		
CHIPPING	ROAD	DON MILLS	ROAD		
CHRISTIE	ST	DAVENPORT	ROAD		
CHRISTIE	ST	DUPONT	ST		
CHRISTIE	ST	ST. CLAIR	AV		
CHURCH	AV	CHURCHILL	AV	YONGE	ST
CHURCH	ST	DAVENPORT	ROAD	YONGE	ST
CHURCH	ST	DUNDAS	ST		
CHURCH	ST	GERRARD	ST		
CHURCH	ST	GOULD	ST		
CHURCH	ST	JANE	ST	MAPLE LEAF	DR
CHURCH	ST	KING	ST		
CHURCH	ST	QUEEN	ST		
CHURCH	ST	SHUTER	ST		
CHURCH	ST	WELLESLEY	ST		
CITY VIEW	DR	DIXON	ROAD	KELFIELD	ST
CLAIR	ROAD	JANE	ST	SPENVALLEY	DR
CLAREMORE	AV	CLIFFSIDE	DR	KINGSTON	ROAD
CLAUDE	AV	THE QUEENSWAY			
CLAYSON	ROAD	WILSON	AV		
CLEARVIEW	HTS	TRETHEWEY	DR		
CLENDENAN	AV	DUNDAS	ST		
CLINTON	ST	COLLEGE	ST		
CLINTON	ST	HARBORD	ST		
CLONMORE	DR	GERRARD	ST		
CLONMORE	DR	HOLLIS	AV	WARDEN	AV
CLOVELLY	AV	OAKWOOD	AV		
CLOVERLAWN	AV	DUFFERIN	ST	GOODWOOD	AV
CLYDESDALE	DR	VICTORIA PARK	AV		
COLBECK	ST	RUNNYMEDE	ROAD		
COLBOURNE LODGE	DR	LAKESHORE	BV		
COLBOURNE LODGE	DR	THE QUEENSWAY			
COLDWATER	ROAD	FARMSTEAD	ROAD	LESLIE	ST
COLLEGE	ST	CRAWFORD	ST		
COLLEGE	ST	DOVERCOURT	ROAD		
COLLEGE	ST	DUFFERIN	ST		
COLLEGE	ST	GRACE	ST		
COLLEGE	ST	HURON	ST		
COLLEGE	ST	MCCAUL	ST		
COLLEGE	ST	OSSINGTON	AV		
COLLEGE	ST	SHERIDAN	AV		
COLLEGE	ST	SPADINA	AV		
COLLEGE	ST	UNIVERSITY	AV		
COLLEGE VIEW	AV	ORIOLE	PKY		
COLLINGWOOD	ST	JADE	ST	KENNEDY	ROAD

COLLINSGROVE	ROAD	KINGSTON	ROAD		
COLLINSGROVE	ROAD	LAWRENCE	AV	LING	ROAD
COMMANDER	BV	MCCOWAN	ROAD		
COMMERCE	BV	EGLINTON	AV		
COMSTOCK	ROAD	WARDEN	AV		
CONACHER	DR	STEELES	AV		
CONCORDE	PL	WYNFORD	DR	WYNFORD HEIGHTS	CR
CONLEY	ST	HIDDEN	TR	STEELES	AV
CONSUMERS	ROAD	HALLCROWN	PL		
CONSUMERS	ROAD	MEADOWACRES	DR	VICTORIA PARK	AV
CONVAIR	DR	RENFORTH	DR		
COPTHORNE	AV	MIDLAND	AV	PASSMORE	AV
CORLEY	AV	EASTWOOD	ROAD	WOODBINE	AV
CORONATION	DR	MORNINGSIDE	AV		
CORVETTE	AV	KENNEDY	ROAD		
COSBURN	AV	COXWELL	AV		
COSBURN	AV	DONLANDS	AV		
COSBURN	AV	GREENWOOD	AV		
COSBURN	AV	WOODBINE	AV		
COUGAR	CT	LUELLA	ST	MARKHAM	ROAD
COURAGE	AV	JANE	ST		
COURCELETTE	ROAD	KINGSTON	ROAD		
COXWELL	AV	COXWELL	BV	O'CONNOR	DR
COXWELL	AV	DANFORTH	AV		
COXWELL	AV	DUNDAS	ST		
COXWELL	AV	EASTERN	AV		
COXWELL	AV	GLEBEHOLME	BV		
COXWELL	AV	HANSON	ST		
COXWELL	AV	LAKESHORE	BV		
COXWELL	AV	MORTIMER	AV		
COXWELL	AV	PLAINS	ROAD		
COXWELL	AV	QUEEN	ST		
COXWELL	AV	SAMMON	AV		
CRAIGTON	DR	JONESVILLE	CR	VICTORIA PARK	AV
CREDIT UNION	DR	EGLINTON	AV	SWIFT	DR
CRESCENT	ROAD	YONGE	ST		
CRESCENT TOWN	ROAD	DAWES	ROAD		
CRESCENT TOWN	ROAD	VICTORIA PARK	AV		
CROATIA	ST	DUFFERIN	ST		
CROCKFORD	BV	LAWRENCE	AV		
CROMWELL	ROAD	GUILDWOOD	PKY	KINGSTON	ROAD
CULFORD	ROAD	LAWRENCE	AV		
CUMMER	AV	DREWRY	AV	YONGE	ST
CUMMER	AV	LESLIE	ST	MCNICOLL	AV
CUMMER	AV	WILLOWDALE	AV		
CURLEW	DR	LYNVALLEY	CR	VICTORIA PARK	AV
DANFORTH	AV	DANFORTH	ROAD		
DANFORTH	AV	DAWES	ROAD		
DANFORTH	AV	DONLANDS	AV		
DANFORTH	AV	EAST LYNN	AV	WOODMOUNT	AV
DANFORTH	ROAD	EGLINTON	AV		

DANFORTH	ROAD	FALMOUTH	AV	GLENSHEPHARD	DR
DANFORTH	AV	GLEBEMOUNT	AV		
DANFORTH	AV	GLEDHILL	AV	PATRICIA	DR
DANFORTH	ROAD	GORDONRIDGE	PL	WOLFE	AV
DANFORTH	AV	GOUGH	AV		
DANFORTH	AV	GREENWOOD	AV		
DANFORTH	AV	JONES	AV		
DANFORTH	ROAD	KENNEDY	ROAD		
DANFORTH	AV	LINNSMORE	CR		
DANFORTH	AV	LOGAN	AV		
DANFORTH	ROAD	MACK	AV	MYSTIC	AV
DANFORTH	AV	MAIN	ST		
DANFORTH	ROAD	MIDLAND	AV		
DANFORTH	AV	MONARCH PARK	AV		
DANFORTH	AV	PAPE	AV		
DANFORTH	AV	PHARMACY	AV		
DANFORTH	AV	PLAYTER	BV		
DANFORTH	ROAD	SEMINOLE	AV		
DANFORTH	AV	SIBLEY	AV		
DANFORTH	ROAD	ST. CLAIR	AV		
DANFORTH	ROAD	TRUDELLE	ST		
DANFORTH	AV	VICTORIA PARK	AV		
DANFORTH	ROAD	WARDEN	AV		
DANFORTH	AV	WARDEN	AV		
DANFORTH	AV	WESTLAKE	AV		
DANFORTH	ROAD	WINTER	AV		
DANFORTH	AV	WOODBINE	AV		
DANFORTH	AV	WOODINGTON	AV		
DANFORTH	AV	WOODYCREST	AV		
DAVENPORT	ROAD	DOVERCOURT	ROAD		
DAVENPORT	ROAD	DUFFERIN	ST		
DAVENPORT	ROAD	DUPONT	ST		
DAVENPORT	ROAD	OAKWOOD	AV		
DAVENPORT	ROAD	OLD WESTON	ROAD		
DAVENPORT	ROAD	OSLER	ST		
DAVENPORT	ROAD	OSSINGTON	AV		
DAVENPORT	ROAD	SHAW	ST		
DAVENPORT	ROAD	SPADINA	ROAD		
DAVENPORT	ROAD	UXBRIDGE	AV		
DAVISVILLE	AV	MOUNT PLEASANT	ROAD		
DAWES	ROAD	GOWER	ST		
DAWES	ROAD	PARK VISTA			
DAWES	ROAD	VICTORIA PARK	AV		
DEAN PARK	ROAD	SHEPPARD	AV		
DEAUVILLE	LANE	ST. DENNIS	DR		
DEER PARK	CR	GRANITE	PL	ST. CLAIR	AV
DEERFORD	ROAD	DON MILLS	ROAD		
DENISON	ROAD	JANE	ST	TRETHEWEY	DR
DENISON	ROAD	WESTON	ROAD		
DENLOW	BV	LESLIE	ST	SOUTHWELL	DR
DENSLEY	AV	FLAMBOROUGH	DR	KEELE	ST

DENTON	AV	VICTORIA PARK	AV		
DEWSON	ST	DOVERCOURT	ROAD		
DEWSON	ST	OSSINGTON	AV		
DIRECTOR	CT	ROSSDEAN	DR	STEELES	AV
DIXON	AV	DUNDAS	ST	KINGSTON	ROAD
DIXON	ROAD	GOLFWOOD	HTS		
DIXON	ROAD	ISLINGTON	AV		
DIXON	ROAD	KIPLING	AV		
DIXON	ROAD	MARTIN GROVE	ROAD		
DIXON	ROAD	ROYAL YORK	ROAD	ST. PHILLIPS	ROAD
DOHME	AV	O'CONNOR	DR		
DOLOMITE	DR	DUFFERIN	ST		
DON	RDWY	LAKESHORE	BV		
DON MILLS	ROAD	DUNCAN MILL	ROAD	GRAYDON HALL	DR
DON MILLS	ROAD	EGLINTON	AV		
DON MILLS	ROAD	ESTERBROOKE	AV	FAIRVIEW MALL	DR
DON MILLS	ROAD	FINCH	AV		
DON MILLS	ROAD	GODSTONE	ROAD		
DON MILLS	ROAD	GOODVIEW	ROAD		
DON MILLS	ROAD	GREENWOOD	AV	O'CONNOR	DR
DON MILLS	ROAD	HAVENBROOK	BV	PARKWAY FOREST	DR
DON MILLS	ROAD	LAWRENCE	AV		
DON MILLS	ROAD	LEITH HILL	ROAD		
DON MILLS	ROAD	MALLARD	ROAD		
DON MILLS	ROAD	MCNICOLL	AV		
DON MILLS	ROAD	MOATFIELD	DR		
DON MILLS	ROAD	ROCHEFORT	DR		
DON MILLS	ROAD	SENECA HILL	DR		
DON MILLS	ROAD	SHADBERRY	DR		
DON MILLS	ROAD	SHEPPARD	AV		
DON MILLS	ROAD	ST. DENNIS	DR		
DON MILLS	ROAD	STEELES	AV		
DON MILLS	ROAD	VAN HORNE	AV		
DON MILLS	ROAD	WYNFORD	DR		
DON MILLS	ROAD	YORK MILLS	ROAD		
DONALD	AV	KEELE	ST		
DONCASTER	AV	MAIN	ST		
DONLANDS	AV	MILLWOOD	ROAD	PAPE	AV
DONLANDS	AV	MORTIMER	AV		
DONLANDS	AV	O'CONNOR	DR		
DONLANDS	AV	SAMMON	AV		
DORIS	AV	GREENFIELD	AV		
DORIS	AV	SHEPPARD	AV		
DOVEHOUSE	AV	KEELE	ST		
DOVERCOURT	ROAD	DUNDAS	ST		
DOVERCOURT	ROAD	DUPONT	ST		
DOVERCOURT	ROAD	HEPBOURNE	ST		
DOVERCOURT	ROAD	QUEEN	ST		
DOVERCOURT	ROAD	ST. ANNES	ROAD		
DREWRY	AV	HILDA	AV		
DRIFTWOOD	AV	FINCH	AV		

DRIFTWOOD	AV	JANE	ST	MILO PARK	GATE
DUBRAY	AV	WILSON	AV		
DUFFERIN	ST	DUNDAS	ST		
DUFFERIN	ST	DUPONT	ST		
DUFFERIN	ST	EGLINTON	AV		
DUFFERIN	ST	FINCH	AV		
DUFFERIN	ST	GEARY	AV		
DUFFERIN	ST	GLENCAIRN	AV		
DUFFERIN	ST	HALLAM	ST		
DUFFERIN	ST	HOLMESDALE	ROAD	MARTIN	ST
DUFFERIN	ST	HOPE	ST		
DUFFERIN	ST	KING	ST		
DUFFERIN	ST	LAWRENCE	AV		
DUFFERIN	ST	LIBERTY	ST		
DUFFERIN	ST	MARTINROSS	AV		
DUFFERIN	ST	ORFUS	ROAD		
DUFFERIN	ST	PLAYFAIR	AV	WENDERLY	DR
DUFFERIN	ST	QUEEN	ST		
DUFFERIN	ST	RIDELLE	AV		
DUFFERIN	ST	ROGERS	ROAD		
DUFFERIN	ST	ROWAN	AV		
DUFFERIN	ST	SAMOR	ROAD		
DUFFERIN	ST	SHANLY	ST		
DUFFERIN	ST	ST. CLAIR	AV		
DUFFERIN	ST	STAYNER	AV	WINGOLD	AV
DUFFERIN	ST	STEELES	AV		
DUFFERIN	ST	SUPERTEST	ROAD		
DUFFERIN	ST	SYLVAN	AV		
DUFFERIN	ST	TYCOS	DR		
DUFFERIN	ST	WALLACE	AV		
DUFFERIN	ST	WILSON	AV		
DUFFLAW	ROAD	LAWRENCE	AV		
DUNCAN	ST	MCCAUL	ST	QUEEN	ST
DUNCANWOODS	DR	ISLINGTON	AV	ROWNTREE MILL	ROAD
DUNDALK	DR	ELLESMERE	ROAD	WYE VALLEY	ROAD
DUNDAS	ST	EAST MALL	CR		
DUNDAS	ST	GILMOUR	AV		
DUNDAS	ST	GLENLAKE	AV		
DUNDAS	ST	GRACE	ST		
DUNDAS	ST	GREENWOOD	AV		
DUNDAS	ST	HIGH PARK	AV		
DUNDAS	ST	HIGHFIELD	ROAD		
DUNDAS	ST	HOWLAND	AV		
DUNDAS	ST	HUMBERSIDE	AV		
DUNDAS	ST	INDIAN RD	CR		
DUNDAS	ST	ISLINGTON	AV		
DUNDAS	ST	JANE	ST		
DUNDAS	ST	JARVIS	ST		
DUNDAS	ST	JONES	AV		
DUNDAS	ST	KEELE	ST		
DUNDAS	ST	LANSDOWNE	AV		

DUNDAS	ST	LESLIE	ST		
DUNDAS	ST	LOGAN	AV		
DUNDAS	ST	MANNING	AV		
DUNDAS	ST	MEDLAND	ST		
DUNDAS	ST	MUNRO	ST		
DUNDAS	ST	NEILSON	DR	WEST MALL	CR
DUNDAS	ST	OLD OAK	DR	WIMBLETON	ROAD
DUNDAS	ST	ONTARIO	ST		
DUNDAS	ST	OSSINGTON	AV		
DUNDAS	ST	PACIFIC	AV		
DUNDAS	ST	PALMERSTON	BV		
DUNDAS	ST	PAPE	AV		
DUNDAS	ST	PARLIAMENT	ST		
DUNDAS	ST	PAULART	DR		
DUNDAS	ST	POPLAR	AV	SUBWAY	CR
DUNDAS	ST	PRINCE EDWARD	DR		
DUNDAS	ST	RIVER	ST		
DUNDAS	ST	ROYALAVON	CR		
DUNDAS	ST	RUNNYMEDE	ROAD		
DUNDAS	ST	SCARLETT	ROAD		
DUNDAS	ST	SHAVER	AV	SHORNCLIFFE	ROAD
DUNDAS	ST	SHAW	ST		
DUNDAS	ST	SHERBOURNE	ST		
DUNDAS	ST	SORAUREN	AV		
DUNDAS	ST	SPADINA	AV		
DUNDAS	ST	ST. CLARENS	AV		
DUNDAS	ST	STERLING	ROAD		
DUNDAS	ST	SUMACH	ST		
DUNDAS	ST	UNIVERSITY	AV		
DUNDAS	ST	VICTORIA	ST		
DUNDAS	ST	WINDERMERE	AV		
DUNDAS	ST	WOODFIELD	ROAD		
DUNDAS	SQ	YONGE	ST		
DUNN	AV	KING	ST		
DUNN	AV	QUEEN	ST		
DUNVEGAN	ROAD	ST. CLAIR	AV		
DUPLEX	AV	EGLINTON	AV		
DUPLEX	AV	JEDBURGH	ROAD	LAWRENCE	AV
DUPONT	ST	HURON	ST		
DUPONT	ST	LANSDOWNE	AV		
DUPONT	ST	OSSINGTON	AV		
DUPONT	ST	SHAW	ST		
DUPONT	ST	SPADINA	ROAD		
DUPONT	ST	ST. GEORGE	ST		
DUPONT	ST	SYMINGTON	AV		
DUVAL	DR	LAWRENCE	AV		
EARLSCOURT	AV	ST. CLAIR	AV		
EAST	DR	JANE	ST	OUTLOOK	AV
EASTERN	AV	KNOX	AV		
EASTERN	AV	LESLIE	ST		
EASTERN	AV	LOGAN	AV		

EASTERN	AV	PAPE	AV		
EASTPARK	BV	MARKHAM	ROAD	STEVENWOOD	ROAD
EDDYSTONE	AV	JANE	ST		
EDEN VALLEY	DR	EGLINTON	AV	RUSSELL	ROAD
EDGAR WOODS	ROAD	STEELES	AV		
EDITHVALE	DR	FINCH	AV		
EDWARD	ST	YONGE	ST		
EGLINTON	AV	EGLINTON	SQ		
EGLINTON	AV	EMMETT	AV		
EGLINTON	AV	ENNERDALE	ROAD		
EGLINTON	AV	EXPLORER	DR		
EGLINTON	AV	FALMOUTH	AV	GILDER	DR
EGLINTON	AV	FLANDERS	ROAD		
EGLINTON	AV	FORMAN	AV		
EGLINTON	AV	GLEN CEDAR	ROAD	OLD PARK	ROAD
EGLINTON	AV	GLENARDEN	ROAD	WESTOVER HILL	ROAD
EGLINTON	AV	GLENHOLME	AV		
EGLINTON	AV	HARVIE	AV	RONALD	AV
EGLINTON	AV	HEDDINGTON	AV		
EGLINTON	AV	HOLLY	ST		
EGLINTON	AV	IONVIEW	ROAD		
EGLINTON	AV	ISLINGTON	AV		
EGLINTON	AV	JANE	ST		
EGLINTON	AV	KEELE	ST	TRETHEWEY	DR
EGLINTON	AV	KENNEDY	ROAD		
EGLINTON	AV	KINGSTON	ROAD		
EGLINTON	AV	KIPLING	AV		
EGLINTON	AV	LAIRD	DR		
EGLINTON	AV	LASCELLES	BV		
EGLINTON	AV	LESLIE	ST		
EGLINTON	AV	MARKHAM	ROAD		
EGLINTON	AV	MARLEE	AV		
EGLINTON	AV	MARTIN GROVE	ROAD		
EGLINTON	AV	MASON	ROAD		
EGLINTON	AV	MATHESON	BV		
EGLINTON	AV	MCCOWAN	ROAD		
EGLINTON	AV	MIDLAND	AV		
EGLINTON	AV	MOUNT PLEASANT	ROAD		
EGLINTON	AV	NORTHCLIFFE	BV		
EGLINTON	SQ	O'CONNOR	DR	VICTORIA PARK	AV
EGLINTON	AV	OAKWOOD	AV		
EGLINTON	AV	OLD FOREST HILL	ROAD		
EGLINTON	AV	ORIOLE	PKY		
EGLINTON	AV	PARK HILL	ROAD	WINNETT	AV
EGLINTON	AV	PHARMACY	AV		
EGLINTON	AV	RAKELY	CT	SPECTRUM	WAY
EGLINTON	AV	REDPATH	AV		
EGLINTON	AV	RENFORTH	DR		
EGLINTON	AV	RICHARDSON	AV		
EGLINTON	AV	ROSEMOUNT	DR		
EGLINTON	AV	ROYAL YORK	ROAD		

EGLINTON	AV	SATELITE	DR		
EGLINTON	AV	SCARLETT	ROAD		
EGLINTON	AV	SINNOTT	ROAD		
EGLINTON	AV	SPADINA	ROAD		
EGLINTON	AV	SUTHERLAND	DR		
EGLINTON	AV	THE EAST	MALL		
EGLINTON	AV	THERMOS	ROAD		
EGLINTON	AV	VESTA	DR		
EGLINTON	AV	VICTORIA PARK	AV		
EGLINTON	AV	WARDEN	AV		
EGLINTON	AV	WESTON	ROAD		
EGLINTON	AV	WINONA	DR		
EGLINTON	AV	YONGE	ST		
EILEEN	AV	SCARLETT	ROAD		
ELANA	DR	FINCH	AV	YORK GATE	BV
ELEVENTH	LINE	STEELES	AV		
ELINOR	AV	LAWRENCE	AV		
ELIZABETH	ST	ELM	ST		
ELLERSLIE	AV	NORTON	AV	YONGE	ST
ELLESMERE	ROAD	HELICON	GATE	SCARBOROUGH GOLF CLUB	ROAD
ELLESMERE	ROAD	KENNEDY	ROAD		
ELLESMERE	ROAD	KINGSTON	ROAD		
ELLESMERE	ROAD	MARKHAM	ROAD		
ELLESMERE	ROAD	MCCOWAN	ROAD		
ELLESMERE	ROAD	MEADOWVALE	ROAD		
ELLESMERE	ROAD	MIDLAND	AV		
ELLESMERE	ROAD	MORNINGSIDE	AV		
ELLESMERE	ROAD	MORRISH	ROAD		
ELLESMERE	ROAD	NEILSON	ROAD		
ELLESMERE	ROAD	PARKWOODS VILLAGE	DR	VICTORIA PARK	AV
ELLESMERE	ROAD	PHARMACY	AV		
ELLESMERE	ROAD	WARDEN	AV		
ELLIS	AV	LAKESHORE	BV		
ELLIS	AV	THE QUEENSWAY			
ELM	ST	MURRAY	ST		
ELM	ST	UNIVERSITY	AV		
ELM BANK	ROAD	PHARMACY	AV		
ELMER	AV	KINGSTON	ROAD		
ELMHURST	AV	GREENFIELD	AV	YONGE	ST
ELMHURST	DR	ISLINGTON	AV		
ELMWOOD	AV	NORTH YORK	BV	YONGE	ST
ELSMERE	AV	LITTLE	AV	WESTON	ROAD
ELVASTON	DR	VICTORIA PARK	AV		
EMERALD	LANE	STEELES	AV	VILLAGE	GATE
EMPRESS	AV	PARK HOME	AV	YONGE	ST
EMPRESS	AV	WILLOWDALE	AV		
ESANDAR	DR	LAIRD	DR		
ESNA PARK	DR	PHARMACY	AV	STEELES	AV
EVANS	AV	HORNER	AV		
EVANS	AV	ISLINGTON	AV		
EVANS	AV	KIPLING	AV		

EVANS	AV	ROYAL YORK	ROAD		
EVANS	AV	SHERWAY	GATE		
EVANS	AV	THE EAST	MALL		
EVANS	AV	THE WEST	MALL		
FAIRFAX	CR	WARDEN	AV		
FAIRLAWN	AV	YONGE	ST		
FAIRVIEW MALL	DR	GODSTONE	ROAD		
FALLINGBROOK	ROAD	KINGSTON	ROAD		
FALSTAFF	AV	KEELE	ST		
FAYWOOD	BV	SHEPPARD	AV	WILMINGTON	AV
FELSTEAD	AV	GREENWOOD	AV		
FENLEY	DR	ISLINGTON	AV	WINNIPEG	ROAD
FENMAR	DR	ORMONT	DR		
FENMAR	DR	PINE VALLEY	DR	STEELES	AV
FENMAR	DR	WESTON	ROAD		
FENN	AV	YORK MILLS	ROAD		
FENSIDE	DR	YORK MILLS	ROAD		
FENWOOD	HTS	KINGSTON	ROAD		
FERNCREST	GATE	VAN HORNE	AV	VICTORIA PARK	AV
FERRIER	ST	STEELES	AV		
FIFTH	ST	LAKESHORE	BV		
FINCH	AV	FINCHDENE	SQ		
FINCH	AV	GOLDFINCH	CT	TORRESDALE	AV
FINCH	AV	GRANTBROOK	ST		
FINCH	AV	HEATHVIEW	AV	TOLLERTON	AV
FINCH	AV	HUMBERLINE	DR		
FINCH	AV	HWY 27			
FINCH	AV	ISLINGTON	AV		
FINCH	AV	JANE	ST		
FINCH	AV	JAYZEL	DR		
FINCH	AV	KEELE	ST		
FINCH	AV	KENNEDY	ROAD		
FINCH	AV	KENNETH	AV		
FINCH	AV	KIPLING	AV		
FINCH	AV	LESLIE	ST		
FINCH	AV	MARKHAM	ROAD		
FINCH	AV	MARTIN GROVE	ROAD		
FINCH	AV	MCCOWAN	ROAD		
FINCH	AV	MIDDLEFIELD	ROAD		
FINCH	AV	MIDLAND	AV		
FINCH	AV	MILLIKEN	BV		
FINCH	AV	MILVAN	DR	RUMIKE	ROAD
FINCH	AV	NEILSON	ROAD		
FINCH	AV	NORFINCH	DR	OAKDALE	ROAD
FINCH	AV	PELICAN	GATE		
FINCH	AV	PHARMACY	AV		
FINCH	AV	SENLAC	ROAD		
FINCH	AV	SENTINEL	ROAD		
FINCH	AV	SKYMARK	DR		
FINCH	AV	TALBOT	ROAD		
FINCH	AV	TANGIERS	ROAD		

FINCH	AV	TAPSCOTT	ROAD		
FINCH	AV	TOBERMORY	DR		
FINCH	AV	VICTORIA PARK	AV		
FINCH	AV	WARDEN	AV		
FINCH	AV	WESTMORE	DR		
FINCH	AV	WESTON	ROAD		
FINCH	AV	WILFRED	AV		
FINCH	AV	WILLOWDALE	AV		
FINCH	AV	WILMINGTON	AV		
FINCH	AV	YONGE	ST		
FIRVALLEY	CT	WARDEN	AV		
FLETCHER	PL	ISLINGTON	AV		
FORBES	ROAD	KENNEDY	ROAD		
FOREST HILL	ROAD	ST. CLAIR	AV		
FORTUNE	GATE	LAWRENCE	AV		
FOUR OAKS	GATE	O'CONNOR	DR		
FOXWELL	ST	JANE	ST	WOOLNER	AV
FOXWELL	ST	SCARLETT	ROAD		
FRITH	ROAD	JANE	ST		
FRONT	ST	JOHN	ST		
FRONT	ST	PARLIAMENT	ST		
FRONT	ST	SPADINA	AV		
FRONT	ST	YONGE	ST		
FUTURITY	GATE	STEELES	AV		
GALLOWAY	ROAD	KINGSTON	ROAD		
GALLOWAY	ROAD	LAWRENCE	AV		
GARRATT	BV	WILSON	AV		
GARYRAY	DR	SIGNET	DR		
GARYRAY	DR	WESTON	ROAD		
GATEWAY	BV	GRENOBLE	DR		
GAUDAUR	ROAD	STEELES	AV		
GAYDON	AV	LILAC	AV	WESTON	ROAD
GENTHORN	AV	KIPLING	AV		
GEORGE ANDERSON	DR	KEELE	ST		
GERRARD	ST	GREENWOOD	AV		
GERRARD	ST	JARVIS	ST		
GERRARD	ST	JONES	AV		
GERRARD	ST	LOGAN	AV		
GERRARD	ST	MAIN	ST		
GERRARD	ST	MALVERN	AV		
GERRARD	ST	MARJORY	AV		
GERRARD	ST	PAPE	AV		
GERRARD	ST	PARLIAMENT	ST		
GERRARD	ST	RIVER	ST		
GERRARD	ST	SHERBOURNE	ST		
GERRARD	ST	UNIVERSITY	AV		
GERRARD	ST	VICTORIA PARK	AV		
GERRARD	ST	WOODBINE	AV		
GERRARD	ST	YONGE	ST		
GERVAIS	DR	WYNFORD	DR		
GIHON SPRING	DR	STEELES	AV		

GILTSPUR	DR	JANE	ST		
GLADSTONE	AV	QUEEN	ST		
GLAMORGAN	AV	KENNEDY	ROAD	PROGRESS	AV
GLEBEMOUNT	AV	MORTIMER	AV		
GLEBEMOUNT	AV	O'CONNOR	DR	TAYLOR	DR
GLEN EDEN	CR	SELWYN	AV	ST. CLAIR	AV
GLEN EVEREST	ROAD	KINGSTON	ROAD		
GLEN MANOR	DR	QUEEN	ST		
GLEN WATFORD	DR	SHEPPARD	AV		
GLENCAIRN	AV	MARLEE	AV		
GLENDINNING	AV	GORDON BAKER	ROAD	PHARMACY	AV
GLENGOWAN	ROAD	MOUNT PLEASANT	ROAD		
GLENGROVE	AV	YONGE	ST		
GLENHOLME	AV	ROGERS	ROAD		
GLENLAKE	AV	KEELE	ST		
GLENWOOD	CR	O'CONNOR	DR		
GODDARD	ST	SHEPPARD	AV		
GORDON BAKER	ROAD	VICTORIA PARK	AV		
GORMLEY	AV	ORIOLE	PKY		
GOVERNMENT	ROAD	THE KINGSWAY			
GOWER	ST	VICTORIA PARK	AV		
GRACE	ST	HARBORD	ST		
GRACEFIELD	AV	KEELE	ST		
GRANDRAVINE	DR	KEELE	ST		
GREENBRAE	CRCT	GREENCEDAR	CRCT	LAWRENCE	AV
GREENCEDAR	CRCT	GREENCREST	CRCT	MARKHAM	ROAD
GREENCREST	CRCT	GREENHOLM	CRCT	LAWRENCE	AV
GREENWOOD	AV	MEMORIAL PARK	AV		
GREENWOOD	AV	MORTIMER	AV		
GREENWOOD	AV	QUEEN	ST		
GREENWOOD	AV	SAMMON	AV		
GUILDWOOD	PKY	LIVINGSTON	ROAD		
GULLIVER	ROAD	INGRAM	DR	KEELE	ST
GUNNS	ROAD	ST. CLAIR	AV		
GUNNS	ROAD	WESTON	ROAD		
HANEY	AV	JANE	ST		
HARBORD	ST	HURON	ST		
HARBORD	ST	MANNING	AV		
HARBORD	ST	MONTROSE	AV		
HARBORD	ST	OSSINGTON	AV		
HARBORD	ST	PALMERSTON	BV		
HARBORD	ST	SHAW	ST		
HARBORD	ST	SPADINA	AV		
HARDING	AV	JANE	ST		
HARRISON	ROAD	YORK MILLS	ROAD		
HAVENDALE	ROAD	KENNEDY	ROAD		
HAVENVIEW	ROAD	SHEPPARD	AV	SHORTING	ROAD
HAWKSBURY	DR	REAN	DR	SHEPPARD	AV
HEATH	ST	SPADINA	ROAD		
HEATH	ST	YONGE	ST		
HEDGEWOOD	ROAD	YORK MILLS	ROAD		

HENDERSON	AV	MAXOME	AV	STEELES	AV
HICKORY TREE	ROAD	LAWRENCE	AV	LITTLE	AV
HIGH PARK	BV	PARKSIDE	DR		
HIGHLAND	CR	UPPER HIGHLAND	CR	YORK MILLS	ROAD
HIGHVIEW	AV	LEXFIELD	AV	WILSON	AV
HIGHWOOD	AV	SHERWOOD	AV	WARDEN	AV
HILDA	AV	STEELES	AV		
HILLCROFT	DR	STEELES	AV	STRAWBERRY HILLS	DR
HOLSWADE	ROAD	SUNRISE	AV	VICTORIA PARK	AV
HORNER	AV	KIPLING	AV		
HOSKIN	AV	QUEENS PARK	CR		
HOUNSLOW HEATH	ROAD	SILVERTHORN	AV	ST. CLAIR	AV
HOWARD PARK	AV	PARKSIDE	DR		
HOWDEN	ROAD	LAWRENCE	AV	UNDERWRITERS	ROAD
HULLMAR	DR	JANE	ST		
HUMBER COLLEGE	BV	HWY 27			
HUMBERSIDE	AV	KEELE	ST		
HUMBERWOOD	BV	REXDALE	BV		
HUNTINGWOOD	DR	KENNEDY	ROAD		
HUNTINGWOOD	DR	MCCOWAN	ROAD	MIDDLEFIELD	ROAD
HUNTINGWOOD	DR	MIDLAND	AV		
HUNTINGWOOD	DR	OLD SHEPPARD	AV	VICTORIA PARK	AV
HUNTINGWOOD	DR	WARDEN	AV		
HWY 27		QUEENS PLATE	DR		
HWY 27		REXDALE	BV		
HWY 27		STEELES	AV		
IDAGROVE	GATE	SHEPPARD	AV		
INDIAN VALLEY	CR	PARKSIDE	DR		
INDUSTRY	ST	TRETHEWEY	DR		
INGLEWOOD	DR	MOUNT PLEASANT	ROAD		
INGLEWOOD	DR	ST. CLAIR	AV		
INNISWOOD	DR	PHARMACY	AV		
INVERGORDON	AV	MCCOWAN	ROAD	PITFIELD	ROAD
IRONDALE	DR	PEARCE	ROAD	STEELES	AV
ISABELLA	ST	JARVIS	ST		
ISLAND	ROAD	PORT UNION	ROAD		
ISLINGTON	AV	JUDSON	ST		
ISLINGTON	AV	JUTLAND	ROAD		
ISLINGTON	AV	LAKESHORE	BV	SEVENTH	ST
ISLINGTON	AV	MILADY	ROAD		
ISLINGTON	AV	MILLWICK	DR	MUIR	AV
ISLINGTON	AV	MONOGRAM	PL		
ISLINGTON	AV	NEW TORONTO	ST		
ISLINGTON	AV	POPLAR HEIGHTS	DR	PRINCESS MARGARET	BV
ISLINGTON	AV	RATHBURN	ROAD		
ISLINGTON	AV	REXDALE	BV		
ISLINGTON	AV	SATTERLY	ROAD		
ISLINGTON	AV	STEELES	AV		
ISLINGTON	AV	THE QUEENSWAY			
ISLINGTON	AV	THE WESTWAY			
ISLINGTON	AV	TITAN	ROAD		

JAMESON	AV	KING	ST		
JAMESON	AV	LAKESHORE	BV		
JANE	ST	JOHN	ST		
JANE	ST	LAMBTON	AV		
JANE	ST	LAWRENCE	AV		
JANE	ST	PRITCHARD	AV		
JANE	ST	QUEENS	DR		
JANE	ST	RITA	DR	STANLEY	ROAD
JANE	ST	SHEPPARD	AV		
JANE	ST	SHOREHAM	DR		
JANE	ST	ST. CLAIR	AV		
JANE	ST	ST. JOHN'S	ROAD		
JANE	ST	STEELES	AV		
JANE	ST	STONG	CT	YORK GATE	BV
JANE	ST	WESTON	ROAD		
JANE	ST	WILSON	AV		
JARVIS	ST	KING	ST		
JARVIS	ST	LAKESHORE	BV		
JARVIS	ST	MAITLAND	PL	MAITLAND	ST
JARVIS	ST	QUEEN	ST		
JARVIS	ST	QUEENS	QUAY		
JARVIS	ST	RICHMOND	ST		
JARVIS	ST	SHUTER	ST		
JARVIS	ST	THE ESPLANADE			
JARVIS	ST	WELLESLEY	ST		
JEFFERSON	AV	KING	ST		
JESMOND	AV	OAKWOOD	AV		
JETHRO	ROAD	WILSON	AV		
JOEL SWIRSKY	BV	WILSON HEIGHTS	BV		
JOHN	ST	KING	ST		
JOHN	ST	QUEEN	ST		
JOHN	ST	RICHMOND	ST		
JOHN	ST	WELLINGTON	ST		
JOHN	ST	WESTON	ROAD		
JOHN STONER	DR	MORNINGSIDE	AV		
JONES	AV	QUEEN	ST		
JULIAN	ROAD	WILSON	AV		
JUNCTION	ROAD	KEELE	ST		
KANE	AV	LAVENDER	ROAD	OLD WESTON	ROAD
KANE	AV	ROGERS	ROAD		
KEELE	ST	LAWRENCE	AV		
KEELE	ST	MAPLE LEAF	DR		
KEELE	ST	MURRAY ROSS	PKY		
KEELE	ST	NORTH PARK	DR		
KEELE	ST	QUINAN	DR	WYNDALE	DR
KEELE	ST	ROGERS	ROAD		
KEELE	ST	RUSTIC	ROAD		
KEELE	ST	SHEPPARD	AV		
KEELE	ST	ST. CLAIR	AV	WESTON	ROAD
KEELE	ST	ST. REGIS	CR		
KEELE	ST	STEELES	AV		

KEELE	ST	TORO	ROAD		
KEELE	ST	WEST TORONTO	ST		
KEELE	ST	WHITBURN	CR		
KEELE	ST	WILSON	AV		
KEELE	ST	WYCOMBE	ROAD		
KELVIN GROVE	AV	PUTNAM	GATE	STEELES	AV
KENNARD	AV	W. R. ALLEN	ROAD		
KENNEDY	ROAD	LAWRENCE	AV		
KENNEDY	ROAD	MCNICOLL	AV		
KENNEDY	ROAD	MERRIAN	ROAD		
KENNEDY	ROAD	NORCAP	AV		
KENNEDY	ROAD	PASSMORE	AV	PURCELL	BV
KENNEDY	ROAD	RADNOR	AV		
KENNEDY	ROAD	RANSTONE	GDNS		
KENNEDY	ROAD	SHEPPARD	AV		
KENNEDY	ROAD	ST. CLAIR	AV		
KENNEDY	ROAD	STEELES	AV		
KENNEDY	ROAD	TRANSWAY	CR		
KENNEDY	ROAD	TROJAN	GATE		
KENNETH	AV	LEONA	DR	SHEPPARD	AV
KENWOOD	AV	VAUGHAN	ROAD		
KILBARRY	ROAD	ORIOLE	PKY		
KING	ST	PARLIAMENT	ST		
KING	ST	SHAW	ST		
KING	ST	SPADINA	AV		
KING	ST	STRACHAN	AV		
KING	ST	TECUMSETH	ST		
KING	ST	UNIVERSITY	AV		
KING	ST	WESTON	ROAD		
KING	ST	YONGE	ST		
KING HIGH	AV	WILSON	AV		
KINGSTON	ROAD	LAWRENCE	AV		
KINGSTON	ROAD	MAIN	ST	SOUTHWOOD	DR
KINGSTON	ROAD	MANSE	ROAD		
KINGSTON	ROAD	MARKHAM	ROAD		
KINGSTON	ROAD	MASON	ROAD	WHITECAP	BV
KINGSTON	ROAD	MIDLAND	AV		
KINGSTON	ROAD	MORNINGSIDE	AV		
KINGSTON	ROAD	OLD KINGSTON	ROAD		
KINGSTON	ROAD	OVERTURE	ROAD	PAYZAC	AV
KINGSTON	ROAD	POPLAR	ROAD		
KINGSTON	ROAD	PORT UNION	ROAD	SHEPPARD	AV
KINGSTON	ROAD	QUEEN	ST		
KINGSTON	ROAD	RIDGEMOOR	AV	SHARPE	ST
KINGSTON	ROAD	RYLANDER	BV		
KINGSTON	ROAD	SANDOWN	AV		
KINGSTON	ROAD	SCARBOROUGH	ROAD		
KINGSTON	ROAD	SCARBOROUGH GOLF CLUB	ROAD		
KINGSTON	ROAD	VICTORIA PARK	AV		
KINGSTON	ROAD	WARDEN	AV		
KINGSTON	ROAD	WOODBINE	AV		

KIPLING	AV	LAKESHORE	BV		
KIPLING	AV	MATTICE	AV		
KIPLING	AV	MOUNT OLIVE	DR	PANORAMA	CT
KIPLING	AV	NEW TORONTO	ST		
KIPLING	AV	NORTH QUEEN	ST		
KIPLING	AV	PRINCESS MARGARET	BV		
KIPLING	AV	RATHBURN	ROAD		
KIPLING	AV	REXDALE	BV		
KIPLING	AV	SNARESBROOK	DR		
KIPLING	AV	STEELES	AV		
KIPLING	AV	THE QUEENSWAY			
KIPLING	AV	THE WESTWAY			
KIPLING	AV	TORLAKE	CR		
KIPLING	AV	WIDDICOMBE HILL	BV		
KIRKWOOD	ROAD	LESLIE	ST		
KODIAK	CR	SHEPPARD	AV	YUKON	LANE
LA ROSE	AV	ROYAL YORK	ROAD		
LAIRD	DR	MCRAE	DR	WICKSTEED	AV
LAIRD	DR	MILLWOOD	ROAD	SOUTHVALE	DR
LAKESHORE	BV	LEGION	ROAD		
LAKESHORE	BV	LESLIE	ST		
LAKESHORE	BV	LOGAN	AV		
LAKESHORE	BV	LONG BRANCH	AV		
LAKESHORE	BV	MILES	ROAD	SYMONS	ST
LAKESHORE	BV	MIMICO	AV		
LAKESHORE	BV	PALACE PIER	CT		
LAKESHORE	BV	PARK LAWN	ROAD		
LAKESHORE	BV	PARKSIDE	DR		
LAKESHORE	BV	PARLIAMENT	ST		
LAKESHORE	BV	ROYAL YORK	ROAD		
LAKESHORE	BV	SHERBOURNE	ST		
LAKESHORE	BV	STADIUM	ROAD		
LAKESHORE	BV	STRACHAN	AV		
LAKESHORE	BV	SUPERIOR	AV		
LAKESHORE	BV	TENTH	ST		
LAKESHORE	BV	THIRTEENTH	ST		
LAKESHORE	BV	THIRTIETH	ST		
LAKESHORE	BV	THIRTY-SEVENTH	ST		
LAKESHORE	BV	TWENTYSECOND	ST	TWENTYTHIRD	ST
LAKESHORE	BV	TWENTYSEVENTH	ST		
LAKESHORE	BV	WINDERMERE	AV		
LAMBTON	AV	WESTON	ROAD		
LANARK	AV	OAKWOOD	AV		
LANSDOWNE	AV	QUEEN	ST		
LANSDOWNE	AV	ST. CLAIR	AV		
LANSDOWNE	AV	WALLACE	AV		
LAPSLEY	ROAD	SHEPPARD	AV	WASHBURN	WAY
LAURA	ROAD	SHEPPARD	AV		
LAURELEAF	ROAD	STEELES	AV		
LAWRENCE	AV	LEDBURY	ST		
LAWRENCE	AV	LESLIE	ST		

LAWRENCE	AV	MARKHAM	ROAD		
LAWRENCE	AV	MARLEE	AV		
LAWRENCE	AV	MCCOWAN	ROAD		
LAWRENCE	AV	MIDLAND	AV		
LAWRENCE	AV	MILDENHALL	ROAD		
LAWRENCE	AV	MORNINGSIDE	AV		
LAWRENCE	AV	MOUNT PLEASANT	ROAD		
LAWRENCE	AV	ORTON PARK	ROAD		
LAWRENCE	AV	OVERTURE	ROAD		
LAWRENCE	AV	PHARMACY	AV		
LAWRENCE	AV	PIMLICO	ROAD		
LAWRENCE	AV	PINE	ST		
LAWRENCE	AV	PORT UNION	ROAD		
LAWRENCE	AV	RALPH	ST		
LAWRENCE	AV	ROYAL YORK	ROAD	THE WESTWAY	
LAWRENCE	AV	SCARBOROUGH GOLF CLUB	ROAD		
LAWRENCE	AV	SCARLETT	ROAD		
LAWRENCE	AV	SHERMOUNT	AV		
LAWRENCE	AV	TOWER	DR		
LAWRENCE	AV	VARNA	DR		
LAWRENCE	AV	VICTORIA PARK	AV		
LAWRENCE	AV	WARDEN	AV		
LAWRENCE	AV	WESTON	ROAD		
LAWRENCE	AV	WEXFORD	BV		
LAWRENCE	AV	WOODCLIFF	PL		
LAWRENCE	AV	YONGE	ST		
LEE	AV	QUEEN	ST		
LESLIE	ST	MAROWYNE	DR		
LESLIE	ST	NYMARK	AV		
LESLIE	ST	QUEEN	ST		
LESLIE	ST	SHEPPARD	AV		
LESLIE	ST	STEELES	AV		
LESLIE	ST	TALWOOD	DR		
LESLIE	ST	TANGLE	BRWY	VAN HORNE	AV
LESLIE	ST	YORK MILLS	ROAD		
LESMILL	ROAD	YORK MILLS	ROAD		
LINDEN	AV	ST. CLAIR	AV		
LOCKIE	AV	MIDLAND	AV		
LOGAN	AV	MORTIMER	AV		
LOGAN	AV	QUEEN	ST		
LOMA	ROAD	THE QUEENSWAY			
LONSDALE	ROAD	SPADINA	ROAD		
LOWTHER	AV	SPADINA	ROAD		
LUMSDEN	AV	MAIN	ST		
MACPHERSON	AV	ROWANWOOD	AV	YONGE	ST
MACPHERSON	AV	SPADINA	ROAD		
MADAWASKA	AV	MOORE PARK	AV	YONGE	ST
MAGELLAN	DR	SHEPPARD	AV		
MAINSHEP	ROAD	WESTON	ROAD		
MALVERN	ST	SHEPPARD	AV		
MANHATTAN	DR	WARDEN	AV		

MANOR	ROAD	YONGE	ST		
MARCOS	BV	MIDLAND	AV	ROMULUS	DR
MARKHAM	ROAD	MCLEVIN	AV	NUGGET	AV
MARKHAM	ROAD	MCNICOLL	AV		
MARKHAM	ROAD	MILNER	AV		
MARKHAM	ROAD	NASHDENE	ROAD		
MARKHAM	ROAD	PAINTED POST	DR		
MARKHAM	ROAD	PASSMORE	AV		
MARKHAM	ROAD	PROGRESS	AV	PROGRESS	CT
MARKHAM	ROAD	SHEPPARD	AV		
MARKHAM	ROAD	STEELES	AV		
MARKHAM	ROAD	TUXEDO	CT		
MARLEE	AV	ROSELAWN	AV		
MARTIN GROVE	ROAD	MERCURY	ROAD	WESTHUMBER	BV
MARTIN GROVE	ROAD	PORTERFIELD	ROAD		
MARTIN GROVE	ROAD	RACINE	ROAD		
MARTIN GROVE	ROAD	REXDALE	BV		
MARTIN GROVE	ROAD	STEELES	AV		
MATHEWS	ROAD	KELVIN	AV	WALSH	AV
MCCORMACK	ST	WESTON	ROAD		
MCCOWAN	ROAD	MCNICOLL	AV		
MCCOWAN	ROAD	NUGGET	AV		
MCCOWAN	ROAD	SHEPPARD	AV		
MCCOWAN	ROAD	STEELES	AV		
MCCOWAN	ROAD	TRITON	ROAD		
MCLEVIN	AV	NEILSON	ROAD		
MCNICOLL	AV	MIDLAND	AV		
MCNICOLL	AV	PHARMACY	AV		
MCNICOLL	AV	VICTORIA PARK	AV		
MCNICOLL	AV	WARDEN	AV		
MCRAE	DR	MILLWOOD	ROAD		
MEADOWVALE	ROAD	SHEPPARD	AV		
MEDONTE	AV	TIAGO	AV	VICTORIA PARK	AV
MELROSE	AV	TEDDINGTON PARK	AV	YONGE	ST
MERTON	ST	MOUNT PLEASANT	ROAD		
MERTON	ST	YONGE	ST		
METROPOLITAN	ROAD	WARDEN	AV		
MIDLAND	AV	PROGRESS	AV		
MIDLAND	AV	PRUDENTIAL	DR		
MIDLAND	AV	SHEPPARD	AV		
MIDLAND	AV	ST. CLAIR	AV		
MIDLAND	AV	STANSBURY	CR		
MIDLAND	AV	STEELES	AV		
MIDLAND	AV	VERDUN	AV		
MILITARY	TR	MORNINGSIDE	AV		
MILITARY	TR	NEILSON	ROAD		
MILL	ST	YONGE	ST		
MILLWICK	DR	PLUNKETT	ROAD		
MILLWOOD	ROAD	OVERLEA	BV		
MILLWOOD	ROAD	REDWAY	ROAD	VILLAGE STATION	ROAD
MILNER	AV	MILNER BUSINESS	CT		

MILNER	AV	MORNINGSIDE	AV		
MIMICO	AV	ROYAL YORK	ROAD		
MOORE	AV	MOUNT PLEASANT	ROAD		
MORECAMBE	GATE	PAWNEE	AV	VICTORIA PARK	AV
MORNINGSIDE	AV	SEWELLS	ROAD		
MORNINGSIDE	AV	SHEPPARD	AV		
MORNINGSIDE	AV	SOUTH KINGSWAY			
MORNINGSIDE	AV	WINDERMERE	AV		
MORTIMER	AV	PAPE	AV		
MORTIMER	AV	WOODBINE	AV		
MOUNT PLEASANT	ROAD	SHERWOOD	AV		
MOUNT PLEASANT	ROAD	ST. CLAIR	AV		
MOUNT PLEASANT	ROAD	ST. LEONARDS	AV		
MOUNTCASTLE	GATE	STEELES	AV		
MURISON	BV	SHEPPARD	AV		
MURRAY ROSS	PKY	NIAGARA	BV	SENTINEL	ROAD
MURRAY ROSS	PKY	STEELES	AV		
NASSAU	ST	SPADINA	AV		
NATURE	PAWY	SHEPPARD	AV		
NEILSON	ROAD	SEWELLS	ROAD	TAPSCOTT	ROAD
NEILSON	ROAD	SHEPPARD	AV		
NEWTON	DR	PLEASANT	AV	YONGE	ST
NORTH QUEEN	ST	THE EAST	MALL		
NORTH QUEEN	ST	THE QUEENSWAY			
NORTH WEST	GATE	STEELES	AV		
NORTHCLIFFE	BV	ST. CLAIR	AV		
NORTHLAND	AV	WESTON	ROAD		
O'CONNOR	DR	PAPE	AV		
O'CONNOR	DR	ST. CLAIR	AV		
O'CONNOR	DR	SUNRISE	AV		
O'CONNOR	DR	WOODBINE	AV		
OAK	ST	WESTON	ROAD		
OAKDALE	ROAD	SHEPPARD	AV		
OAKDALE	ROAD	TORBARRIE	ROAD		
OAKWOOD	AV	ROGERS	ROAD		
OAKWOOD	AV	ST. CLAIR	AV		
OAKWOOD	AV	VAUGHAN	ROAD		
OLD ENGLISH	LANE	STEELES	AV		
OLD FOREST HILL	ROAD	SPADINA	ROAD		
OLD WESTON	ROAD	ST. CLAIR	AV		
OLD WESTON	ROAD	TOWNSLEY	ST		
OLD WESTON	ROAD	TURNBERRY	AV		
ORIOLE	PKY	OXTON	AV		
ORMONT	DR	WESTON	ROAD		
OSCAR ROMERO	WAY	ST. CLAIR	AV		
OSSINGTON	AV	QUEEN	ST		
OVERBROOK	PL	STEEPROCK	DR	W. R. ALLEN	ROAD
OVERBROOK	PL	WILMINGTON	AV		
OVERLEA	BV	WILLIAM MORGAN	DR		
OXFORD	DR	WESTON	ROAD		
PAGET	ROAD	VICTORIA PARK	AV		

PARK LAWN	ROAD	THE QUEENSWAY			
PARLIAMENT	ST	SHUTER	ST		
PARLIAMENT	ST	WELLESLEY	ST		
PATRICIA	AV	YONGE	ST		
PATRICK	BV	VICTORIA PARK	AV		
PETER	ST	QUEEN	ST	SOHO	ST
PETER	ST	RICHMOND	ST		
PETROLIA	ROAD	STEELES	AV	TANDEM	ROAD
PHARMACY	AV	SHEPPARD	AV		
PHARMACY	AV	ST. CLAIR	AV		
PICKERING TOWN	LINE	STEELES	AV	TAUNTON	ROAD
PLAINS	ROAD	WOODBINE	AV		
PLAXTON	DR	ST. CLAIR	AV		
PLEASANT HOME	BV	WILSON	AV		
PLEASANT VIEW	DR	VICTORIA PARK	AV		
POPLAR PLAINS	ROAD	ST. CLAIR	AV		
PORTLAND	ST	RICHMOND	ST		
POYNTZ	AV	YONGE	ST		
QUEEN	ST	RIVER	ST		
QUEEN	ST	SHERBOURNE	ST		
QUEEN	ST	SORAUREN	AV		
QUEEN	ST	SPADINA	AV		
QUEEN	ST	SUMACH	ST		
QUEEN	ST	UNIVERSITY	AV		
QUEEN	ST	WOODBINE	AV		
QUEEN	ST	WOODFIELD	ROAD		
QUEEN	ST	YONGE	ST		
QUEENS	QUAY	SPADINA	AV		
QUEENS	QUAY	YONGE	ST		
QUEENS	QUAY	YORK	ST		
QUEENS PARK	CR	WELLESLEY	ST		
QUEENS PLATE	DR	REXDALE	BV		
RANLEIGH	AV	YONGE	ST		
RATHBURN	ROAD	THE EAST	MALL		
RATHBURN	ROAD	THE WEST	MALL		
RAY	AV	WESTON	ROAD		
REINER	ROAD	WILSON HEIGHTS	BV		
REXLEIGH	DR	ST. CLAIR	AV		
RICHMOND	ST	SHERBOURNE	ST		
RICHMOND	ST	UNIVERSITY	AV		
RICHMOND	ST	VICTORIA	ST		
RICHMOND	ST	YORK	ST		
RICHVIEW	ROAD	SCARLETT	ROAD		
RIDLEY	BV	WILSON	AV		
RIVER	ST	SHUTER	ST		
ROGERS	ROAD	SILVERTHORN	AV		
ROGERS	ROAD	WESTON	ROAD		
ROYAL YORK	ROAD	THE QUEENSWAY			
RUNNYMEDE	ROAD	ST. CLAIR	AV		
RUSSELL HILL	ROAD	ST. CLAIR	AV		
SANDFIELD	ROAD	YORK MILLS	ROAD		

SANTAMONICA	BV	ST. CLAIR	AV		
SCARLETT	ROAD	SCARLETTWOOD	CT		
SCARLETT	ROAD	ST. CLAIR	AV		
SENTINEL	ROAD	SHEPPARD	AV		
SETTLERS	ROAD	SHEPPARD	AV		
SHAUGHNESSY	BV	SHEPPARD	AV		
SHEPPARD	AV	TUSCAN	GATE		
SHEPPARD	AV	VANDORF	ST		
SHEPPARD	AV	VICTORIA PARK	AV		
SHEPPARD	AV	W. R. ALLEN	ROAD		
SHEPPARD	AV	WARDEN	AV		
SHEPPARD	AV	WESTON	ROAD		
SHEPPARD	AV	WILFRED	AV		
SHEPPARD	AV	WILLOWDALE	AV		
SHEPPARD	AV	WILSON HEIGHTS	BV		
SHEPPARD	AV	YONGE	ST		
SHERBOURNE	ST	SHUTER	ST		
SHERBOURNE	ST	WELLESLEY	ST		
SIGNET	DR	STEELES	AV		
SILVERDALE	CR	VALENTINE	DR	YORK MILLS	ROAD
SIMCOE	ST	WELLINGTON	ST		
SLOANE	AV	VICTORIA PARK	AV		
SPADINA	ROAD	ST. CLAIR	AV		
SPADINA	AV	SULLIVAN	ST		
ST. CLAIR	AV	TWEEDSMUIR	AV		
ST. CLAIR	AV	VAUGHAN	ROAD		
ST. CLAIR	AV	VIA ITALIA			
ST. CLAIR	AV	VICTORIA PARK	AV		
ST. CLAIR	AV	WARDEN	AV		
ST. CLAIR	AV	WARREN	ROAD		
ST. CLAIR	AV	WELLS HILL	AV		
ST. CLAIR	AV	WESTBOURNE	AV		
ST. CLAIR	AV	WINONA	DR		
ST. CLAIR	AV	WYCHWOOD	AV		
ST. CLAIR	AV	YONGE	ST		
ST. DENNIS	DR	WYNFORD	DR		
ST. LAWRENCE	AV	THE QUEENSWAY			
ST. PHILLIPS	ROAD	WESTON	ROAD		
STARVIEW	LANE	WESTON	ROAD		
STEELES	AV	STEINWAY	BV		
STEELES	AV	TAPSCOTT	ROAD		
STEELES	AV	THURMAN	ROAD	TORRESDALE	AV
STEELES	AV	TOWNSEND	ROAD		
STEELES	AV	VICTORIA PARK	AV		
STEELES	AV	WAGGONER WELLS	LANE		
STEELES	AV	WARDEN	AV		
STEELES	AV	WESTON	ROAD		
STEELES	AV	WILLOWDALE	AV		
STEELES	AV	YONGE	ST		
STEPHEN	DR	THE QUEENSWAY			
SURREY	AV	VICTORIA PARK	AV		

TAYMALL	AV	THE QUEENSWAY		WADSWORTH	BV
TEMPO	AV	VICTORIA PARK	AV		
THE EAST	MALL	THE QUEENSWAY			
THE ESPLANADE		YONGE	ST		
THE QUEENSWAY		THE WEST	MALL		
THE QUEENSWAY		WINDERMERE	AV		
THE QUEENSWAY		ZORRA	ST		
THE WEST	MALL	WEST MALL	CR		
TIPPETT	ROAD	WILSON	AV	WILSON HEIGHTS	BV
TORYORK	DR	WESTON	ROAD		
TOWER	DR	WARDEN	AV		
TRANSIT	ROAD	W. R. ALLEN	ROAD		
TRANSIT	ROAD	WILSON	AV		
TRETHEWEY	DR	YORE	ROAD		
UNIVERSITY	AV	WELLINGTON	ST		
VAUGHAN	ROAD	WINONA	DR		
VICTORIA PARK	AV	YORK MILLS	ROAD		
WARDEN	AV	WARDENCOURT	DR		
WARDEN	AV	WAYNE	AV		
WATERLOO	AV	WILSON HEIGHTS	BV		
WELLINGTON	ST	YONGE	ST		
WENDELL	AV	WILSON	AV		
WILSON	AV	YONGE	ST	YORK MILLS	ROAD
YONGE	BV	YONGE	ST		

LINK DATABASE

STREET	TYPE	BEGINNING	TYPE	END	TYPE	DIRECTION
ADELAIDE	ST	BATHURST	ST	SPADINA	AV	EW
ADELAIDE	ST	JARVIS	ST	PARLIAMENT	ST	EW
ADELAIDE	ST	SPADINA	AV	UNIVERSITY	AV	EW
ADELAIDE	ST	UNIVERSITY	AV	YONGE	ST	EW
ADELAIDE	ST	YONGE	ST	JARVIS	ST	EW
ALBION	ROAD	FINCH	AV	KIPLING	AV	EW
ALBION	ROAD	HWY 27		FINCH	AV	EW
ALBION	ROAD	KIPLING	AV	ISLINGTON	AV	EW
ANNETTE	ST	JANE	ST	DUNDAS	ST	EW
AVENUE	ROAD	EGLINTON	AV	LAWRENCE	AV	NS
BATHURST	ST	COLLEGE	ST	HARBORD	ST	NS
BATHURST	ST	DUNDAS	ST	COLLEGE	ST	NS
BATHURST	ST	HARBORD	ST	BLOOR	ST	NS
BATHURST	ST	ST. CLAIR	AV	EGLINTON	AV	NS
BATHURST	ST	WILSON	AV	SHEPPARD	AV	NS
BAY	ST	COLLEGE	ST	BLOOR	ST	NS
BAYVIEW	AV	FINCH	AV	STEELES	AV	NS
BAYVIEW	AV	MOORE	AV	EGLINTON	AV	NS
BIRCHMOUNT	ROAD	EGLINTON	AV	LAWRENCE	AV	NS
BIRCHMOUNT	ROAD	FINCH	AV	STEELES	AV	NS
BLOOR	ST	BATHURST	ST	SPADINA	AV	EW
BLOOR	ST	DUFFERIN	ST	OSSINGTON	AV	EW
BLOOR	ST	ISLINGTON	AV	ROYAL YORK	ROAD	EW
BLOOR	ST	THE EAST	MALL	KIPLING	AV	EW
BRIMLEY	ROAD	EGLINTON	AV	LAWRENCE	AV	NS
BRIMLEY	ROAD	SHEPPARD	AV	FINCH	AV	NS
BROADVIEW	AV	GERRARD	ST	DANFORTH	AV	NS
BROWN'S	LINE	LAKESHORE	BV	EVANS	AV	NS
BURNHAMTHORPE	ROAD	CENTENNIAL PARK	ROAD	HWY 427		EW
BURNHAMTHORPE	ROAD	HWY 427		KIPLING	AV	EW
BURNHAMTHORPE	ROAD	KIPLING	AV	DUNDAS	ST	EW
CALEDONIA	ROAD	EGLINTON	AV	LAWRENCE	AV	NS
CALEDONIA	ROAD	LAWRENCE	AV	BRIDGELAND	AV	NS
CALEDONIA	ROAD	ST. CLAIR	AV	EGLINTON	AV	NS
CARLTON	ST	JARVIS	ST	PARLIAMENT	ST	EW
CARLTON	ST	YONGE	ST	JARVIS	ST	EW
COLLEGE	ST	BATHURST	ST	SPADINA	AV	EW
COLLEGE	ST	OSSINGTON	AV	BATHURST	ST	EW
COXWELL	AV	GERRARD	ST	DANFORTH	AV	NS
DANFORTH	ROAD	BIRCHMOUNT	ROAD	KENNEDY	ROAD	EW
DANFORTH	AV	BROADVIEW	AV	PAPE	AV	EW
DANFORTH	AV	COXWELL	AV	WOODBINE	AV	EW
DANFORTH	ROAD	MIDLAND	AV	BRIMLEY	ROAD	EW
DANFORTH	AV	VICTORIA PARK	AV	DANFORTH	ROAD	EW
DAVENPORT	ROAD	BATHURST	ST	DUPONT	ST	EW
DAVENPORT	ROAD	DUFFERIN	ST	OSSINGTON	AV	EW
DAVENPORT	ROAD	DUPONT	ST	AVENUE	ROAD	EW
DAVENPORT	ROAD	OLD WESTON	ROAD	DUFFERIN	ST	EW

DAVENPORT	ROAD	OSSINGTON	AV	BATHURST	ST	EW
DAWES	ROAD	DANFORTH	AV	VICTORIA PARK	AV	NS
DIXON	ROAD	ISLINGTON	AV	ROYAL YORK	ROAD	EW
DIXON	ROAD	KIPLING	AV	ISLINGTON	AV	EW
DON MILLS	ROAD	FINCH	AV	STEELES	AV	NS
DON MILLS	ROAD	OVERLEA	BV	EGLINTON	AV	NS
DUFFERIN	ST	BLOOR	ST	DUPONT	ST	NS
DUFFERIN	ST	EGLINTON	AV	LAWRENCE	AV	NS
DUFFERIN	ST	FINCH	AV	STEELES	AV	NS
DUNDAS	ST	DUFFERIN	ST	OSSINGTON	AV	EW
DUNDAS	ST	JANE	ST	KEELE	ST	EW
DUNDAS	ST	LANSDOWNE	AV	DUFFERIN	ST	EW
DUNDAS	ST	NEILSON	DR	KIPLING	AV	EW
DUNDAS	ST	PAPE	AV	COXWELL	AV	EW
DUNDAS	ST	PARLIAMENT	ST	BROADVIEW	AV	EW
DUPONT	ST	BATHURST	ST	DAVENPORT	ROAD	EW
DUPONT	ST	DUFFERIN	ST	OSSINGTON	AV	EW
DUPONT	ST	DUNDAS	ST	DUFFERIN	ST	EW
DUPONT	ST	OSSINGTON	AV	BATHURST	ST	EW
EASTERN	AV	BROADVIEW	AV	PAPE	AV	EW
EASTERN	AV	PAPE	AV	COXWELL	AV	EW
EGLINTON	AV	AVENUE	ROAD	YONGE	ST	EW
EGLINTON	AV	BATHURST	ST	AVENUE	ROAD	EW
EGLINTON	AV	BAYVIEW	AV	LAIRD	DR	EW
EGLINTON	AV	BIRCHMOUNT	ROAD	KENNEDY	ROAD	EW
EGLINTON	AV	DON MILLS	ROAD	VICTORIA PARK	AV	EW
EGLINTON	AV	ISLINGTON	AV	ROYAL YORK	ROAD	EW
EGLINTON	AV	JANE	ST	WESTON	ROAD	EW
EGLINTON	AV	KEELE	ST	DUFFERIN	ST	EW
EGLINTON	AV	KENNEDY	ROAD	MIDLAND	AV	EW
EGLINTON	AV	KIPLING	AV	ISLINGTON	AV	EW
EGLINTON	AV	LAIRD	DR	LESLIE	ST	EW
EGLINTON	AV	LESLIE	ST	DON MILLS	ROAD	EW
EGLINTON	AV	MARKHAM	ROAD	KINGSTON	ROAD	EW
EGLINTON	AV	MIDLAND	AV	BRIMLEY	ROAD	EW
EGLINTON	AV	MOUNT PLEASANT	ROAD	BAYVIEW	AV	EW
EGLINTON	AV	ROYAL YORK	ROAD	SCARLETT	ROAD	EW
EGLINTON	AV	SCARLETT	ROAD	JANE	ST	EW
EGLINTON	AV	SPECTRUM	WAY	RENFORTH	DR	EW
EGLINTON	AV	VICTORIA PARK	AV	WARDEN	AV	EW
EGLINTON	AV	W. R. ALLEN	ROAD	BATHURST	ST	EW
EGLINTON	AV	WARDEN	AV	BIRCHMOUNT	ROAD	EW
EGLINTON	AV	YONGE	ST	MOUNT PLEASANT	ROAD	EW
ELLESMERE	ROAD	BIRCHMOUNT	ROAD	KENNEDY	ROAD	EW
ELLESMERE	ROAD	BRIMLEY	ROAD	MCCOWAN	ROAD	EW
ELLESMERE	ROAD	KENNEDY	ROAD	MIDLAND	AV	EW
ELLESMERE	ROAD	MCCOWAN	ROAD	MARKHAM	ROAD	EW
ELLESMERE	ROAD	MIDLAND	AV	BRIMLEY	ROAD	EW
ELLESMERE	ROAD	VICTORIA PARK	AV	WARDEN	AV	EW
ELLESMERE	ROAD	WARDEN	AV	BIRCHMOUNT	ROAD	EW
EVANS	AV	KIPLING	AV	ISLINGTON	AV	EW

EVANS	AV	THE EAST	MALL	KIPLING	AV	EW
FINCH	AV	BATHURST	ST	YONGE	ST	EW
FINCH	AV	BAYVIEW	AV	LESLIE	ST	EW
FINCH	AV	BIRCHMOUNT	ROAD	KENNEDY	ROAD	EW
FINCH	AV	DON MILLS	ROAD	VICTORIA PARK	AV	EW
FINCH	AV	DUFFERIN	ST	BATHURST	ST	EW
FINCH	AV	ISLINGTON	AV	WESTON	ROAD	EW
FINCH	AV	JANE	ST	KEELE	ST	EW
FINCH	AV	KEELE	ST	DUFFERIN	ST	EW
FINCH	AV	KENNEDY	ROAD	MIDLAND	AV	EW
FINCH	AV	KIPLING	AV	ISLINGTON	AV	EW
FINCH	AV	LESLIE	ST	DON MILLS	ROAD	EW
FINCH	AV	MARKHAM	ROAD	NEILSON	ROAD	EW
FINCH	AV	MIDLAND	AV	BRIMLEY	ROAD	EW
FINCH	AV	WESTON	ROAD	JANE	ST	EW
FINCH	AV	YONGE	ST	BAYVIEW	AV	EW
FRONT	ST	BATHURST	ST	SPADINA	AV	EW
FRONT	ST	JARVIS	ST	PARLIAMENT	ST	EW
FRONT	ST	SPADINA	AV	UNIVERSITY	AV	EW
GERRARD	ST	BROADVIEW	AV	PAPE	AV	EW
GERRARD	ST	JARVIS	ST	PARLIAMENT	ST	EW
GERRARD	ST	PARLIAMENT	ST	BROADVIEW	AV	EW
GERRARD	ST	WOODBINE	AV	VICTORIA PARK	AV	EW
GREENWOOD	AV	GERRARD	ST	DANFORTH	AV	NS
HARBORD	ST	BATHURST	ST	SPADINA	AV	EW
HARBORD	ST	OSSINGTON	AV	BATHURST	ST	EW
ISLINGTON	AV	EGLINTON	AV	DIXON	ROAD	NS
ISLINGTON	AV	FINCH	AV	STEELES	AV	NS
ISLINGTON	AV	REXDALE	BV	ALBION	ROAD	NS
JANE	ST	SHEPPARD	AV	FINCH	AV	NS
JARVIS	ST	KING	ST	QUEEN	ST	NS
JARVIS	ST	QUEEN	ST	DUNDAS	ST	NS
KEELE	ST	FINCH	AV	STEELES	AV	NS
KEELE	ST	ROGERS	ROAD	EGLINTON	AV	NS
KEELE	ST	SHEPPARD	AV	FINCH	AV	NS
KENNEDY	ROAD	LAWRENCE	AV	ELLESMERE	ROAD	NS
KING	ST	JAMESON	AV	DUFFERIN	ST	EW
KING	ST	SPADINA	AV	UNIVERSITY	AV	EW
KING	ST	YONGE	ST	JARVIS	ST	EW
KINGSTON	ROAD	BRIMLEY	ROAD	MCCOWAN	ROAD	EW
KINGSTON	ROAD	MARKHAM	ROAD	MORNINGSIDE	AV	EW
KINGSTON	ROAD	MCCOWAN	ROAD	MARKHAM	ROAD	EW
KINGSTON	ROAD	MIDLAND	AV	BRIMLEY	ROAD	EW
KINGSTON	ROAD	VICTORIA PARK	AV	WARDEN	AV	EW
KINGSTON	ROAD	WARDEN	AV	BIRCHMOUNT	ROAD	EW
KINGSTON	ROAD	WOODBINE	AV	VICTORIA PARK	AV	EW
KIPLING	AV	BURNHAMTHORPE	ROAD	RATHBURN	ROAD	NS
KIPLING	AV	FINCH	AV	STEELES	AV	NS
KIPLING	AV	REXDALE	BV	ALBION	ROAD	NS
LAIRD	DR	SOUTHVALE	DR	EGLINTON	AV	NS
LAKESHORE	BV	KIPLING	AV	ISLINGTON	AV	EW

LANSDOWNE	AV	QUEEN	ST	DUNDAS	ST	NS
LAWRENCE	AV	AVENUE	ROAD	YONGE	ST	EW
LAWRENCE	AV	BATHURST	ST	AVENUE	ROAD	EW
LAWRENCE	AV	BIRCHMOUNT	ROAD	KENNEDY	ROAD	EW
LAWRENCE	AV	BRIMLEY	ROAD	MCCOWAN	ROAD	EW
LAWRENCE	AV	DON VALLEY	PKY	VICTORIA PARK	AV	EW
LAWRENCE	AV	DUFFERIN	ST	BATHURST	ST	EW
LAWRENCE	AV	KEELE	ST	DUFFERIN	ST	EW
LAWRENCE	AV	KENNEDY	ROAD	MIDLAND	AV	EW
LAWRENCE	AV	KINGSTON	ROAD	PORT UNION	ROAD	EW
LAWRENCE	AV	LESLIE	ST	DON VALLEY	PKY	EW
LAWRENCE	AV	MARKHAM	ROAD	KINGSTON	ROAD	EW
LAWRENCE	AV	MCCOWAN	ROAD	MARKHAM	ROAD	EW
LAWRENCE	AV	MIDLAND	AV	BRIMLEY	ROAD	EW
LAWRENCE	AV	VICTORIA PARK	AV	WARDEN	AV	EW
LAWRENCE	AV	WARDEN	AV	BIRCHMOUNT	ROAD	EW
LAWRENCE	AV	WESTON	ROAD	JANE	ST	EW
LESLIE	ST	EGLINTON	AV	LAWRENCE	AV	NS
LESLIE	ST	SHEPPARD	AV	FINCH	AV	NS
MARKHAM	ROAD	FINCH	AV	STEELES	AV	NS
MARKHAM	ROAD	SHEPPARD	AV	FINCH	AV	NS
MARTIN GROVE	ROAD	FINCH	AV	STEELES	AV	NS
MARTIN GROVE	ROAD	REXDALE	BV	ALBION	ROAD	NS
MCCOWAN	ROAD	LAWRENCE	AV	ELLESMERE	ROAD	NS
MCNICOLL	AV	BIRCHMOUNT	ROAD	KENNEDY	ROAD	EW
MCNICOLL	AV	DON MILLS	ROAD	VICTORIA PARK	AV	EW
MCNICOLL	AV	WARDEN	AV	BIRCHMOUNT	ROAD	EW
MEADOWVALE	ROAD	ELLESMERE	ROAD	SHEPPARD	AV	NS
MIDLAND	AV	DANFORTH	ROAD	EGLINTON	AV	NS
MIDLAND	AV	ELLESMERE	ROAD	SHEPPARD	AV	NS
MIDLAND	AV	FINCH	AV	STEELES	AV	NS
MILNER	AV	MARKHAM	ROAD	MORNINGSIDE	AV	EW
MILNER	AV	MCCOWAN	ROAD	MARKHAM	ROAD	EW
MILNER	AV	MORNINGSIDE	AV	COLLINS	ROAD	EW
MOORE	AV	BAYVIEW	AV	ASHTOR	AV	EW
MOORE	AV	MOUNT PLEASANT	ROAD	BAYVIEW	AV	EW
MORNINGSIDE	AV	KINGSTON	ROAD	ELLESMERE	ROAD	NS
MORTIMER	AV	BROADVIEW	AV	PAPE	AV	EW
MORTIMER	AV	COXWELL	AV	WOODBINE	AV	EW
MORTIMER	AV	PAPE	AV	COXWELL	AV	EW
MOUNT PLEASANT	ROAD	MOORE	AV	EGLINTON	AV	NS
NEILSON	ROAD	SHEPPARD	AV	FINCH	AV	NS
O'CONNOR	DR	COXWELL	AV	WOODBINE	AV	EW
O'CONNOR	DR	PAPE	AV	COXWELL	AV	EW
O'CONNOR	DR	ST. CLAIR	AV	VICTORIA PARK	AV	EW
O'CONNOR	DR	WOODBINE	AV	ST. CLAIR	AV	EW
OSSINGTON	AV	COLLEGE	ST	HARBORD	ST	NS
OSSINGTON	AV	HARBORD	ST	BLOOR	ST	NS
OVERLEA	BV	MILLWOOD	ROAD	DON MILLS	ROAD	EW
PAPE	AV	DANFORTH	AV	O'CONNOR	DR	NS
PARKSIDE	DR	LAKESHORE	BV	BLOOR	ST	NS

PARLIAMENT	ST	CARLTON	ST	BLOOR	ST	NS
PROGRESS	AV	KENNEDY	ROAD	MIDLAND	AV	EW
PROGRESS	AV	MIDLAND	AV	BRIMLEY	ROAD	EW
QUEEN	ST	BATHURST	ST	SPADINA	AV	EW
QUEEN	ST	JARVIS	ST	PARLIAMENT	ST	EW
QUEEN	ST	OSSINGTON	AV	BATHURST	ST	EW
QUEEN	ST	PAPE	AV	COXWELL	AV	EW
RATHBURN	ROAD	KIPLING	AV	ISLINGTON	AV	EW
REXDALE	BV	HWY 427		HWY 27		EW
REXDALE	BV	KIPLING	AV	ISLINGTON	AV	EW
RICHMOND	ST	BATHURST	ST	SPADINA	AV	EW
RICHMOND	ST	JARVIS	ST	PARLIAMENT	ST	EW
RICHMOND	ST	SPADINA	AV	UNIVERSITY	AV	EW
RICHMOND	ST	UNIVERSITY	AV	YONGE	ST	EW
RICHMOND	ST	YONGE	ST	JARVIS	ST	EW
ROGERS	ROAD	CALEDONIA	ROAD	DUFFERIN	ST	EW
ROGERS	ROAD	DUFFERIN	ST	OAKWOOD	AV	EW
ROGERS	ROAD	OLD WESTON	ROAD	CALEDONIA	ROAD	EW
SHEPPARD	AV	BATHURST	ST	YONGE	ST	EW
SHEPPARD	AV	BAYVIEW	AV	LESLIE	ST	EW
SHEPPARD	AV	BIRCHMOUNT	ROAD	KENNEDY	ROAD	EW
SHEPPARD	AV	BRIMLEY	ROAD	MCCOWAN	ROAD	EW
SHEPPARD	AV	DON MILLS	ROAD	VICTORIA PARK	AV	EW
SHEPPARD	AV	JANE	ST	KEELE	ST	EW
SHEPPARD	AV	KENNEDY	ROAD	MIDLAND	AV	EW
SHEPPARD	AV	LESLIE	ST	DON MILLS	ROAD	EW
SHEPPARD	AV	MARKHAM	ROAD	NEILSON	ROAD	EW
SHEPPARD	AV	MCCOWAN	ROAD	MARKHAM	ROAD	EW
SHEPPARD	AV	MIDLAND	AV	BRIMLEY	ROAD	EW
SHEPPARD	AV	MORNINGSIDE	AV	MEADOWVALE	ROAD	EW
SHEPPARD	AV	NEILSON	ROAD	MORNINGSIDE	AV	EW
SHEPPARD	AV	WARDEN	AV	BIRCHMOUNT	ROAD	EW
SHEPPARD	AV	WESTON	ROAD	JANE	ST	EW
SHEPPARD	AV	YONGE	ST	BAYVIEW	AV	EW
SPADINA	ROAD	BLOOR	ST	DUPONT	ST	NS
SPADINA	AV	KING	ST	QUEEN	ST	NS
ST. CLAIR	AV	AVENUE	ROAD	YONGE	ST	EW
ST. CLAIR	AV	BATHURST	ST	AVENUE	ROAD	EW
ST. CLAIR	AV	BIRCHMOUNT	ROAD	KENNEDY	ROAD	EW
ST. CLAIR	AV	DUFFERIN	ST	BATHURST	ST	EW
ST. CLAIR	AV	JANE	ST	KEELE	ST	EW
ST. CLAIR	AV	KENNEDY	ROAD	MIDLAND	AV	EW
ST. CLAIR	AV	MIDLAND	AV	KINGSTON	ROAD	EW
ST. CLAIR	AV	O'CONNOR	DR	VICTORIA PARK	AV	EW
ST. CLAIR	AV	SCARLETT	ROAD	JANE	ST	EW
ST. CLAIR	AV	VICTORIA PARK	AV	WARDEN	AV	EW
ST. CLAIR	AV	WARDEN	AV	BIRCHMOUNT	ROAD	EW
ST. CLAIR	AV	YONGE	ST	MOUNT PLEASANT	ROAD	EW
STEELES	AV	BATHURST	ST	YONGE	ST	EW
STEELES	AV	BAYVIEW	AV	LESLIE	ST	EW
STEELES	AV	BIRCHMOUNT	ROAD	KENNEDY	ROAD	EW

STEELES	AV	BRIMLEY	ROAD	MCCOWAN	ROAD	EW
STEELES	AV	DON MILLS	ROAD	VICTORIA PARK	AV	EW
STEELES	AV	DUFFERIN	ST	BATHURST	ST	EW
STEELES	AV	HWY 27		KIPLING	AV	EW
STEELES	AV	ISLINGTON	AV	WESTON	ROAD	EW
STEELES	AV	JANE	ST	KEELE	ST	EW
STEELES	AV	KEELE	ST	DUFFERIN	ST	EW
STEELES	AV	KENNEDY	ROAD	MIDLAND	AV	EW
STEELES	AV	KIPLING	AV	ISLINGTON	AV	EW
STEELES	AV	LESLIE	ST	DON MILLS	ROAD	EW
STEELES	AV	MARKHAM	ROAD	THE END		EW
STEELES	AV	MCCOWAN	ROAD	MARKHAM	ROAD	EW
STEELES	AV	MIDLAND	AV	BRIMLEY	ROAD	EW
STEELES	AV	VICTORIA PARK	AV	WARDEN	AV	EW
STEELES	AV	WESTON	ROAD	JANE	ST	EW
STEELES	AV	YONGE	ST	BAYVIEW	AV	EW
THE QUEENSWAY		ISLINGTON	AV	ROYAL YORK	ROAD	EW
THE QUEENSWAY		KIPLING	AV	ISLINGTON	AV	EW
THE QUEENSWAY		THE EAST	MALL	KIPLING	AV	EW
TRETHEWEY	DR	JANE	ST	BLACK CREEK	DR	EW
UNIVERSITY	AV	DUNDAS	ST	COLLEGE	ST	NS
UNIVERSITY	AV	QUEEN	ST	DUNDAS	ST	NS
VAUGHAN	ROAD	NORTHCLIFFE	BV	ST. CLAIR	AV	EW
VICTORIA PARK	AV	EGLINTON	AV	LAWRENCE	AV	NS
VICTORIA PARK	AV	KINGSTON	ROAD	GERRARD	ST	NS
VICTORIA PARK	AV	SHEPPARD	AV	FINCH	AV	NS
WARDEN	AV	KINGSTON	ROAD	DANFORTH	AV	NS
WARDEN	AV	ST. CLAIR	AV	EGLINTON	AV	NS
WELLESLEY	ST	QUEENS PARK	CR	BAY	ST	EW
WELLESLEY	ST	YONGE	ST	JARVIS	ST	EW
WELLINGTON	ST	SPADINA	AV	UNIVERSITY	AV	EW
WELLINGTON	ST	UNIVERSITY	AV	YONGE	ST	EW
WELLINGTON	ST	YONGE	ST	CHURCH	ST	EW
WESTON	ROAD	SHEPPARD	AV	FINCH	AV	NS
WILSON	AV	AVENUE	ROAD	YONGE	ST	EW
WILSON	AV	BATHURST	ST	AVENUE	ROAD	EW
WILSON	AV	DUFFERIN	ST	BATHURST	ST	EW
WILSON	AV	JANE	ST	KEELE	ST	EW
WILSON	AV	KEELE	ST	DUFFERIN	ST	EW
WOODBINE	AV	DANFORTH	AV	O'CONNOR	DR	NS
WOODBINE	AV	QUEEN	ST	KINGSTON	ROAD	NS
YONGE	ST	DUNDAS	ST	CARLTON	ST	NS
YONGE	ST	SHEPPARD	AV	FINCH	AV	NS
YONGE	ST	ST. CLAIR	AV	EGLINTON	AV	NS
YORK MILLS	ROAD	BAYVIEW	AV	LESLIE	ST	EW
YORK MILLS	ROAD	DON MILLS	ROAD	VICTORIA PARK	AV	EW
YORK MILLS	ROAD	LESLIE	ST	DON MILLS	ROAD	EW
YORK MILLS	ROAD	YONGE	ST	BAYVIEW	AV	EW

APPENDIX B

PROCEDURE TO ESTIMATE MISSING COUNTS

INTRODUCTION

The purpose of this paper is to describe a procedure to estimate the Annual Average Daily Traffic (AADT) for the years that traffic counts are not available at intersections. This work originated from a research project at the University of Toronto that studied the development of accident prediction models (APMs) at signalized and unsignalized intersections. In this project, the models incorporate the year-to-year variation or accident trend (*1*). A complete database is required whenever this type of model is used; indeed, the employment of incomplete data may lead to biased models (*2*).

The original database consists of 1,551 intersections located in Toronto, Ontario. They are under the jurisdiction of Metro Transportation (the transportation agency of the City of Toronto). This database provided data for the creation of several APMs with trend. In order to have reliable models, a large sample size and detailed information on each intersection in the sample are needed. In addition, it is important to have data for as many years as possible. Unfortunately, since the field recording of traffic counts is expensive and the resources of Metro Transportation (or any other transportation agencies) are limited, traffic counts can only be recorded for a restricted number of sites each year. These counts are also recorded during a limited number of hours. For instance, at Metro Transportation, traffic counts are performed at intersections every two or three years. They are also recorded for a total of 8 hours per day (6 hours during the peak periods and a 2-hour off-peak period). It is, therefore, necessary to estimate the counts of the missing years for every intersection in the sample. Thus, this paper presents the steps and the procedure that was used to estimate the missing traffic counts at these 1,551 intersections. The estimation of hourly flows is also described in this procedure.

Four steps were required to estimate the missing traffic flows. The first step involved the expansion of 8-hour traffic counts to Annual Average Daily Traffic (AADT) for every movement at an intersection: left-turns, through, and right-turns of each leg. The expansion was performed for the years for which counts are available. The second step dealt with the estimation of the missing AADTs for every intersection. In this step, the AADT of every movement was summed to create the total entering flow for each intersection. The third step consisted in the creation of hourly traffic factors based on the available 24-hour counts provided by Metro Transportation. The final step pertained to the estimation of hourly traffic counts based on the factors performed in the third step. An example is presented in each step to better illustrate the procedure.

DATA

The original database obtained from Metro Transportation consists of two types of computer file. The first type pertains to traffic counts that are performed at signalized intersections by observers (8-hour), while the second type consists of traffic counts that are recorded on city streets by automatic counters (24-hour). The traffic flow data is available from 1985 to 1996 for the observed counts, and from 1992 to 1996 for the automatic counts. For each type, a different computer file exists for every year of available data.

Observed traffic counts are performed at intersections during the morning, mid-day, and afternoon peaks, and one off-peak period. Two-hour counts start at 7:30 a.m., 11:00 a.m., and 4:00 p.m. for the peak periods. For the off-peak period, traffic counts are performed for 1 hour in the morning and afternoon starting at 10:00 a.m. and 2:00 p.m. respectively. Traffic counts are divided into 15-minute periods and include all possible movements at an intersection (e.g., 12 movements for a 4-legged intersection). This type of traffic count is recorded at the 1,551 intersections.

For the second type, traffic counts are collected between intersections for a 24-hour period by automatic counters. These counts are divided into 15-minute periods for a total of 96 periods per 24-hour. They are performed for a minimum of 24 hours (defined as 1 count) and can be recorded up to an entire year (defined as 365 counts) for permanent counting stations. In addition, these counts are available for both traveling directions on the street where the automatic counters are placed on. The 24-hour counts are used to estimate hourly factors of intersections described in the fifth section.

The second type of traffic counts were performed 28,042 times between 1992 and 1996. In other words, 28,042 24-hour counts are available to estimate hourly factors. However, during a preliminary analysis, it was discovered that many traffic counts had recording errors. For instance, some automatic counters did not record traffic flows for various time periods (a series of 0s during these periods reflected this error). In order to minimize the number of errors, each 24-hour count was screened to remove any suspicious recordings. This procedure was performed by comparing traffic flows between different time periods and examining if these flows reflected the actual flow for that time period (e.g., a traffic count at 4 a.m. that is much higher than the one at 9 a.m. would be flagged as a suspicious count). All traffic counts were also verified for abnormality by looking for a high number of sequential 0s. This process lead to new a sample of 24,381 traffic counts. These counts were performed on 639 road sections.

EXPANSION FROM 8-HOUR COUNTS TO AADT (1ST STEP)

Several expansion factors were used to transform 8-hour observed traffic counts to AADT. These factors were created by Metro Transportation from their permanent counting stations. The expansion factors are divided into five categories. The first category consists of roads which are classified as freeways or expressways. The second category pertains to roads located in the downtown core. The expansion factors used in this category are the ones created in the '80s by the Market Investigation Services of the Traffic Division, as data is not yet available from permanent counting stations. More accurate expansion factors are currently being computed for this category. The third category includes roads that are classified as suburban arterial roads. The fourth category consists of roads in industrial and commercial areas. The last category refers to roads that are classified as residential streets.

For each category, a different expansion factor exists for the day of the week and the month of the year. Therefore, there is a total of 84 expansion factors (7 days x12 months) for each category. One should note that each leg of an intersection is classified according to one of the five categories.

For each leg of an intersection, the appropriate factor was read from the list of expansion factors and written into a spreadsheet manually. Table 1 shows the expansion factors used for the intersection of Davisville and Mount Pleasant Avenue for 1996; the traffic count was performed on Thursday, July 18. Then, each factor was multiplied by the total 8-hour traffic counts of each approach to expand the results to AADT. This procedure was performed for the 12 years of available data (1985 to 1996) and for every intersection. Tables 2a and 2b (see page 4) illustrate the results of the multiplication of the expansion factors with the traffic counts for each movement of Davisville and Mount Pleasant. Similar calculations were prepared for each intersection when observers counted traffic.

TABLE 1. Expansion factors for Davisville and Mount Pleasant for Thursday, July 18, 1996

Approach	Road Type	Expansion Factor
North	Sub-Urban Arterial (3)	1.991
South	Downtown Arterial (2)	1.857
East	Residential Street (5)	2.006
West	Residential Street (5)	2.006

ESTIMATING ENTERING FLOWS (AADT) FOR THE MISSING YEARS (2ND STEP)

The intersection of Davisville and Mount Pleasant is used to illustrate the steps taken to estimate the missing AADTs. The AADT of each movement was initially added to compute the total entering flow of the intersection. Table 3 shows the total entering flow for the intersection of Davisville and Mount Pleasant between 1985 and 1996.

TABLE 3. Total entering flow for Davisville and Mount Pleasant in vehicles per day

1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
51236	54132			45877		37780					46432

The task is to estimate the total entering AADT values of the missing years. To fill in the blanks, we assume that the traffic from year-to-year is made of two components. The first component represents a Toronto-wide change, common to all roads. The second component is specific to each road and is approximately linear. The procedure used will be illustrated by numerical examples using the aforementioned intersection.

To estimate the Toronto-wide change, the average entering flow of each intersection was calculated. Thus, for the above intersection the average entering flow for the years in which counts were performed was 47091 vpd. Then, each entering flow was divided by this average to normalized the entering flow. Therefore, the row of numbers should have a mean of 1. Table 4 shows the normalized entering flow for Davisville and Mount Pleasant.

TABLE 4. Normalized entering flow for Davisville and Mount Pleasant

1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
1.09	1.15			0.97		0.80					0.99

The process described above was performed for each intersection in the database. The mean of the normalized entering flows was then computed for each year to estimate the Toronto-wide change. The results are presented in Table 5 and Figure 1. During this process, six intersections were removed from the analysis due to traffic count errors.

TABLE 2a. Original traffic counts (8-hour) per movement for Davisville and Mount Pleasant in vehicles per hour

	North Approach			South Approach			East Approach			West Approach			Total
	R	T	L	R	T	L	R	T	L	R	T	L	
1985	289	8002	700	552	10035	295	558	1857	673	286	2752	416	26417
1986	354	7976	711	370	10590	270	546	2047	708	284	3697	334	27887
1989	183	8157	588	608	8674	315	812	1575	724	222	1322	469	23649
1991	275	5602	564	548	7554	221	524	1771	753	201	1212	276	19500
1996	480	6719	714	654	8728	420	820	2147	877	414	1397	564	23934

TABLE 2b. Expanded traffic counts (AADT) per movement for Davisville and Mount Pleasant in vehicles per day

	North Approach			South Approach			East Approach			West Approach			Total
	R	T	L	R	T	L	R	T	L	R	T	L	
1985	576	15932	1394	1026	18636	548	1120	3726	1350	574	5521	835	51236
1986	705	15880	1416	687	19666	501	1095	4106	1420	570	7416	610	54132
1989	363	16241	1171	1129	16108	585	1628	3159	1452	445	2653	942	45877
1991	547	11153	1123	1017	14029	410	1051	3552	1510	404	2431	554	37780
1996	956	13378	1422	1214	16208	780	1759	4307	1759	830	2802	1131	46432

TABLE 5. Means of normalized entering flows

	Number of Intersections	Mean Index
1985	378	0.906
1986	461	0.958
1987	303	0.989
1988	116	0.99
1989	516	1.023
1990	291	1.001
1991	523	0.999
1992	382	1.008
1993	449	1.013
1994	390	1.031
1995	506	1.032
1996	310	1.034

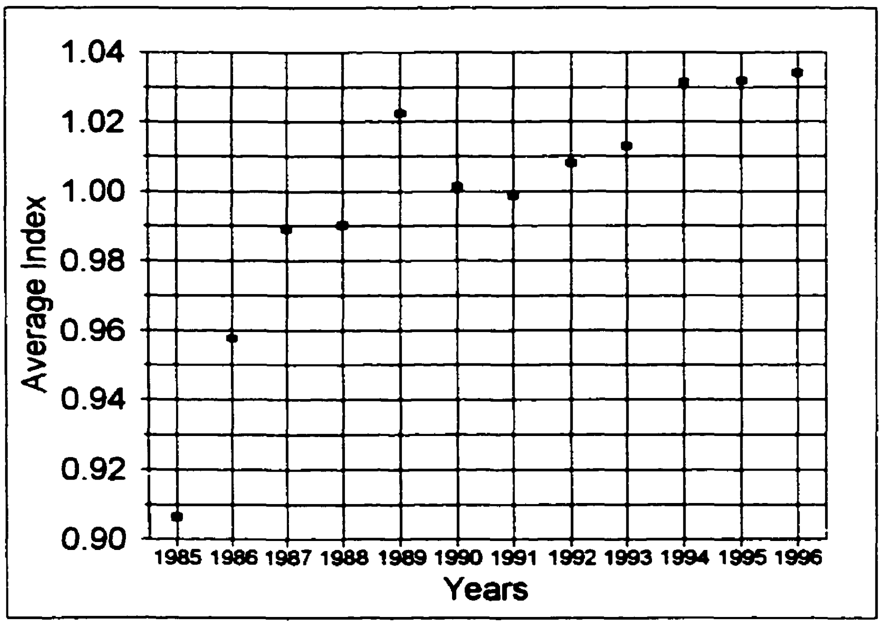

FIGURE 1. Toronto-wide average normalized entering flows

In preparation for the next step in which we estimate the trend that is specific to each intersection, we have to remove the Toronto-wide trend from the normalized entering flows of each intersection. We do this by adjusting the normalized index of each intersection with the average normalized index For example, the normalized entering flow and Toronto-wide normalized entering flow in 1985 for Davisville and Mount Pleasant were 1.088 and 0.906 respectively. Was the Toronto-wide trend absent, one should expect the normalized entering flow to be 1.088 / 0.906 = 1.201. This process was performed for every year. All entering flows were similarly adjusted.

Once the normalized entering flows were adjusted, a linear equation was fitted for each intersection. The equation of the fitted line is of the form:

$$Y = \alpha + \beta \times x \tag{1}$$

where,

Y = fitted adjusted normalized entering flow
α, β = parameters to be estimated
x= number of years since 1985

When fewer than two counts were available, α was set to be the average of the entering flows and $\beta = 0$. When more than two counts were available, the line was fitted by the least square method. For the intersection used for illustration, $\alpha = 1.174$ and $\beta = -0.028$.

The standard deviation of the estimates, $\sigma(AADT)$, was computed according to the methodology developed by Hauer (3). From this, we can observe that the standard deviation is a function of the standard deviation of each intersection and the Toronto-wide trend simultaneously. Two standard deviations can be computed depending if a site has more than two counts available. Equation (2) is used for sites with less than two counts while equation (3) is used for sites with more than two counts:

$$\sigma(AADT) = MI \times AC \times \left[\frac{\sigma^2}{n} + (x - \bar{x})^2 VAR(\beta)\right]^{0.5} \tag{2}$$

$$\sigma(AADT) = MI \times AC \times \left[\frac{\sigma^2}{n} + \frac{(x - \bar{x})^2 \sigma^2}{(\sum x_i - n\bar{x}^2)}\right]^{0.5} \tag{3}$$

where,

$\sigma(AADT)$ = standard deviation of the estimated entering flow
MI = regional-wide mean index
AC = average count
$\sigma = 0.1638$
$VAR(\beta) = 0.007$
n = number of counts for each site
x= number of years since 1985

The standard deviation estimated by equation (3) is performed through the least-square method. It is only used for the purpose of illustration. For more information on the computation of the standard deviation of the estimates, the reader is referred to appendix A of Hauer's paper (*3*).

The estimated entering flows calculated from equation (2) were then re-adjusted to restore the Toronto-wide trend. The results for the intersection used in the illustration is presented in Figure 2. Note that the standard deviation indicated in this figure is the one for estimated entering flows. This is not the standard deviation of the traffic counts.

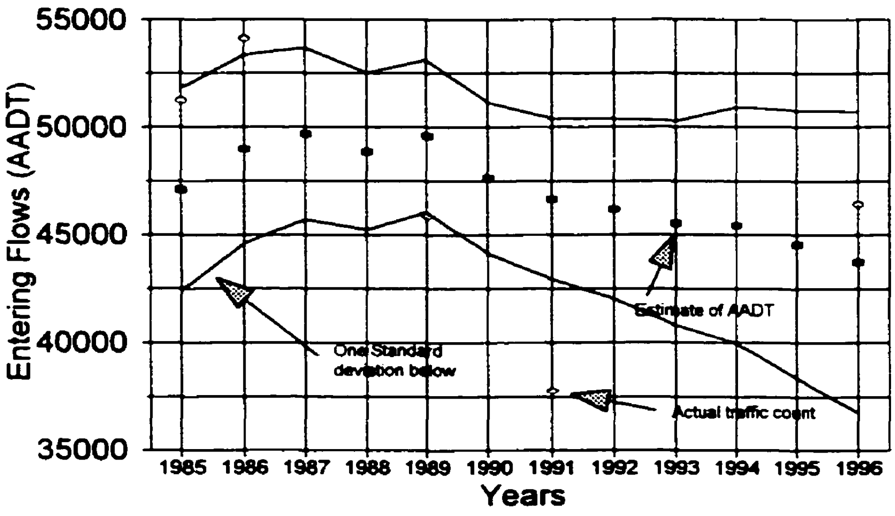

FIGURE 2. Estimated entering flows (AADT) and traffic counts

The entire regression analysis was performed with a computer program written in QuickBASIC (*4*). This program was adapted and modified from the original program written by Hauer (*1*). The modification was required to use the Toronto database as input.

ESTIMATING THE TRAFFIC FLOW FOR EACH APPROACH AND MOVEMENT (3RD STEP)

Once the entering flow of each intersection is estimated, we then need to re-assign the total entering flow to the respective leg and movement. For each available count described in step 1, the traffic flow (AADT) of each movement was divided by the total entering flow for every intersection; defined here as a proportion of the total entering flow. Then, the average proportion of each movement was computed when more than one year of data was available. There is a possibility of 12 different proportions for any given intersection, (4 legs multiplied by 3 movements). This process was also carried out with a computer program written in QuickBASIC.

To continue with the same example, the twelve proportions for Davisville and Mount Pleasant were computed by dividing the values of the different movements found in Table 2b with the total entering flow also found in this table. The results are shown in Table 6.

Once the proportion of every movement was computed, the flows were then re-assigned to their respective leg and movement. This was performed by multiplying the total estimated entering flow (computed in step 2) by the proportions calculated above. The re-assignment process was conducted for every intersection and for every year. Table 7 illustrates the product of this procedure for Davisville and Mount Pleasant. The number inside the parentheses represents the standard deviation of the estimated flow.

TABLE 6. Proportion of traffic from the total entering flow for Davisville and Mount Pleasant

	North Approach			South Approach			East Approach			West Approach			Total
	R	T	L	R	T	L	R	T	L	R	T	L	
1985	0.0112	0.3109	0.0272	0.0200	0.3637	0.0107	0.0219	0.0727	0.0263	0.0112	0.1077	0.0163	1.0
1986	0.0130	0.2934	0.0262	0.0127	0.3633	0.0093	0.0202	0.0759	0.0262	0.0105	0.1370	0.0124	1.0
1989	0.0079	0.3540	0.0255	0.0246	0.3511	0.0127	0.0355	0.0689	0.0317	0.0097	0.0578	0.0205	1.0
1991	0.0145	0.2952	0.0297	0.0269	0.3713	0.0109	0.0278	0.0940	0.0400	0.0107	0.0643	0.0147	1.0
1996	0.0206	0.2881	0.0306	0.0262	0.3491	0.0168	0.0354	0.0928	0.0379	0.0179	0.0604	0.0244	1.0
Avg	**0.0134**	**0.3083**	**0.0278**	**0.0221**	**0.3597**	**0.0121**	**0.0282**	**0.0808**	**0.0324**	**0.0120**	**0.0855**	**0.0176**	**1.0**
S.D.	*0.0042*	*0.0241*	*0.0020*	*0.0053*	*0.0084*	*0.0026*	*0.0065*	*0.0105*	*0.0057*	*0.0030*	*0.0316*	*0.0043*	

TABLE 7. Re-assigned flows for Davisville and Mount Pleasant per approach and per movement in vehicles per day (AADT)

Approach	North			South			Total
	15291 (2669)			17226 (2783)			32517
Movement	Right	Through	Left	Right	Through	Left	
	588 (206)	13485 (2400)	1218 (213)	966 (277)	15732 (2535)	528 (142)	
Approach	East			West			
	6185 (1155)			5034 (1630)			11219
Movement	Right	Through	Left	Right	Through	Left	
	1232 (344)	3536 (727)	1418 (337)	525 (155)	3737 (1505)	772 (224)	
Total							43736
• The number inside the parentheses is the standard deviation							

The expected value and standard deviation were estimated with the use of the moments of a product and are defined by the following equations (5):

$$E[XY] = E[X]E[Y] \tag{4}$$

$$\sigma[XY] = \left(E[X]^2 VAR[Y] + E[Y]^2 VAR[X] + VAR[X]VAR[Y]\right)^{0.5} \tag{5}$$

Equations (4) and (5) are used for the product of two independent variables. In our case, we have our total entering flow, 43736 vpd, defined as X and the estimated proportion, described in Table 6, defined as Y. Equation (5) is only used for the purpose of illustration.

ESTIMATING HOURLY FLOWS (4TH STEP)

In order to estimate hourly factors, one has to use the 24-hour traffic counts. These counts show the traffic flow pattern for an entire day on various streets in Toronto. The traffic flow pattern is then used to create hourly factors. For each 24-hour period, traffic counts are grouped into 24 periods, each period representing a different hour. The hourly factors are computed by dividing the number of vehicles in each period by the total number of vehicles for that 24-hour. For the road sections that had more than one day of counts, the average daily traffic flow pattern was computed. Figure 3 shows the traffic flow pattern for North (or South Bound) leg of Davisville and Mount Pleasant. An automatic counter was placed on the North side of this intersection. One can note that no standard deviation was computed as only one 24-hour traffic count was performed at this intersection.

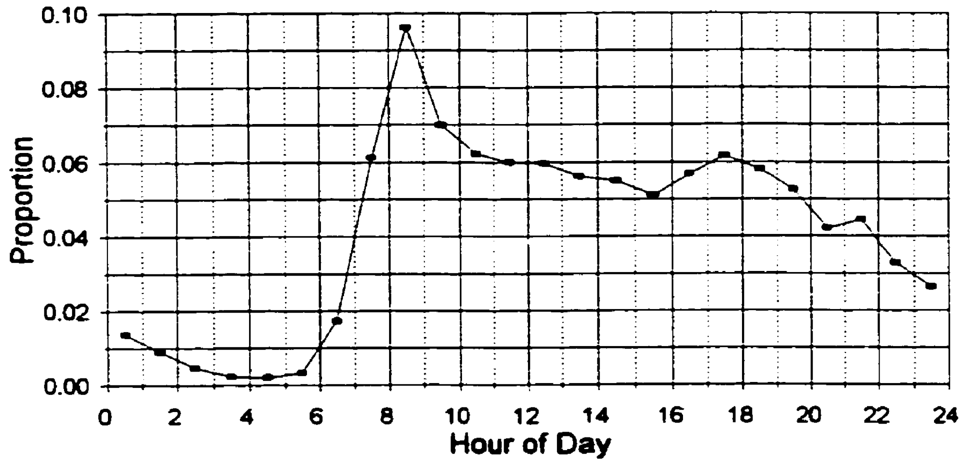

FIGURE 3. Traffic flow pattern for the SB approach of Davisville and Mount Pleasant

The strategy adopted to estimate hourly factors for each of the 1,545 intersections (1,551 - 6) consisted of using the 24-hour traffic counts located on one or more of the approaches of these intersections; the automatic counters are usually placed beside an intersection. This strategy increases the reliability of the traffic flow pattern as the counts are performed right beside that intersection. Since the 24-hour traffic counts are performed simultaneously for both traveling directions, one has information for at least two approaches of an intersection. For instance, an automatic counter located on the South approach would provide the traffic flow pattern for both the South and North approach. For the intersections that did not have a traffic flow pattern on anyone of their legs, the average traffic flow pattern of the other available approaches were used.

Unfortunately, the strategy described above has some limitations. Since only 639 of the 1,546 intersections have 24-hour counts performed on one of their legs, an alternative strategy to estimate the traffic flow pattern for these intersections was used. The alternate strategy consisted of creating an average Toronto-wide traffic flow pattern or hourly factors according to the average computed from the 639 road sections. This strategy was used for intersections that did not have a 24-hour count on one of its leg. The Toronto-wide traffic flow pattern was applied to each leg of these intersections.

Once these hourly factors are created, estimated daily flow (AADT) for each movement of an intersection is multiplied by these factors. Therefore, for a 4-way intersection, the 12 daily flows are multiplied by the hourly factors. This step enables us to estimate hourly flows for different period of the day. In particular, one can attempt to model nighttime accidents (e.g., 9:00 p.m. to 6:00 a.m.) or morning peak period accidents (e.g., 6:00 a.m. to 9:00 a.m.) more accurately.

Figure 4 shows the hourly flows for the through movement of the Southbound (SB) approach in 1996. This figure also shows the actual traffic counts performed on Thursday, July 18, 1996. It is important to note that this count is not an adjusted annual average. The figure illustrates that a small discrepancy exists between the actual counts and estimated flows. This can be explained by the fact that the hourly flow was computed on a different day than the actual count. However, the estimated traffic flow pattern appears to follow quite well the flow pattern of the unadjusted counts. The standard deviation in Figure 4 was also estimated with the properties of equations (4) and (5).

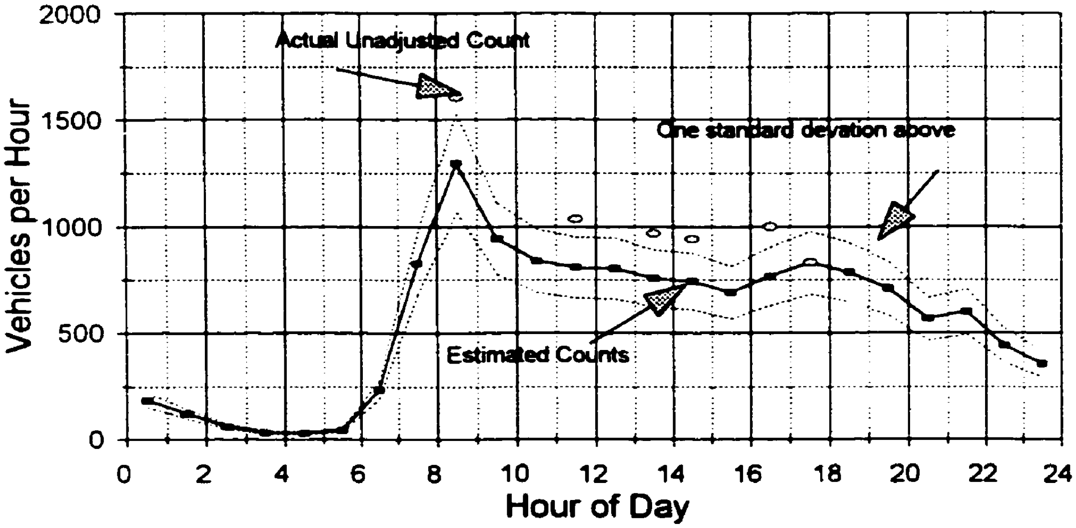

FIGURE 4. Estimated 1996 traffic counts for different time periods for the through South Bound approach of Davisville and Mount Pleasant

OUTPUT

The final output consists of two computer files. The output had to be separated into two distinct files to reduce the size of the computer files. In fact, many spreadsheet software packages are unable to handle a high number of columns (24 hourly factors x 12 movements = 288 columns). The first file includes the estimated AADT for every leg and movement for each intersection between 1985 and 1996. The second file, for the same intersections, comprises all hourly factors described in step 4. At the accident prediction modeling stage, one just need to multiply specific columns of each file depending on specific time periods that the modeler is interested in.

SUMMARY AND CONCLUSION

In the estimation of intersection safety, it is important to have information on traffic flow and accidents for as many years as possible. This particularly important when one intends of using APMs with trend. Unfortunately, traffic counts are not performed at every intersection for every year. Thus, the objective of this paper was to describe a procedure to estimate the missing AADT values and hourly flows at 1,551 intersections located in Toronto, Ontario.

Four steps were required to estimate the missing traffic flows. The expansion of 8-hour traffic counts to AADT for each movement of a leg was explained in the first step. The expansion factors were provided by Metro Transportation. Then, the estimation of the missing AADTs for each intersection in the database was presented in the second step. The traffic flow of each leg were initially added to create the total entering flow for each intersection for every year. The missing entering flows were then estimated with a computer program written in QuickBASIC. The re-assignment the total estimated entering flow to the respective leg and movement was described in the third step. To do so, the estimated entering flow was multiplied by specific factors (defined as proportions) computed with the data described in the first step. The estimation of hourly flows was explained in the fourth step. To compute the flows, a 24-hour traffic flow pattern was created for each intersection in the database. Then, the daily flow of each leg and movement was multiplied by the respective traffic flow patterns.

The final output was subdivided into two computer files. The first file contains the volumes in AADT for every intersection while the second file includes all the hourly factors for every intersection. At the modeling stage, one needs to multiply the two files together according to the period of time being modeled or other characteristics. With accidents and traffic flow available for every year, it is believed that one can develop more accurate and robust APMs.

The four-step procedure shows that missing traffic counts and hourly flows can be estimated accurately. It is, however, suggested that localized traffic counts be used to adjust the estimated flows whenever possible, as described in step 4. This is particularly important for APMs that are developed for different time periods. The procedure proposed in this paper can be very time consuming if an agency does not have computer programs that could handle the procedure. Thus, it is advised to automate the various steps to reduce the amount of work which is required to use the procedure.

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APPENDIX C

THEORY ON THE GENERALIZED ESTIMATING EQUATIONS

INTRODUCTION

Longitudinal studies play an important role in social and health sciences, particularly in the domain of medicine and epidemiology. They are primarily used when measurements are repeatedly collected for the same individuals in order to examine the time-trend effect of drugs and treatments among others. In these studies, multiple observations on the same individual often, if not always, produce a data set that has a positive temporal correlation. Regression models are very useful when one is interested in examining the relationship between an outcome and a series of covariates. These models always assume that the covariates are independent from one another. However, since a temporal correlation exists for repeated measurements, these models are not suitable when one is interested in studying the time-trend effect of the outcome. The generalized estimating equations (GEE) procedure proposed by Liang and Zeger (*1*), and Zeger and Liang (*2*) enables a modeler to develop proper and unbiased statistical models for repeatedly measured data. Thus, the objective of this paper is to present the application of the GEE procedure to traffic safety studies when several years of data are available. The GEE procedure is particularly useful for accident prediction models (APMs) that incorporate trend. To illustrate the application, the GEE procedure is used to develop APMs from a sample of 4-way signalized intersections. In this paper, we further investigate and compare the application of traditional APMs with APMs with trend (defined as time effect models in this context).

The use of longitudinal studies in traffic safety can be very beneficial. For instance, they can be used to examine the trend in the expected number of accidents. Indeed, for "before and after" studies, the accident trend during the before period can be used to predict more accurately what the expected number of accidents would have been for the after period. Similarly, APMs that include trend are able to capture factors that vary with time as opposed to traditional models such as changes in traffic flow, in weather, in economic situation, in the criteria of a reportable accident. Models that include trend often provide better estimates than traditional models.

In the traffic safety literature, few methods have been proposed on how to estimate the coefficients (α,βs) of APMs with trend. For instance, Maher and Summersgill (*3*) proposed an iterative solution based on a method known as "constructed variables" presented in McCullagh and Nelder (*4*) to find the proper estimate of the coefficients. They suggested, however, that the year-to-year relationship in modeling should be avoided whenever possible because of the difficulty in handling the temporal correlation. A variation of this iterative solution is also presented in Mountain *et al.* (*5*). These authors used an approach proposed by Atkinson (*6*). Hauer (*7*) put forward a multinomial maximum likelihood function to estimate the coefficients. This function made use of several assumptions and implications. Hauer's function is classified as a transition model (TM). Shankar *et al.* (*8*) applied random-effects models (REM) for median cross-over accidents and the coefficients were estimated with the maximum likelihood method. They used a REM proposed by Guo (*9*). TM and REM are discussed in a subsequent section.

The methods proposed above are quite useful to estimate the coefficients but, with the exception of the TM, none take specifically into consideration the temporal correlation, as opposed to the GEE procedure; the TM makes use of the temporal correlation but their application is quite different than the GEE procedure. Some of the methods are also cumbersome to use and need numerous mathematical manipulations which may be out of grasp for the average modeler. One should always try to incorporate the temporal correlation in the estimation of coefficients. If it is not, the models may be mispecified or inadequate leading to biased estimates. The problem can be more important for models that include many covariates, especially when some covariates are marginally significant, and have highly correlated data.

The main advantage of the GEE procedure relies in its direct use of the temporal correlation in the estimation of the coefficients. The procedure can be used even if the extent and the type of correlation is unknown. Several statistical software packages already have a built-in GEE function which facilitate its application. However, it is important for the modeler to understand the underlying theory behind the GEE in order to apply the procedure properly. Thus, this paper presents the tools to apply the procedure appropriately.

The appendix is separated into three sections. In the first section, the problem associated with temporal correlated data is briefly addressed. The techniques used to estimate the coefficients of traditional APMs are explained in the second section. The characteristics of longitudinal studies and the GEE procedure are presented in the third section.

PROBLEM DEFINITION

In order to have APMs with more significant coefficients, one has to have data on accidents and other characteristics (covariates) for as many years as possible. With many years of data, it is possible to examine the year-to-year variation or trend in accident counts and capture the influence of factors that change every year. In order to examine the year-to-year trend and the influence of factors, the data has to be separated by year (or any other time period) where each year is treated as a separate observation. Unfortunately, the disaggregation of the data in this manner creates a temporal correlation within the data set. To illustrate the temporal correlation, consider this simple example. Let a time effect linear model representing the measurements of two groups of people (i=1 or i=2) be the following for time t=0 and t=1 (*10*):

$$Y_{it} = \beta_0 + \beta_1 t + \epsilon_{it}, \tag{1}$$

where,

Y_{it} = the measurement on the subject i at time t;
t = the measurement at time t=0 and t=1;
ϵ_{it} = random errors, ϵ_{it}~$N(0,\sigma^2)$;
β_0, β_1 = coefficients to be estimated.

The least squares (LS) estimate of the coefficient β_1 is the following:

$$\hat{\beta}_1 = \frac{1}{I} \sum_{i}^{I} (Y_{i1} - Y_{i0}). \tag{2}$$

The variance of the LS estimate $\hat{\beta}_1$ then becomes

$$VAR(\hat{\beta}_1) = VAR\left(\sum_{i}^{I} (Y_{i1} - Y_{i0}) \right) = 2\frac{\sigma^2}{I}(1-\rho). \tag{3}$$

In equation (3), ρ represents the temporal correlation for the subject i. If the observation is positively correlated (ρ>0), which often occurs when repeated measurements are performed for the same subject (or site), the variance of β_1 will become overestimated. In this case, the modeler may arrive at a wrong conclusion when she or he examines the model's outcome. More generally, ignoring the temporal correlation may also have an impact on the proper selection of coefficients as some coefficients may be rejected because of the inflated variance. If the variables are truly independent the value of ρ=0.

ACCIDENT PREDICTION MODELS WITHOUT TREND

The coefficients of traditional APMs cannot be estimated by ordinary linear regression such as the LS and weighted least squares (WLS) methods. These methods cannot be used since the variation in the number of accidents should be described by a discrete distribution; the variance in the number of accidents increases as the flow increases; and, the number of accidents cannot be negative. The coefficients of such APMs are usually estimated by the generalized least square methods and the models are usually classified as generalized linear models (GLM). The GLM are briefly reviewed here but an extensive description can be found in McCullagh and Nelder (*4*), Dunlop (*10*), and Myers (*11*).

The GLM were introduced by Nelder and Wedderburn (*12*) who examined the relationship between a general family of error distributions and linear regression models. The normal distribution of errors is in fact a special case of the GLM. The GLM were put forward to overcome the limitations of the WLS (and LS) regressions, as described above. In addition, traditional models also assume that the relationship between the different covariates is linear in nature which is not always true. For instance, a phenomena that follows a binary process cannot be evaluated by an additive model.

GLM usually consists of three components:

1. The *random component*, **Y**, that has to be part of the exponential family distribution. Consequently, there is no assumption that the variance VAR(y_i) is homogeneous. However, it is assumed that y_i varies with the x's through μ_i alone.

2. The *systematic component*: the covariates $x_1, x_2, \ldots, x_p$ that produce a linear predictor given by

$$\begin{aligned} \eta_i &= \beta_0 + \beta_1 x_{i1} + \ldots + \beta_p x_{ip} = \mathbf{x}_i' \boldsymbol{\beta} \\ \boldsymbol{\eta} &= \mathbf{X}\boldsymbol{\beta} \end{aligned} \quad (4)$$

3. The *link function*, $g(\cdot)$ that connects the random and systematic components given by $\mu = \eta$ and $\eta_i = g(\mu_i)$.

The third component basically means that μ and η are in fact identical. The important property of the GLM is that the random component, hence the density function (or probability function in the discrete case), has to be part of the exponential family (e.g., normal, Poisson, binomial and the like). In the context of traffic safety, it is often assumed that accident counts follow the Poisson or negative binomial distributions (*13, 14*). There exist many model forms, but the most common one (for intersections) is usually the following:

$$E\{\kappa\} = \alpha F_1^{\beta_1} F_2^{\beta_2}, \quad (5a)$$

or the GLM linear version

$$\ln(E\{\kappa\}) = \ln(\alpha) + \beta_1 \ln(F_1) + \beta_2 \ln(F_2), \quad (5b)$$

where,

$E\{\kappa\}$ = the expected number of accidents per unit of time;
F_1, F_2 = the entering flows (veh/day, veh/hour, etc..) on the major and minor roads respectively;
α, β_1, β_2 = coefficients to be estimated.

It is not our goal to explain every characteristic of the GLM as it is explained elsewhere (*4*) but one can find the estimate of $\hat{\beta}$ by equations (6) or (7). The first equation is the following (*11, pg. 346*):

$$\boldsymbol{X}'\Delta\boldsymbol{e} = \boldsymbol{0}, \tag{6}$$

where,

$\boldsymbol{e} = (\boldsymbol{y} - \mu) = (\boldsymbol{y} - g^{-1}(\boldsymbol{X}\beta))$ since $\mathbf{X}\beta = g(\mu)$;
Δ = a diagonal matrix that reflects the link function.

The diagonal of the matrix , $\delta_i(i=1, 2, 3 \ldots, n)$, is given by $\delta_i = \dfrac{\partial\theta_i}{\partial(\boldsymbol{x}'_i\beta)}$.

The variable θ_i of the diagonal matrix of equation (6) is defined as the link function between μ_i and $\boldsymbol{x}'_i\beta$. Equation (6) is solved by the maximum likelihood procedure. McCullagh and Nelder (*4*) proposed a variant of the Newton-Raphson method to find the solution of the likelihood procedure.

The estimate of the coefficients can also be found by solving the following equation (*4, pg. 333*):

$$\boldsymbol{D}'\boldsymbol{V}^{-1}(\boldsymbol{Y} - \mu) = \boldsymbol{0}, \tag{7}$$

where,

$\mu = g^{-1}(\boldsymbol{X}\beta)$;
$\boldsymbol{V} = diag[\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2]$;

$$\boldsymbol{D} = \frac{\partial\mu}{\partial\beta} = \begin{bmatrix} \dfrac{\partial\mu_1}{\partial\beta_1} & \cdots & \dfrac{\partial\mu_1}{\partial\beta_p} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial\mu_n}{\partial\beta_1} & \cdots & \dfrac{\partial\mu_n}{\partial\beta_p} \end{bmatrix}.$$

The solution of equation (7) can be quite extensive, particularly if the matrix $\boldsymbol{V}$ is a function of μ. Green (*15*) proposed an iterative weighted least squares method which uses the estimate of the mean to estimate the weight matrix at each step. The matrix is then used to estimate the values of the βs. One performs theses steps until convergence occurs. The covariance matrix of the GLM is given by $cov(\hat{\beta}) = \sigma^2(\boldsymbol{X}'\boldsymbol{V}^{-1}\boldsymbol{X})^{-1}$.

The application of APMs without trend is well developed and the reader is referred to the work of Kulmala (*13*), Nicholson and Turner (*14*), Hauer *et al.* (*16*), Miaou (*17*), and Persaud and Nguyen (*18*) for a detailed explanation of these models.

LONGITUDINAL STUDIES

Longitudinal studies are basically an expansion of the traditional GLM in which a second dimension is added in the analysis. In the models described in the previous section, each subject (individual, site, etc..) was measured only once. In longitudinal studies, the subjects are measured more than once, usually observed at a different time t. At this point, it is necessary to introduce a new set of notations.

Let the subjects $i = 1, \ldots, I$ be ascertained at time $t = 1, \ldots, T_i$.

The total number of observations now becomes $N = \sum_{i=1}^{I} T_i$.

The outcome vector for the observation j can be defined as $\mathbf{Y}_i = [\mathbf{Y}_{i1}, \ldots, \mathbf{Y}_{iT_i}]'$ and the covariates defined as $\mathbf{X}_i = [\mathbf{X}_{i1}, \ldots, \mathbf{X}_{iT_i}]'$.

The mean and the variance of observation i are $E(\mathbf{Y}_i) = \mu_i$ and $VAR(\mathbf{Y}_i) = \mathbf{V}_i$ respectively, where the tk element of the $t_i \times t_i$ matrix V_i is the covariance between Y_{it} and Y_{ik} denoted by $\mathrm{Cov}(Y_{it}, Y_{ik}) = v_{itk}$; $k \neq t$ for $k = 1, \ldots, T_i$.

Generally, longitudinal models have the following form:

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 x_{it1} + \ldots \beta_p x_{itp} + \epsilon_{it} \\ Y_{it} &= x_{it}'\beta + \epsilon_{it} \end{aligned}, \qquad (8)$$

where $\beta = (\beta_0, \ldots, \beta_p)$ is *p-vector* of coefficients to be estimated. The matrix notation for equation (8) is

$$\mathbf{Y}_i = \mathbf{X}_i\beta + \epsilon_i, \qquad (9)$$

where $\mathbf{X}_i$ is a $n_i \times p$ matrix with $\mathbf{x}_{it}$ in the t^{th} row and $\epsilon_i = (\epsilon_{i1}, \ldots, \epsilon_{in_i})$.

Before explaining the characteristics of the GEE, we need to describe the different applications of the GLMs to longitudinal data. The applications can usually be grouped into three categories: *marginal*, *random effects*, and *transition* models. These three categories are briefly described below. As the reader will find out, the application of the models varies depending on the type of outcome sought. The characteristics of the models described below are taken from Chapter 6 of Diggle *et al.* (*19*).

MARGINAL MODELS

In a marginal model, one attempts to model the marginal expectation, $E(Y_{it})$, in relation to a series of explanatory variables. In other words, one tries to model the average response over a population that share a common value of $\boldsymbol{x}$. As an example, the GLM described above would be considered marginal models. The characteristics of marginal models are the following:

1. The marginal expectation of the response, $E(Y_{it}) = \mu_{it}$, depends on the explanatory variables, x_{it}, with the link function $h(\mu_{it}) = x_{it}'\beta$;

2. The marginal variance depends on the marginal mean according to $VAR(Y_{it}) = v(\mu_{it})\phi$ where v is a known variance function and ϕ is a scale parameter which may have to be estimated;

3. The (temporal) correlation between Y_{it} and Y_{ik} is a function of the marginal means and perhaps of additional variables λ, i.e. $Corr(Y_{it}, Y_{ik}) = \rho(\mu_{it}, \mu_{ik}; \lambda)$ where $\rho(\cdot)$ is a known function. The vector λ is used to describe the correlation type (e.g., independent, dependent, autoregressive, etc..).

In the evaluation of traffic safety, most APMs with trend, described in the introduction, are classified as marginal models.

RANDOM EFFECTS MODELS

Random effects models are used to assess an outcome when the regression coefficients vary from one observation to the next. This is in contrast to marginal models where the regression coefficients are assumed to be the same for every observation. The variability between the observations can be explained by the incomplete information (or unmeasured factors) that a modeler has about the sample. It is assumed that the regression coefficients vary from observation to observation according to a distribution, F. This kind of model is most useful when the goal is to make inferences about the actual observations rather than the population average (as performed for marginal models). In addition, this kind of model further assumes that repeated observations for a subject are independent. The characteristics of random effects models are:

1. Given $\boldsymbol{U}_i$, the responses $Y_{i1}, \ldots, Y_{in_i}$, are mutually independent and follow a GLM with a condition probability function $f(y_{it}|\boldsymbol{U}_i)$. The conditional moments are $E(Y_{it}|\boldsymbol{U}_i) = u_{it}$ and $VAR(Y_{it}|\boldsymbol{U}_i) = v_{it}$ respectively, where v is a known variance function. The link function is $h(\mu_{it}) = \boldsymbol{x}_{it}'\beta^* + \boldsymbol{d}_{it}'\boldsymbol{U}_i$ where $\boldsymbol{d}_{it}$ is a subset of $\boldsymbol{x}_{it}$.

2. The random effects, $\boldsymbol{U}_i$, $i = 1, \ldots, I$, are mutually independent with a common underlying multivariate distribution, F.

TRANSITION MODELS

Transition models (often known as autoregressive models) are used specifically when a temporal correlation among $Y_{i1},\ldots,Y_{in_i}$ exists and that the past values, $Y_{i1},\ldots,Y_{it-1}$, directly influence the present observation. In this case, the past observations are treated as additional explanatory variables. The transition models can be defined as follows:

1. Let $H_{it} = \{y_{it},\ldots,y_{it-1}\}$ represent the past values for the observation i. Furthermore, let $E(Y_{it}|H_{it}) = u_{it}^{c}$ and $VAR(Y_{it}|H_{it}) = v_{it}^{c}$ be the conditional mean and variance of Y_{it} respectively.

2. Given H_{it}, the link function and the variance are $h(\mu_{it}^{c}) = x_{it}'\beta^{**} + \sum_{r=1}^{s} f_r(H_{it};\lambda)$ and $v_{it} = v(\mu_{it}^{c})\phi$ respectively.

As shown in the link function of point 2 above, the past outcomes are transformed by the known function f_r and are redefined as additional explanatory variables.

THE GENERALIZED ESTIMATING EQUATIONS PROCEDURE

The coefficients for the three models above can be estimated using the traditional maximum likelihood methods. One should be careful, however, that every model should be correctly specified, especially for the latter two. In the case of marginal models, the likelihood function can, in many instances, be very complicated to define and solve. For instance, additional assumptions are routinely needed to specify the likelihood function of non-Gaussian data. And, even if these assumptions are made, the likelihood often involves numerous nuisance parameters that must be estimated in addition to the explanatory variables. To overcome this difficulty, an alternative method known as the GEE was proposed by Liang and Zeger (*1*), and Zeger and Liang (2). The GEE approach is classified as a multinomial analogue of a quasi-likelihood function. The estimate of the coefficients can be found with the following equation:

$$\sum_{i=1}^{I} \boldsymbol{D}_i'\hat{\boldsymbol{V}}_i^{-1}(\boldsymbol{Y}_i - \boldsymbol{\mu}_i) = \boldsymbol{0}, \tag{10}$$

where $\mathbf{D} = \partial\mu / \partial\beta$. The only difference with equation (7) is that the matrix $\boldsymbol{V}$ now contains nonzero elements outside the diagonal. As described in the second section, repeated measurements are usually positively correlated. The temporal correlation can be described by a $n_i \times n_i$ matrix $R(\lambda)$, where λ represent the type of correlation with $\lambda = [\lambda_1,\ldots,\lambda_{n-1}]'$ and $\lambda_i = corr(Y_{it},Y_{ik})$ *for* $t,k = 1,\ldots,n-1$ $t \neq k$, and n_i is the number of subjects. Therefore, the new covariance matrix now becomes:

$$\boldsymbol{V}_i = \boldsymbol{A}_i^{1/2}\boldsymbol{R}_i(\lambda)\boldsymbol{A}_i^{1/2}, \tag{11}$$

where A_i is an n_i x n_i matrix with $diag[V(\mu_{i1}), \dots V(\mu_{iT_i})]$. The covariance matrix is given by

$$cov(\hat{\beta}) = \sigma^2 \left[\sum_{i=1}^{I} \boldsymbol{D}_i' \boldsymbol{V}_i^{-1} \boldsymbol{D}_i \right]^{-1} . \tag{12}$$

One can find the solution by simultaneously solving equations (11) and (12) with the iterative reweighted least squares method described earlier (*15*). This method is necessary since the estimates of both β *and* λ need to be found.

In order to solve the GEE correctly, every element of the correlation matrix $\boldsymbol{R}_i$ have to be known. However, in many instances, it is not possible to know the proper correlation type for the repeated measurements. To overcome this drawback, Liang and Zeger (*1*) proposed the use of a "working" matrix $\hat{\boldsymbol{V}}_i$ of the correlation matrix $\boldsymbol{V}_i$ which is based on the correlation matrix $\hat{\boldsymbol{R}}_i$. The estimate of the coefficients is found with the following equation:

$$\sum_{i=1}^{I} \boldsymbol{D}_i' \hat{\boldsymbol{V}}_i^{-1} (\boldsymbol{Y}_i - \mu_i) = \boldsymbol{0} . \tag{13}$$

The covariance matrix of equation (13) is given by

$$cov(\hat{\beta}) = \sigma^2 \left[\sum_{i=1}^{I} \boldsymbol{D}_i' \hat{\boldsymbol{V}}_i^{-1} \boldsymbol{D}_i \right]^{-1} \left[\sum_{i=1}^{I} \boldsymbol{D}_i' \hat{\boldsymbol{V}}_i^{-1} \boldsymbol{V}_i \hat{\boldsymbol{V}}_i^{-1} \boldsymbol{D}_i \right] \left[\sum_{i=1}^{I} \boldsymbol{D}_i' \hat{\boldsymbol{V}}_i^{-1} \boldsymbol{D}_i \right]^{-1} . \tag{14}$$

The proposed methodology above, i.e. in equations (13) and (14), possesses one very useful property. The coefficient $\hat{\beta}$ nearly always provide consistent estimates of β even if the matrix $\boldsymbol{V}_i$ has been improperly estimated. Thus, the confidence interval for β will always be correct even when the covariance matrix is incorrectly specified. Therefore, it is not necessary to examine the type of temporal correlation beforehand (independent, dependent, etc..). Techniques on how to analyze and interpret autocorrelation can be found in books on time series analysis such as the ones by Box and Jenkins (*20*) and Diggle (*21*). One important drawback, however, comes with this property. In order to assume that $\hat{\beta}$ is the proper estimate of β, it is required that the observation for each subject be known and available. If missing values exist, the estimate of the coefficients may be biased. The extent of the bias is influenced by the type of missing values, e.g. random or informative. Note that in the case of $\hat{\boldsymbol{V}}_i = \boldsymbol{V}_i$, equation (14) becomes the covariance matrix of equation (12).

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APPENDIX D

THEORY OF GRAPHS AND DANTZIG ALGORITHM

NETWORK THEORY

As discussed in Chapter 2, a transportation network is defined by a series of nodes and links connecting these nodes. With this in mind, it is important to understand the underlying mathematical representation of transportation networks. The theory behind the coding of networks is particularly significant for the people who intend to use various shortest path algorithms. Thus, the application of the theory of graphs to transportation networks is explained in this section. An example that summarizes the definitions described below is presented at the end of this section.

Every network can be represented mathematically with the theory of graphs. This theory originated from the work of Leonhard Euler in 1736 who wanted to study the so-called Konisberg (in East Russia) bridge problem (Minieka, 1978). More specifically, Euler wanted to examine if it was possible to leave his home and cross each of the seven bridges located in this municipality exactly once and then return home; this is an application of the postman problem extensively studied in operations research. Since then, this theory has been applied to various fields (e.g. transportation, communication, etc.). In addition, important improvements occurred with the linear programming techniques.

A (directed) *graph* consists of two parts, a series of *nodes* and a series of *links*. A graph G is denoted by the symbol $\{N; L\}$, where N represents a series of nodes labeled $i, j, k, \ldots$, or $n_1, n_2, n_3, \ldots$, and L pertains to a series of links or directed links labeled $(i, j), (i, k), \ldots$, or $(n_1, n_2), (n_2, n_3), \ldots$, the links connecting these nodes. A directed link means that a direction is associated with the link; for instance, the link (n_1, n_2) implies that it starts at node n_1 and ends at node n_2. The nodes are usually labeled in an increasing order and it is not necessary for all the nodes to be connected together. But, if a link (n_1, n_2) exists, it is symbolized as $(n_1, n_2) \in L$. Therefore, a graph G might be labeled this way:

$$G : \{n_1, n_2, n_3; (n_1, n_2), (n_2, n_3)\} \tag{1}$$

Equation (1) shows that the graph G has three nodes and two links. It should be pointed out that more than one link can be connected the same nodes. If this is the case, one can label the links as follows: $(n_1, n_2)_1$, $(n_1, n_2)_2$, etc. Finally, it is also possible to label the links in numerical order, e.g., $l_1, l_2, l_3, \ldots$, rather than by using the (n_1, n_2) format.

A directed graph has many properties. The *routes* (or *chains)* and *cycles* are some properties of directed graphs important to transportation networks. First, a *route* connecting a node n_1 to a node n_r is a sequence of ordered links $(n_1, n_2), (n_2, n_3), \ldots (n_{r-1}, n_r)$ with $n_j \neq n_k$ for any j and k, and $(n_i, n_{i+1}) \in L$. In other words, the meaning of this definition simply shows that if one can go from n_1 to n_2 and a link (n_2, n_3) exists, then one can go from n_1 to n_3, even if there is no link connecting n_1 and

n_3. One should note that a route from n_1 to n_r does not necessarily implies that a route n_r to n_1 prevails. Second, a *cycle* is a sequence of ordered links $(n_1, n_2), (n_2, n_3), \ldots, (n_{r-1}, n_1)$ with $n_j \neq n_k$ for any j and k, and $(n_i, n_{i+1}) \in L$, $(n_{r-1}, n_1) \in L$. A cycle can also be defined as a closed route where one would travel from n_1 to n_1 without passing through the same node more than once. Finally, a node n_r is *accessible* from a node n_1 if and only if there exist a route connecting n_1 to n_r.

Other properties of a directed graph include the *partial graph*, the *subgraph*, the *complete* and *bipartite graphs*, a *cut-set*, a *spanning tree*, and a *spanning forest*. The description of these properties can be found in Potts and Oliver (1972), Minieka (1978), Newell (1980), and Gould (1988).

At this point, one can wonder why these various characteristics and definitions are described in this section. With the help of the definitions above, it is possible to construct or transform a graph into a matrix format. This transformation is performed with the help of an example. Let Figure 1 represents a simple network with four nodes and seven directed links.

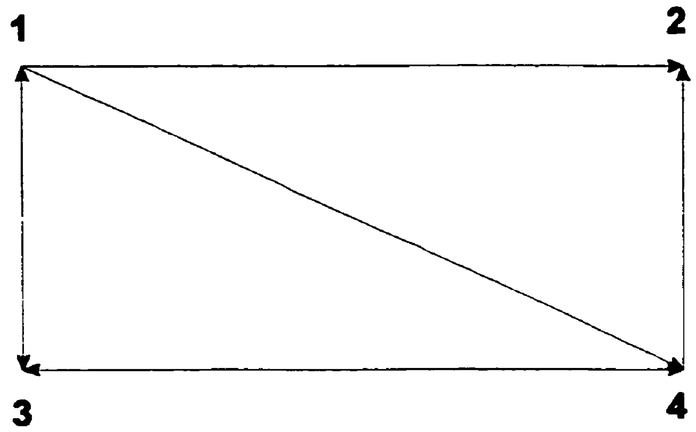

FIGURE 1 Simple network

In Figure 1, the graph G is defined as follows:

$$G : \{1,2,3,4;(1,2),(1,3),(1,4),(3,1),(3,4),(4,2),(4,3)\} \tag{2}$$

To illustrate the various descriptions above, a *route j* between nodes 1 and 2 and a *cycle k* from node 1 could respectively be:

$$R_j : \{(1,4),(4,2)\} \text{ and } C_k : \{(1,4),(4,3),(3,1)\} \tag{3}$$

The graph G can also be represented by the following two matrices:

TABLE 1a Node-link incidence matrix

N/L	(1,2)	(1,3)	(1,4)	(3,1)	(3,4)	(4,2)	(4,3)
1	-1	-1	-1	1	0	0	0
2	1	0	0	0	0	1	0
3	0	1	0	-1	-1	0	1
4	0	0	1	0	1	-1	-1

where,

$$a_{ij} = \begin{cases} 1 & \textit{if arrow points towards the node,} \\ -1 & \textit{if arrow points away the node,} \\ 0 & \textit{otherwise.} \end{cases}$$

TABLE 1b Alternative cost matrix

N/N	1	2	3	4
1	∞	d_{12}	d_{13}	d_{14}
2	∞	∞	∞	∞
3	d_{31}	∞	∞	d_{34}
4	∞	d_{42}	d_{43}	∞

where,

$$a_{ij} = \begin{cases} d_{ij} & \textit{cost of a link if it exists,} \\ \infty & \textit{if a link does not exists.} \end{cases}$$

The matrix presented in Table 1a is called a *node-link incidence* matrix. It is primarily used with linear programming techniques. As depicted in the linear formulation of equation (4), matrix A is the *node-link incidence* and matrix x is a series of cost functions:

$$\begin{aligned} \text{Minimize} \quad & \mathbf{cx} \\ \text{Subject to} \quad & \mathbf{Ax} \geq \mathbf{b} \\ & \mathbf{x} \geq \mathbf{0} \end{aligned} \tag{4}$$

The matrix format presented in Table 1b is utilized to find the least cost paths on a network. It is a transformed version of the matrix format of Table 1a where the cost value is directly assigned inside the matrix. The value d_{ij} can be either positive or negative. The reader is referred to Bazaraa *et al.* (1990) and Winston (1994) for an extensive discussion on linear programming techniques and other types of system optimization related to transportation networks. With this brief introduction on the theory of graphs, it is now possible to explain how to find the shortest path on a network, which is described in the next section.

SHORTEST PATH ALGORITHM

There exist many algorithms used to find the shortest path on a network. Some algorithms estimate the shortest path between any two given nodes only (e.g., Dijkstra) while others estimate the path between every pair of nodes simultaneously (e.g., Floyd, Dantzig). For the purpose of this work, it is more useful to find all the shortest routes simultaneously since, once the algorithm is completed, the shortest route between every pair of nodes is automatically be found.

There are basically two well known algorithms that estimate the shortest path between any pair of nodes: the Floyd and Dantzig algorithms. The Floyd algorithm, developed in 1962, is fairly similar to the Dantzig algorithm, created in 1967. The only difference is in the order the operations are performed. Both, obviously, arrive at the same results. Since their conception, many researchers (e.g., Taboulier, Hoffman) subsequently improved these algorithms. The modifications improved mainly the convergence speed of the optimal solution. In the 1970s, this aspect was important since computers were relatively slow. For the sake of simplicity, it is more appropriate to describe the Dantzig algorithm.

The Dantzig algorithm is a three-step procedure that employs a series of recursive equations. It is briefly described below, but a complete description can be found in Minieka (1978). Before presenting the steps of the algorithm, it is necessary to introduce the proper notation. First, it is required to number the links in a sequential manner such as $L = 1, 2, \ldots, N$. Then, let d_{ij}^{m} be the shortest distance (or least cost) from node *i* to node *j*, where *m* is the intermediate node(s) connecting *i* to *j*. Thus, d_{ij}^{0} means there are no intermediate nodes between node *i* and node *j*. If no path exists, then set $d_{ij}^{m} = \infty$. For every node *i*, set $d_{ii}^{0} = 0$. Finally, d_{ij}^{N} represents the shortest distance between node *i* and *j* (after the completion of the algorithm).

To find the shortest path (d_{ij}^{N}) between each pair of nodes, it is important to define the cost matrix described in Table 1b. This matrix D^m is a N x N matrix whose ijth element is equal to d_{ij}^{m}. The main goal is to find the final matrix D^N. The Dantzig algorithm is therefore used to find this final matrix.

> **Step 1**: determine the initial matrix D^0 whose ij element is equal to d_{ij}^{0}, the shortest distance between node *i* and node *j* (without intermediate nodes). Again, if no link exists between any nodes, set $d_{ij}^{m} = \infty$. Let D^m be an m x m matrix with ijth element denoted by d_{ij}^{m} .

Step 2: find each element of the matrix D^m for m = 1, 2, ... , **N**. The elements of D^m are estimated from the elements of the matrix D^{m-1} with the following four recursive equations:

$$d_{mj}^{m} = \min_{i=1,2,\ldots,m-1}\{d_{mi}^{0} + d_{mj}^{m-1}\} \quad (j = 1,2,\ldots,m-1) \tag{5}$$

$$d_{im}^{m} = \min_{j-1,2,\ldots,m-1}\{d_{ij}^{m-1} + d_{jm}^{0}\} \quad (i = 1,2,\ldots,m-1) \tag{6}$$

$$d_{ij}^{m} = \min\{d_{im}^{m} + d_{mj}^{m}, d_{ij}^{m-1}\} \quad (i,j = 1,2,\ldots,m-1) \tag{7}$$

$$d_{ii}^{m} = 0 \tag{8}$$

Repeat steps 2 and 3 until matrix D^N is complete.

Step 3: record the actual shortest path, p_{ij}, between each pair of node ij. For this, the initial matrix D^0 and the final matrix D^N have to be used. The path is found such that:

$$d_{ij}^{N} = d_{ik}^{N} + d_{kj}^{0} \tag{9}$$

The Dantzig algorithm requires $2N^3$ iterations to converge. The reader is referred to Minieka (1978) and Yen (1977) for a more detailed explanation on possible improvements to the Dantzig algorithm.

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APPENDIX E

CUMULATIVE RESIDUALS FOR THE MODELS OF CHAPTER FOUR

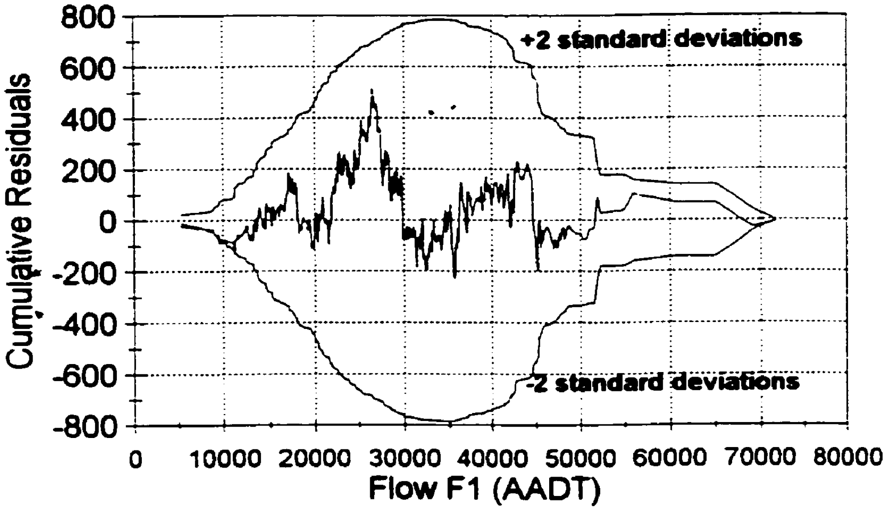

FIGURE E1 Cumulative residuals for signalized 4-legged intersections (F_1 and all accidents)

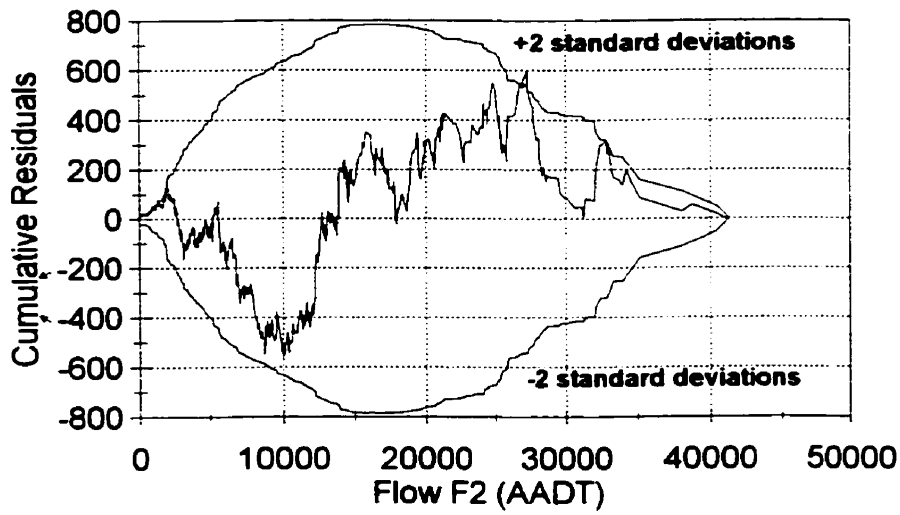

FIGURE E2 Cumulative residuals for signalized 4-legged intersections (F_2 and all accidents)

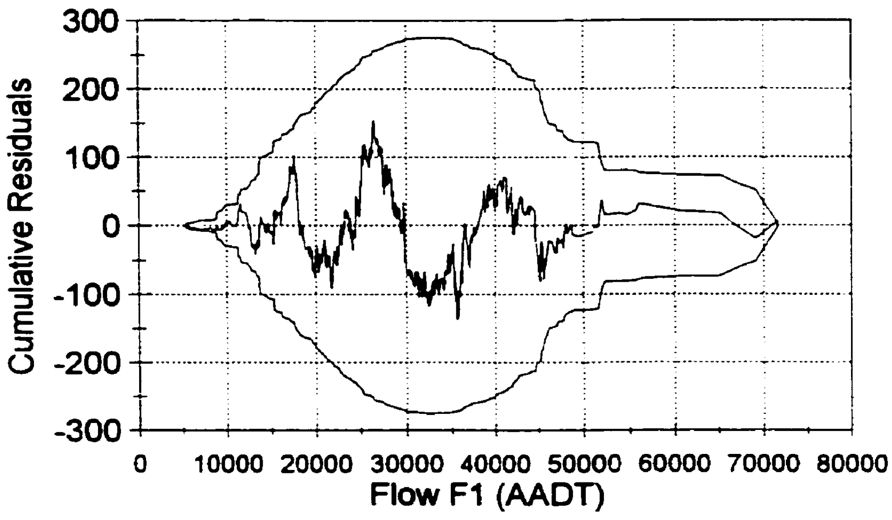

FIGURE E3 Cumulative Residuals for signalized 4-legged intersections (F_1 and injury accidents)

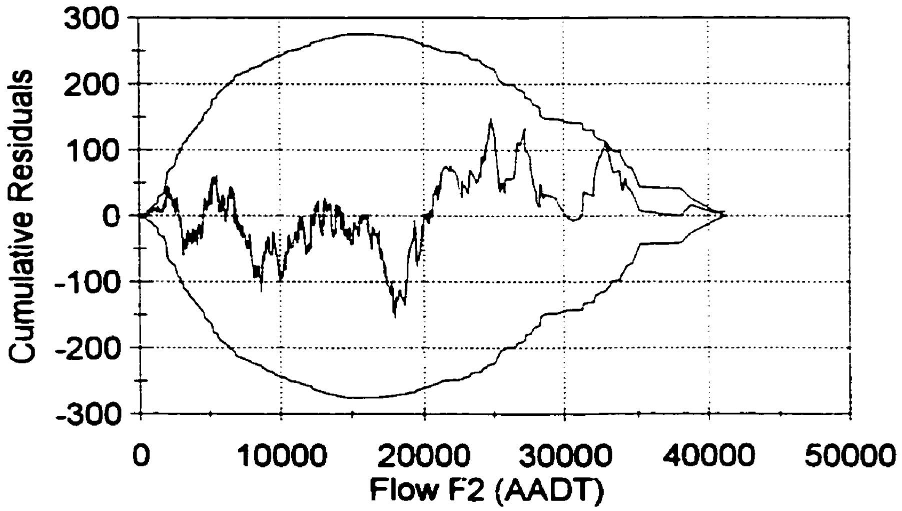

FIGURE E4 Cumulative Residuals for signalized 4-legged intersections (F_2 and injury accidents)

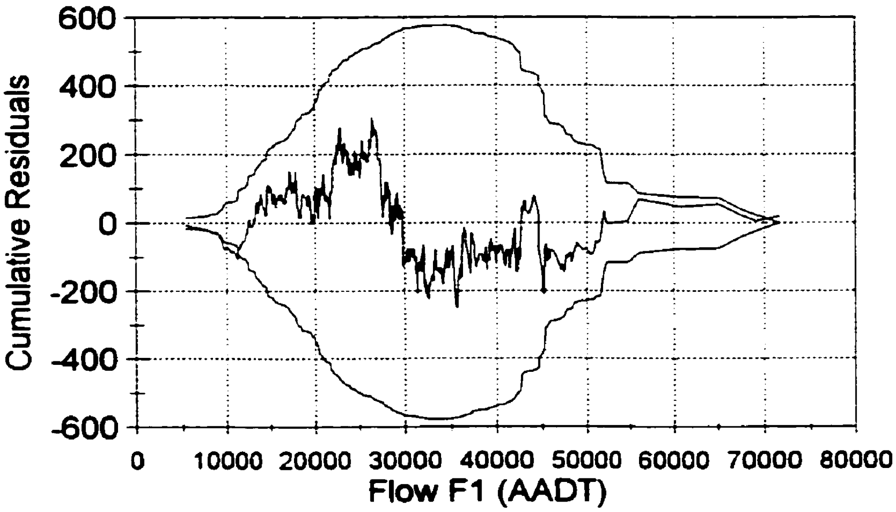

FIGURE E5 Cumulative Residuals for signalized 4-legged intersections (F_1 and PDO accidents)

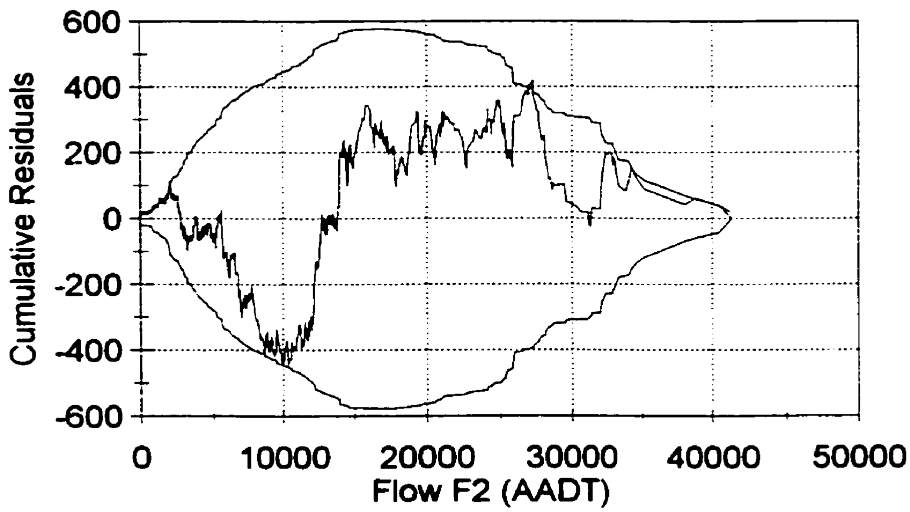

FIGURE E6 Cumulative Residuals for signalized 4-legged intersections (F_2 and PDO accidents)

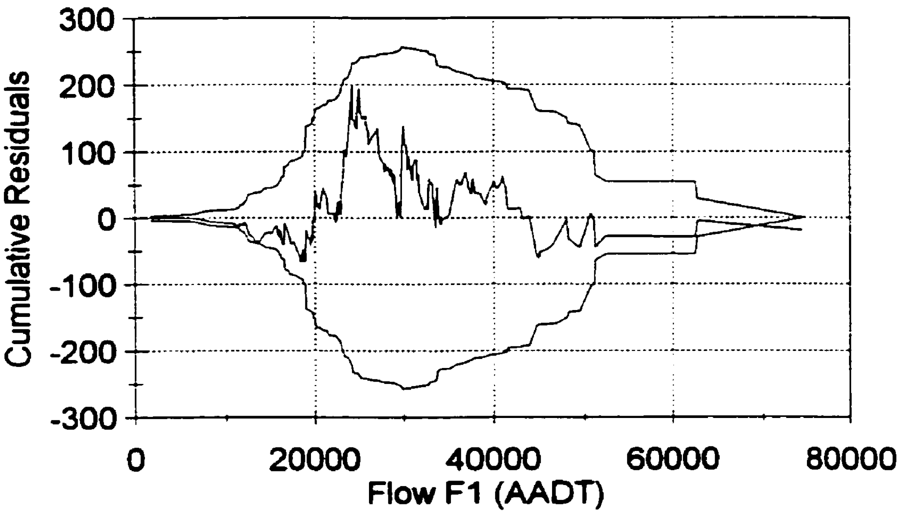

FIGURE E7 Cumulative Residuals for signalized 3-legged intersections (F_1 and all accidents)

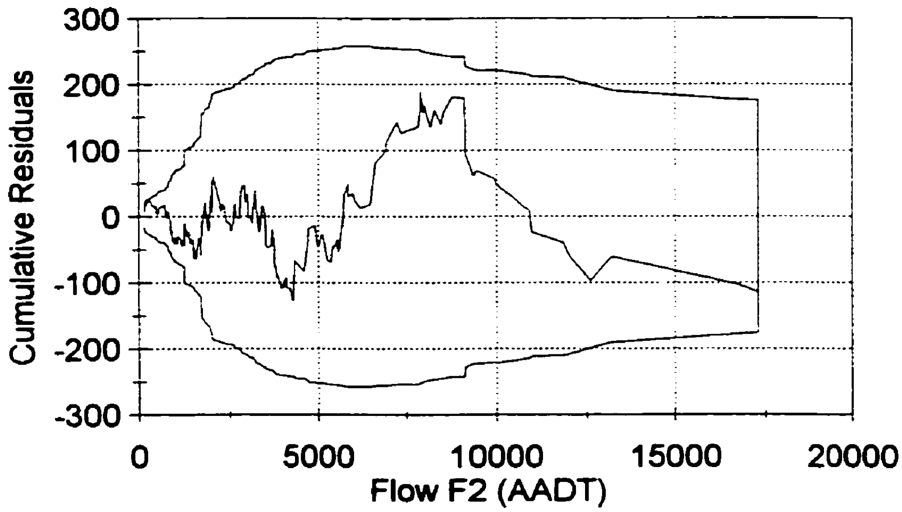

FIGURE E8 Cumulative Residuals for signalized 3-legged intersections (F_2 and all accidents)

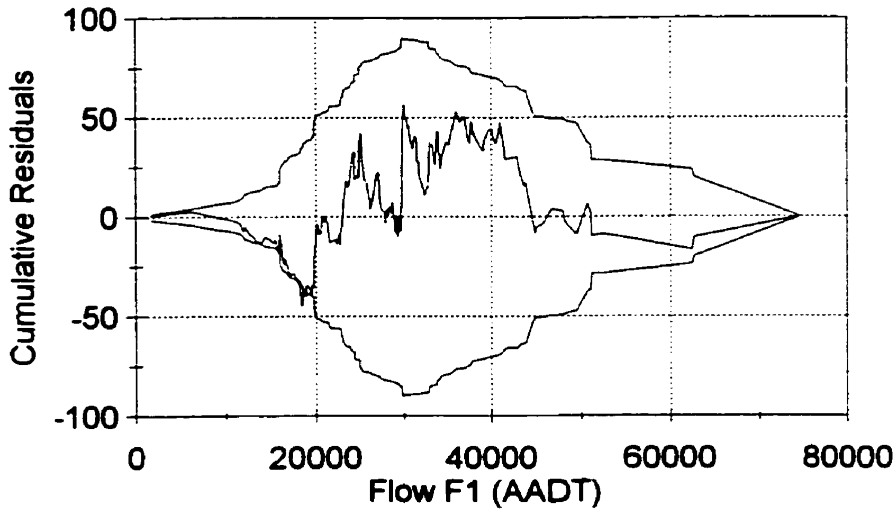

FIGURE E9 Cumulative Residuals for signalized 3-legged intersections (F_1 and injury accidents)

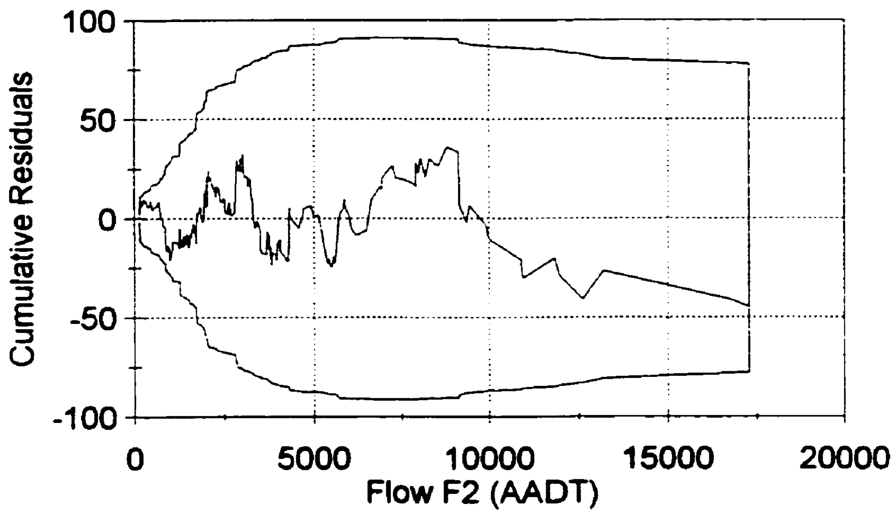

FIGURE E10 Cumulative Residuals for signalized 3-legged intersections (F_2 and injury accidents)

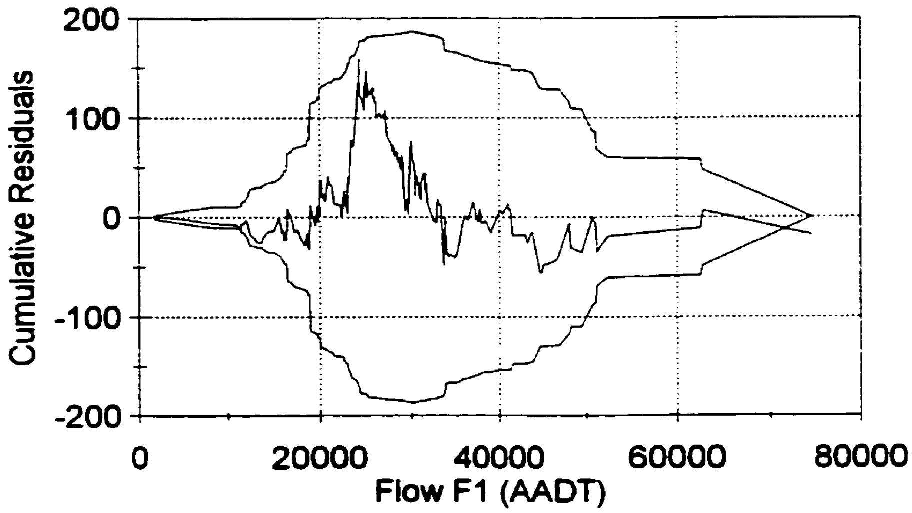

FIGURE E11 Cumulative Residuals for signalized 3-legged intersections (F_1 and PDO accidents)

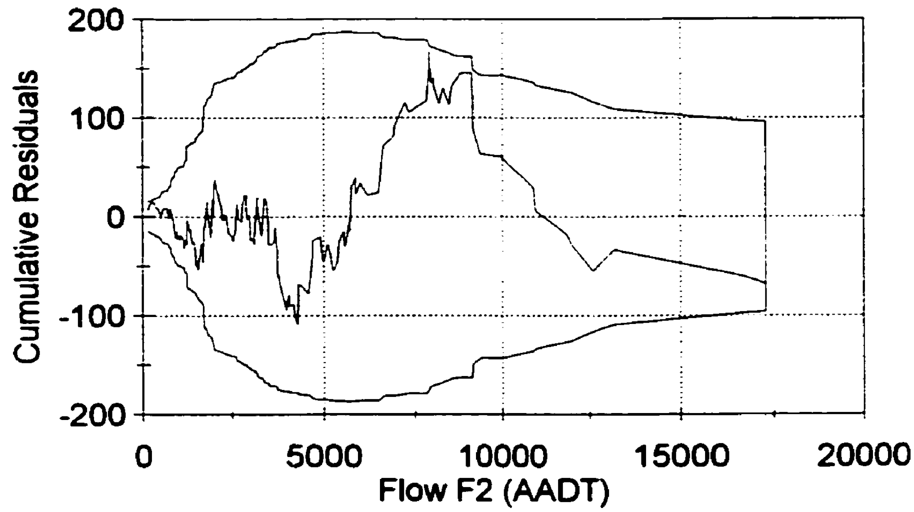

FIGURE E12 Cumulative Residuals for signalized 3-legged intersections (F_2 and PDO accidents)

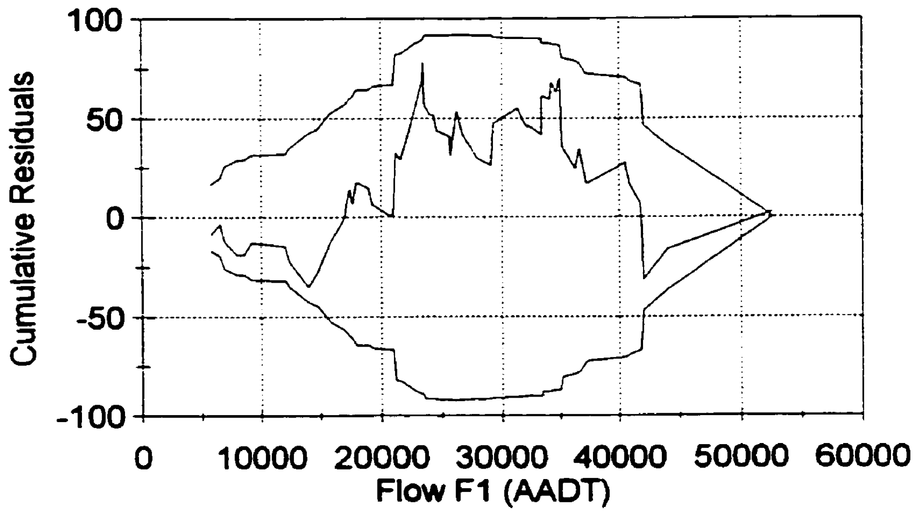

FIGURE E13 Cumulative Residuals for unsignalized 4-legged intersections (F_1 and all accidents)

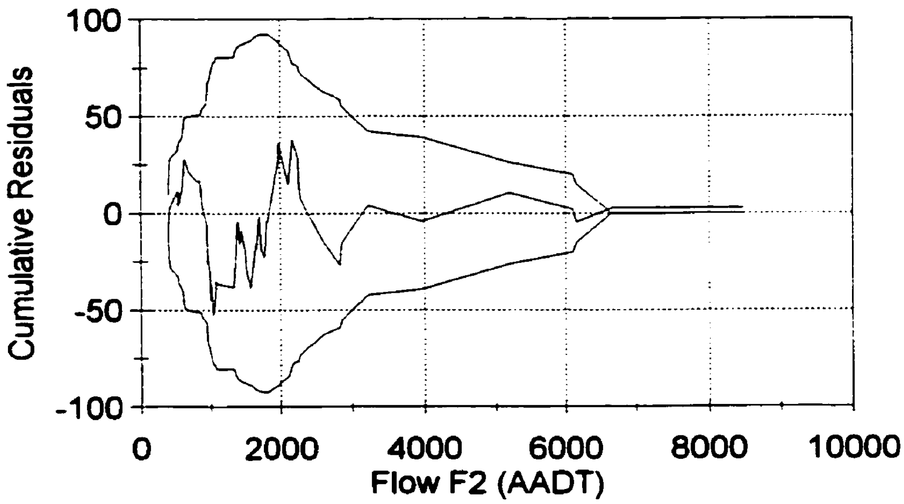

FIGURE E14 Cumulative Residuals for unsignalized 4-legged intersections (F_2 and all accidents)

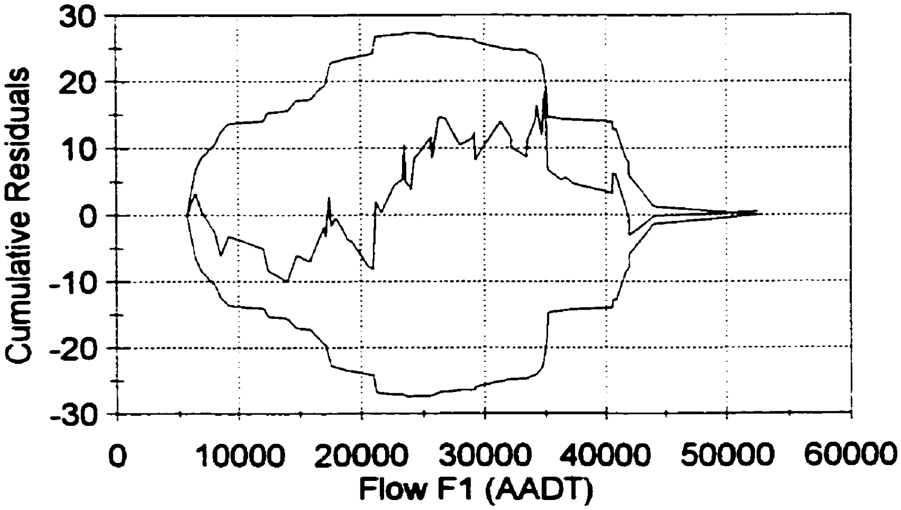

FIGURE E15 Cumulative Residuals for unsignalized 4-legged intersections (F_1 and injury accidents)

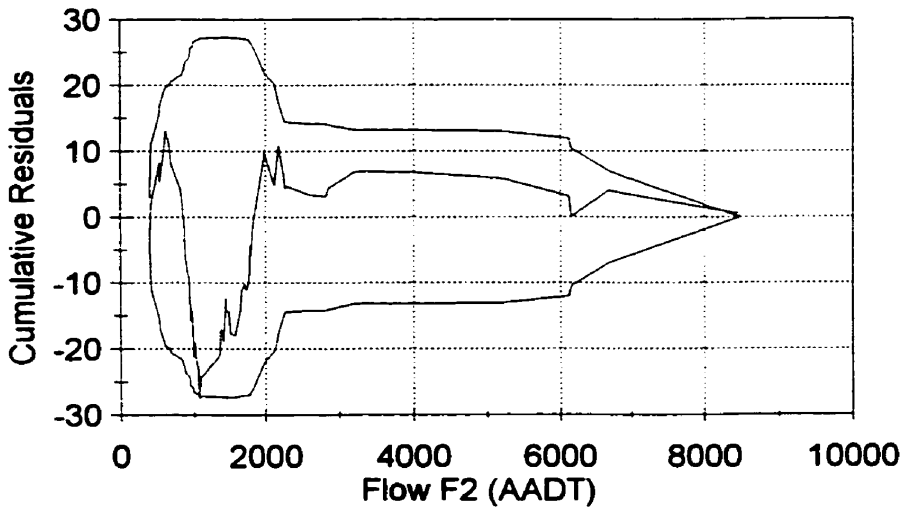

FIGURE E16 Cumulative Residuals for unsignalized 4-legged intersections (F_2 and injury accidents)

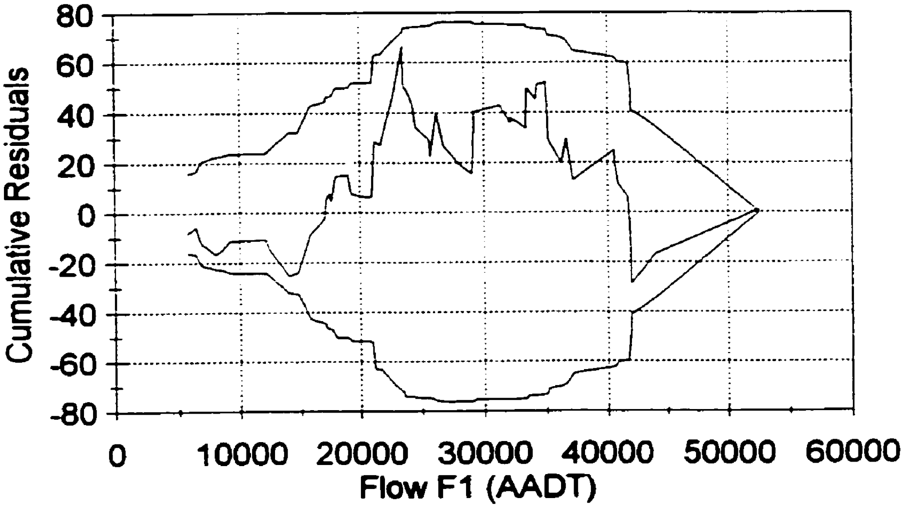

FIGURE E17 Cumulative Residuals for unsignalized 4-legged intersections (F_1 and PDO accidents)

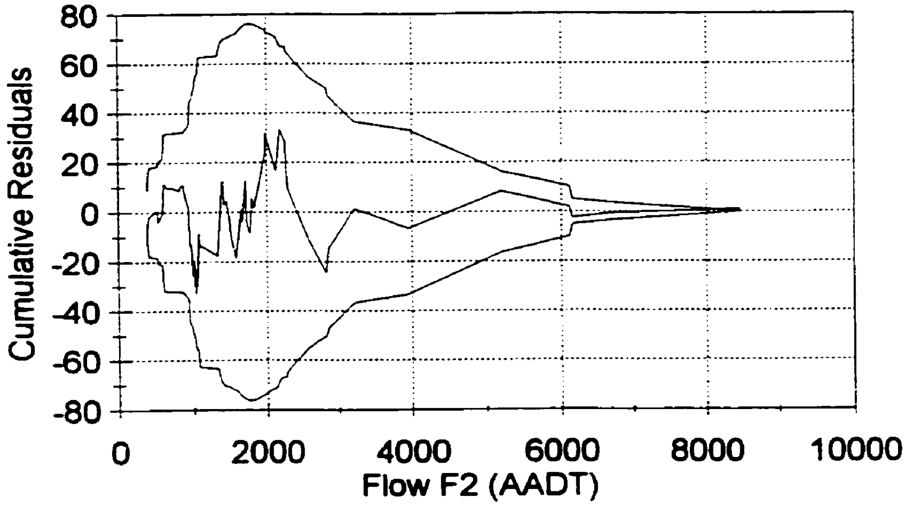

FIGURE E18 Cumulative Residuals for unsignalized 4-legged intersections (F_2 and PDO accidents)

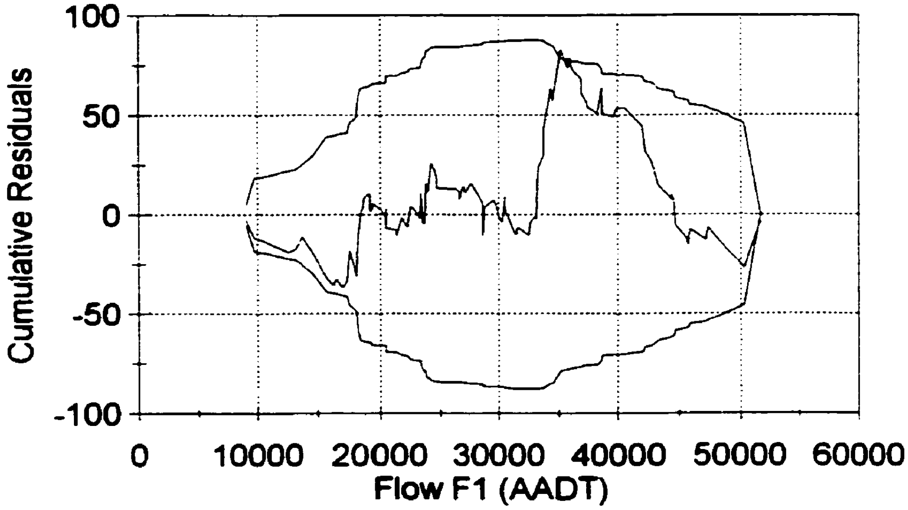

FIGURE E19 Cumulative Residuals for unsignalized 3-legged intersections (F_1 and all accidents)

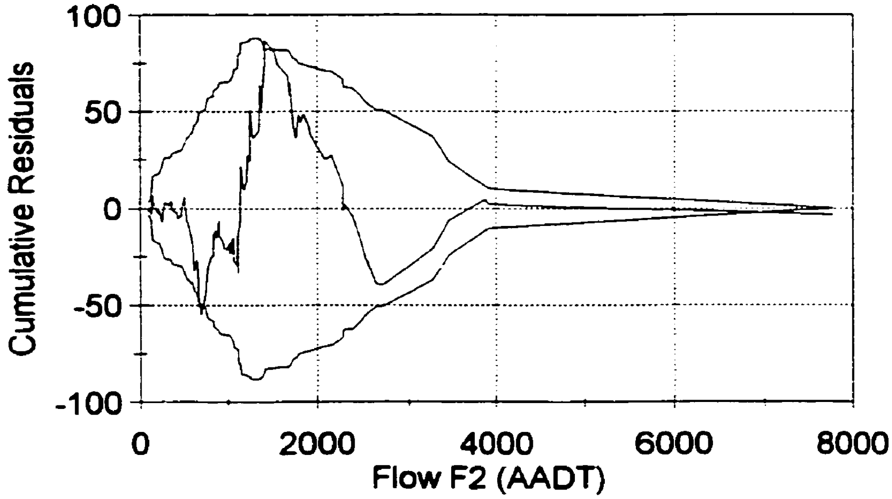

FIGURE E20 Cumulative Residuals for unsignalized 3-legged intersections (F_2 and all accidents)

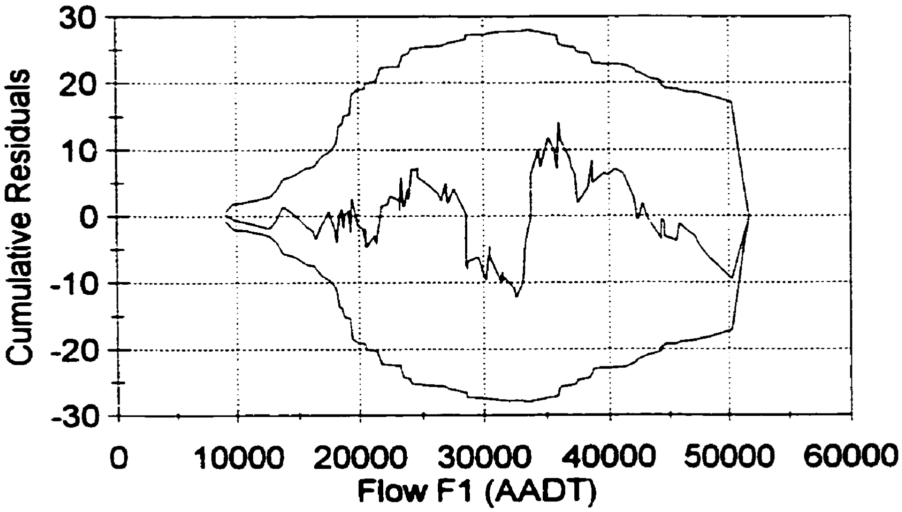

FIGURE E21 Cumulative Residuals for unsignalized 3-legged intersections (F_1 and injury accidents)

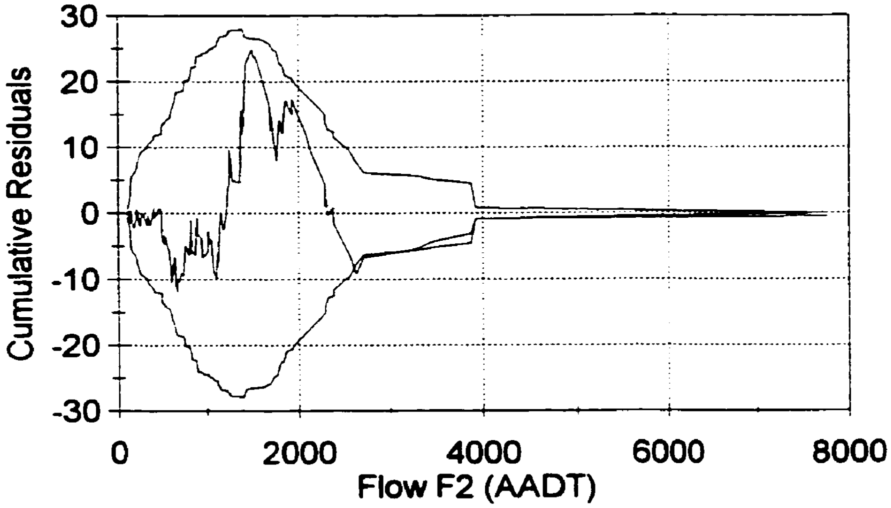

FIGURE E22 Cumulative Residuals for unsignalized 3-legged intersections (F_2 and injury accidents)

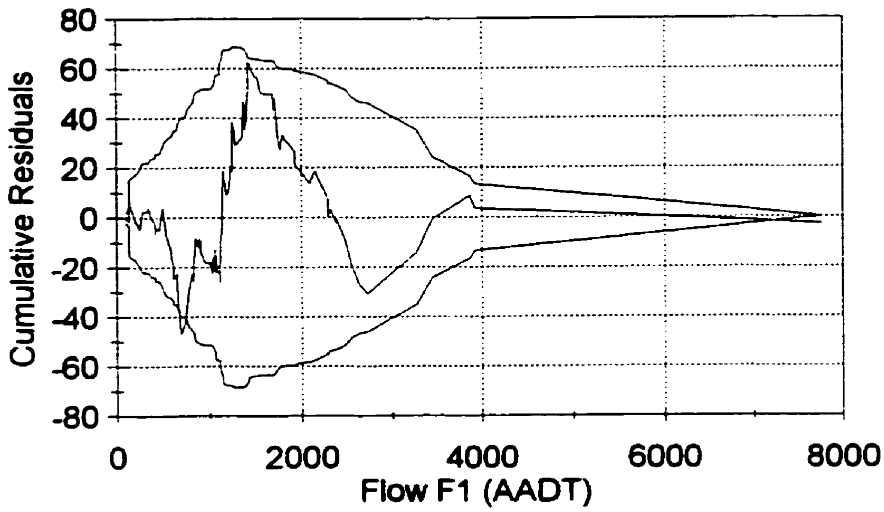

FIGURE E23 Cumulative Residuals for unsignalized 3-legged intersections (F_1 and PDO accidents)

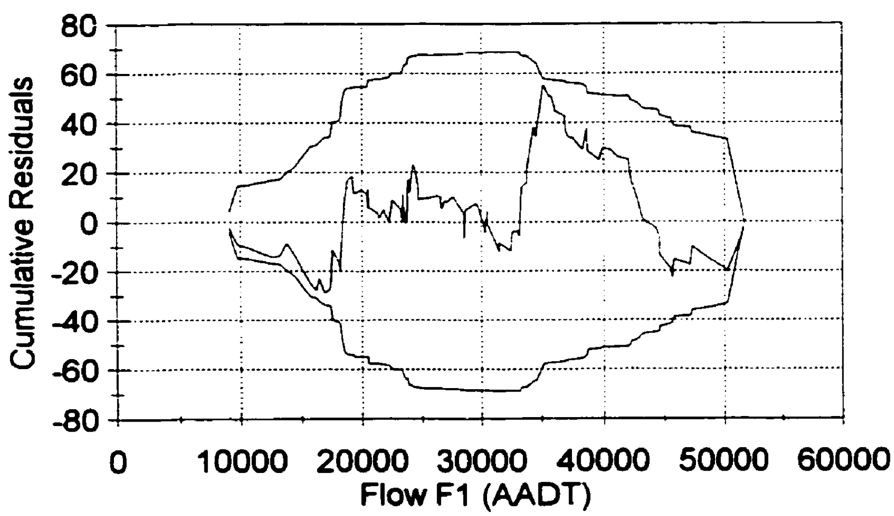

FIGURE E24 Cumulative Residuals for unsignalized 3-legged intersections (F_2 and PDO accidents)

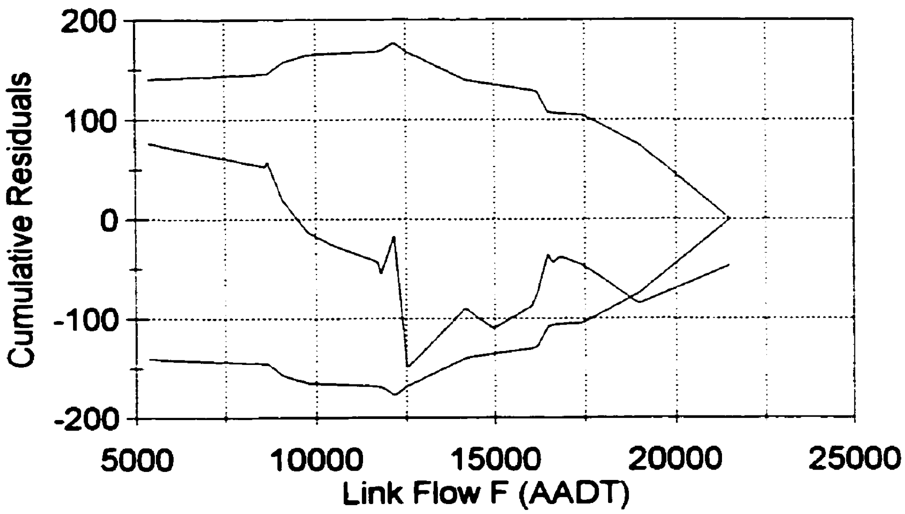

FIGURE E25 Cumulative Residuals for 2-lane roads (all accidents)

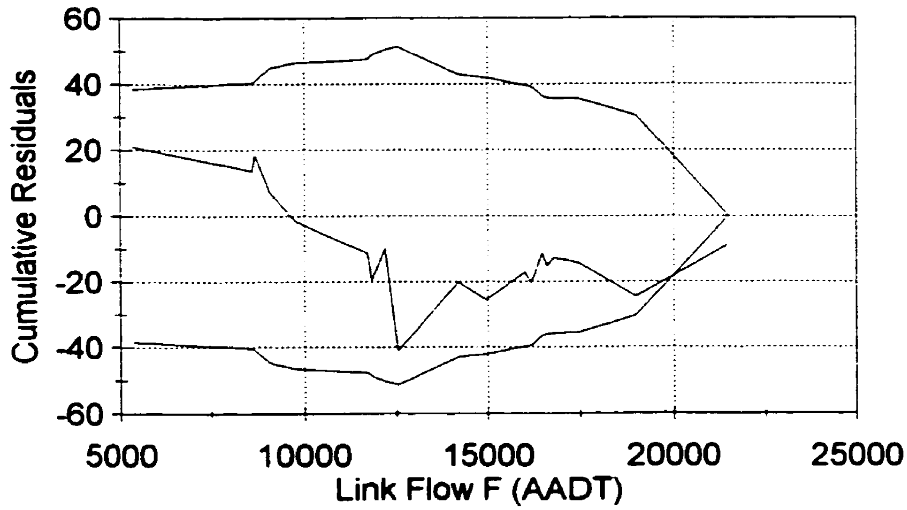

FIGURE E26 Cumulative Residuals for 2-lane roads (injury accidents)

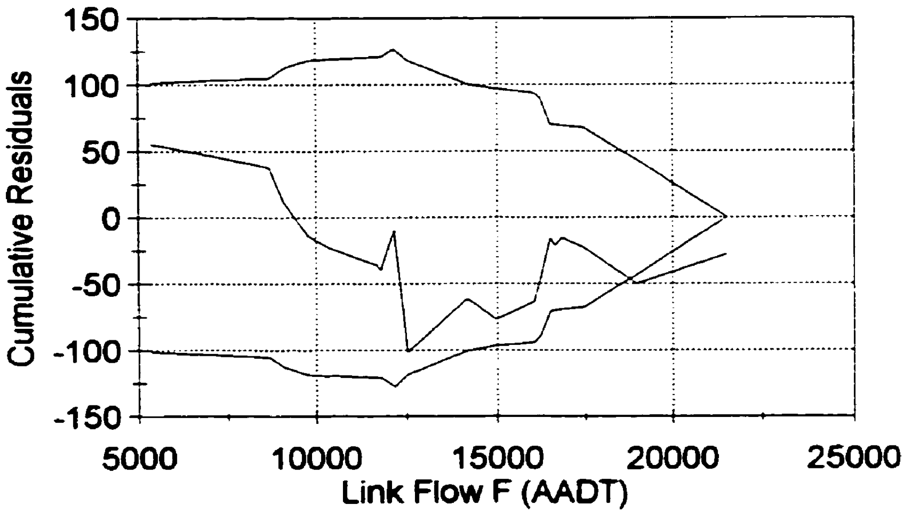

FIGURE E27 Cumulative Residuals for 2-lane roads (PDO accidents)

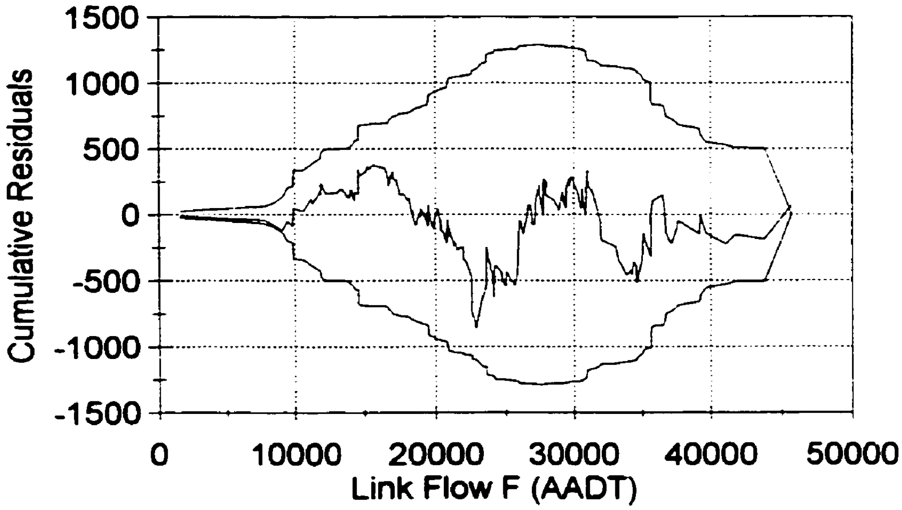

FIGURE E28 Cumulative Residuals for 4-lane roads (all accidents)

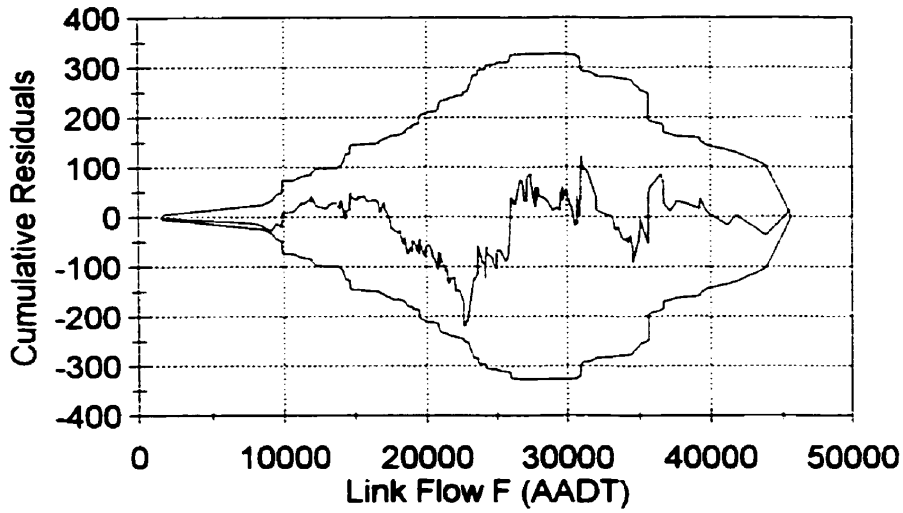

FIGURE E29 Cumulative Residuals for 4-lane roads (injury accidents)

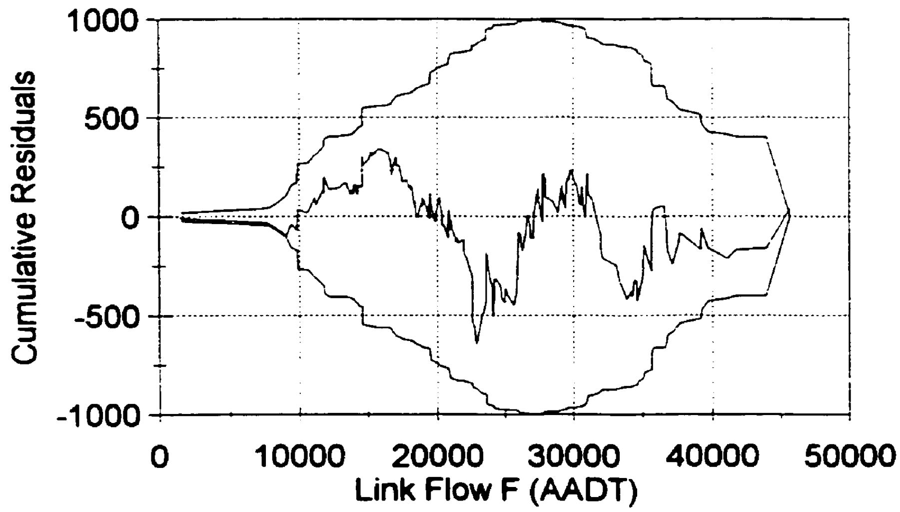

FIGURE E30 Cumulative Residuals for 4-lane roads (PDO accidents)

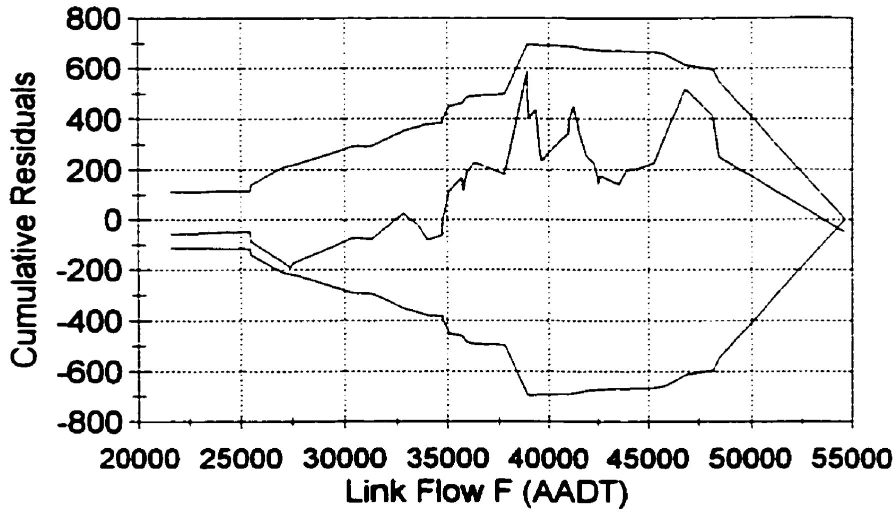

FIGURE E31 Cumulative Residuals for 6-lane roads (all accidents)

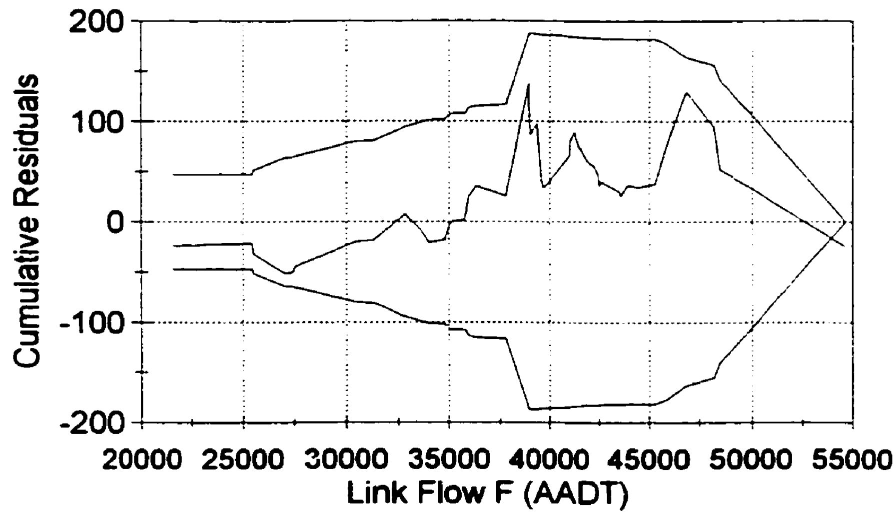

FIGURE E32 Cumulative Residuals for 6-lane roads (injury accidents)

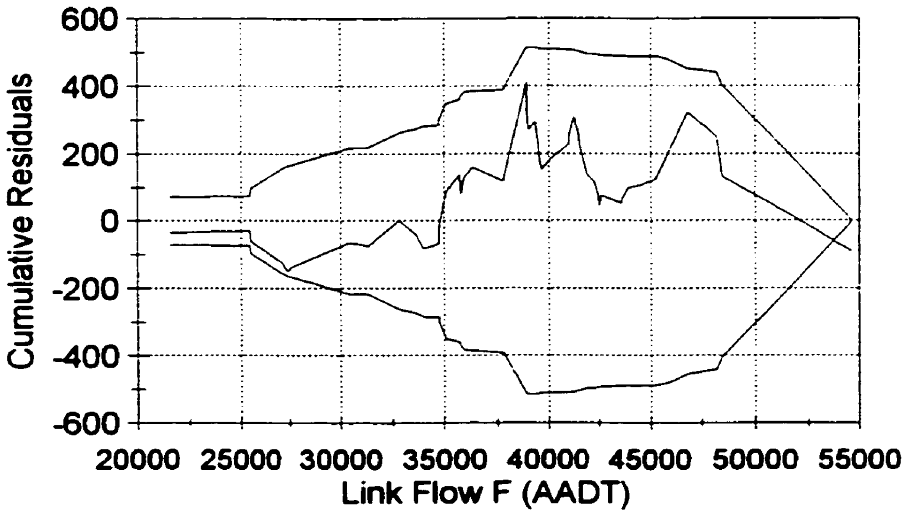

FIGURE E33 Cumulative Residuals for 6-lane roads (PDO accidents)

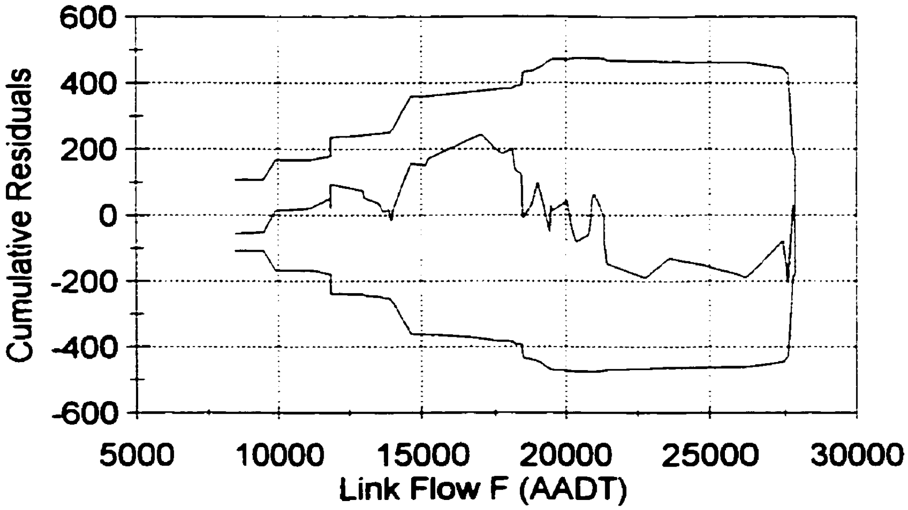

FIGURE E34 Cumulative Residuals for 4-lane roads (CBD and all accidents)

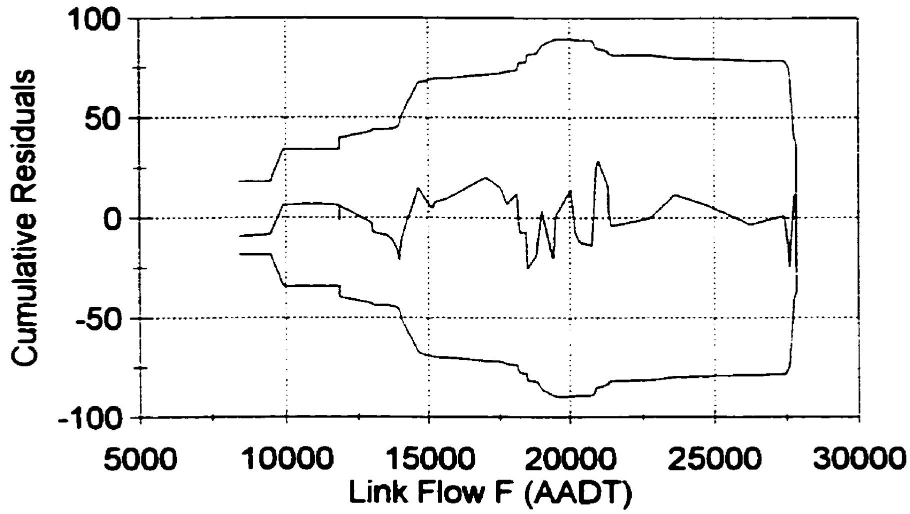

FIGURE E35 Cumulative Residuals for 4-lane roads (CBD and injury accidents)

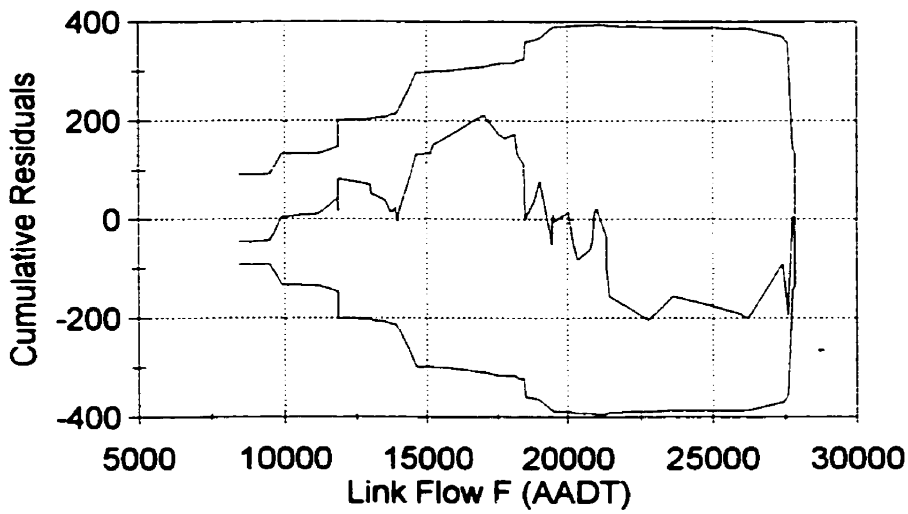

FIGURE E36 Cumulative Residuals for 4-lane roads (CBD and PDO accidents)

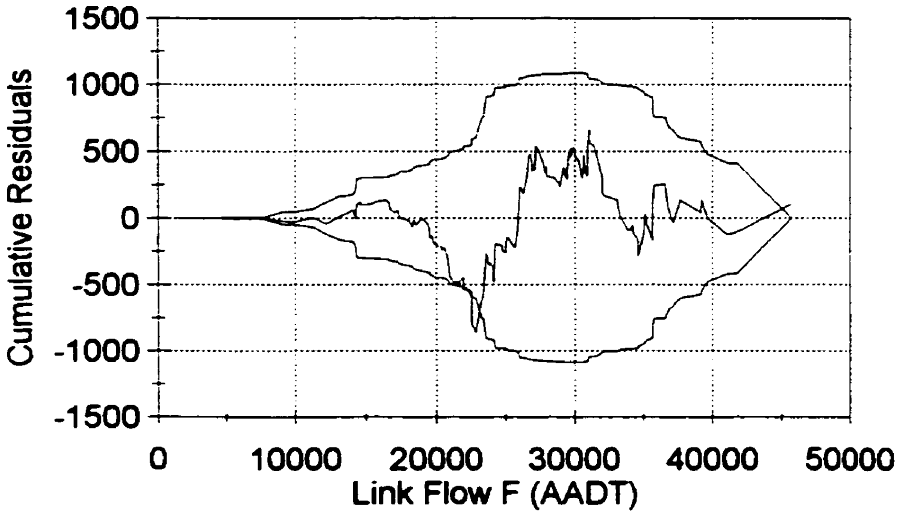

FIGURE E37 Cumulative Residuals for 4-lane roads (non-CBD and all accidents)

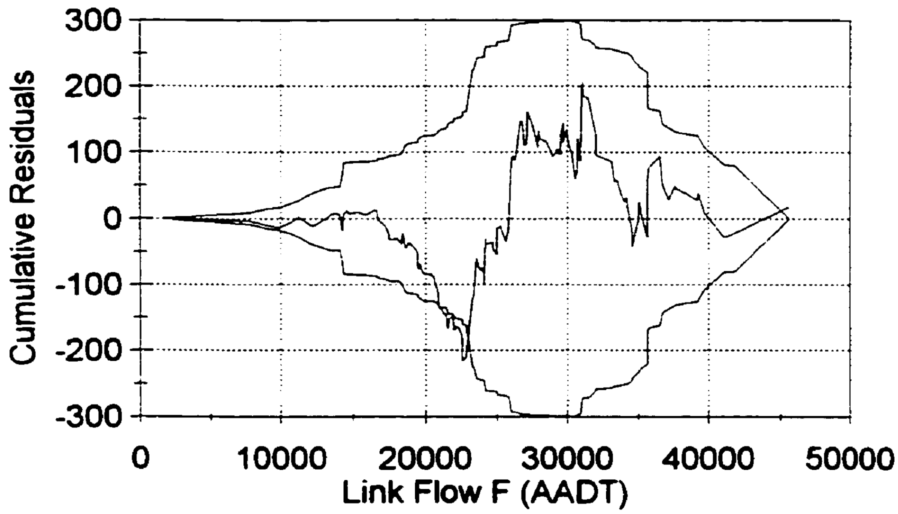

FIGURE E38 Cumulative Residuals for 4-lane roads (non-CBD and injury accidents)

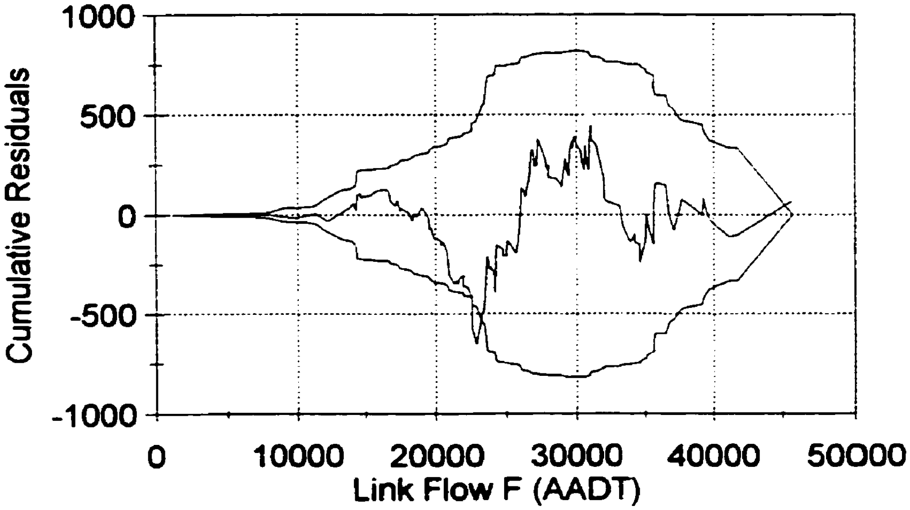

FIGURE E39 Cumulative Residuals for 4-lane roads (non-CBD and PDO accidents)

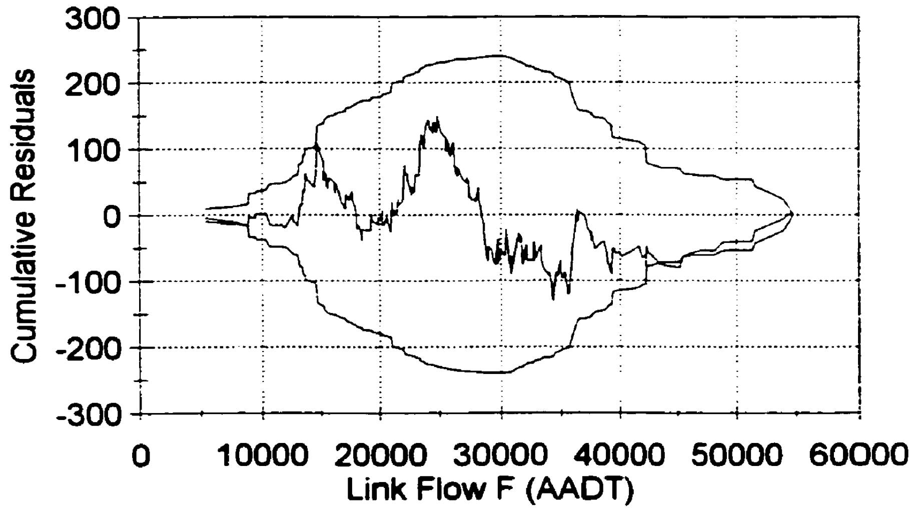

FIGURE E40 Cumulative Residuals for signalized 4-legged intersections (link flow, F, and all accidents)

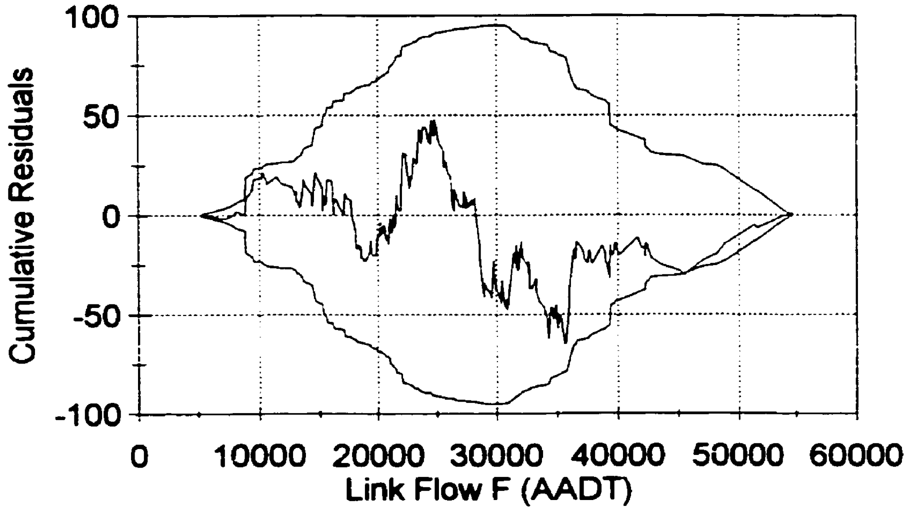

FIGURE E41 Cumulative Residuals for signalized 4-legged intersections (link flow, F, and injury accidents)

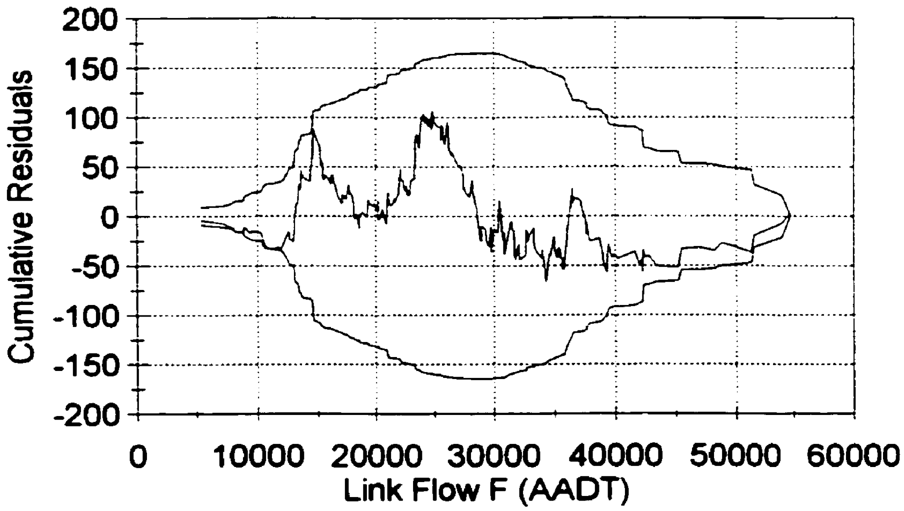

FIGURE E42 Cumulative Residuals for signalized 4-legged intersections (link flow, F, and PDO accidents)

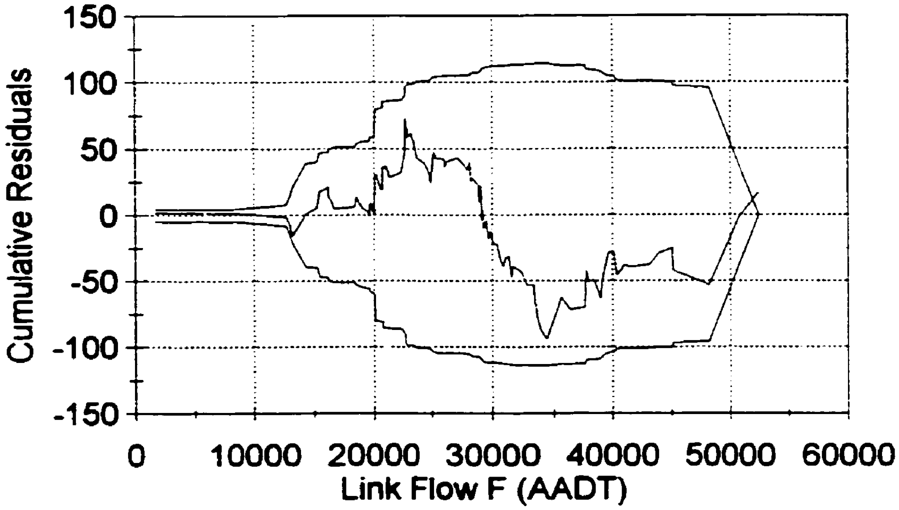

FIGURE E43 Cumulative Residuals for signalized 3-legged intersections (link flow, F, and all accidents)

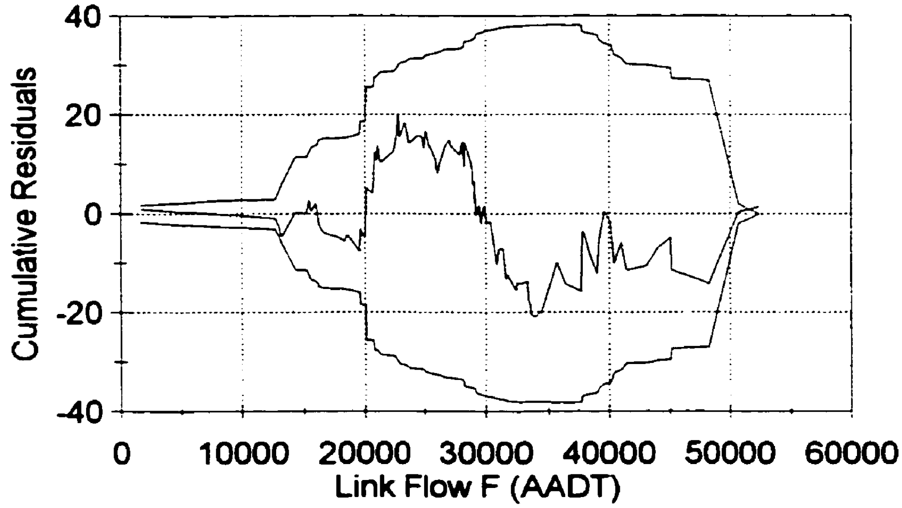

FIGURE E44 Cumulative Residuals for signalized 3-legged intersections (link flow, F, and injury accidents)

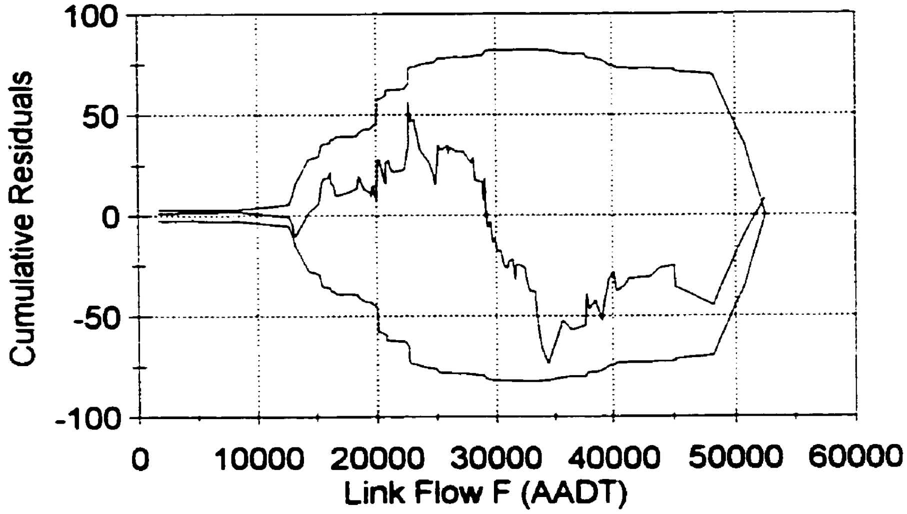

FIGURE E45 Cumulative Residuals for signalized 3-legged intersections (link flow, F, and PDO accidents)

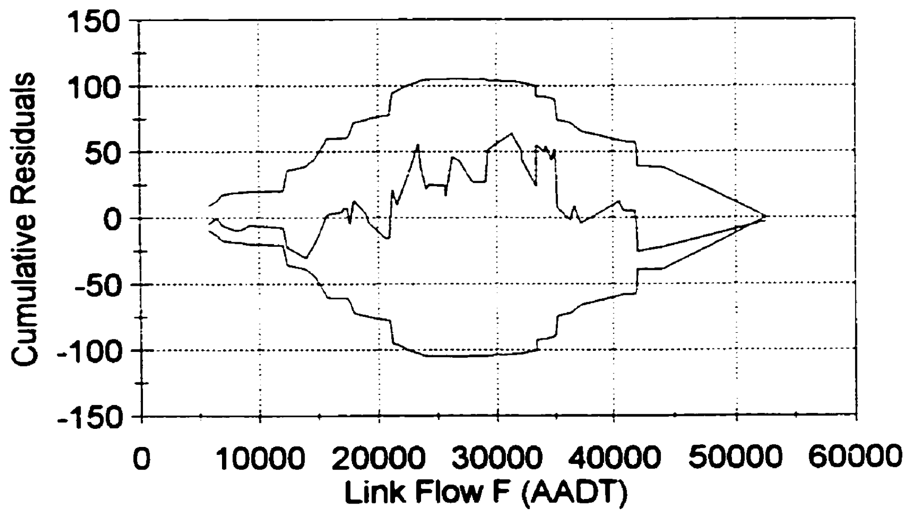

FIGURE E46 Cumulative Residuals for unsignalized 4-legged intersections (link flow, F, and all accidents)

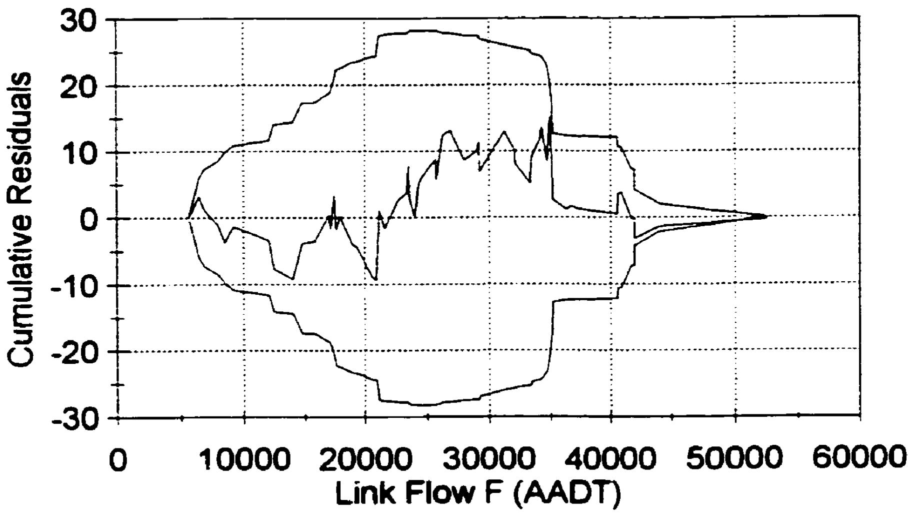

FIGURE E47 Cumulative Residuals for unsignalized 4-legged intersections (link flow, F, and injury accidents)

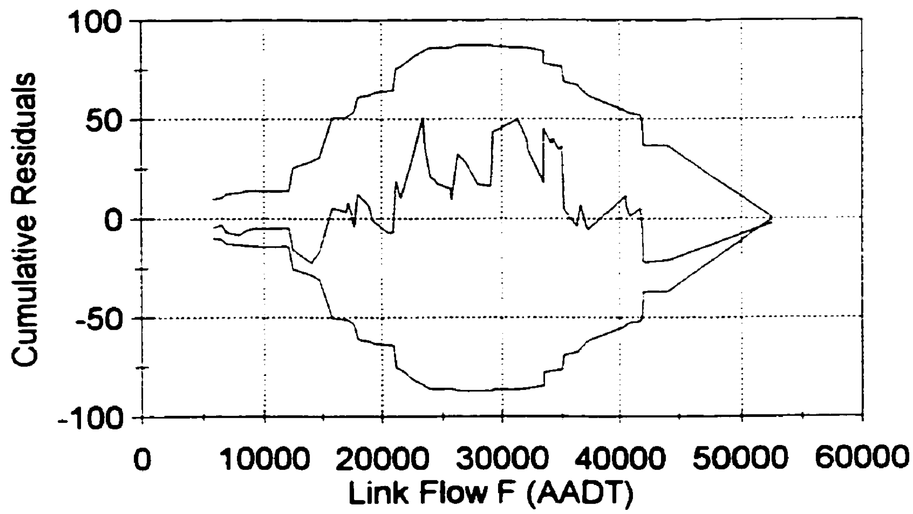

FIGURE E48 Cumulative Residuals for unsignalized 4-legged intersections (link flow, F, and PDO accidents)

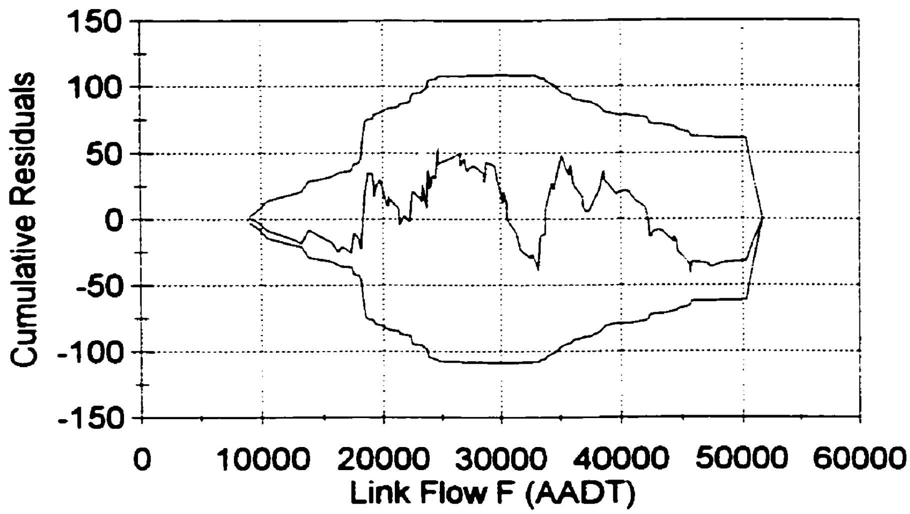

FIGURE E49 Cumulative Residuals for unsignalized 3-legged intersections (link flow, F, and all accidents)

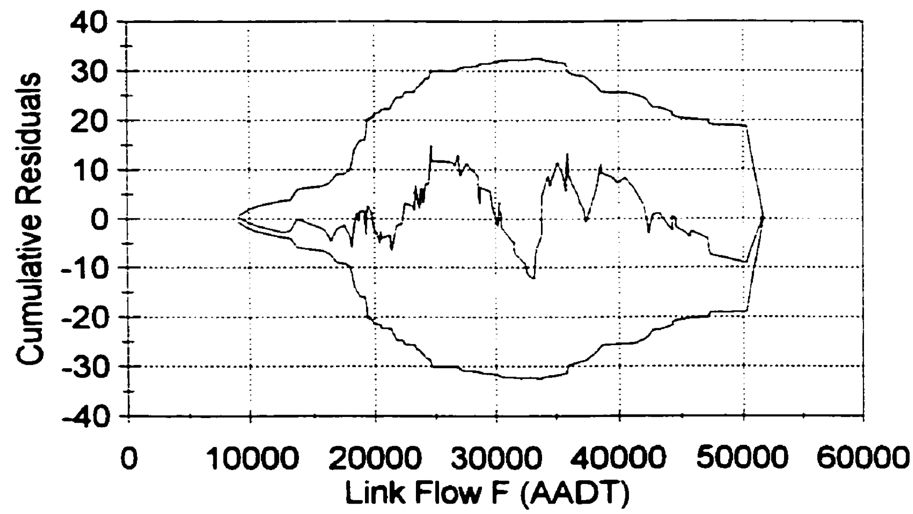

FIGURE E50 Cumulative Residuals for unsignalized 3-legged intersections (link flow, F, and injury accidents)

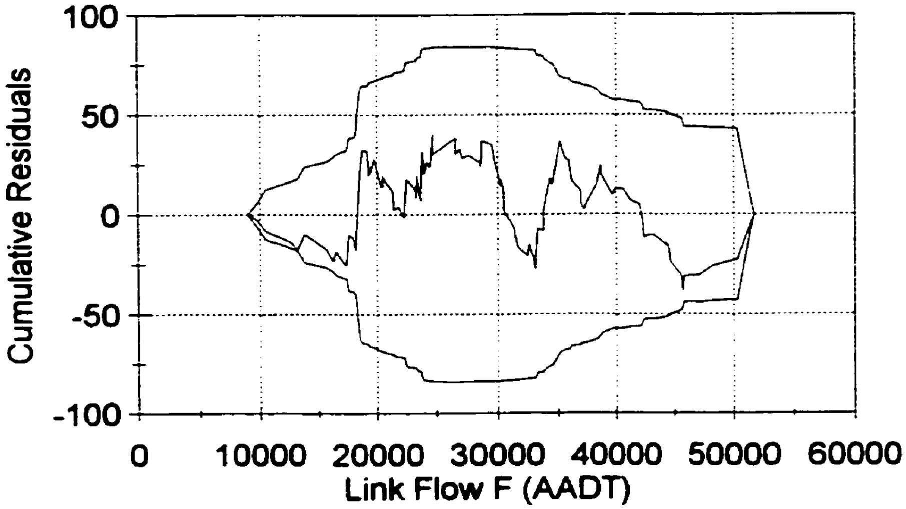

FIGURE E51 Cumulative Residuals for unsignalized 3-legged intersections (link flow, F, and PDO accidents)

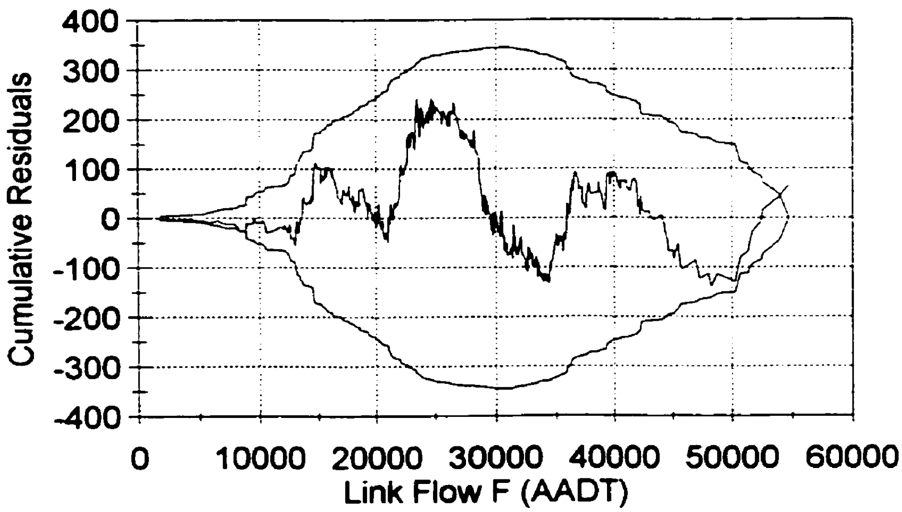

FIGURE E52 Cumulative Residuals for all intersections combined (link flow, F, and all accidents)

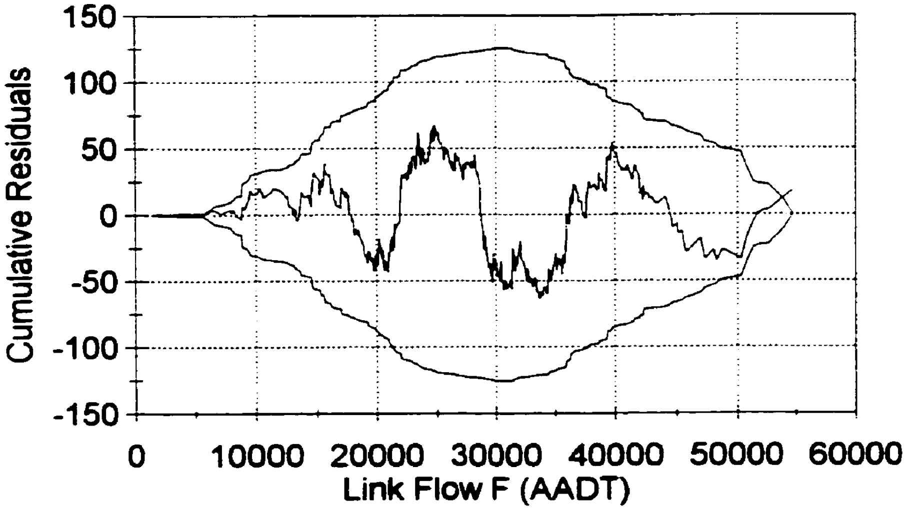

FIGURE E53 Cumulative Residuals for all intersections combined (link flow, F, and injury accidents)

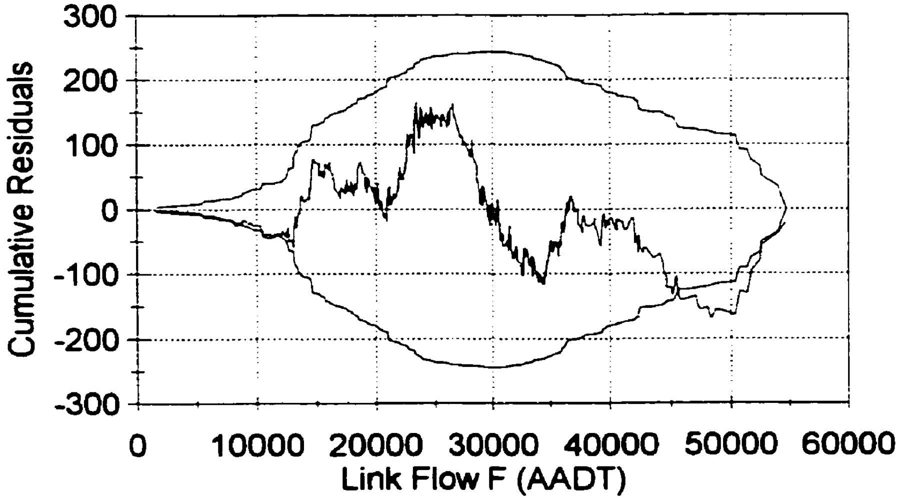

FIGURE E54 Cumulative Residuals for all intersections combined (link flow, F, and PDO accidents)

APPENDIX F

COMPUTER CODES

ESTIMATION OF MISSING COUNTS

```
'     TRAFF_B.BAS
'     Last modified Sept 18, 1997
'     Traffic count data are read in (1), averages calculated, counts
'     are normalized (divided by sample mean of counts) (2).
'     The mean index is determined for all road sections in our data
'     has been calculated separately. We then calculate an
'     "adjusted" normalized index for each road section and year.
'     This is done by dividing the normalized index obtained earlier
'     by the mean index for all road sections.
'     The next step is to estimate the parameters of a linear trend
'     for each site (4).
'     Having established that the sigma of an adjusted count is 0.1638,
'     and does not depend of the traffic flow, we estimate the
'     variance of b(i) (4).
'     The average of the VAR{b(i)} is 0.000609. The variance of the
'     estimated b(i) is 0.001296. The varinace of the true slopes is
'     therefore about 0.000687=0.0007. We use this to shrink the b(i).
'     The next step is to use a(i) and shrunkb(i) to calculate estimated adjusted
'     values for each j, multiply by the mean index and multiply by
'     the average count tp give estimates of AADT for each i and j.
'     Finally, the standard deviation of each estimated AADT is calculated.



'     Output is in TRAFFIC.PRN
'
'     Notation:
'           i       is a counter for road sections
'           j       is a counter for the 13 years of data for each section
'           average(i) average of available traffic counts
'           count(i)   number of traffic counts for site i
'           index(i,j) traffic count normalized so that average is 1
'           n(j)       number of counts in year j
'           avgindex(j) the state-wide average of the normalized indeces
'           adjindex(i,j) index(i,j)/avgindex(j)
'           x(j)        in the regression, the year j for which
'                       we have a count. j=1 for 1975.
'           y(j)        the adjusted index in year j
'           a(i)        intercept for site i. (adjusted index for j=0)
```

```
'          b(i)      slope for site i.
'          varb(i)   variance of the slope estimated by regression.
'          shrunkb(i) shrunk slope for site i.
'          AADT(i,j)  estimate of AADT.
'          sdaadt(i,j) standard deviation of the estimated AADT.

'        Four input files are used:
'          aadt_1.txt (700 lines/1-700) last = 700
'          aadt_2.txt (700 lines/701-1400) last = 700
'          aadt_3.txt (700 lines/use the first 149 lines) last = 696
'

REM $DYNAMIC

CLS

filename$ = "d:\aadt\input\aadt_3.txt"
OPEN filename$ FOR INPUT AS #1
OPEN "d:\aadt\output\prob_3.txt" FOR OUTPUT AS #2     'any lines with problems
OPEN "d:\aadt\output\tra_out3.txt" FOR OUTPUT AS #3   'output file
OPEN "d:\aadt\output\verify3.txt" FOR OUTPUT AS #4    'a file to verify the input data
PRINT #2, filename$
' PRINT #3, filename$

DIM SHARED traffic(700, 12), average(700), count(700), index(700, 12), adjindex(700,
12)
DIM SHARED avgindex(12), x(12), y(12), a(700), b(700), varb(700), shrunkb(700)
DIM SHARED aadt(700, 12), sdaadt(700, 12), xbar(700), Sxx(700)

'     1. Reading in the traffic count data.
'     ___________________________________

INPUT "last=", last
FOR i = 1 TO last
LINE INPUT #1, line$

   traffic(i, 1) = VAL(MID$(line$, 1, 11))
   traffic(i, 2) = VAL(MID$(line$, 12, 11))
   traffic(i, 3) = VAL(MID$(line$, 23, 11))
   traffic(i, 4) = VAL(MID$(line$, 34, 11))
   traffic(i, 5) = VAL(MID$(line$, 45, 11))
   traffic(i, 6) = VAL(MID$(line$, 56, 11))
   traffic(i, 7) = VAL(MID$(line$, 67, 11))
```

```
   traffic(i, 8) = VAL(MID$(line$, 78, 11))
   traffic(i, 9) = VAL(MID$(line$, 89, 11))
   traffic(i, 10) = VAL(MID$(line$, 100, 11))
   traffic(i, 11) = VAL(MID$(line$, 111, 11))
   traffic(i, 12) = VAL(MID$(line$, 122, 11))

   WRITE #4, i, traffic(i, 1), traffic(i, 2), traffic(i, 3), traffic(i, 4), traffic(i, 5), traffic(i, 6),
traffic(i, 7), traffic(i, 8), traffic(i, 9), traffic(i, 10), traffic(i, 11), traffic(i, 12)

NEXT i

CLOSE #1
'
'     2. Calculating the sample mean of counts and normalizing
'     ________________________________________________________
FOR i = 1 TO last
     sum = 0
     count(i) = 0
     FOR j = 1 TO 12
     IF traffic(i, j) > 0 THEN
     count(i) = count(i) + 1
     sum = sum + traffic(i, j)
     END IF
     NEXT j
     IF count(i) = 0 THEN
     PRINT i, "no traffic counts"
     WRITE #2, i, count(i), traffic(i, 1), traffic(i, 2), traffic(i, 3), traffic(i, 4), traffic(i, 5),
traffic(i, 6), traffic(i, 7), traffic(i, 8), traffic(i, 9), traffic(i, 10), traffic(i, 11), traffic(i, 12)
     GOTO 20
     END IF
     IF count(i) = 1 THEN PRINT i
     average(i) = sum / count(i)

     FOR j = 1 TO 12
          index(i, j) = traffic(i, j) / average(i)
     NEXT j
20
NEXT i

'     3. Setting the 13 state-wide average indeces avgindex(j).
'     ________________________________________________________

avgindex(1) = .906
```

```
avgindex(2) = .958
avgindex(3) = .989
avgindex(4) = .99
avgindex(5) = 1.023
avgindex(6) = 1.001
avgindex(7) = .999
avgindex(8) = 1.008
avgindex(9) = 1.013
avgindex(10) = 1.031
avgindex(11) = 1.032
avgindex(12) = 1.034

'     Calculating the adjusted index, adjindex(i,j)
'
FOR i = 1 TO last
FOR j = 1 TO 12
IF index(i, j) > 0 THEN
adjindex(i, j) = index(i, j) / avgindex(j)
END IF
NEXT j
NEXT i

'     4. Linear regression & shrunk estimates of slope.
'     ________________________________________________

FOR i = 1 TO last

'          4.1. Preparing the data for one line
     k = 0
     FOR j = 1 TO 12
          IF adjindex(i, j) > 0 THEN
               k = k + 1
               x(k) = j
               y(k) = adjindex(i, j)
          END IF
          NEXT j
          n = k
IF n > 0 THEN
'          4.2 Estimating intercept a(i),slope b(i) and shrunkb(i)

     sumx = 0
     sumy = 0
     sumxx = 0
```

```
        sumxy = 0
        FOR k = 1 TO n
            sumx = sumx + x(k)
            sumy = sumy + y(k)
            sumxx = sumxx + x(k) ^ 2
            sumxy = sumxy + x(k) * y(k)
        NEXT k

        xbar(i) = sumx / n
        ybar = sumy / n
        Sxx(i) = sumxx - n * xbar(i) ^ 2
        Sxy = sumxy - n * xbar(i) * ybar
        IF n = 1 OR n = 2 THEN
            b(i) = 0
            a(i) = ybar
        ELSE
            b(i) = Sxy / Sxx(i)
            varb(i) = .1638 ^ 2 / Sxx(i)
            shrunkb(i) = .0007 * b(i) / (.0007 + varb(i))
            a(i) = ybar - shrunkb(i) * xbar(i)
        END IF
'           4.3 Printing warnings about funny slopes and intercepts.

        IF a(i) < .5 OR a(i) > 1.5 THEN
                funnyint$ = "funny intercept"
                PRINT , i, a(i), b(i), shrunkb(i); "funny intercept"
                WRITE #2, i, a(i), b(i), shrunkb(i), funnyint$
        END IF

        IF b(i) < -.5 OR b(i) > .5 THEN
                funnyslo$ = "funny slope"
                WRITE #2, i, b(i), shrunkb(i), funnyslo$
                PRINT , i, b(i), shrunkb(i); "funny slope"
        END IF
    END IF
    NEXT i

'       5. Calculation of estimated AADTs and their standard deviations.
'       _______________________________________________________________
    FOR i = 1 TO last
    IF count(i) > 0 THEN
        FOR j = 1 TO 12
        aadt(i, j) = (a(i) + shrunkb(i) * j) * avgindex(j) * average(i)
```

```
      IF count(i) = 1 OR count(i) = 2 THEN
      sdaadt(i, j) = avgindex(j) * average(i) * (.1638 ^ 2 / count(i) + (j - xbar(i)) ^ 2 *
.0007) ^ .5
      ELSE
      sdaadt(i, j) = avgindex(j) * average(i) * .1638 * (1 / count(i) + (j - xbar(i)) ^ 2 /
Sxx(i)) ^ .5
      END IF
      NEXT j
END IF
NEXT i


'     printing to file
FOR i = 1 TO last
IF count(i) > 0 THEN
      PRINT i;

      FOR j = 1 TO 11
            PRINT USING "######"; aadt(i, j);
      NEXT j
      PRINT USING "######"; aadt(i, 12)

      WRITE #3, i, aadt(i, 1), aadt(i, 2), aadt(i, 3), aadt(i, 4), aadt(i, 5), aadt(i, 6), aadt(i,
7), aadt(i, 8), aadt(i, 9), aadt(i, 10), aadt(i, 11), aadt(i, 12)

'     FOR j = 1 TO 11
'           PRINT USING "######"; sdaadt(i, j);
'     NEXT j
'     PRINT USING "######"; sdaadt(i, 12)

'     WRITE #3, i, sdaadt(i, 1), sdaadt(i, 2), sdaadt(i, 3), sdaadt(i, 4), sdaadt(i, 5),
sdaadt(i, 6), sdaadt(i, 7), sdaadt(i, 8), sdaadt(i, 9), sdaadt(i, 10), sdaadt(i, 11), sdaadt(i.
12)

'     WRITE #3, i, traffic(i, 1), traffic(i, 2), traffic(i, 3), traffic(i, 4), traffic(i, 5), traffic(i, 6),
traffic(i, 7), traffic(i, 8), traffic(i, 9), traffic(i, 10), traffic(i, 11), traffic(i, 12)

END IF
NEXT i
END
```

RE-ASSIGN ENTERING FLOWS TO TURNING MOVEMENTS

```
'    MOVE_PRO.BAS
'    Last modified Sept 18, 1997
'    This program adds turning/through movements from an intersection
'    with the same street names and
'    compute the average for each turning/through movement.  There is a total
'    of 12 movements, three for each approach.
'
'    For an intersection, many traffic counts are performed either
'    for different years or during the same year. Each line has a traffic
'    count. The intersection with the same street names
'    have to follow each other.
'
'    Variables:
'      road1$(i) = name of the first street
'      road2$(i) = name of the second street
'      prop(i, j) = proportion of traffic for movement j
'      add(i, j) = the addition of the movement j for the same street names
'      avg(i, j) = the average of movement j for the same street names
'      newroad1$(i) = the name of the first street used in the output file
'                Only one street name is printed from the input file
'      newprop(i, j) = the average proportion for movement j
'
'      There are ten files used for input
'        input_1.txt (last = 498)
'        input_2.txt (last = 496)
'        input_3.txt (last = 499)
'        input_4.txt (last = 494)
'        input_5.txt (last = 501)
'        input_6.txt (last = 499)
'        input_7.txt (last = 500)
'        input_8.txt (last = 497)
'        input_9.txt (last = 500)
'        input_10.txt (last = 190)


CLS

REM $DYNAMIC
```

```
filename$ = "d:\temp\input_10.txt"          'input file
OPEN filename$ FOR INPUT AS #1
OPEN "d:\temp\out_10.txt" FOR OUTPUT AS #2   'output file

DIM SHARED road1$(800), road2$(800), prop(800, 12), add(800, 12), avg(800, 12)
DIM SHARED newroad1$(800), newroad2$(800), newprop(800, 12)

'Reading the data

INPUT "last=", last
FOR i = 1 TO last
LINE INPUT #1, line$

  road1$(i) = MID$(line$, 1, 17)
  road2$(i) = MID$(line$, 18, 21)
  prop(i, 1) = VAL(MID$(line$, 39, 9))
  prop(i, 2) = VAL(MID$(line$, 48, 9))
  prop(i, 3) = VAL(MID$(line$, 57, 9))
  prop(i, 4) = VAL(MID$(line$, 66, 9))
  prop(i, 5) = VAL(MID$(line$, 75, 9))
  prop(i, 6) = VAL(MID$(line$, 84, 9))
  prop(i, 7) = VAL(MID$(line$, 93, 9))
  prop(i, 8) = VAL(MID$(line$, 102, 9))
  prop(i, 9) = VAL(MID$(line$, 111, 9))
  prop(i, 10) = VAL(MID$(line$, 120, 9))
  prop(i, 11) = VAL(MID$(line$, 129, 9))
  prop(i, 12) = VAL(MID$(line$, 138, 9))

NEXT i

'Add bogus names to enable the arrays to go over the "last"

road1$(last + 1) = "a"
road1$(last + 2) = "b"
road1$(last + 3) = "c"
road1$(last + 4) = "d"
road1$(last + 5) = "e"
road1$(last + 6) = "f"
road1$(last + 7) = "g"
road1$(last + 8) = "h"
road1$(last + 9) = "i"
road1$(last + 10) = "j"
road1$(last + 11) = "k"
```

```
road1$(last + 12) = "l"
road1$(last + 13) = "m"
road1$(last + 14) = "n"
road1$(last + 15) = "o"

road2$(last + 1) = "a"
road2$(last + 2) = "b"
road2$(last + 3) = "c"
road2$(last + 4) = "d"
road2$(last + 5) = "e"
road2$(last + 6) = "f"
road2$(last + 7) = "g"
road2$(last + 8) = "h"
road2$(last + 9) = "i"
road2$(last + 10) = "j"
road2$(last + 11) = "k"
road2$(last + 12) = "l"
road2$(last + 13) = "m"
road2$(last + 14) = "n"
road2$(last + 15) = "o"


CLOSE #1

'Main program that reads line i and compares it from lines (i + 1) to (i + 15).
'Then, it takes the average of every line with similar street name.
'The program returns only one line with the average.

FOR i = 1 TO last

  IF i = m OR i = n OR i = o OR i = p OR i = q OR i = r OR i = s OR i = t OR i = u OR i =
v OR i = w OR i = x OR i = y OR i = z OR i = z1 THEN
    'WRITE #2, road1$(i), road2$(i), 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
  ELSE

  k = 1
  IF road1$(i) = road1$(i + 1) AND road2$(i) = road2$(i + 1) THEN
    k = k + 1
    m = i + 1
    FOR j = 1 TO 12
     add(i, j) = prop(i, j) + prop(i + 1, j)
    NEXT j
```

```
IF road1$(i) = road1$(i + 2) AND road2$(i) = road2$(i + 2) THEN
 k = k + 1
 n = i + 2
 FOR j = 1 TO 12
  add(i, j) = add(i, j) + prop(i + 2, j)
 NEXT j
END IF

IF road1$(i) = road1$(i + 3) AND road2$(i) = road2$(i + 3) THEN
 k = k + 1
 o = i + 3
 FOR j = 1 TO 12
  add(i, j) = add(i, j) + prop(i + 3, j)
 NEXT j
END IF

IF road1$(i) = road1$(i + 4) AND road2$(i) = road2$(i + 4) THEN
  k = k + 1
  p = i + 4
  FOR j = 1 TO 12
    add(i, j) = add(i, j) + prop(i + 4, j)
  NEXT j
END IF

IF road1$(i) = road1$(i + 5) AND road2$(i) = road2$(i + 5) THEN
  k = k + 1
  q = i + 5
  FOR j = 1 TO 12
    add(i, j) = add(i, j) + prop(i + 5, j)
  NEXT j
END IF

IF road1$(i) = road1$(i + 6) AND road2$(i) = road2$(i + 6) THEN
 k = k + 1
 r = i + 6
 FOR j = 1 TO 12
  add(i, j) = add(i, j) + prop(i + 6, j)
 NEXT j
END IF

IF road1$(i) = road1$(i + 7) AND road2$(i) = road2$(i + 7) THEN
 k = k + 1
 s = i + 7
```

```
  FOR j = 1 TO 12
   add(i, j) = add(i, j) + prop(i + 7, j)
  NEXT j
END IF

IF road1$(i) = road1$(i + 8) AND road2$(i) = road2$(i + 8) THEN
  k = k + 1
  t = i + 8
  FOR j = 1 TO 12
   add(i, j) = add(i, j) + prop(i + 8, j)
  NEXT j
END IF

IF road1$(i) = road1$(i + 9) AND road2$(i) = road2$(i + 9) THEN
  k = k + 1
  u = i + 9
  FOR j = 1 TO 12
   add(i, j) = add(i, j) + prop(i + 9, j)
  NEXT j
END IF

IF road1$(i) = road1$(i + 10) AND road2$(i) = road2$(i + 10) THEN
 k = k + 1
 v = i + 10
 FOR j = 1 TO 12
  add(i, j) = add(i, j) + prop(i + 10, j)
 NEXT j
END IF

IF road1$(i) = road1$(i + 11) AND road2$(i) = road2$(i + 11) THEN
 k = k + 1
 w = i + 11
 FOR j = 1 TO 12
  add(i, j) = add(i, j) + prop(i + 11, j)
 NEXT j
END IF

IF road1$(i) = road1$(i + 12) AND road2$(i) = road2$(i + 12) THEN
  k = k + 1
  x = i + 12
  FOR j = 1 TO 12
   add(i, j) = add(i, j) + prop(i + 12, j)
  NEXT j
```

```
 END IF

 IF road1$(i) = road1$(i + 13) AND road2$(i) = road2$(i + 13) THEN
   k = k + 1
   y = i + 13
   FOR j = 1 TO 12
     add(i, j) = add(i, j) + prop(i + 13, j)
   NEXT j
 END IF

 IF road1$(i) = road1$(i + 14) AND road2$(i) = road2$(i + 14) THEN
   k = k + 1
   z = i + 14
   FOR j = 1 TO 12
     add(i, j) = add(i, j) + prop(i + 14, j)
   NEXT j
 END IF

 IF road1$(i) = road1$(i + 15) AND road2$(i) = road2$(i + 15) THEN
   k = k + 1
   z1 = i + 15
   FOR j = 1 TO 12
     add(i, j) = add(i, j) + prop(i + 15, j)
   NEXT j
 END IF

 count = count + 1

 FOR j = 1 TO 12
   avg(i, j) = add(i, j) / k
   newprop(count, j) = avg(i, j)  'assign one street name
 NEXT j

 newroad1$(count) = road1$(i)
 newroad2$(count) = road2$(i)

 'WRITE #2, road1$(i), road2$(i), avg(i, 1), avg(i, 2), avg(i, 3), avg(i, 4), avg(i, 5),
avg(i, 6), avg(i, 7), avg(i, 8), avg(i, 9), avg(i, 10), avg(i, 11), avg(i, 12)

ELSE

count = count + 1
```

```
  FOR j = 1 TO 12
    newprop(count, j) = prop(i, j)
  NEXT j

  newroad1$(count) = road1$(i)
  newroad2$(count) = road2$(i)

  'WRITE #2, road1$(i), road2$(i), prop(i, 1), prop(i, 2), prop(i, 3), prop(i, 4), prop(i, 5),
prop(i, 6), prop(i, 7), prop(i, 8), prop(i, 9), prop(i, 10), prop(i, 11), prop(i, 12)

 END IF

END IF

NEXT i

'Print the results

FOR i = 1 TO count

 WRITE #2, newroad1$(i), newroad2$(i), newprop(i, 1), newprop(i, 2), newprop(i, 3),
newprop(i, 4), newprop(i, 5), newprop(i, 6), newprop(i, 7), newprop(i, 8), newprop(i, 9),
newprop(i, 10), newprop(i, 11), newprop(i, 12)

NEXT i
END
```

DANTZIG ALGORITHM

```
CLS

filename$ = "c:\phd_th~1\network\TEMP\matrix2.txt"
OPEN filename$ FOR INPUT AS #1
OPEN "c:\phd_th~1\network\TEMP\matout.txt" FOR OUTPUT AS #2
OPEN "c:\phd_th~1\network\temp\maoure.txt" FOR OUTPUT AS #3

node = 36

DIM SHARED D(node, node)

WHILE NOT EOF(1)
 FOR i = 1 TO node
  FOR j = 1 TO node
   INPUT #1, D(i, j)
   'PRINT D(i, j)
  NEXT j
 NEXT i
WEND

CLOSE #1

FOR i = 1 TO node
 D(i, i) = 99999
NEXT i

FOR k = 1 TO node
 FOR l = 1 TO node - 1
  FOR j = 1 TO node - 1
   x = D(j, l) + D(l, k)
   IF x < D(j, k) THEN D(j, k) = x

   y = D(k, l) + D(l, j)
   IF y < D(k, j) THEN D(k, j) = y
  NEXT j

  z = D(k, l) + D(l, k)
  IF z < D(k, k) THEN D(k, k) = z
 NEXT l
NEXT k
```

```
FOR k = 1 TO node
   FOR i = 1 TO node - 1
     FOR j = 1 TO node - 1
       w = D(i, k) + D(k, j)
       IF w < D(i, j) THEN D(i, j) = w
     NEXT j
   NEXT i
NEXT k


FOR i = 1 TO node
  WRITE #2, 1, D(i, 1), D(i, 2), D(i, 3), D(i, 4), D(i, 5), D(i, 6), D(i, 7), D(i, 8), D(i, 9), D(i,
10), D(i, 11), D(i, 12)
NEXT i

FOR i = 1 TO node
  WRITE #2, 2, D(i, 13), D(i, 14), D(i, 15), D(i, 16), D(i, 17), D(i, 18), D(i, 19), D(i, 20),
D(i, 21), D(i, 22), D(i, 23), D(i, 24)
NEXT i

FOR i = 1 TO node
  WRITE #2, 3, D(i, 25), D(i, 26), D(i, 27), D(i, 28), D(i, 29), D(i, 30), D(i, 31), D(i, 32),
D(i, 33), D(i, 34), D(i, 35), D(i, 36)
NEXT i

WRITE #3, D(31, 31), D(31, 32), D(31, 33), D(31, 34), D(31, 35), D(31, 36)
WRITE #3, D(32, 31), D(32, 32), D(32, 33), D(32, 34), D(32, 35), D(32, 36)
WRITE #3, D(33, 31), D(33, 32), D(33, 33), D(33, 34), D(33, 35), D(33, 36)
WRITE #3, D(34, 31), D(34, 32), D(34, 33), D(34, 34), D(34, 35), D(34, 36)
WRITE #3, D(35, 31), D(35, 32), D(35, 33), D(35, 34), D(35, 35), D(35, 36)
WRITE #3, D(36, 31), D(36, 32), D(36, 33), D(36, 34), D(36, 35), D(36, 36)

'FOR i = 1 TO node
'  FOR j = 1 TO node - 1
'    PRINT #2, USING "######.##"; D(i, j);
'  NEXT j
'  PRINT #2, USING "######.##"; D(i, node)
'NEXT i


CLOSE #2
CLOSE #3
```

```
END
```

FLOYD ALGORITHM

```
CLS

filename$ = "c:\phd_th~1\network\TEMP\Matrix2.txt"
OPEN filename$ FOR INPUT AS #1
OPEN "c:\phd_th~1\network\TEMP\matout2.txt" FOR OUTPUT AS #2
OPEN "c:\phd_th~1\network\temp\maouret.txt" FOR OUTPUT AS #3

node = 108

DIM SHARED D(node, node)

WHILE NOT EOF(1)
  FOR i = 1 TO node
    FOR j = 1 TO node
      INPUT #1, D(i, j)
      'PRINT D(i, j)
    NEXT j
  NEXT i
WEND

CLOSE #1

FOR i = 1 TO node
  D(i, i) = 99999
NEXT i


FOR k = 1 TO node
  FOR i = 1 TO node
    FOR j = 1 TO node
      x = D(i, k) + D(k, j)
      IF x < D(i, j) THEN D(i, j) = x
    NEXT j
  NEXT i
NEXT k

FOR i = 103 TO node
```

```
  WRITE #2, D(i, 103), D(i, 104), D(i, 105), D(i, 106), D(i, 107), D(i, 108) ', D(i, 108), D(i,
8), D(i, 9), D(i, 10), D(i, 11), D(i, 12), D(i, 13), D(i, 14), D(i, 15), D(i, 16), D(i, 17), D(i,
18), D(i, 19), D(i, 20)
NEXT i


CLOSE #2
CLOSE #3

END
```