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ANALYSIS OF ACCIDENT POTENTIAL AT UNSIGNALISED URBAN JUNCTIONS IN GHANA

by

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Abstract

Until now the unsafety or accident potential of road locations has been assessed usually solely from their accident history. But this approach has been criticised as fundamentally misleading and inaccurate by many authors. Safety evaluation, particularly in Ghana, is also still restricted to isolated blackspot analysis. Because of its site-specific nature, this represents a less efficient use of scarce resources whilst there is generally a dearth of knowledge regarding the accident potential associated with various road locations and features.

Based on a case-study of unsignalised urban junctions in Ghana, this dissertation presents the Empirical Bayesian procedure for the estimation of site-specific accident potential as a superior alternative that automatically addresses the shortcomings inherent in the sole use of recorded accident counts. The refined estimate is produced from a uniquely weighted combination of the recorded accident counts of the particular site and the expected accidents for sites with similar characteristics as the one under study.

A unique feature of this study is the demonstration of the framework for integrating comprehensive accident model predictions with the Empirical Bayesian procedure, to improve further upon the quality of the estimates and extend the applicability of the procedure to relatively smaller reference populations. Despite the acknowledged advantages of this approach, little work has been done in this direction, largely due to the absence of appropriate prediction models, particularly for traffic conditions in developing countries.

Thus, a key part of this study has been the development of accident prediction models for unsignalised T- and X-junctions. The models were of two types, namely, the coarse or flow-based, which included only traffic exposure functions as the explanatory variable, and the full or comprehensive models, containing both exposure functions and other significant road and traffic variables. Separate models have been developed to predict the three-year frequency of total accidents, injury accidents and five other types of accidents defined by the primary collision types involved. The unique ability of the Bayesian analysis to treat accident potential at a site as a random variable was utilised to outline new probabilistic criteria for accident blackspot identification. Existing criteria for ranking accident blackspots for treatment have also been revised and an improved criterion called the Amended Potential Accident Reduction proposed.

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Table of Contents

Chapter 5 Development of Accident Prediction Models........................... **81**

Chapter 6 Empirical Bayesian Estimation of Accident Potential and Development of Revised "Blackspot" Decision Criteria...................................... 138

List of Tables

List of Figures

Glossary of Accident-Types

Definitions by Severity:

FATAL	An accident in which, at least, one of the casualties dies within 30 days of its occurrence.
SEVERE INJURY	A non-fatal accident in which the worst casualty sustains injuries that require hospitalisation for a minimum duration of 24 hours.
MINOR (SLIGHT) INJURY	Accident in which the worst casualty sustains injuries that require only first-aid treatment
DAMAGE-ONLY	Accident resulting only in damage to property
PERSONAL INJURY ACCIDENT (PIA)	A fatal, severe or minor injury accident

Definitions by Collision-type:

HEAD-ON	Accident-type in which the primary collision (initial impact) involves the front parts of two vehicles crashing into each other.
PEDESTRIAN ACCIDENT	Accident in which a pedestrian is hit by any type of vehicle in the primary collision
REAR-END	Accident in which the initial impact involves the nose (front part) of one vehicle crashing into the rear (tail) of another vehicle.

RIGHT-ANGLE	Accident in which the two vehicles involved in the primary collision crash with each other, approximately, at a right-angle.
SIDE-SWIPE	Accident in which the initial impact involves one vehicle crashing into the side of another vehicle at an angle less than 90 degrees.
SINGLE VEHICLE	Accident in which the primary collision involves only one vehicle and no other road-user.

CHAPTER 1
INTRODUCTION

1.1 The Problem of Traffic Accidents

To say that Ghana has a traffic accident problem is an understatement. It is estimated that 15,000 road traffic accidents occur each year resulting in 20,000 injuries and substantial damage to property. Fatality rates over the last ten years have also averaged 90 per 10,000 registered vehicles (Salifu, 1996; BRRI, 1999). This rate of deaths is more than 50 times that of Sweden, for example, an industrialised country with one of the highest levels of motorization but one of the lowest accident rates. When it is considered that the above statistics are based on police reported accidents, then it is not difficult to imagine that the problem could be much worse than portrayed, given the high likelihood of under-reporting.

Going by the experience of the industrialised countries, Ghana's current car-ownership ratio of 80 cars per thousand population is quite low and the country has yet to launch into the rapid motorization phase as the economy improves. With increasing numbers of vehicles will come increasing potential for accidents and the problem, therefore, is set to get worse before it gets better. Countries like Sweden and the United Kingdom have worked tirelessly over the years to ensure that accident rates (per 10,000 vehicles) are now on a downward trend even as the number of vehicles on the roads continues to grow. They have achieved this through concerted and targeted action in the areas of legislation and enforcement, road safety campaigns, driver training and licensing, engineering interventions and higher safety standards of vehicles along with many other measures. We in Ghana can learn from these experiences as we strive to build the capacity to tackle the imminent "explosion" in traffic accidents.

Fortunately, recently reported findings that the country could be losing up to US$ 70 million per annum through road traffic accidents alone (Ghee *et al*, 1997) are beginning to hit the right chord. Policy-makers in Ghana are beginning to appreciate that road traffic accidents are as much an economic problem as they are a threat to public health. Road safety improvement, therefore, is currently an urgent national priority. The most recent demonstration of this was the passing by Parliament of the National Road Safety Commission Act, at the close of 1999. The Act has effectively transformed and empowered the former National Road Safety Committee to take up the challenge of direction, co-ordination and control of a more structured approach to road safety issues in Ghana. The current thesis is intended as a contribution towards this national effort, particularly, in the specific areas of road safety engineering assessments and intervention strategies.

Although human error, in one form or another, has been identified as the main contributory factor to most accidents, road-related factors are no less important. Since there is rarely one isolated cause of an accident, human factors will often occur alongside engineering-related deficiencies in the road infrastructure. For example, accidents resulting from persistent over-shooting of the stop line at junctions are usually associated with improper junction layout design and the absence of channelisation or adequate road markings. Engineering factors become dominant where there is a clustering of accidents of a particular type at a specific location in the road network. Engineering measures, therefore, have a vital role to play in accident reduction and nowhere is the potential for making a big impact more apparent than at urban junctions. More than 2 in every 3 accidents recorded in Ghana occur in urban areas and, of these, about 50 per cent occur at junctions.

1.2 The Problem of Unsignalised Junctions

Junctions, as an integral part of every road network, have the function of resolving the conflicts between opposing streams of traffic. To ensure that this function is performed efficiently, a variety of means is usually employed, ranging from simple road-line markings and signs, through channelisation with ghost islands or physical demarcation, to the use of traffic signals. It would appear that the main criterion for preferring one type of control to another is often the desire to minimise delay and increase capacity (TRL, 1991; MUTCD, 1978; HCM, 1997). Although safety considerations do sometimes play a role (ITE, 1982), the analytical basis of safety warrants has been strongly criticised by a number of researchers as being "shaky" (e.g. Persaud, 1988; and Hauer *et al.*, 1989).

For the broad group of unsignalised (non-signal-controlled) junctions, however, the choice is often between different levels of priority control. This group constitutes the preponderant majority of junctions in urban areas of Ghana, probably due to their simplicity and relatively cheap costs of installation and maintenance. Because priority junction controls are usually not self-enforcing, the potential for inter-vehicular conflict and accidents at such junctions is usually very high, especially in conditions where driving quality can at best be described as suspect (Salifu, 1998).

Notwithstanding the important role unsignalised junctions play in traffic management, and the fact that they currently account for about 70 per cent of all accidents at urban junctions in Ghana, little to date is known about their accident potential relative to other types of junction. Also, little or no information exists about the accident potential of the many different types of unsignalised junction. The absence of such information is clearly a significant handicap in the safe and efficient management of traffic in urban areas.

1.3 Drawbacks of the Current Approach to Safety Appraisal

Currently, evaluations of junction safety are accomplished only by means of isolated blackspot studies (e.g. BRRI, 1998 and 1999). Under these studies, accident-prone locations (blackspots) are identified and ranked for treatment using the total number of accidents recorded for a given period of time as the sole criterion. The subsequent analysis is then based on the principle of identifying a clustering of "treatable" accident types and common deficiencies in the site characteristics, which might have given rise to the accidents.

Thus, the current method does not account for the intensity of use or exposure to accident at any site and it is also statistically deficient, because it fails to address the "regression-to-mean" effect, i.e. the fact that sites with above-average accident numbers or rates in one period must be expected to show a decrease in a subsequent period even without treatment, and *vice versa*. The site-specific focus of the method also means that it is resource-intensive, since the findings from one site are often inapplicable to other sites. Another significant drawback is that the method is entirely dependent on the availability of relevant accident records. Unfortunately, the data is often several years in arrears, due to the lengthy processes involved in its retrieval and processing. As a result, by the time data is available for analysis, it has often become obsolete, because the site conditions may have changed already.

1.4 Justification for a New Approach to Safety Appraisal

In the light of the above shortcomings of the current method and the reality of shrinking budgetary allocation to road safety work, a new proactive approach is required that will be more cost-effective, with broader applicability and improved accuracy. Such is the methodology that the current study has sought to establish. A key component of this alternative approach is the collection of "standard" accident data, at a representative sample of "identical" junctions, covering a wide range of traffic and road conditions and the determination of causal relationships between these factors and accidents at the selected junctions.

These relationships and their predictions are then integrated into a tool for appraisal of the accident potential and the effectiveness of intervention at any one of the "family" of junctions. In this way, comprehensive accident prediction models can be utilised both as a tool for investigating the type and scale of influence of various road and traffic factors on accidents and also as an input into the Empirical Bayes procedure for improved accident estimation. The establishment of such quantified relationships, between accidents, on the one hand, and traffic flows and site characteristics, on the other, should also enable priorities for improvement to be more realistically assessed (Hall and Surl, 1981). In spite of the apparent potential advantages of this procedure, it is rarely used in practice, primarily due to the problems of identifying suitable predictive models (Mountain *et al*, 1995 and 1998).

Unsignalised urban junctions have been targeted for this study, because immediate significant impact could be made with safety improvements, given the strategic role they play in traffic management and their large share of the accident burden. Unfortunately, results from several previous investigations into the relative safety merits of various types of non-signalised (priority) junction controls and a comparison of these with signal control (e.g. Polus, 1985; Lum and Parker, 1982; Chadda and Parker, 1983; Lum and Stockton, 1982; Frith and Harte, 1986; and Frith and Dery, 1987) remain largely contradictory.

On the other hand, most studies on accident prediction modelling have addressed rural or urban signalised intersections (e.g. Kulmala, 1995; Lau and May, 1986; and Hauer *et al*, 1989). The few which have targeted unsignalised intersections in urban areas (eg. Rodriguez and Sayed, 1999; and Layfield *et al.* 1996) have been based on data from industrialised countries, where road and traffic conditions can be quite distinct from that in a typical developing country, such as Ghana (Salifu, 1996; and Hills and Jacobs, 1981). The need for further in-depth research on the subject of junction control and accidents, as outlined in this study, is therefore self-evident. In the context of road safety and traffic management in Ghana, this study is expected to lead to qualitative improvements in accident blackspot programmes, as well as provide an opportunity to re-examine the rationale for choosing the thresholds for application of specific junction control options, essentially, from a safety perspective.

1.5 Objectives and Scope of the Study

The main aim of this study, therefore, is to develop suitable accident prediction models, as an integral part of a more cost-effective tool for accident appraisal and evaluating alternative interventions at unsignalised urban junctions in Ghana. To accomplish this, the following objectives were set:

- to review previous research that has addressed the subject of safety appraisal and accident prediction modelling for junctions, especially unsignalised urban junctions;

- to retrieve and analyse accident data, in order to establish the scale and main characteristics of accidents occurring at unsignalised junctions in urban areas;

- to collect data on traffic volumes, spot (approach) speeds and aspects of junction geometry and control at a representative sample of unsignalised urban intersections and analyse these, in conjunction with the relevant accident data, to determine the relative risks of accidents for traffic using different junction types;

- to assess the relative contributions of specific road and traffic factors to accidents at given junction types, using appropriate statistical methods, and to formulate models for the reliable prediction of accidents at such junctions; and

- to establish guidelines for the integrated use of model predictions and Empirical Bayesian accident estimation procedure for more refined accident "blackspot" identification and ranking.

In terms of scope, the study focuses on unsignalised junctions in urban areas of Ghana. A representative sample was selected from amongst junctions in a designated case-study area, which had not experienced any major changes over the preceding three-year period (1996-1998) and at least one of whose arms is an arterial road. The junction was deemed to include its centre and immediate area of influence, which for the purpose of this study was defined as the area within 25 meters from the centre of the intersection along each arm. This definition is consistent with the guidelines for coding the location of the accident data. However, it is to be noted that the concept of a junction's zone of influence is much more complicated than that. Essentially, it is the area within a given distance from the centre of the junction along any of the arms, over which traffic activity (i.e. queuing, collisions, etc.) is influenced by what is happening at or in the immediate vicinity of the centre of the junction. In principle, therefore, its extent can vary from site to site, depending on site and traffic conditions, and even for a given site, this is likely to change at different times of the day.

1.6 Structure of the Thesis

The rest of the thesis is organised, as follows:

Chapter 2 presents a detailed review of the relevant literature relating to methods used in the assessment of junction safety and comparative studies for the evaluation of the safety merits of various types of junction control. State-of-the-art methodologies for the development of accident prediction models have also been reviewed. In Chapter 3 are discussed the design of the case-study, methodology for data collection and the type of data collected. The chapter closes with a presentation of the junction types covered by the study and detailed examination of the characteristics of the accumulated database.

Chapter 4 discusses the main characteristics of accidents at unsignalised urban junctions in Ghana. This is done at three main levels. To start with, the subject is put in perspective with a discussion of urban accidents in general. Then the scope is narrowed down to accidents pertaining to unsignalised junctions. The third level is a more quantitative comparative evaluation of the accident records of the different types of junctions in the case-study database. From these analyses, candidate parameters that appeared to have some association with accidents were selected to be tested, among others in Chapter 5, as independent parameters for accident prediction models. Thus, Chapter 5 presents the methodology and procedures adopted for the development of accident prediction models and discusses the different models developed.

The use of Empirical Bayesian procedures, as part of a proposed new approach to safety appraisal, accident blackspot identification and ranking, is discussed in Chapter 6. The particular role of accident prediction models in this context has been highlighted. Also presented in this chapter are nomographs representing probabilistic decision criteria for identifying accident blackspots at T- and X-junction sites.

Finally, the main findings of this study and recommendations for further research are presented in Chapter 7.

CHAPTER 2
REVIEW OF PREVIOUS STUDIES

2.1 Introduction

In order that the state-of-the-art methodologies for safety appraisal and accident prediction be identified and utilised for the current study, a comprehensive review of published works on relevant previous studies was carried out. The review was also intended as a means of appraising these methods and related findings, to structure the current study in a way that it will address the gaps in knowledge in the selected area and achieve reasonable quality assurance in the data collection and analysis.

The Transport Operations Research Group (TORG) and Robinson libraries of the University of Newcastle upon Tyne provided the main sources of reference material, complemented by occasional WorldWideWeb Internet searches. A scan of papers published in Ghana was also undertaken, to identify those which might be relevant to the current study. The pertinent literature, located amongst peer-reviewed journals, periodicals and other technical publications, could be placed under one or another of four categories; namely "before and after studies", "accident prediction models and statistical methods", "traffic conflict analysis" and "other related studies". The review is presented under these broad headings.

2.2 "Before and After" Studies

Studies of this nature generally deal with the comparison of safety levels during equivalent periods before and after the implementation of specific road measures. Support for this approach is offered by Hauer and Lovell (1986), who insist that the safety effects of various measures are better extracted from real-life implementations than from experiments that are staged to meet the dicta of rigorous scientific design. Their contention is that the implementation of a real measure, such as safety interventions, is usually fashioned by the circumstances of the real world and only seldom by the requirements of scientific experimental design. Since most data on the safety effects of measures come in the form of before and after accident counts anyway, it was hardly surprising that the bulk of literature located was in the category of "before and after" studies.

2.2.1 Safety Effects of Increasing Levels of Junction Control

Polus (1985) carried out a study of this nature, where he investigated the associated changes in accident rates when "YIELD" signs were replaced with "STOP" signs, at selected unsignalised urban intersections, because of their accident history. He reported that the increase in the level of control at such junctions through replacing "YIELD" with "STOP" signs tends to increase vehicle accidents but reduced pedestrian accidents. On the whole, therefore, he concluded that increasing the level of control at unsignalised junctions would not necessarily result in an overall reduction in accidents, although it might reduce, on average, the severity of injuries.

Although Lovell and Hauer (1986) presented contrary evidence, after reviewing a number of studies on the conversion of two-way to four-way controls, many other studies reported by Lum and Parker (1982), Chadda and Parker (1983), Upchurch (1983), Lum and Stockton (1982), David and Norman (1975) generally agreed with the conclusions of Polus (1985) and decried the "over-use" of "STOP" signs or four-way control, as being merely restrictive and not justified by the operational and environmental impacts resulting from their use.

Furthermore, King and Goldblatt (1986) investigated the change in accident patterns accompanying changes in intersection control. Using analysis of variance and regression techniques, they observed that, whilst there was a definite shift in the distribution of accident-types, there was no clear-cut evidence that the installation of signals had reduced accidents overall. On the contrary, they noted, in some cases, signalised intersections could actually have higher accident rates. Frith and Harte (1986) and Frith and Dery (1987), however, were less equivocal after carrying out similar studies. Whereas the former observed that "in appropriate situations, all control-changes offer considerable safety benefits", the latter presented contrary results, albeit acknowledged as not being statistically significant, and urged caution in assuming that signalising an intersection will automatically lead to an aggravation of its underlying accident problem.

Other researchers have discussed the problem from the perspective of warranted and unwarranted changes in traffic control. For example, Hanna *et al* (1976) compared the safety performance of warranted and unwarranted signal installations on rural roads and found similar accident rates for both types of installation. In other words, whether the signals were installed at locations meeting the requirements for replacement of unsignalized control or not, the resultant effect on accident numbers was the same. On the other hand, Hakkert and Mahalel (1978) and King and Goldblatt (1975), from studies of urban intersections, reported a tendency for accident rates to increase with signalisation, especially at intersections not meeting the volume or accident warrants.

Similarly, Persaud (1988 and 1986) reviewed a number of studies that investigated the effect of increasing the level of junction control through conversion from two-way to multi-way stop control. He reported that the observation by most of these studies was that the measure appeared more effective when implemented on intersecting roads, where the traffic volumes are nearly equal and the total of these volumes is between 6,000 and 12,000 vehicles per day. This seemed to agree, generally, with the provisions of the Manual on Uniform Traffic Control Devices (MUTCD, 1978). The Manual stipulates that multi-way (4-way) stop control is warranted where "the volume of traffic on the intersecting roads is approximately equal" and "the total vehicular volume entering the intersection from all approaches averages at least 500 vehicles per hour for any 8 hours of an average day".

However, in his own study following the review of previous studies, Persaud (1988 and 1986) seemed to contradict the above conclusions. He argued that there was no credible evidence to suggest that stepping up the level of control at a junction is effective in reducing accidents only for certain ranges of total entering traffic volumes. Neither is it apparent, in his opinion, that the safety effectiveness of such a change in control depends on how this volume is split among the approaches. Instead, he concluded that, in the case of the conversion of two-way to muti-way stop control, the safety effectiveness of the measure (i.e. percent reduction in accidents) was higher only at sites with greater numbers of expected accidents.

The apparent implication of Persaud's (1988 and 1986) conclusion is that, there is no obvious relationship between the expected number of accidents at a site, i.e. the site's accident potential, and the total traffic inflows or the relative split of the flows among the junction approaches. That is intriguing, to say the least. Junction throughput and the share of minor road traffic are generally seen as indices of exposure of traffic to the risk of accident and if these are said not to have any influence on accident numbers, then it leaves one with some confounding questions. First of all, what then will constitute an appropriate exposure index and, secondly, is one to believe, as Persaud's (1988 and 1986) conclusions appeared to imply, that traffic accidents could arise out of zero traffic flows? In an attempt to escape these difficult questions, the author suggests that "there could be other exposure measures which could have an influence", although he is unable to suggest any credible alternative.

Hauer *et al* (1989) also cast doubt on the credibility of traffic control warrants as safety interventions, as well as on studies that appear to lend uncritical credence to them. The authors are of the view that the analytical basis in either case is faulty and tends to lead to exaggerated conclusions about the effectiveness of traffic control measures. One of the key criticisms of these studies was that they were based on comparisons of "before" and "after" accident counts, when instead they ought to be comparing "after" accidents with expected accidents, with the measure not having been implemented.

Despite the lack of consistency, the above findings have some potentially interesting implications for traffic management and safety overall. The very rationale and appropriateness of safety warrants, as recommended in various manuals (i.e. MUTCD, 1978; DOT (USA), 1981 and Highway Capacity Manual, 1997) has been questioned, since, as a rule, these manuals will recommend higher levels of control at sites with high accident rates. As a result, it is has often been taken for granted that increasing the level of control at junctions, through signalisation for example, is an effective remedy for unsignalised sites with bad accident records. But, as the above results would show, the issues are probably, not as clear-cut as that.

In practical terms, what the findings mean, if only on account of their safety performance, is that unsignalised junctions could be maintained to cater for some levels of traffic currently deemed manageable only by signals. In the process, by delaying the introduction of signals, or other "higher order" type of control, the extra resources that would otherwise be required could be utilised for more effective safety interventions elsewhere in the network. Also, reducing the incidence of restrictive controls, which are not justified on account of the accident savings in particular, is likely to increase their effectiveness and the respect for them by drivers at other places where they are warranted. Such developments should have an overall positive impact on network-wide safety levels. But clearly, more information is required, particularly with regard to what could be the acceptable threshold limits and conditions for extending the deployment of non-signalised junctions for traffic management, essentially from a safety perspective.

Thus, Rosenbaun (1983), Polus(1985) and Frith and Dery(1987) have all called for *further research that will provide better experimental evidence into safety at unsignalised intersections, particularly, in the development of more empirically derived guidelines for use of "YIELD" versus "STOP" signs, including models for the prediction of accident rates at different types of intersections for differing traffic control and characteristics.*

The inconsistencies in the results of many "before and after" studies have been attributed to a variety of reasons. The main one, cited by a couple of researchers (e.g. Persaud, 1988; Lovell and Hauer, 1986; and Hauer and Lovel, 1986), is that most of the reported studies fail to account for the regression-to-mean effect. Regression-to-mean is the tendency for accidents at a given site to increase or decrease in successive periods, independent of the effect of traffic measures or the underlying growth trends of traffic through the site. Consequently, part of what has usually been presented as the effectiveness of some traffic measures, in the opinion of Lovell and Hauer (1986), is actually an "artefact" of the regression-to-mean. The other important point, according to Hauer *et al*, (1989), is that "before and after" studies are almost always too small to be statistically conclusive and there is always the threat to the validity of inferences beyond those that the data permits.

Commenting on the results of cross-sectional (i.e. "with" or "without") studies in which the safety performance of traffic signals is compared with unsignalised junctions, Persaud (1988), like Frith and Dery(1987), criticised so-called "incorrect inferences" and advocated caution in using comparisons which invariably lead to the conclusion that signals have a poorer record, because (as he noted) the sites for signals could have had a bad previous accident record even before their installation. This refrain, however, appears to be begging the question, for the fact remains that even after the signal installation, the accident situation did not improve or may even have worsened. The inescapable conclusion, therefore, would be that signalisation, at best, does not solve the problem.

To improve the credibility of "before and after" studies, which Hauer and Lovell (1986) admit constitute a "ubiquitous source of information", despite their shortcomings, Persaud (1988) recommended the adoption of more refined safety appraisal methods that will account for the regression-to-mean effects, as described by Hauer and Persaud(1983 and 1987) and Hauer *et al* (1986). He calls for *"a fresh start, using recent data and more advanced methods of analysis to come up with reasonably accurate answers to the question: Given a set of circumstances for an intersection (approach volumes and speeds, geometry, accident history, junction control etc.), what is the expected safety impact of installing a signal?"*. To accomplish this task successfully, the importance of adequate knowledge of the safety status of various pre-signalisation (non-signalised) intersection controls cannot be over-emphasised.

2.2.2 Accounting for Regression-to-mean Effects

Many researchers have demonstrated that the regression-to-mean phenomenon is real, significant and warrants consideration in any accident analysis, particularly those involving unusually high accident frequencies. For example, Wright and Boyle (1987) estimated that up to 30 per cent of apparent reductions in accident frequencies at potential blackspot sites could be due to the regression-to-mean phenomenon. Similar estimates (20-25 per cent) were reported by Mountain *et al* (1998), in a study of remedial treatments at 1500 high risk sites identified by 10 local authorities in England. At this scale, it must be clear how the effectiveness of most remedial measures, in simple "before and after" comparisons, can easily be overestimated. Also, because the magnitude of the effect varies from one site and treatment type to another (Abbess *et al*, 1981; Wright *et al*, 1988; Kulmala, 1994; and Mountain *et al*, 1998), direct cross-sectional comparisons could be equally misleading.

Persaud and Hauer(1984), Hauer and Lovell (1986) and Wright et al (1988) present a number of methods by which accident data analyses can be purged of the biasing effects of regression-to-mean. The use of matched control groups is recommended, because it offers a good opportunity for obtaining estimates of the accident frequency during the "after" period, in the absence of any intervention and, by so doing, it isolates the true effects of the intervention from the regression-to-mean. But the problem with this method lies in the difficulty of identifying similar sites in the control group, which would have recorded the same number of accidents in the "before" period. There is also the potential for "contamination" of sites in the control group, through the phenomenon of "accident migration" (Persaud, 1986; Wright and Boyle, 1987; and Maher, 1987).

Alternatively, other methods, both parametric and non-parametric, are offered. The non-parametric method, as presented by Persaud and Hauer (1984), uses observed accident frequencies to estimate the expected number of future accidents, based on the sole assumption that accidents at a given site (e.g. junction) are Poisson-distributed. Unlike the alternative method, no assumptions are made about the underlying distribution of accidents across sites. To estimate the number of accidents (α_k) expected to occur during an equivalent after period at a junction that experienced k accidents in the before period, for example, the following factors need to be known: N_k – the number of junctions with k accidents in the population of similar junctions, N_{k+1} – the number of junctions with (k+1) accidents in the population of similar junctions. Then, $\alpha_k=[(k+1)N_{k+1}]/N_k$.

The parametric or Bayesian method, on the other hand, relies on a further assumption that the means of accidents across a population of similar systems (junctions) are approximately Gamma-distributed. With the two assumptions (i.e. Poisson for individual junction accident frequency and Gamma for mean accident frequency across all junctions in a population), the number of junctions of the given population with *k* accidents, according to Persaud and Hauer (1984), must generally obey the Negative Binomial distribution. Thus, the expected number of accidents $\alpha_{k(exp)}$ in the after period at a junction that had *k* accidents in the before period is given by $\alpha_{k(exp)}=[(k+1)N_{k+1(exp)}]/N_{k(exp)}$. To employ this method, the before period accident data are used to obtain the sample mean and variance for the population and from these, are estimated the parameters of the Gamma distribution. Following comparative assessments of the two methods, by applying them to a large number and variety of data-sets, Persaud and Hauer (1984) and Hauer and Persaud (1987) concluded that the Bayesian method generally provides more reliable estimates. This corroborated the evidence of Abbess *et al* (1981), who had reported that the Bayesian approach automatically takes care of the regression-to-mean effect. For systems with zero or one accident, however, the authors found that the non-parametric method gave slightly better results and its use may be preferred under such conditions.

A related study was undertaken by Mountain *et al* (1992a and 1992b), in which the accuracy of two variants of the Bayesian method were compared with a "regression method", through application on a group of treated intersections and links. The first variant (EB1) relied on computations of sample means and variance (i.e. method of moments), whereas the second (EB2) used predictive equations, as in the COBA9 Manual, to produce estimates of the effectiveness of different treatments. In the "regression method", accidents at untreated sites in two consecutive time-periods were fitted into a regression equation to determine coefficients which, in turn, were used to compute expected mean accident frequency for a site. The conclusion was that there appeared to be little to choose between the two EB methods and the regression method in terms of the accuracy of the estimates, although the quality of the estimates in each case depended on the quality of the data used to calculate the regression coefficients.

In an alternative approach, Hauer and Lovell (1986) suggested that the main task is to obtain a good estimate of the number of accidents expected to be recorded during the after-period, had the treatment not been implemented. To do this, the authors present two options. For both cases, let x be the number of accidents recorded at a given site (e.g. junction) during the before-period. Then, the expression $\xi(x) = M(x)$; where $\xi(x)$ is the estimator function and M(x) is the "average after-period count of accidents on those entities (junctions) that recorded x accidents in the before-period and were left without treatment", amounts to stating that: "it is expected that had the treated entity (junction), which in the before period recorded x accidents, been left untreated, it would have recorded during the after period, on average, what has in fact materialised on similar junctions that were left untreated". Thus, the junctions with x before accidents, which were left untreated, are regarded as a control group. Although this is relatively easy to compute, the difficulty in selecting appropriately matched control groups of the right sample size makes this type of estimate subject to random fluctuations and less reliable.

The second and more preferred estimator is given by $\xi(x) = (x+1)\ n(x+1)/n(x)$; where n(x) and n(x+1) are the number of similar entities recording x and (x+1) accidents in the before-period respectively. The advantage of this estimator, in the opinion of the authors, is that it is justified on theoretical grounds and also that only data about accidents occurring in the before period are required. To obtain smooth estimates, two distinct approaches are suggested. First, a continuous function $\xi_1(x)$ may be fitted to the points (x+1) n(x+1)/n(x). When the plot of points indicates a non-linear fit, ordinary least-squares curve fitting techniques are used to obtain $\xi_1(x)$. Otherwise, the second approach is to compute the estimator as $\xi_2(x) = x + \left(\bar{x}/s^2\right).\left(\bar{x} - x\right)$, where $\bar{x}$ and s are the sample mean and variance respectively.

In the study on intersections (Mountain *et al*, 1992a), little difference in the accuracy of estimates was observed between the empirical Bayes and regression methods. But, on application to the link data (Mountain *et al*, 1992b), the EB2 appeared to offer better estimates. The apparent discrepancy in results was attributed by the authors to the different volumes and levels of aggregation of data. Hauer and Lovell (1986) recommended both the "regression" and Empirical Bayes approaches, preferring the former in conditions when the plot of points indicates a non-linear trend.

The connection between data volume, level of aggregation and accuracy of estimates was stressed by Wright *et al* (1988), who observed that the accuracy of the parametric method, in particular, is enhanced when it is applied to accident data accumulated over a long time and when study sites are disaggragated according to layout and physical characteristics. Splitting the observed accidents into "treatable" and "non-treatable", however, did not appear to cause any appreciable improvement in the precision of the estimates. Curiously, Wright *et al* (1988), just as Mountain *et al* (1992a and 1992b) subsequently, observed also that the proposed parametric (Bayesian) method appears to be quite insensitive to assumptions about the form of the distribution of accident rates between different sites. This assumption, incidentally, is a distinctive feature of that methodology. Kulmala (1994 and 1995) employed accident-prediction models to account for the bias due to the regression-to-mean. The models were used first to determine the expected number of accidents before the implementation of a measure. The expected number of accidents during the "after" period, if the measure had not been implemented, was then estimated by correcting for changes in traffic volumes, etc. Following the lead of Hauer and Lovell (1986), the author suggested that an even better estimate could be obtained by feeding the model prediction into the Empirical Bayes formula.

In the studies reported by Kulmala (1994 and 1995), likelihood functions were used to determine the accuracy of the estimates of effects of road improvement measures. Road lighting, stop signs, signal control and the lowering of the speed-limit were found to decrease accidents, whereas additional lanes for turning vehicles and road widening, for example, did not have any significant effect. Fridstrom *et al* (1995) also used prediction models, albeit in a uniquely different way. Using generalised Poisson regression models, the authors were able to decompose the total variation in accident-frequency estimates into purely random and systematic (causal) parts. By so doing, the true effects of the intervention measures were isolated from the spurious effects, such as the regression-to-mean.

2.3 Accident-Prediction Models

2.3.1 Functional Form of Models

Although the single event of an accident is almost impossible to predict, due to its rare and random nature, researchers have found that the aggregation of a large number of accidents over a sufficiently wide area and/or long period of time tends to exhibit a level of predictability that can be described by means of mathematical/statistical relationships (Fridstrom *et al*, 1995). Multivariate accident-prediction models represent a form of such relationships between accident frequency and a set of determining factors. These are empirically derived and vary in form, depending on the explanatory variables used.

The relationship between accidents and traffic flow as a measure of exposure, in particular, has received considerable attention over the years. Tanner (1953), for example, is credited with one of the earliest of such studies on intersections. He analysed accident and traffic flow data for more than 200 rural T-junctions in the United Kingdom and suggested that accident numbers were approximately proportional to the root of the product of the two-way major road traffic volume and turning flows from the minor road. Since then, numerous other forms of relationship, often conflicting, have been proposed.

Hakkert and Mahalel (1978) considered and tested a number of variables they believed would influence the expected number of accidents. They reported that the most appropriate model was one in which accidents were proportional to the product of intersecting vehicle flows. However, other empirical research (e.g. Leong, 1973) found that, contrary to this observation, the number of accidents related to the product of flows, each raised to a power less than one. This "product-of-flows-to-power" relationship received the support of Hauer *et al* (1989) and Hauer and Persaud (1987), who studied accidents at signalised intersections and at highway-railway at-grade crossings, respectively.

In addition, however, Hauer *at al* (1989) also noted that, to obtain logically sound models from such relationships, it is important that the frequency of collisions are related to the traffic flows to which the colliding vehicles belong. This pre-supposes that collisions are categorised by the movement of vehicles prior to the accident and not by initial impact as is often the case. Model forms identified by Lau and May (1986) for signalised intersections were of this form. McGuigan (1981) investigated the "root product flow" after Tanner (1953) and "throughput" or "sum of inflows" relationships and reported that preference for the former over the latter was not universally justified.

This view was endorsed by Worsey (1985) but sharply criticised by Hauer *et al* (1989), as being logically unsatisfactory, as it ("sum of flows") implies the possibility of accidents occurring between conflicting streams of traffic even when one of the flows is zero. The possibility of predicting equal numbers of accidents for a given value of the inflows, irrespective of the distribution of flows between the major and minor arms of a junction was identified, by Mountain and Fawaz (1996), as another logical inconsistency of this model form.

In reality, Mountain and Fawaz (1996) observed that more accidents might be expected when flows from both minor and major arms are of a similar magnitude than when there is a large difference between the two. To overcome the logical inconsistencies of the "sum of inflows" model, Moutain and Fawaz (1996) offered an alternative model, in which the ratio of minor to major road inflows or the proportion of traffic entering via the minor arm are used separately as additional variables. Despite the criticisms, the "sum of inflows" model still appears to be favoured by some researchers (e.g. Jadaan and Nicholson, 1992).

The variety of model forms and views presented here mirrors the continuing confusion regarding the most appropriate form of exposure index, as has been acknowledged by Jadaan and Nicholson (1992). At one extreme, Jovanis and Chang (1986) contend that there is no reason to prefer any one of the functional forms to another whilst, at the other, Hauer (1995) is categorical that substantial empirical evidence now shows that various types of accidents at intersections are indeed a function of some power of the conflicting flows.

Yet another dimension is presented by Lalani and Walker (1981), who also studied the relationship between accident frequency and average daily traffic volumes, and concluded that, while meaningful correlations were developed for signalised intersections and urban arterial segments, no relationship was found between accidents and volumes at unsignalised intersections.

What is probably beyond contention, however, is that model forms may reflect the type and quality of data and that conducting exploratory analysis of the specific data could provide useful clues as to the best functional form to adopt. For example, it has been acknowledged that improving the stratification or dis-aggregation of data increases the likelihood of achieving strong, statistically significant and logically plausible relationships between accidents and traffic flow (Hauer and Persaud, 1987; Hauer *et al*, 1989; Jadaan and Nicholson, 1992; and Mountain and Fawaz, 1996).

The model forms, which rely solely on traffic flows for predicting expected accidents are referred to as "coarse" models. Whilst such models have the advantage of being simple in form, they are useful only as a rough guide for identification of unusually hazardous locations, as well as for the prediction of the effect of traffic flow changes on accident occurrence. Any relationships found are more likely to be associative rather than causal relationships (Mountain and Fawaz, 1996; Layfield *et al.*, 1996; and Summersgill *et al*, 1996).

Flow-based models alone are, therefore, inadequate for the purposes of the current study, the main objectives of which include establishing causal relationships between accident frequency at junctions and a comprehensive range of measurable junction and flow variables. Comprehensive accident prediction models are required, in order to quantify the effect of not only individual treatments but also the complete set of road characteristics, including traffic flows, site features and detailed geometry and traffic control variables.

A series of studies reported by the Transport Research Laboratory (TRL) of the United Kingdom, over the last decade or so, address the subject of comprehensive accident-prediction models for various types of intersections. These include Maycock and Hall (1984) and Pickering *et al* (1986), which discuss accidents at 4-arm roundabouts and rural T-junctions in the United Kingdom respectively. The studies reported by Layfield *et al* (1996) and Summersgill *et al* (1996) are of particular interest to this study, because they addressed cross-roads and T-junctions in urban areas, respectively.

The basic methodology adopted for all these studies has been described, in considerable detail, by Maher and Summersgill (1996). Among others, they highlight the underlying assumptions and peculiar problems, such as low mean value, over-dispersion, dis-aggregation of data, that need to be solved to produce reliable models. Apart from the TRL studies, other reports by Kulmala (1994 and 1995) and Bonneson and McCoy (1993) provide useful reference points for comprehensive modelling of accidents at unsignalised rural intersections.

It is obvious from the above that the subject of comprehensive prediction modelling of accidents at unsignalised urban junctions remains largely unexplored. That is why conclusions from the few reported studies may be considered as tentative only and should form the basis for further independent study (Amis, 1996; and Layfield *et al*, 1996). For example, the approach of Layfield *et al* (1996) and Summersgill *et al* (1996) in examining the effect of only speed limits, as opposed to actual speed, on accident occurrence could be improved because, in practice, speed limits are not necessarily indicative of actual levels of speed observed. In addition to addressing this issue, efforts were made under the current study to include junctions with dual-carriageway arterial roads, few of which have been covered by the reported studies.

It is also significant to note that the models developed so far are based on data from industrialised countries, with high vehicle-ownership levels, and from road and traffic conditions very different in many respects from that in a typical developing country. Therefore, it will be reasonable to anticipate that the significant explanatory variables and the size of their influence are likely to be different in either case. This would underscore the need for the development of relevant "home grown" models for a country such as Ghana.

2.3.2 Statistical Methods

The key tool in the model development process is multiple regression analysis, two types of which have been used in the literature surveyed; classical techniques and the generalised linear modelling approach. Classical least-squares (ordinary) regression techniques were used in developing the early accident predictive models (e.g. Lalani and Walker, 1981; and McGuigan, 1978). However, as observed by Milton and Mannering (1998), recent research has shown that ordinary least-squares regression has some statistical properties that are undesirable for accident data analysis. These include the intrinsic assumption of homoscedascity (i.e. equal variance of the error terms for all values of the predictor variable) and the possibility of predicting accident frequency with negative values. In reality, accident counts are sporadic, discrete and non-negative and their occurrence pattern would be more akin to a Poisson process, like any count data.

The assumption of homoscedasticity under ordinary linear regression was invalidated, by Jovanis and Chang (1986), in a study of the relationship of accidents to total vehicle-miles travelled, when it was discovered that the variance of accident frequency or accident rate (the dependent variable) increased with increasing vehicle-miles. In the circumstances, therefore, the authors concluded that although the use of ordinary regression would not affect the values of the estimated parameters, it could invalidate any hypothesis tests concerning the significance of the parameters, because it distorts the confidence intervals on which the parameters are based. Consequently, Jovanis and Chang (1986) argued for the use of the Poisson distribution as a more reliable basis for the prediction of accidents.

However, an attribute of the Poisson distribution, namely that the mean of the predicted variable is equal to its variance, does not usually hold when a substantial proportion of the database comprises zero accident counts, as is often the case in accident prediction modelling. Thus, whilst generally agreeing with Jovanis and Chang (1986), Miaou and Lum (1993) criticised the Poisson distribution as inadequate when over-dispersion is present in the data. With over-dispersed data (i.e. when the mean is less than the variance), Miaou and Lum (1993) observe that the Poisson model tends to produce inaccurate estimates. As a solution to this problem, the authors recommended the adoption of the Negative Binomial distribution, a more general probability distribution, which relaxes the constraints on the mean and variance. Following this lead, Milton and Mannering (1998) used and confirmed the general superiority of the Negative Binomial distribution assumption for accident modelling.

In other, more recent studies, (e.g. Layfield, *et al*, 1996; Summersgill, *et al*, 1996; Mountain and Fawaz, 1996; Kulmala, 1994 and 1995; and Hauer *et al* 1989), the technique of "generalised linear models", using the software package GLIM (McCullah and Nelder, 1989; and Aitkin, *et al*, 1989) has facilitated the use of more generalised probability distributions like the Negative Binomial. The GLIM approach is preferable because it allows the representation of accident counts as coming from the family of exponential distributions, from which one can be chosen to correspond to the data used and it yields maximum likelihood estimates of parameters, i.e. values of parameters that are most likely to have given rise to the accident data.

The adoption of the Negative Binomial error structure as the overall distribution stems from the assumptions that the numbers of accidents at any site, like all observed counts, follow a Poisson distribution, while between-site variations in mean accidents follow a Gamma distribution (Hauer and Persaud, 1987). The shape parameter of the between-site variations (Gamma distribution) in mean accident frequencies is estimated through an iterative process (Mountain and Fawaz, 1996).

It is noteworthy that, notwithstanding the above developments, some authors in recent studies (eg. Ben-Akiva, *et al*, 1999) have continued to use the classical regression techniques in accident modelling. In doing this, they try to avoid the problem of predicting negative accident frequencies or accident rates by subjecting the predictive equation to *a priori* constraints. Alternatively, non-linear models may also be used in place of linear ones to avoid the prediction of negative values. The trouble with the latter type of manipulation, as observed by Jovanis and Chang (1986), is that it leads to indeterminate solutions such as the logarithm of zero, as the non-linear models are linearised using the log-transformation process. Confronted with this situation, some authors opt to add a small nominal figure e.g. 0.02 to all zero accident frequencies. But both types of manipulations, i.e. either by constraining the model *a priori* or by pre-treatment of zero accident frequencies, are reckoned to result in biased estimates and are therefore undesirable.

2.4 Traffic Conflict Studies

Traffic conflict studies, based on the Traffic Conflict Technique (TCT), originally proposed by Perkins and Harris (1968), have been used as an alternative approach to the evaluation of accident potential of intersections. Basically, the traffic conflict is perceived as a proxy, or surrogate measure, for accidents and the extent of conflicts observed is said to reflect the level of accidents that "might have been". Thus, from the analysis of observed conflicts some patterns emerge on the basis of which deficiencies at the given intersection are identified and promptly remedied. A key advantage of this approach is that the potential accident problem is identified and solved in a more proactive manner, instead of waiting for several years to accumulate enough accident data for analysis. Hence, if applied in a systematic manner, conflict studies could enable traffic engineers to keep pace with (or even ahead of) the development of accident problems within their areas of jurisdiction. Also, because conflicts are much greater in numbers than actual collisions, it means that the database for traffic conflict analyses would normally constitute better statistical samples than the corresponding actual accident data.

However, whereas the initial problems relating to standardisation of definitions of conflict may have been largely resolved (ITE, 1977), more work remains to be done. This is particularly so in respect of standardising procedures for the observance and recording of conflict, categorisation of conflicts by severity and relating conflicts to the actual accidents that occur. These undermine the objective application of the technique and its universal applicability. Considerable efforts continue to be made to improve upon the Swedish version of the Traffic Conflict Technique, in particular, Hyden (1987), Almqvist and Hyden (1994) and Hyden and Almqvist (1995).

Nonetheless, an important question, which remains insufficiently addressed, is whether the safety diagnosis for a given location, reached on the basis of traffic conflict analysis, is as accurate and informative as the one that would have been drawn from the relevant accident data. In response to this question, a number of researchers have investigated the relationship between traffic conflicts and accidents but the findings and conclusions have been anything but consistent. Glauz *et al* (1985), for example, analysed conflicts and historical accident data at 46 signalised and unsignalised intersections in the greater Kansas City area. A methodology was also developed for identification of "expected" and abnormal conflict levels for these intersections. The conclusions returned were that, overall, certain types of traffic conflicts can produce estimates of average accident rates nearly as good as those produced from historical accident data.

In a different study, Malaterre and Muhlrad (1980) made some findings and conclusions which have serious implication for the relevance of conflict studies as an alternative tool for safety appraisal. They reported that the distribution of risk values (probability of collisions) calculated from conflicts were quite different from the distribution of accidents at any given intersection. Specifically, whereas the risk attributed to "two-wheelers" and "left-turns" was too high, conflicts with right-angle trajectories were underestimated. Overall, they observed that the correlation between risk and injury accidents was as low as 0.14. These led to the conclusion that, far from being constant, the relationship between conflicts and accidents varies not only according to the type of conflict but also according to the type of junction studied. In some cases, the authors further discovered that it is even impossible to find a qualitative connection between conflicts and accidents.

In some sense, the above results are suggesting that the technique of conflict analyses may be unrepeatable and impractical to some extent. For, if conflicts, as proxies, cannot be said to have any consistent qualitative relationship with the actual accidents, then it will not only be difficult to say how representative the former is of the latter but also the safety (accident-prevention) basis of conflict analysis may be in doubt. Many other studies in the past, as reviewed by Glauz and Migletz (1980), have also been unsuccessful in establishing direct relations between conflicts and accidents. Against this background, it would appear that the conflict technique might be more of a traffic management tool than a reliable safety appraisal tool. Interestingly, the objectives of traffic management do not necessarily coincide with safety objectives.

To improve confidence and consistency in the use of traffic conflict analysis for safety purposes, particularly in establishing direct relations between conflicts and actual accidents, Malaterre and Muhlrad (1980) advocate the need for further improvement in the techniques of conflict data collection. In their opinion, sufficient reliability can only be reached through more refined definition of criteria to detect and grade conflicts and more thorough training of observers, neither of which is "ever simple". It is to be noted that more recent developments show that the use of audio-visual equipment could greatly enhance the task of conflict data collection. Very significant progress has also been made in categorising conflicts by severity using the relationship between the time to accident or collision (TA) and vehicle speeds on approach to the junction (Almqvist and Hyden, 1994). The "time to collision or accident" is calculated as the time between the point of taking an evasive action and the likely point of collision had the vehicles continued to travel as before without taking evasive action. All things considered, however, it is acknowledged (Glauz *et al,* 1985) that conflict studies, at least for the moment, are *"very helpful, only if there are insufficient accident data to produce an estimate"*. In other words, it is only the next best approach to analysis of actual accident data.

Our study is based on the analysis of historical accident data. It involves conflict analysis only to the extent that efforts are made to disaggregate and analyse the accident data according to the category of conflicting vehicle movements, prior to the occurrence of the accidents. The proactive attribute of the conflict technique also forms part of our study objective as we seek to develop predictive models, which, once developed, could be used for safety appraisal instead of waiting to accumulate fresh accident data.

2.5 Other Studies

In this section, a review of relevant studies carried out in Ghana is presented.

2.5.1 GHA/DUR Studies

Typical accident "blackspot" studies are carried out by the local Building and Road Research Institute (BRRI) on behalf of the Ghana Highway Authority (GHA) and the Department of Urban Roads (DUR), the main road agencies under the Ministry of Roads and Transport (MRT). The highway study (BRRI, 1998) involved about 50 accident prone-locations on major trunk roads, scattered all over the country. The sites were identified and ranked on account of the total number of accidents recorded over a three-year period. No attempt was made to control for either regression-to-mean effects or intensity of use.

As expected, most of the sites were sections of road with "problem" geometric elements, such as sub-standard curves, restricted sight distances or steep inclines. The analytical technique adopted was to identify a clustering of "treatable" accidents of common type (e.g. skidding, loss of control, etc.), which will normally give an indication of the problem at the particular site and therefore the possible solution. It was assumed that this approach would reduce the susceptibility to random effects of the main method of identifying sites by accident numbers.

The same procedure was employed in the DUR study (BRRI, 1999), in which a predetermined number of "blackspots" was selected from ranked lists for the five main cities of Ghana. This particular study is of interest to the current research, because it gives a good indication of the types of accident occurring in urban areas and their locational distribution. For example, it was discovered that a large majority of junction accidents took place at unsignalised T- and X-junctions. Like the GHA study, it is also of interest because of the concept of "treatable" accidents applied, which might prove useful in redefining the measure for potential accident reduction under this study.

2.5.2 Study of Urban Pedestrian Accidents

This study (Salifu, 1996) was carried out in Ghana's second city (Kumasi), which happens to have the highest vehicle-ownership level (102 per 1000 population) of any city in the country. The objective was to determine the scale of the problem, main characteristics and locational distribution of pedestrian accidents in an urban environment, with a view to recommending remedial measures or appropriate areas of further in-depth research. The study revealed that up to 40 per cent of pedestrian accidents involved children under age 15 and that junctions were prominent as locations at which such accidents took place. More interestingly, pedestrian accidents were found to be rather frequent, even at places with designated crossing facilities like zebra crossings.

A follow-up study (Salifu, 1998) established that, in some cases, as many as 9 in every 10 drivers failed to stop for pedestrians on zebra crossings. This finding would again show the distinct differences in road-users' behaviour between Ghana, a developing country, and a typical industrialised country. Hence, there is the need to undertake local diagnostic studies and review imported "standard" solutions critically before adoption. For example, it is obvious that, with this background, zebra crossings as a safety intervention are not likely to perform as well in Ghana as they do (for example) in the United Kingdom.

2.5.3 Distribution of Vehicle-speeds on Urban Arterial Roads

In another study (Salifu *et al*, 1996), the distribution of vehicle-speeds was assessed in relation to the stipulated maximum speed-limits on selected sections of urban arterial roads. It was discovered that actual speeds were often completely at variance with speed-limits and in many cases more than 4 out of 5 vehicles were exceeding the legal limits. What this means is that in accounting for vehicle-speed as an explanatory variable in accident prediction, it will be unrealistic (in the Ghanaian context) to use speed-limits, as has been done in the TRL studies discussed elsewhere in this report. A more realistic indicator of actual speeds of vehicles, such as the 85-th percentile of the observed speeds, would probably be required.

2.6 Conclusion

A considerable amount of literature has been generated through previous studies into the relative safety merits of various types of priority junction controls and signalised intersections. The bulk of these studies, as reviewed, were of the "before and after" type. The review has confirmed that the results remain largely inconclusive and often contradictory. Differences in the type and volume of data-sets, the methods of analysis and, more significantly, the failure by some authors to account for the regression-to-mean effect were identified as possible reasons for inconsistencies in conclusions reached by various studies.

In the course of the review, it has also been revealed that most studies on accident prediction modelling have dealt with the development of coarse, as opposed to causal, models for rural or urban signalised intersections. Only a few studies have tackled comprehensive modelling of accidents at unsignalised urban junctions and even these were based on data from industrialised countries. Furthermore, the development of prediction models was often pursued as an end in itself, rather than as a means to an end.

Overall, the review has not only underscored the need for the current study, but it has also revealed some innovative methodologies, most of which have been used to enhance the output from this study. Unique features of the current study thus include comprehensive modelling to predict accidents at unsignalised urban junctions, using real data from a developing country, and the integration of these predictive models with the Empirical Bayes procedure to produce refined estimates of accident potential.

CHAPTER 3

DATA COLLECTION

3.1 Introduction

One of the key objectives under this study was to collect relevant road and traffic data that will characterise the environment and operational conditions around typical unsignalised urban junctions in the case-study area. In this chapter, the design of the case-study and methods employed in the data collection process are presented in the first of two sections. The second section discusses the main attributes of the accumulated database, particularly the typology and number of junctions and related data on total traffic inflows, approach speeds, pedestrian numbers, traffic control and the numbers of accidents recorded. The objective of the latter section is to give a descriptive background and context to the analysis of accident characteristics at junctions, which follows in the next chapter.

3.2 Design and Methods

3.2.1 The Study Area and Type of Data

Data collection was limited to the case-study area, which encompassed the Greater Accra and Kumasi Metropolitan Areas. The Greater Accra Metropolitan Area (GAMA) has an estimated population of 3 million and average car-ownership of 82 per 1000 population. The total length of the surfaced urban road network is 213km. By comparison, the Kumasi Metropolitan Area (KMA), which is the second in size in Ghana to GAMA, has about 1.5 million people but its car-ownership, at 102 per 1000 population, is the highest in the country. The total length of the surfaced urban road network in the KMA is 134km. Between them, the two metropolitan areas account for about 60 per cent of national traffic (veh-km) and a similar proportion of the total traffic accidents. It was assumed that with these characteristics, these two cities would be representative enough of urban traffic conditions in Ghana as a whole.

The data collection process involved the selection of the case-study junctions and the collection in the field of data at each one of these junctions covering traffic accidents, traffic flows, including vehicle counts classified by turning movements, and approach spot speeds. Data was also gathered on the essential geometric and site details of the junctions and the number of pedestrians crossing each arm.

3.2.2 Selection of Case-Study Junctions

A judiciously selected sample of junctions, stratified mainly by traffic flow and junction features, was chosen to ensure that as wide a range of flows and junction features as possible would be captured. A purely random (and unstratified) sample of the same size, arguably, would not have guaranteed the inclusion of some key variables likely to have a significant impact on accidents.

An initial list of all identifiable unsignalised junctions was compiled, using the latest 1:50,000 Ordnance Survey maps for the two cities. This was done with the assistance of the respective maintenance engineers of the Department of Urban Roads (DUR), who had a good knowledge of the network conditions. Care was taken to have as wide a geographical spread as possible in order to include junctions with roads at different levels of the urban road hierarchy and with varying road and traffic conditions.

The list comprised 130 sites, 78 in GAMA and 52 in KMA. The proportion of sites in each area roughly reflected the relative sizes of their road networks. A balance of approximately 3 X-junctions to every 5 T-junctions also reflected the estimated proportions in which these junctions are present in the networks. All sites in this initial list were visited in a follow-up reconnaissance survey, during which some were discarded for various reasons, e.g.:

- the site turned out to be a signalised junction, roundabout or other special type of junction;

- the site was thought to have seen some significant changes in features that could have affected its safety status during the study period 1996-1998 inclusive;

- a bus stop, taxi rank or other parking area was close to the site;
- sight distances were obstructed by adjacent development or due to the location of the site on a bend; and
- at least one of the junction's arms was for one-way traffic only, in the case of single carriageways.

At this stage, some basic features of the junctions, i.e. layout, number of lanes on either arm, channelisation, traffic control type, etc. were recorded. 15-minute counts of traffic were also carried out for the purpose of obtaining quick initial estimates of traffic volumes. The final list of junctions to be included in the case-study was decided after carefully considering and dropping some more sites from the initial list of 130. This further "cull" was to ensure that:

- an approximate ratio of 3 X-junctions to 5 T-junctions and a similar ratio of total sites from KMA and GAMA respectively was maintained, as far as possible;
- a balance of different junction layouts and traffic flow levels was achieved; and
- enough sites of similar geometric characteristics, with different flows in the various junction categories, were available to enable reasonable statistical analysis.

The final sample was made up of 91 sites, of which 57 were T-junctions and 34 X-junctions. Although Layfield *et al* (1996) recommended 15 as an ideal sample size for each junction category of specific features, it was not always possible to meet this requirement. The minimum number of sites for any junction category in the sample was 6, the reason being mainly due to the non-availability of some types of junction meeting the set criteria in the two cities.

The alternative would have been to broaden the scope of the case-study to cover other cities but resource constraints, particularly of available time and money, did not permit. This notwithstanding, it was still thought that making a minimum number of six (6) sites in each junction category, in addition to accumulating an extensive database, provided a sufficiently good basis for reasonable statistical analysis.

3.2.3 Accident Data

Accident data, covering the period 1996-1998 inclusive, for the GAMA and KMA were retrieved from the national database at the Building and Road Research Institute (BRRI). These are records of all accidents reported to the police within the reference period and each of the designated areas. It represents the most comprehensive database on accidents in the country, for the following reasons:

- by law, it is mandatory for motorists to report any accidents involving their vehicle to the police;
- a standard accident report form is normally completed by the police on each reported accident and subsequently forwarded to, or retrieved by, the BRRI. This form (see Appendix 3I) requires comprehensive information on about 90 variables relating to the time, place and circumstances of each accident. Some of the specific variables include the site conditions and details, accident severity and casualty details, driver and vehicle details, sketches of the site location and dispositions of vehicles at the accident scene, time and light conditions, collision type and vehicle manoeuvre prior to collision;
- all accident data are systematically coded and stored for computer analysis at the BRRI, using the Micro-computer Accident Analysis Package (MAAP5) developed by the Transport Research Laboratory of the United Kingdom (Hills *et al*, 1994). This is specialised software equipped with many diverse features for virtually any conceivable manipulation of accident data. Some of these features include cross-tabulations giving a general overview of the accident problem at any level, accident plots on scanned, or vector, maps to enable high accident locations to be easily identified and "stick diagram" analysis, which assists the investigator to do detailed analyses to uncover common factors in groups of accidents; and
- a very concise location-coding system ensures that accidents occurring at specified locations on the network can easily be retrieved, using the appropriate grid-references (X,Y co-ordinates), a link-node reference system, or strip maps.

Naturally, not all accidents will be reported to the police and this data is, therefore, subject to some shortfalls. A study on the incidence rates (per 1000 population) of pedestrian injuries/accidents in the Kumasi municipality (Salifu and Mock, 1998), for example, found that the population-based incidence rate was about ten times the rate based on cases reported to the police. Obviously, this finding was specific to pedestrian injuries in a localised area and cannot be extended to cover all types of accident although it does give some impression about the potential levels of under-reporting. Since no extensive studies have been carried out to estimate the overall extent of under-reporting of accidents, it will be difficult to account for it in any systematic manner in the current study. Thus, the data on which this study is based, although assumed to be reasonably representative, may not necessarily reflect the true extent of accident occurrence on the urban road network. It is also assumed that the level of reporting is consistent even if not complete.

3.2.4 Traffic Flow Data

Traffic flow data gathered included vehicle counts classified by type of vehicle and turning movement, counts of pedestrians crossing all arms of the junction and spot speeds of vehicles as they approached the junction area along each of the major arms. For many of the sites within the Greater Accra Metropolitan Area (GAMA), historical flow data for the study period were obtained from the Department of Urban Roads. For the rest of the sites and all those within the Kumasi Metropolitan Area (KMA), the required data had to be collected through field surveys.

A team of technicians from the Building and Road Research Institute, with considerable experience in traffic data collection, formed the core of the survey team. Other people were specially recruited and trained to undertake the assignment. Whilst out in the field, the less experienced recruits worked under close supervision of the experienced staff. To facilitate the data collection process, field sheets were designed for each type of data. All that was required of enumerators was to tally in the appropriate column or tick an option. To simplify matters further, vehicles were required to be classified only into three broad groups, namely, cars, "trotros" (minibuses) and Heavy Goods Vehicles (HGVs)/Buses.

At each site, one enumerator was assigned to each arm of the junction and tasked to tally the incoming traffic by type and direction of travel through the junction. Two additional enumerators were tasked to count the numbers of pedestrians crossing the major and minor roads, respectively. Traffic counts were carried out at all sites during the morning and evening peak periods from 07.00 to 09.00 and from 17.00 to 19.00 each day from Monday through to Thursday each week. The choice of these times, whilst helping to keep down the cost of undertaking the surveys, also enabled advantage to be taken of conversion factors (established in previous studies commissioned by the DUR) to convert peak hour traffic into Average Annual Daily Traffic (AADT). Using these AADTs and the relevant traffic growth factors, it was then possible to compute the cumulative throughput of traffic for each site for the entire period 1996-1998 inclusive. By the choice of days for the surveys, non-typical weekend traffic was avoided. Pedestrian counts were carried out for the same period as that for vehicle turning movements. No attempt was made to adjust pedestrian traffic for time trends, since there were no appropriate conversion factors. Instead, it was assumed that the average peak hour numbers of pedestrians crossing the minor and major roads respectively had not changed from the times the accidents were recorded.

For the measurement of spot speeds, a team of two people equipped with a Radar Speed Gun was required. One person operated the speed gun whilst the other recorded the readings. At each site, the point at which vehicle speeds were to be measured was marked out discreetly. The point chosen in each case was 25 meters upstream from the centre of the junction along the major arms, representing the presumed limit of the junction's zone of influence.

To take measurements, the team positioned themselves close to the centre of the junction on the near-side shoulder to face on-coming traffic. They operated from a parked car to conceal their presence and that of the speed gun from vehicle-users. Making a more obvious presence with the speed gun could have influenced drivers to reduce their normal speed. After calibrating the speed gun, using a special 50km/h tuning fork, the team proceeded to take the actual measurements.

Vehicle speeds were measured as they approached the junction within the marked distance. The speed of every tenth vehicle, provided it was not in a platoon was measured until a sample size of 40 was achieved. This is the recommended minimum sample size for a typical urban arterial road (Garber and Hoel, 1988). The exercise was carried out on the same days of the week as the traffic counts, but during the off-peak traffic hours of 10.00 to 12 noon and 14.00 to 16.00. Off-peak periods presented the opportunity to capture the more critical speed characteristics. It was assumed that during the overall period for which accident data will be analysed (i.e. 1996-1998 inclusive), the average level and distribution of vehicle spot-speeds did not change significantly and were similar to those measured.

In fact, a comparison of the speed data was made for a few arterial roads constituting the major arms of some of the study junctions with those measured by an earlier study (Salifu *et al*, 1996). This showed that the speed levels had changed very little over the period. Thus, the mean of the spot speeds measured for each site was taken to represent the mean values for the overall time-span (i.e. 1996-1998 inclusive) of the accident records. Other speed parameters, such as the 85-th percentile and the standard deviation, were also computed for each site and the same assumption as made for the mean spot speeds (i.e. constant with time) was applied to them. To enhance the consistency of the data collection process, the same survey teams were maintained throughout the project.

3.2.5 Site and Geometric Data

Junction inventories were carried out in both GAMA and KMA to collect or confirm information relating to the site details. Two teams of two people, each equipped with inventory checklists, a tape measure, pedometer and a car, worked independently on sites in each of these areas. Working on Sundays, the teams were able to move around quickly from one site to another in low traffic and carry out measurements without interference from or disruption to traffic.

The information collected included junction layout, type of major and minor roads (whether single or dual carriageway), numbers and widths of lanes, types of median, or other island, if any, and the dimensions. Other factors were types of traffic control, street lighting and pedestrian crossing facilities, whether designated or not. Due to the absence of as-built drawings for nearly all the sites, it was not possible to measure the radius of curvature of the entry kerb lines, which were considered important. Instead, as a good proxy for this, the widths of the minor roads were measured at the neck of the junctions in each case.

Sight distances were not measured since the case-study junctions were generally on open and level terrain devoid of any obstructions to sight lines. The data on traffic control types also included road markings as well.

3.3 DATABASE CHARACTERISTICS

3.3.1 Number and Typology of Junctions

The distribution of the different junction types in the sample is presented in Table 3.1. Junction types are classified by layout and the presence, or otherwise, of kerbed islands and auxiliary lanes on either the minor or major arms, as presented in Appendix 3II. These are the commonest types of junctions and their numerical distribution in the sample reflects broadly their occurrence in the network.

Table 3.1 Numerical Distribution of Junction Types

*Junction Type**	*1*	*2*	*3*	*4*	*5*	*6*	*TOTAL*
T-junctions	21	7	6	6	9	8	**57**
X-junctions	14	11	6	3	-	-	**34**
TOTAL	-	-	-	-	-	-	**91**

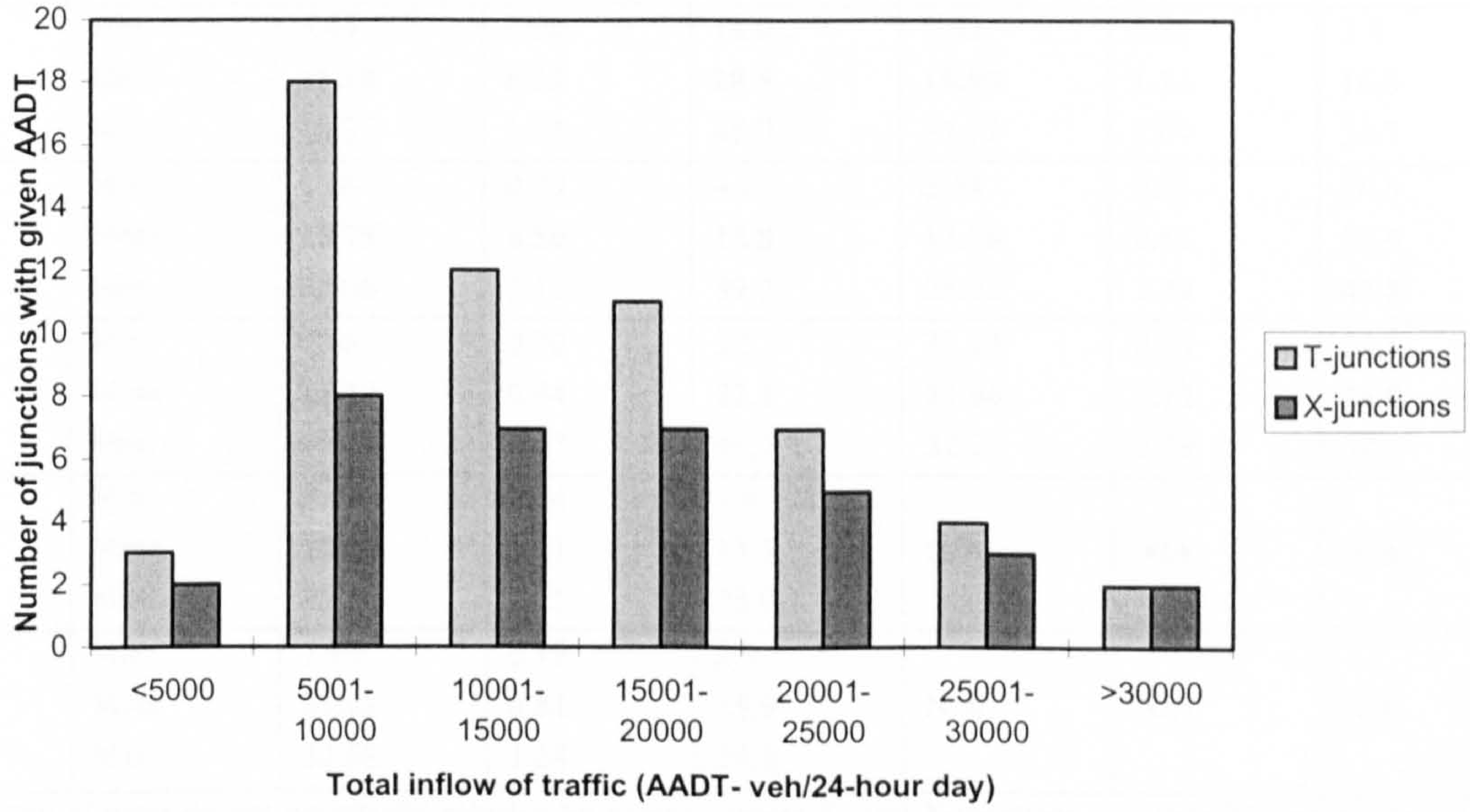
***Description of types do not necessarily coincide by number across T- and X-junctions, e.g. type T2 and X2 do not have similar features. See junction-type classification in Appendix 3II.**

Thus, for both T- and X-junctions, the largest proportion of sites, about 40 percent in either case, belonged to the junction type **1**, which has no features on either arm. Typically, the arms of such junctions are sections of single carriageway roads at the tertiary (minor arterials or collectors) level of the urban road hierarchy. For the T-junctions, types **T-5** and **T-6** are the next largest in the sample, as they account for 16% and 14% respectively of the total number. Although the major road in either case is a dual carriageway, with two approach lanes, **T-6** unlike **T-5** has an additional storage lane for left-turning traffic. In the case of X-junctions, type **X-2** makes up a third of the total, the next highest percentage after **X-1.** The three sites under junction type **X-4** which had left-turn storage lanes on both approaches of the major road, obviously did not meet the requirement of a minimum of 6 sites for statistical analysis. This particular junction type (**X-4**) has been listed separately here for the purpose of illustration only. In the analysis that follows in the next few chapters, the three sites in this group have been added to the sites in type **X-3** with which they share key common features.

3.3.2 Patterns of Vehicle and Pedestrian Flows

Figure 3.1 illustrates the distribution of the main junction types by the total junction inflows, as represented by the Average Annual Daily Traffic (AADT). The flows cover the range from just under 5,000 to over 30,000vehicles/day and it would appear from the chart that the task of selecting a broad-based sample of junctions across this range was relatively successful. The flow band with the highest number of sites for both T- and X-junctions was 5,001-10,000.

Figure 3.1: Distribution of junctions by total inflow of traffic(AADT)



This would underscore the fact that a significant number of the sites were junctions between minor arterial and collector roads. The range of vehicle inflows for the different types of junction, the minor road's share of traffic and the peak hour pedestrian traffic crossing all arms of the junctions are shown in Table 3.2. Comparing the mean vehicle inflows of the junction types with similar features, but which differ only in the number of arms (i.e. **X-1** to **T-1**; **X-2** to **T-5** and **X-3** to **T-6**), only a marginal difference occurs between **X-1** and **T-1.** On the other hand, the inflow of **X-2** is about 3,000 vehicles per day more than that for **T-5.** However, the AADT for **T-6** is about 7,700 more than that for **X-3.** These trends may be slightly unexpected because with effective traffic control and all other things being equal, the X-junctions would be expected to deliver much more traffic than the comparable T-junction. In this case, however, it seems probable that the throughput of the respective X-junctions has been adversely affected by the much larger proportions of minor road traffic and high numbers of pedestrians crossing the arms concerned. These two factors tend to aggravate the conflict situation at unsignalised intersections and, by so doing, impede vehicular flow.

Table 3. 2 Total vehicle inflows range, minor road's share of traffic and peak hour pedestrians crossing junction arms by junction-type

Junction type*	Traffic inflow levels	T-JUNCTIONS			X-JUNCTIONS		
		Vehicle Inflows (AADT) (x 1000)	Peak hour pedestrians Crossing (x 100)	Minor road's share Of traffic (%)	Vehicle Inflows (AADT) (x 1000)	Peak hour pedestrians Crossing (x 100)	Minor road's share Of traffic (%)
1	Min.	4.36	0.21	3.7	3.42	0.18	13.0
	Mean	11.48	0.60	25.4	11.76	1.14	35.6
	Max	25.35	2.02	48.3	24.32	4.08	48.6
2	Min.	5.49	0.08	18.0	9.62	0.25	3.4
	Mean	11.10	0.52	28.8	18.90	1.14	16.0
	Max.	16.85	1.44	46.0	31.07	5.04	34.7
3	Min.	6.68	0.20	4.0	5.54	0.21	14.5
	Mean	15.75	0.50	18.8	13.76	0.81	36.5
	Max.	25.06	1.12	39.2	28.92	2.39	45.8
4	Min.	7.66	0.20	3.5	23.93	0.24	21.5
	Mean	11.79	0.54	22.1	27.64	1.12	25.8
	Max.	15.79	2.07	46.7	32.24	2.79	32.2
5	Min.	3.43	0.24	1.8	N/A	N/A	N/A
	Mean	15.85	1.21	13.7			
	Max.	25.82	3.15	33.0			
6	Min.	7.12	0.19	2.9	N/A	N/A	N/A
	Mean	21.41	0.81	15.9			
	Max.	32.68	1.64	29.6			

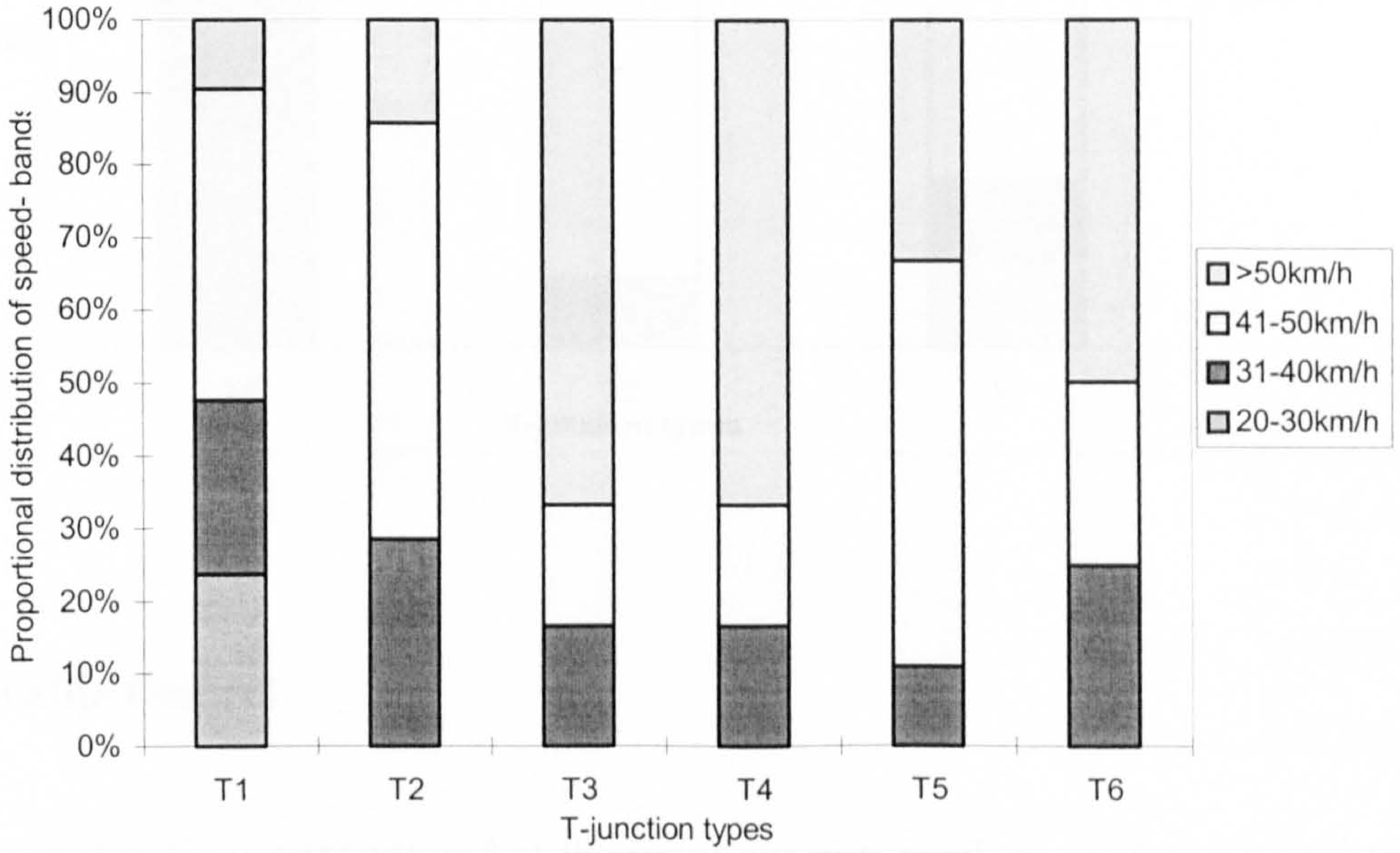
*Description of types do not necessarily coincide by number across T- and X-junctions, e.g. type T2 and X2 do not have similar features. See junction-type classification in Appendix 3II.

The apparent effect of the minor road's share of traffic, in particular, may be seen more clearly in the comparison between **X-3** and **T-6**. It appears that the difference of 7,700 veh/day in AADT between the two junction types is attributable to the fact that **X-3**, the one with the lesser flow, has more than twice the proportion of minor road traffic than **T-6**. Another point worth noting is that, within each junction group, the inflow levels are much higher for the junction types with features on the major arms than those without. This is hardly surprising, since the major junction arms with features were, for the most part, on sections of primary arterial roads.

3.3.3 Vehicle Approach Speeds

The means of spot speeds of vehicles measured as they approached each site were classified in four speed-bands and summarised for each junction type. The results are illustrated in Figure 3.2a and Figure 3.2b respectively, for the various T- and X-junction types. Overall, about 80 percent of mean spot speeds at T-junction sites were 41km/h and above, whilst as many as 42 percent were in excess of 50km/h (the mandatory speed-limit).

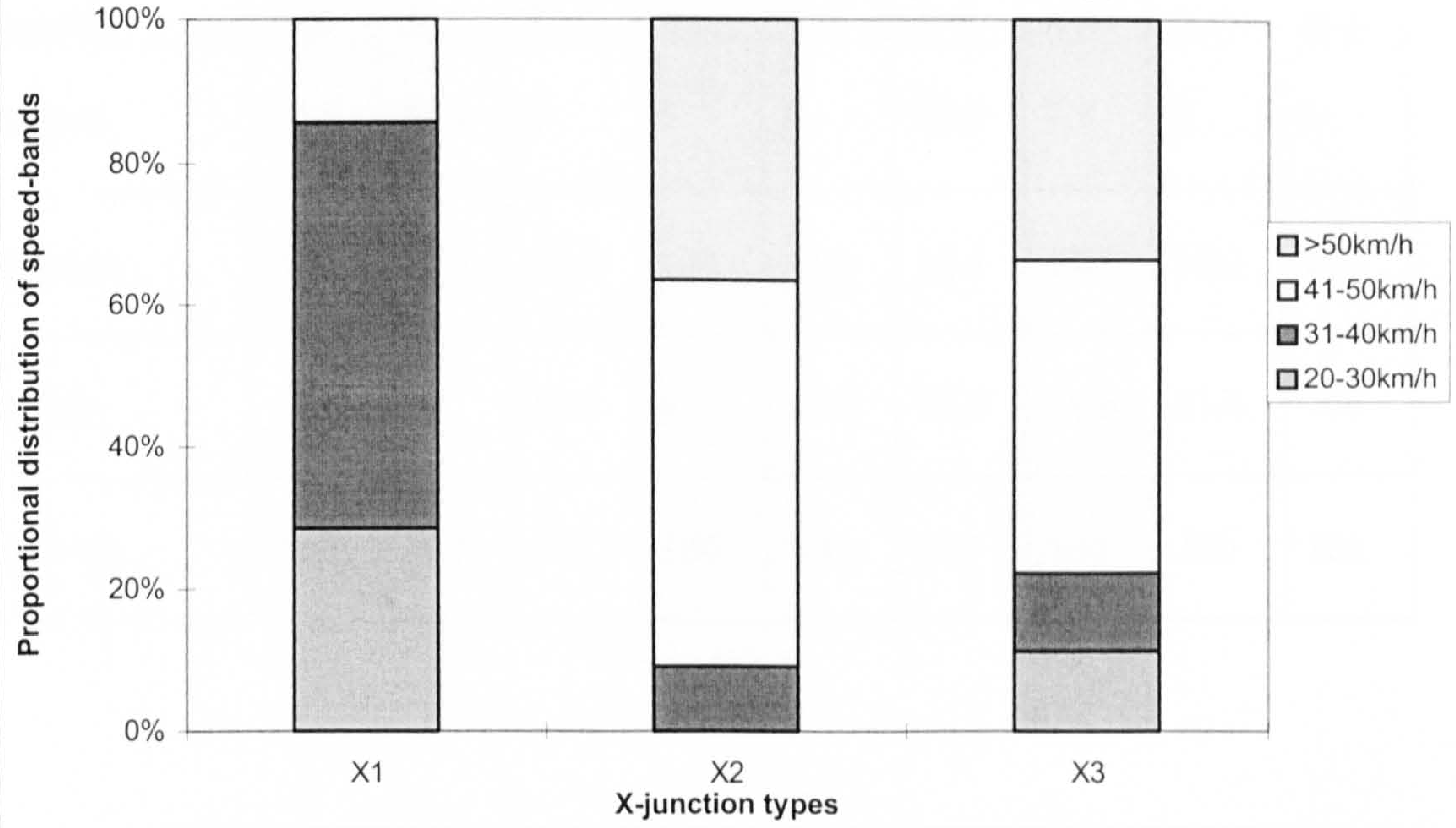
Figure 3.2a. Distribution of mean spot speeds on approach to T-junction sites grouped for different junction types



However, within each junction-group, significant variation exists. The junction types without any features on the major arms (i.e.**T-1** and **T-2**) recorded a higher proportion of low speed-bands (up to and including 40km/h). More than 85 percent of spot speeds on the major approaches to junctions with features (i.e.**T-3**, **T-4**, **T-5** and **T-6**) were in the 41km/h and above speed-bands.

Significantly, the latter group of junctions also had more than 56 percent of speeds above 50km/h, which is the mandatory maximum speed limit for all areas covered by the case-study. The X-junctions (i.e. **X-2** and **X-3)** also recorded 40 per cent of speeds above 50km/h. The import of these speed-trends is that they justify the need, as argued within this study, to use indicators of actual junction approach speeds in the development of accident prediction models instead of the values of general speed-limits. Clearly, contrary to the assumption in many previous studies, the speed-limits cannot in this case be said to be a reasonable proxy for the actual operating speeds.

Figure 3.2b. Distribution of mean spot speeds on approach to X-junction sites grouped for each junction type



3.3.4 Traffic Control

Traffic control options encountered at the junctions surveyed, as evidenced by the signs posted on the minor arms, were of three kinds; no control, yield control and stop control. The percentage distributions of these control measures are presented by junction type in Table 3.3. It can be seen that the large majority of junction types **T-2**, **T-3** and **T-4** were controlled by the YIELD priority arrangement, which requires vehicles on the minor approaches to slow down, and stop if necessary, to give way to traffic entering the junction on the major approach.

On the other hand, at junction types **T-5**, **T6**, **X-1**, **X-2** and **X-3** the dominant control type was STOP. The highest proportion of sites with no control at all were of the junction types **T-1** and **T-2** and, to a slightly lesser extent, at **T-6** sites. Traffic control signs were found only on minor approaches. The only type of signs posted on the major were "junction ahead". However, 22 percent of all T-junction and 16 percent of X-junction sites had no such advisory signs on the major roads.

Table 3.3 Distribution of Junction Control Types by Junction Type

Type of Traffic control	**Proportion of Sites of this Junction Type with given Control (%)**								
	T-1	**T-2**	**T-3**	**T-4**	**T-5**	**T-6**	**X-1**	**X-2**	**X-3**
NONE	23.8	28.6	0	0	0	12.5	7.1	0	0
YIELD	23.8	71.4	66.7	100	11.1	12.5	14.3	18.2	0
STOP	52.4	0	33.3	0	88.9	75.0	78.6	81.8	100
TOTAL	100	100	100	100	100	100	100	100	100

3.3.5 Accident Frequency

A summary of the accident data for the two broad categories of junction, classified by their layouts, is provided in Table 3.4 below. In all, 354 accidents were recorded at all the selected T-junctions during the study period. The corresponding figure for X-junctions was 238. The total number of injury accidents, pedestrian accidents and all accident casualties are also shown in the same table.

Table 3.4 Overall Accident summary at case-study sites for the 3-year period 1996-1998 inclusive

Indicator	T- Junctions	X-Junctions
Number of Junctions	57	34
Total number of all accidents (including damage-only)	354	238
Average number of all accidents per junction	6.21	7.00
Total number of injury accidents	126	91
Average number of injury accidents per junction	2.21	2.68
Total number of all accident casualties	157	129
Average number of casualties per junction	2.75	3.79
Total number of accidents involving pedestrians	63	50
Average number of pedestrian accidents per junction	1.10	1.47

It can be seen that the averages of these figures per junction are higher in all cases for the X-junctions. Thus, even without accounting for exposure, the picture portrayed here is that the X-junctions are more accident prone than T-junctions. The breakdown of the distribution of junctions, according to the number accidents recorded during the period, is given in Tables 3.5 and 3.6 respectively for all accidents and injury accidents.

Table 3.5 Accident Frequency by Type of Junction

All accidents recorded for the period 1996-1998 inclusive	T-junctions		X-junctions	
	Number of sites recording the given number of accidents	Proportion of all sites (%)	Number of sites recording the given number of accidents	Proportion of all sites (%)
0	10	17.6	5	14.7
1	1	1.7	3	8.8
2	2	3.5	0	0
3	5	8.8	3	8.8
4	4	7.0	4	11.8
5	12	21.0	5	14.7
6	3	5.3	0	0
7	5	8.8	4	11.8
8	5	8.8	1	3.0
9	2	3.5	1	3.0
10	1	1.7	0	0
11	1	1.7	1	3.0
12	0	0	2	5.9
13	1	1.7	0	0
14	0	0	1	3.0
15	1	1.7	2	5.9
16	1	1.7	0	0
18	1	1.7	0	0
29	0	0	1	3.0
32	2	3.5	1	3.0
TOTAL	57	100.0	34	100.0

Table 3.6 Distribution of injury accidents by type of junction

Injury accident frequency	T-junctions		X-junctions	
	Number of junctions with given freq. of accidents	Percentage of this number of sites	number of junctions with given freq. of accidents	Percentage of this number of sites
0	14	24.6	8	23.5
1	11	19.3	7	20.6
2	12	21.0	7	20.6
3	6	10.5	4	11.8
4	7	12.3	1	2.9
5	4	7.0	2	5.9
6	1	1.8	0	0
7	0	0	1	2.9
8	1	1.8	2	5.9
10	0	0	1	2.9
11	1	1.8	1	2.9
TOTAL	57	100.0	34	100.0

Approximately 18 percent of T-junction and 15 percent of X-junction sites did not record any accidents at all in the three-year period. The modal number of accidents for both categories of junctions was 5, represented by 21 percent of T-junctions and 14.7 percent of X-junctions. Sites recording 10 accidents or less constituted 87.7 percent in the case of T- junctions and 76.6 percent for X-junctions. As regards injury accidents, almost a quarter of all sites for T- and X-junctions did not record any. About 95 percent of T-junction sites recorded 5 injury accidents or less, as against 85 percent for X-junctions.

3.4 Conclusions

A total of 91 sites were selected for the case study, of which 57 were T-junctions and 34 X-junctions. All sites were classified according to their layout and the presence or otherwise of features, such as kerbed islands or medians on either approach, and auxiliary lanes. This resulted in six main types of T-junction and three types of X-junction. The total traffic inflows into the junctions, as represented by the AADT, were spread fairly uniformly from just under 5,000 vehicles per day to over 30,000. X-junction sites, generally, had higher proportions of minor road traffic and peak period numbers of pedestrians crossing all arms than did the T-junctions.

The data on spot speeds of vehicles, measured as they approached the junction sites, showed that a significant number were operating above the maximum legal speed-limit of 50km/h. The average number of all accidents per junction, over the 3-year period 1996-1998 inclusive, was 7.0 for X-junctions and 6.21 for T-junctions. More T-junctions recorded less than 10 accidents than did X-junctions and about a quarter of all sites recorded no injury accidents at all over the three-year period.

CHAPTER 4

ANALYSIS OF ACCIDENT CHARACTERISTICS AT UNSIGNALISED URBAN JUNCTIONS

4.1 Introduction

The key characteristics of accidents at unsignalised urban junctions in Ghana are discussed under this Chapter at three different levels. First, to put the subject in the right perspective, a general descriptive background to urban accidents as a whole is given and then this is followed by a more detailed analysis of the scale, nature and contributing circumstances of accidents at unsignalised junctions. The third level of analysis involves consideration of the case-study junctions. Here, comparisons of the accident experience between unsignalised junctions typical of different layouts and features, traffic conditions and traffic control are made.

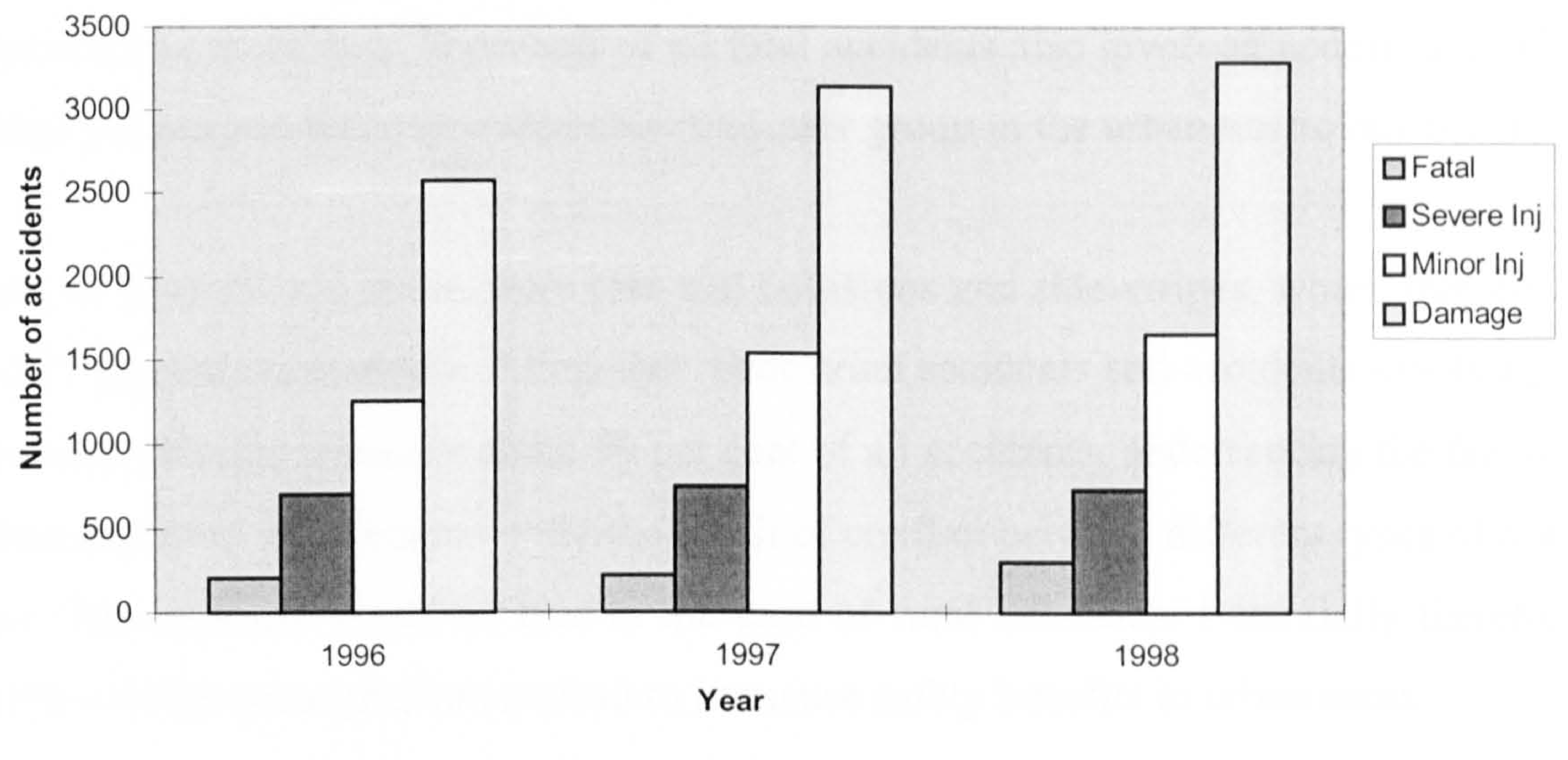
The main measures of unsafety used in the comparisons are the average accident and casualty rates per million vehicles. Throughout these analyses, attempts are made to focus on the key factors underlying observed trends, in order to identify candidate independent parameters for the modelling stage. Given its crucial role in the operation and safety of unsignalised junctions, minor road traffic has been singled out for initial exploratory analysis to establish any specific relationship with accidents, using ordinary regression techniques.

4.2 Overall Trends in Urban Accidents

4.2.1 Incidence and Severity

A total of 16,334 accidents were reported by the police, as having occurred on the surfaced road network of the two case-study cities, during the period 1996-1998 inclusive. As illustrated in Figure 4.1 below, there appeared to be a gradual increase in the number of accidents over the years, starting from a total of 4730 in 1996 to 5642 in 1997 and 5962 in 1998. Whilst it may be difficult to say if this trend reflects the actual incidence of accidents, due to the inevitable shortfalls in reporting over time, it does appear that the distribution of accidents in the various severity groups reflects what is expected. For a typical urban environment, accident numbers would be expected to diminish with increasing severity. This is because the high concentration of traffic in urban areas results in generally low vehicle operating speeds and less likelihood of severe outcomes in the event of a collision.

Figure 4.1 Accident numbers and severity trends (1996-1998 inclusive)



These observed trends give some comfort about the representativeness of the data. It means that shortfalls in the data, whatever their scale, may not be obviously biased towards particular accident types, although the level of underreporting of damage-only accidents is always likely to be higher. It is also likely that the levels of fatalities may be slightly understated because, although officially, a fatality is that which occurs within 30 days of the accident, there are indications that records on fatalities are rarely updated, by the police beyond what happens within 24 hours. On the basis of the current data, however, we can say with some confidence that the ratio of accidents by severity in the urban areas is roughly 1.0:3.0:6.0:13.0 respectively for fatal, severe injury, minor injury and damage-only accidents.

Significantly, the data also shows that the number of fatal accidents in 1998 (301) was up 44 percent on the 1996 level (209) as against a corresponding increase of 26 percent in overall accidents. This probably had to do, in part, with the opening of some key dual-carriageway suburban arterial roads in the intervening period, which facilitated rapid movement of vehicles within the two cities.

4.2.2 Typology of Accidents

Table 4.1 shows the distribution of accident types, classified by the initial impact or collision and dis-aggregated by severity. Clearly, collisions between vehicles and pedestrians constitute the single largest proportion by type (27 percent). It is also apparent that more than 70 percent of all fatal accidents also involved pedestrians. This makes pedestrians the most vulnerable road-user group in the urban traffic environment.

Next, in proportional terms, were rear-end collisions and side-swipes, which formed 23 and 17 percent respectively. Altogether, pedestrian accidents and accidents involving at least two vehicles represent about 90 per cent of all accidents, underscoring the fact that urban accidents are predominantly the result of conflict between different types of road-user. The opposite would be true in the case of rural accidents. Potentially therefore, traffic conflict management can lead to immense safety benefits in urban areas.

Table 4.1 Accident type by severity

Accident Severity	**Accident Type (primary collision)**									**Total**
	Head-on	Rear-end	Right angle	Side swipe	Over-Turned	Hit object	Hit parked vehicle	Hit pedestrian	Other	
Fatal	36	27	29	9	27	6	3	535	62	734
Severe Injury	111	130	134	65	41	39	7	1489	166	2182
Minor Injury	258	434	504	285	67	105	31	2322	424	4430
Damage Only	666	3135	1653	2361	39	313	134	0	666	8967
TOTAL	1071	3726	2320	2720	174	463	175	4346	1318	16313
%	*6.6*	*22.8*	*14.2*	*16.7*	*1.1*	*2.8*	*1.1*	*26.6*	*8.1*	*100*

4.2.3 Locations of Accidents

The locations on the road network of the case-study cities at which accidents took place are presented in Table 4.2. Three main points are worth observing in this respect. First, the proportions of accidents were roughly equally split between links (i.e., sections of road between junctions) and junctions. Although purely based on accident numbers, without accounting for the exposure to accident, this observation is surprising. Links are generally expected to be less accident-prone than junctions, due mainly to the preponderance of inter-vehicular conflicts at the latter. By contrast, data from the United Kingdom (Hills *et al*, 1981) show that about two-thirds of all accidents in built-up areas occur at junctions, whilst in Sweden and Finland (Kulmala, 1995) average accident rates (per million vehicle-kilometres) are about 2.5 times higher at junctions than on link sections. Admittedly, these differences could be due in large measure to the differences in the definition of the junction area or zone of influence. For example, whereas in the current study the junction's zone of influence is defined as the area within 25 metres of the junction's centre, the Finnish study (Kulmala, 1995) defined it (i.e. the junction area) as the road "area within 200 metres from the centre of the junction". Clearly, in the latter case many more accidents occurring on the link sections between junctions will be attributed to junctions.

Table 4.2: Accident Location by Severity

Accident Severity	Location Type								Total
	Not junct.	X-Junct.	T-Junct.	Stag'd junct.	Y-junct.	Round about	Rail cross.	Other	
Fatal	492	50	150	8	5	7	0	21	733
Severe Injury	1443	161	431	16	12	32	8	73	2176
Minor Injury	2685	427	889	42	26	131	11	200	4411
Damage	3926	1242	2337	83	99	808	23	436	8954
TOTAL	8546	1880	3807	149	142	978	42	730	16274

More accidents occur on links in many developing countries, such as Ghana, than in the average industrialised country because of a combination of factors including the relatively poor lane discipline of most drivers. Hence the difference in the accident patterns between the United Kingdom and Ghana, notwithstanding the similar definitions of junction accidents. In the United Kingdom an accident is attributed to a junction if it occurs "within 20 yards" of the junction.

Secondly, of all junction accidents, X- and T-junctions were responsible for 24.3 and 49.2 percent respectively. Thus, between them, the two junction-types alone accounted for more than 70 percent of all accidents occurring at junctions. The third main point worth noting about accident location in the two case-study cities is that 67 percent of fatal accidents were recorded on links. It will be noticed, later on in this chapter, when accident casualties are discussed, that on average, 1.8 fatalities resulted from each fatal accident in the study area. A large majority of such accidents occurred on links. It is known that collisions involving parties previously travelling at high speed tend to have severe consequences due to the amount of energy dissipated. This link between speed and accident severity has been well documented in the literature (e.g. Baruya *et al*, 1999). It is also known that vehicle-operating speeds are usually much higher on links than at junctions.

The overall accident severity ratio (proportion of fatal and severe injury to all injury accidents) for all types of locations was 39.7 per cent and this is twice the 20.1 per cent reported for all built-up roads in Great Britain (Layfield *et al*, 1996). When the severity ratio is taken over all accidents (including damage-only accidents) then the figures for X-junctions and T-junctions were 11.2 per cent and 15.3 per cent respectively. The average severity ratio (over all accidents) for all junctions was 12.6 per cent and the lowest (4.0 per cent) was recorded at roundabouts. It would appear, therefore, that roundabouts have a much better potential for injury reduction than other types of junction.

4.2.4 Ambient Conditions at the Time of Accident

The light conditions and weather in which accidents took place are presented in Table 4.3. 72.1 percent of accidents occurred under daylight conditions, whilst 23.5 percent happened at night and the rest at dawn or dusk. Dawn is approximately the period between 05.30-06.00 hours, whilst dusk occurs between 18.15 and 18.45 hours. Hours of daylight in Ghana are fairly stable for most part of the year. As regards the weather, 98 per cent of accidents were recorded under clear weather conditions. Thus, the typical ambient condition under which accidents took place over the three-year period was clear weather in broad daylight.

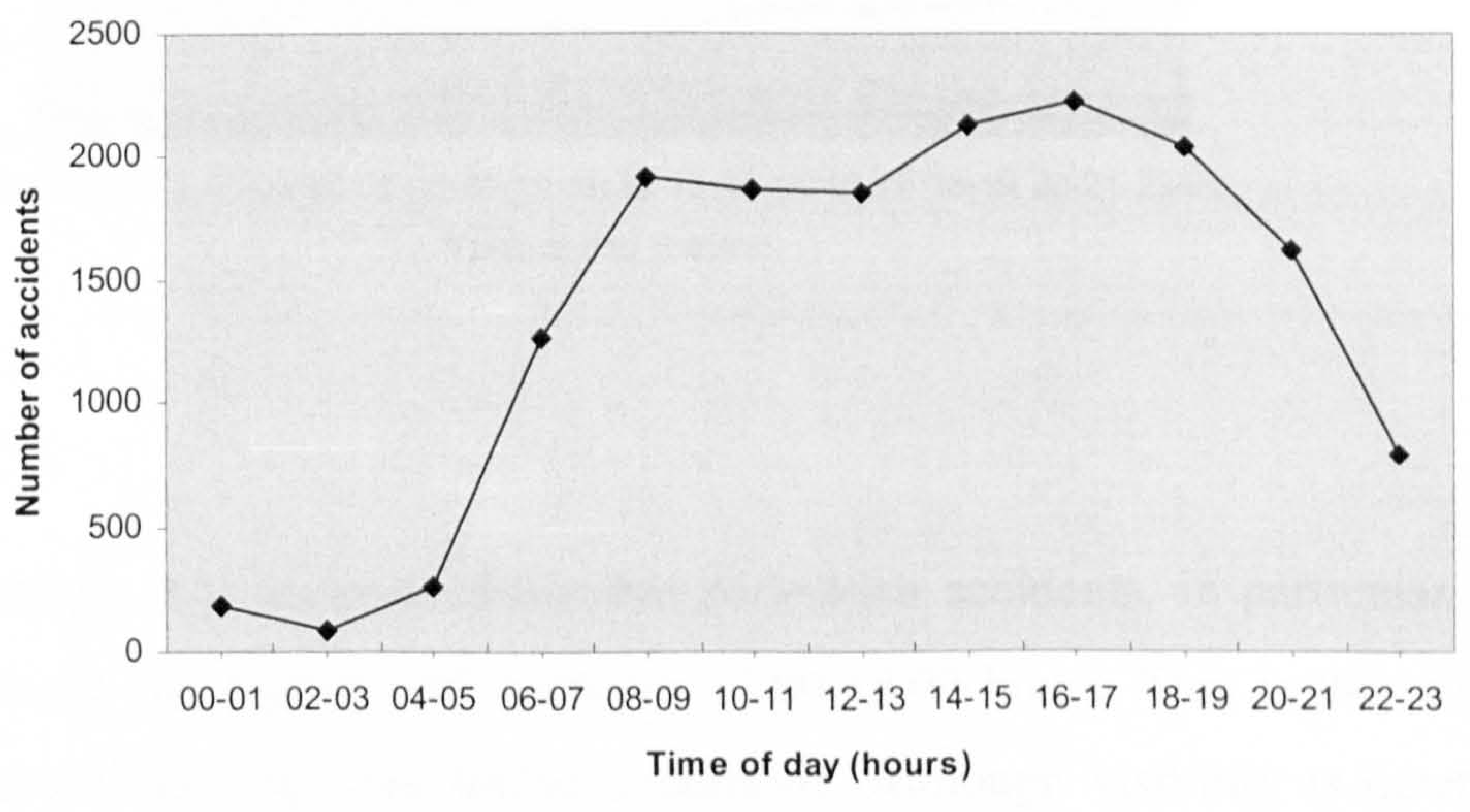
Table 4.3 Accident occurrence by light conditions and weather

Light Conditions	WEATHER						
	Clear	Fog	Rain	Dusty	Dazzle*	Other	Total
Day	11718	4	32	1	2	0	11757
Dawn/Dusk	662	41	2	4	2	2	713
Night	3647	20	28	9	44	77	3825
Total	16027	65	62	14	48	79	16295

* Dazzle includes glare from sunlight and vehicle headlamps

An examination of the specific times at which the accidents occurred reveals some differences in trends for various accident types. Overall (see Figure 4.2a) accident numbers rise sharply from 04-05 hours to a peak at 08-09 hours. Thereafter the numbers drop slightly towards midday and pick up again until 16-17 hours when they peak again, this time at a slightly higher level than at 08-09 hours. After 16-17 hours the accident numbers decline, initially gradually, and then more rapidly after 20-21 hours.

Figure 4.2a Variation of overall accidents by time of day



This pattern is similar to the expected variation in traffic during the day, the notable difference being that the evening peak of accidents occurs slightly earlier (16-17 hours) than the expected for traffic (18-19 hours). Thus the build up to the evening peak traffic period appears to be more crucial from the accident perspective than the peak period itself.

For the different classes of accident, as illustrated in Figure 4.2b(i), two distinct peaks in numbers can also be observed; the first one occurs at 08.00-09.00 hours and this applies to all types of accident. The second peak, however, occurs at different times for different accident types between 14.00 and 19.00 hours. Pedestrian accidents and head-on collisions, for example, peak at 18.00-19.00 hours, whilst rear-end collisions peak at 14.00-15.00 hours. Although these times broadly fit within the peak traffic periods of 07.00-09.00 hours and 17.00-19.00 hours for morning and evening respectively, it is of some interest that not all of them coincide with the identified peak hours, i.e. 08.00-09.00 and 17.00-18.00 hours. More focused research might be required to explain such patterns more fully.

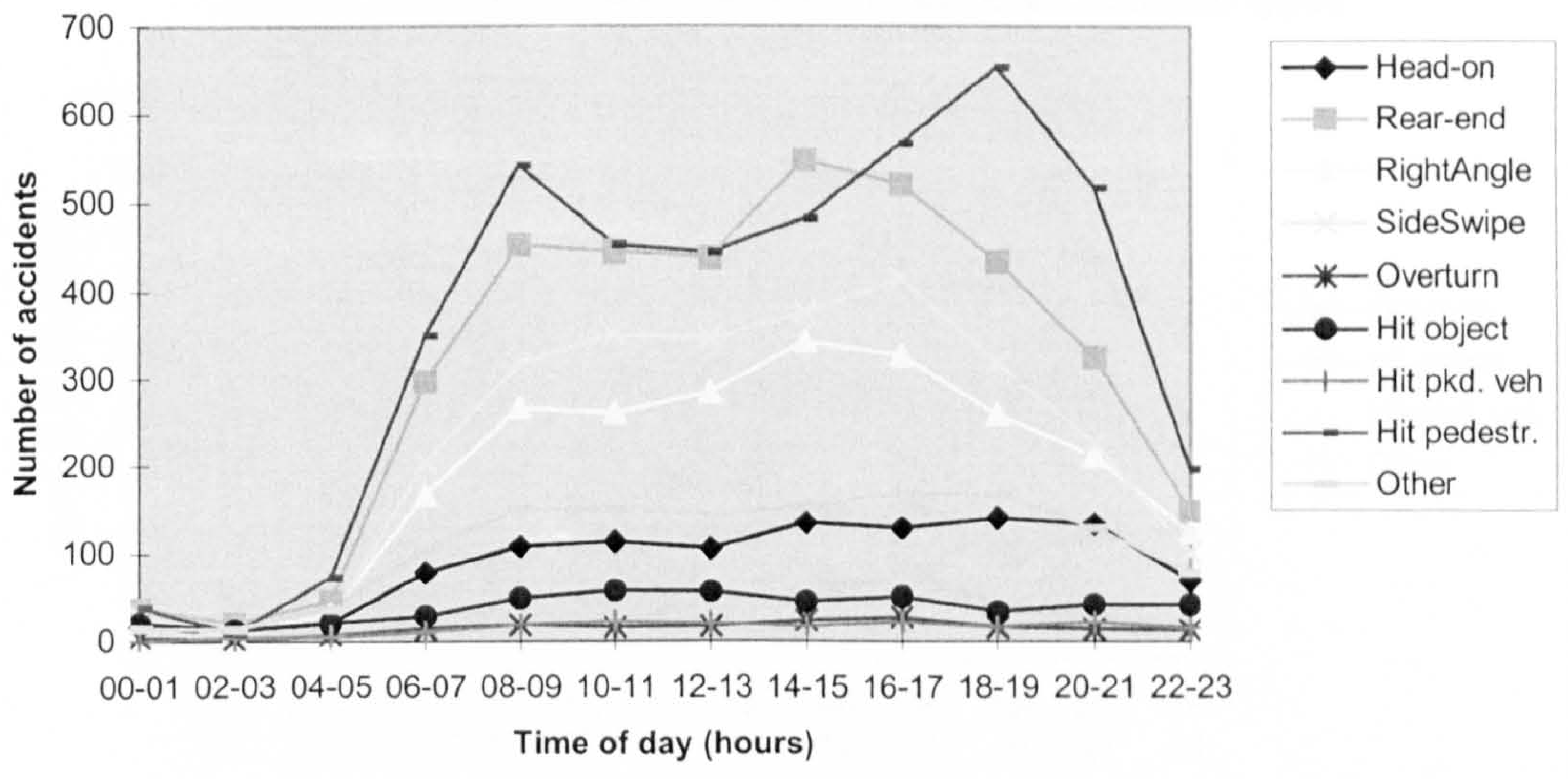
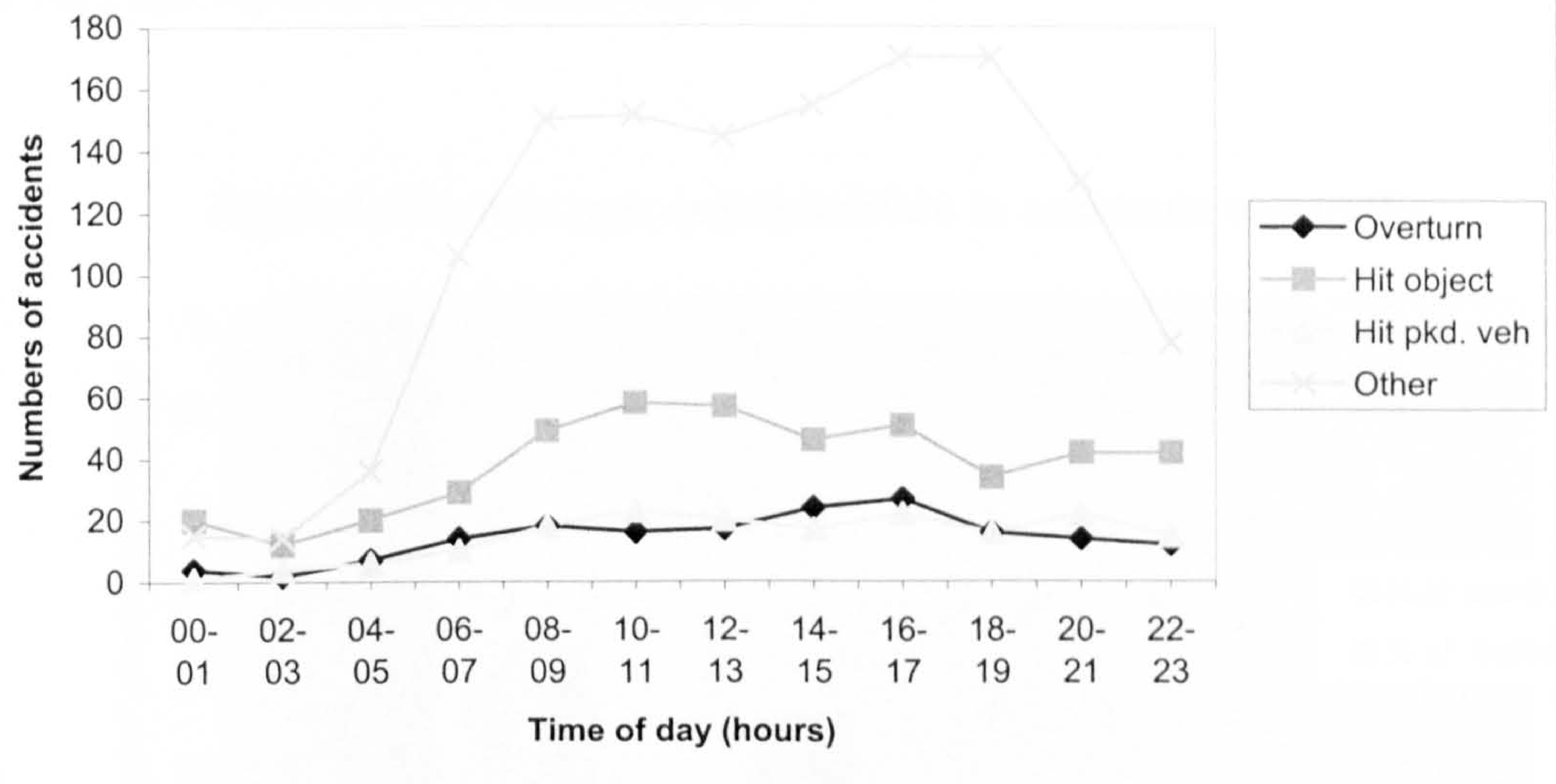


Figure 4.2b(i) Accident type variation by time of day

But, perhaps, it is understandable that pedestrian accidents, in particular, would have their second and higher peak between 17.00-18.00 hours. This is the twilight period, characterised also by peak traffic conditions. Although visibility is deteriorating and pedestrian conspicuity is poor at this time, due to the gradual onset of darkness, commercial drivers, where they are driven by the profit motive, are usually in a frenzy, speeding and sometimes overtaking recklessly in order to maximise the number of trips they make in this period. At the same time, faced with fewer safe gaps in traffic, pedestrians can be oblivious of the fact that their presence on the road is less noticeable at dusk and may also take risks in crossing the roads when and where they choose to. The resulting effect is a relatively higher number and severity of pedestrian accidents. Probably, it is indicative of the conditions of this period that 58 percent of all vehicles involved in pedestrian accidents are commercial vehicles. It is also pertinent to observe that the times of occurrence of both morning and evening peaks of pedestrian accidents suggest the accidents may be involving school children as well. The basic schools in Ghana are organised on a "shift system" with the first stream (shift) attending school from 08.00 hours to 12.30 hours and the second from 13.00 hours to 17.30 hours.

An enlarged illustration of the pattern of some of the accident types represented in Figure 4.2b(i) is presented in Figure 4.2b(ii) for clarity. It shows that the pattern of variation of "other" accidents is similar to that of the overall accidents (see Figure 4.2a).

Figure 4.2b(ii) Enlarged illustration of selected accident types

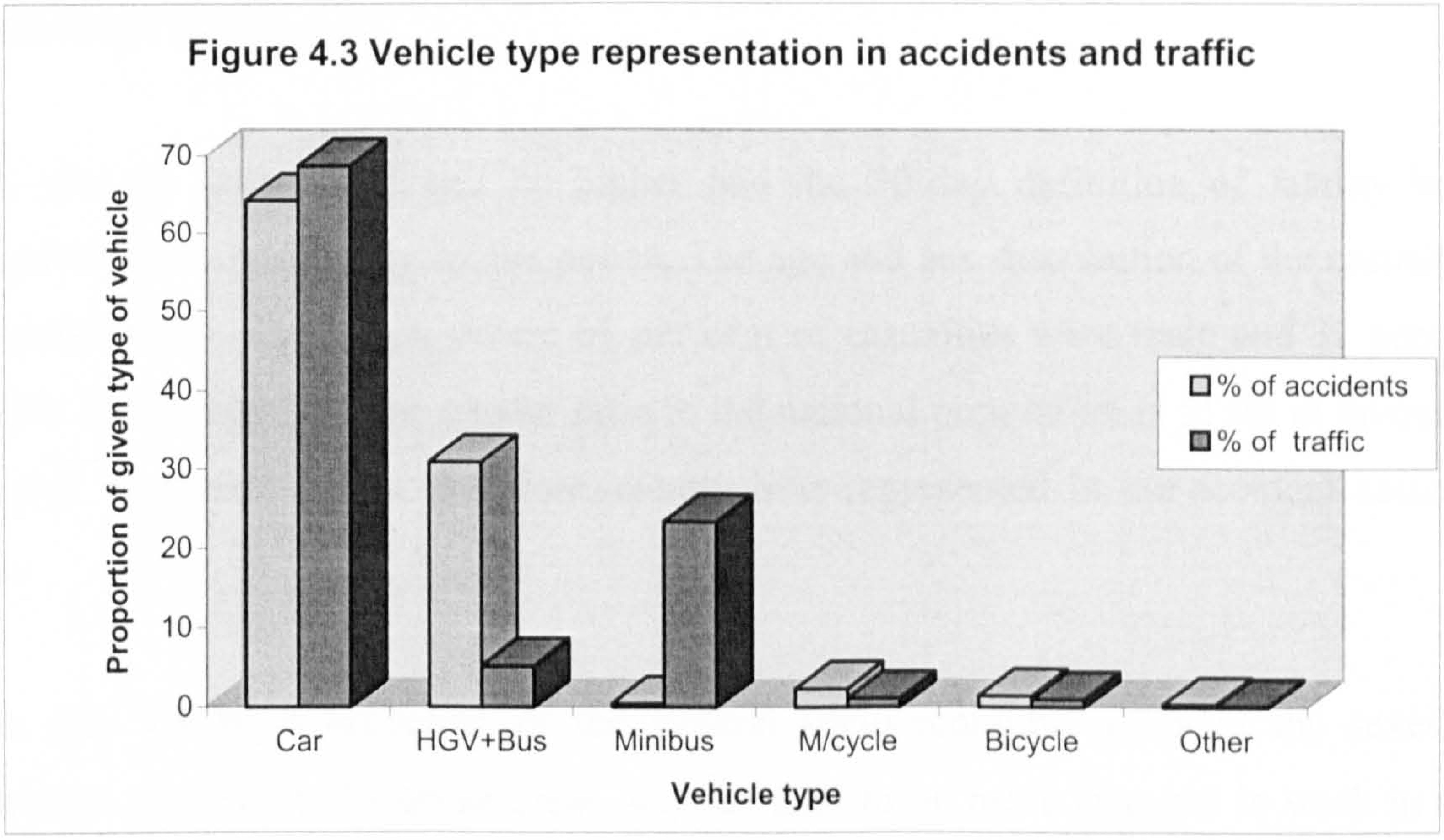


This is hardly surprising, since this rather omnibus category includes any type of accident, which falls outside the other stated types or cannot be classified due to insufficient information. The patterns of the other types of accident shown in Figure 4.2b(ii) are much less defined. They all appear to rise steadily in from 00-01 hours till about 10.00-11.00 hours and thereafter stabilise for the rest of the day.

4.2.5 Vehicle Types involved in Accidents

Of 27,954 vehicles involved in traffic accidents in the two case-study cities during the three year period 1996-1998, 62 per cent were cars (private cars and taxis), 33 percent comprised Heavy Goods Vehicles (HGVs) and high occupancy buses and 2.6 per cent were motorcycles. "Trotros", or minibuses, and bicycles each accounted for approximately 0.5 percent of vehicles involved in accidents. In Figure 4.3, the relative shares of the various types of vehicle in accidents, as well as traffic, are compared.

Whereas the involvement of cars, motor cycles and bicycles in accidents roughly reflects their respective proportions in traffic, minibuses ("trotros") are clearly under-represented. By contrast, heavy goods vehicles (HGVs) and buses are, as a group, alarmingly over-represented in their accident involvement. The proportion of this group's share in accidents is nearly six times their proportion in traffic. From these comparisons, one can say that minibuses or "trotros" appear to be the safest means of transport in the urban areas of Ghana, whilst HGVs and high occupancy buses are relatively the worst in terms of accidents.



Heavy goods vehicles (HGVs) and high occupancy buses, especially the type deployed for commercial purposes, are notorious for their poor maintenance record and rampant overloading practices. It is not uncommon to find a passenger falling off the open top of an HGV. Given such relatively high involvement in accidents, it will not be unreasonable to consider the proportion of HGVs and buses in traffic as one of the potential independent traffic variables for accident-prediction modelling. However, with better training of drivers of HGVs and buses, better enforcement of traffic regulations on loading and speeding, etc. it would be expected that over time, HGVs and buses may cease to be over-represented in accidents and their initial influence in any models, if any, would reduce. The latter point underscores the need for regular review of accident prediction models to take account of general changes in the traffic safety situation.

4.2.6 Accident Casualties

The 16,334 accidents recorded during the three years resulted in a total of 10,493 casualties, comprising 1,306 fatalities, 3,227 severely injured and 5,960 slightly injured. Thus overall, there were 64 casualties for every 100 accidents and nearly two deaths (1.8) for each fatal accident. This fatality ratio appears quite high for typical urban traffic conditions and may, in part, be attributable to the fact that most fatal accidents occur on links, which are (most probably) sections of high-speed major arterial or sub-urban roads. Rampant overcrowding in public transport vehicles is another likely reason for this high fatality ratio.

And yet, the ratio could still be higher had the 30-day definition of fatality been complied with consistently by the police. The age and sex distribution of the casualties are presented in Figure 4.4, where 68 per cent of casualties were male and 32 percent female. By comparison, the gender ratio in the national population is 51:49 in favour of females. The male sex is, therefore, clearly over-represented in the accident casualty data.

This may yet be a reflection of the general socio-economic roles of the sexes in Ghanaian society. In the urban areas, women tend to be more engaged in work in and around the home and could, therefore, be said to cover far fewer person-kilometres in traffic in any given time and, by implication, are less exposed to the risk of accidents than their male counterparts.

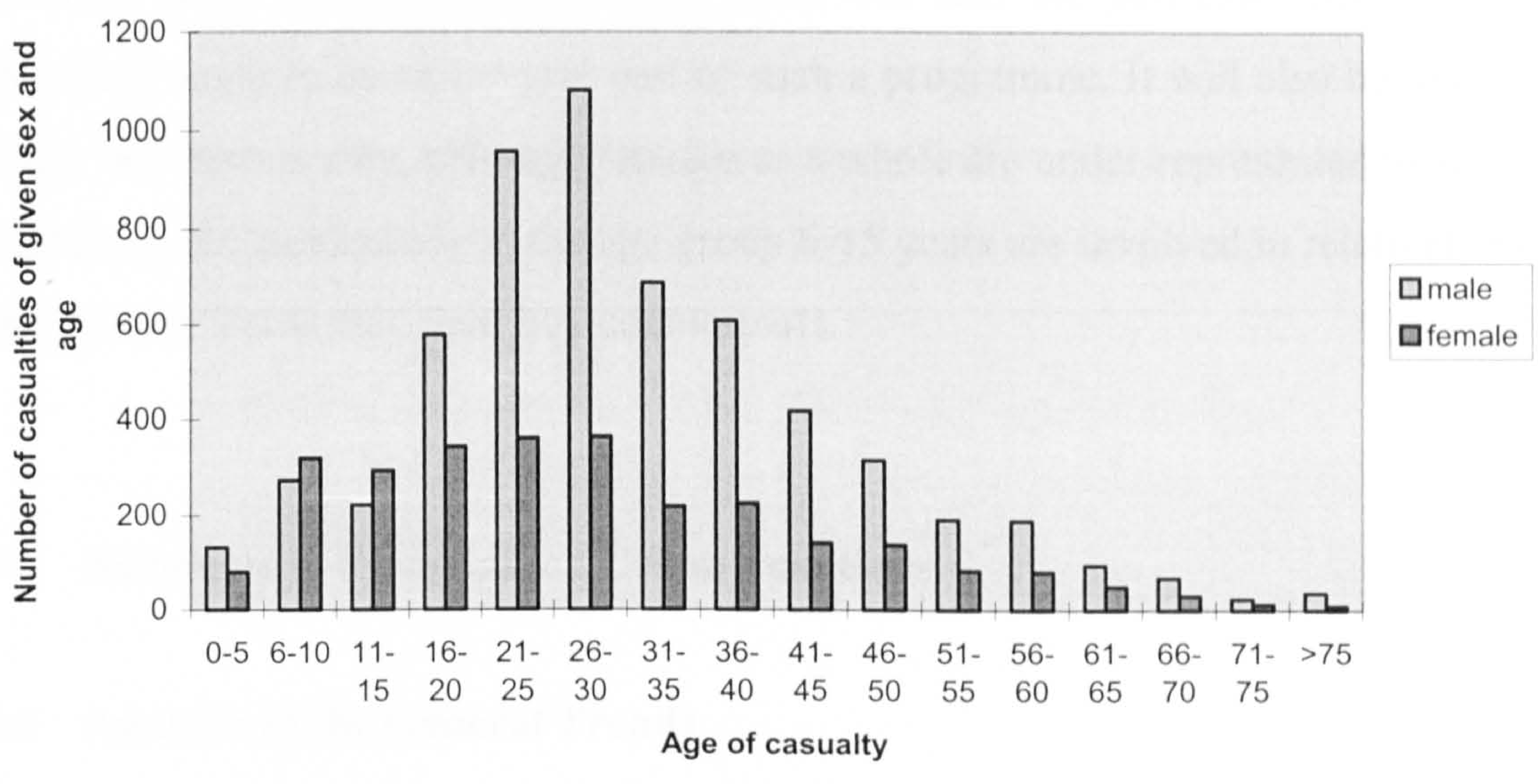


Figure 4.4 Distribution of all casualties by age and sex

A slightly different picture emerges when child (up to 15 years) casualties only are examined. Whereas, child casualties constitute just over 15 percent overall, within the two sex groups, the girls, by proportion within the female group, represent more than twice as many casualties as the boys within the male group. Further analysis (Figure 4.5) reveals that for children up to 15 years most were pedestrian casualties rather than passengers or other types of road-user. This is evidenced by the general skewing of the histogram (Figure 4.5) towards the lower age-group, relative to the distribution of all casualties in Figure 4.4.

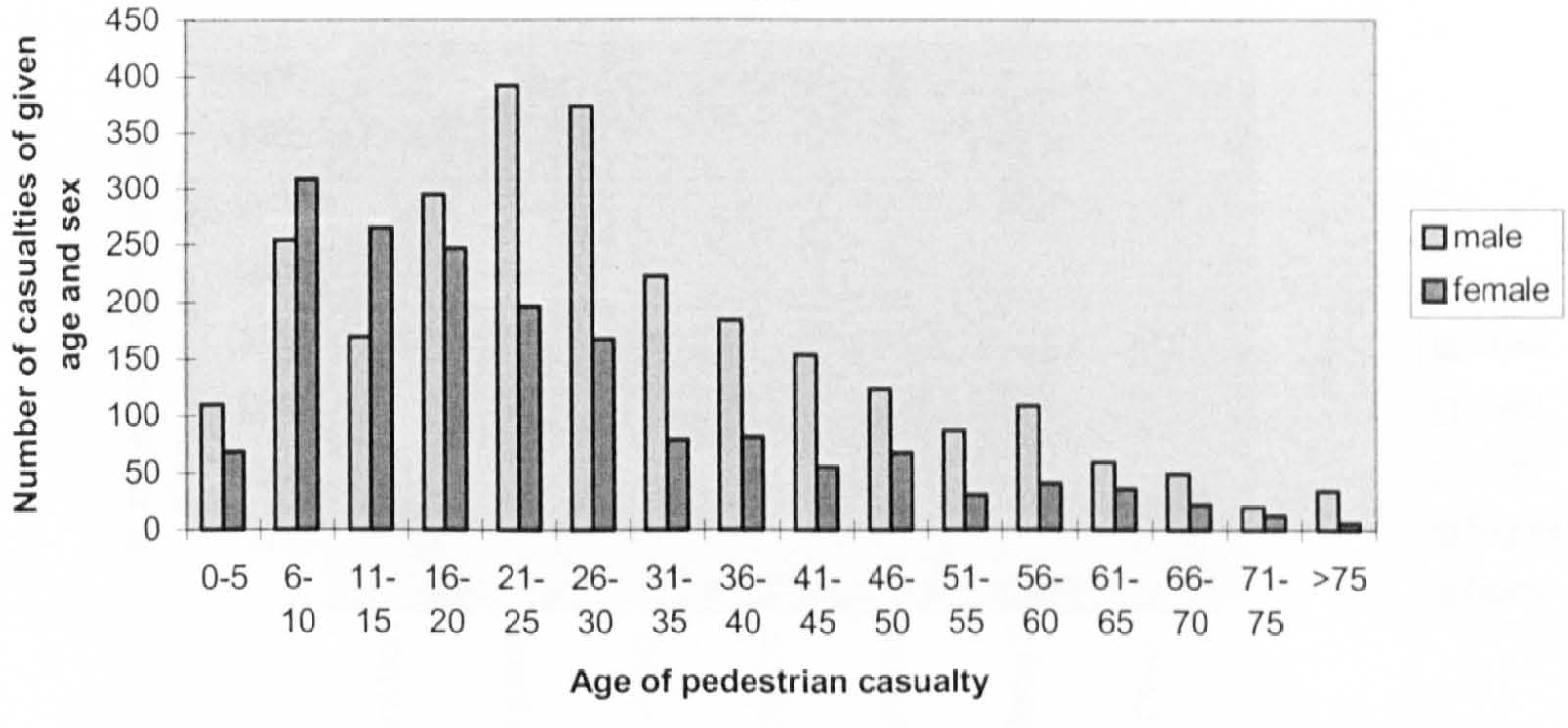


Figure 4.5 Distribution of Pedestrian Casualties by Age and Sex

On the whole, about 90 per cent of all child casualties are pedestrians, whilst about 30 per cent of pedestrian casualties are children under age 15. Under these circumstances, any programme for the reduction of road accident casualties will not only have to have pedestrian safety as an important focal point, but also the particular needs of child pedestrians ought to be an integral part of such a programme. It will also be helpful to identify the reasons why, although females as a whole are under-represented in accident casualties, girls, particularly in the age group 6-15 years are involved in relatively more pedestrian accidents than their boy counterparts.

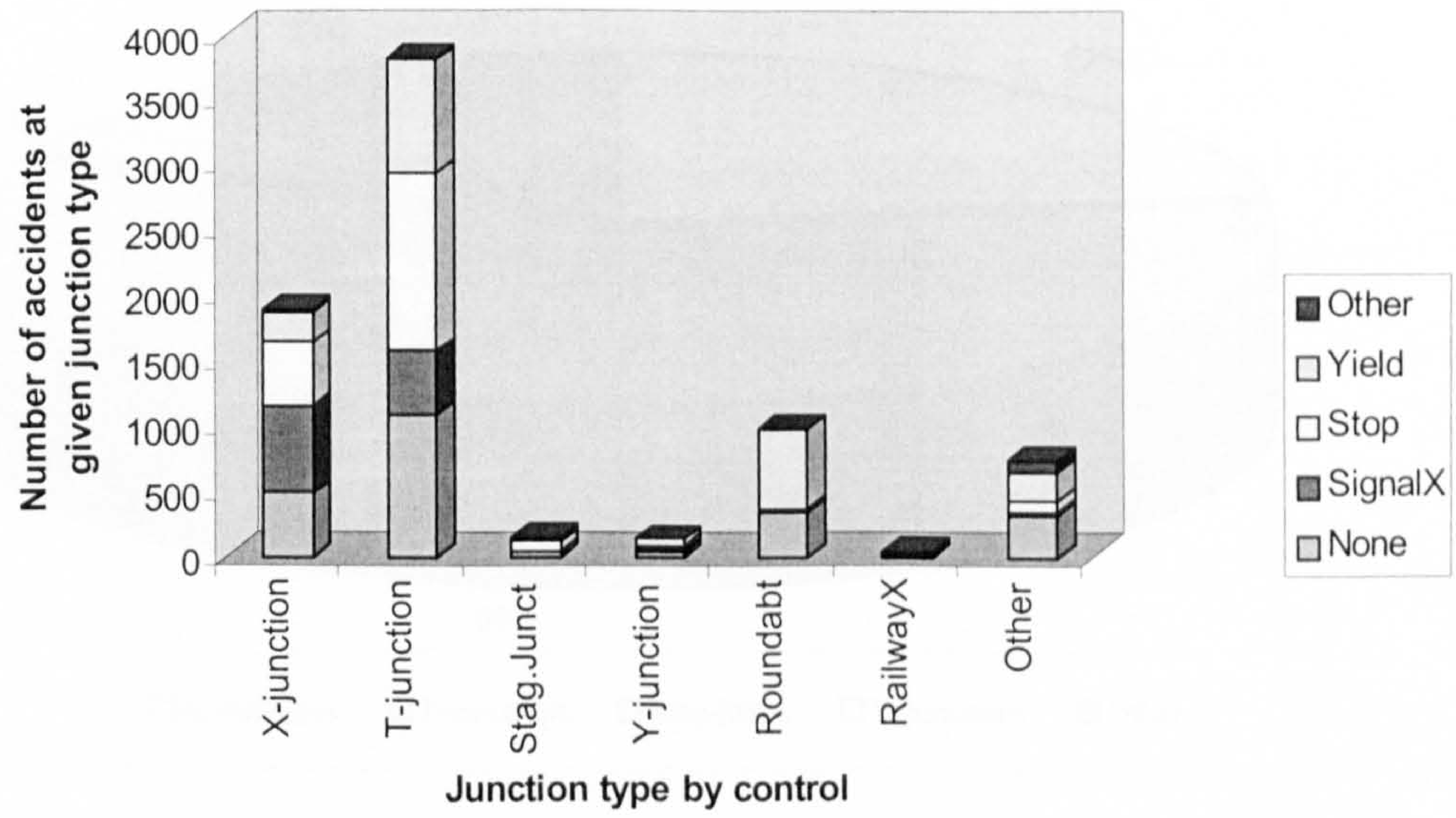
4.3 Accidents at Unsignalised Urban Junctions

4.3.1 Analysis of the General Trends

4.3.1.1 The Scale

When the type of traffic control at junctions is considered, as illustrated in Figure 4.6, it becomes apparent that just under 30 percent of junction accidents occurred at signalised locations and another 13 percent at roundabouts. Unsignalised junctions accounted for more than three out of five of all accidents at junctions. Within the broad group of unsignalised junctions, the proportional distribution of accidents at the different types of

Figure 4.6 Representation of junctions by traffic control in accidents

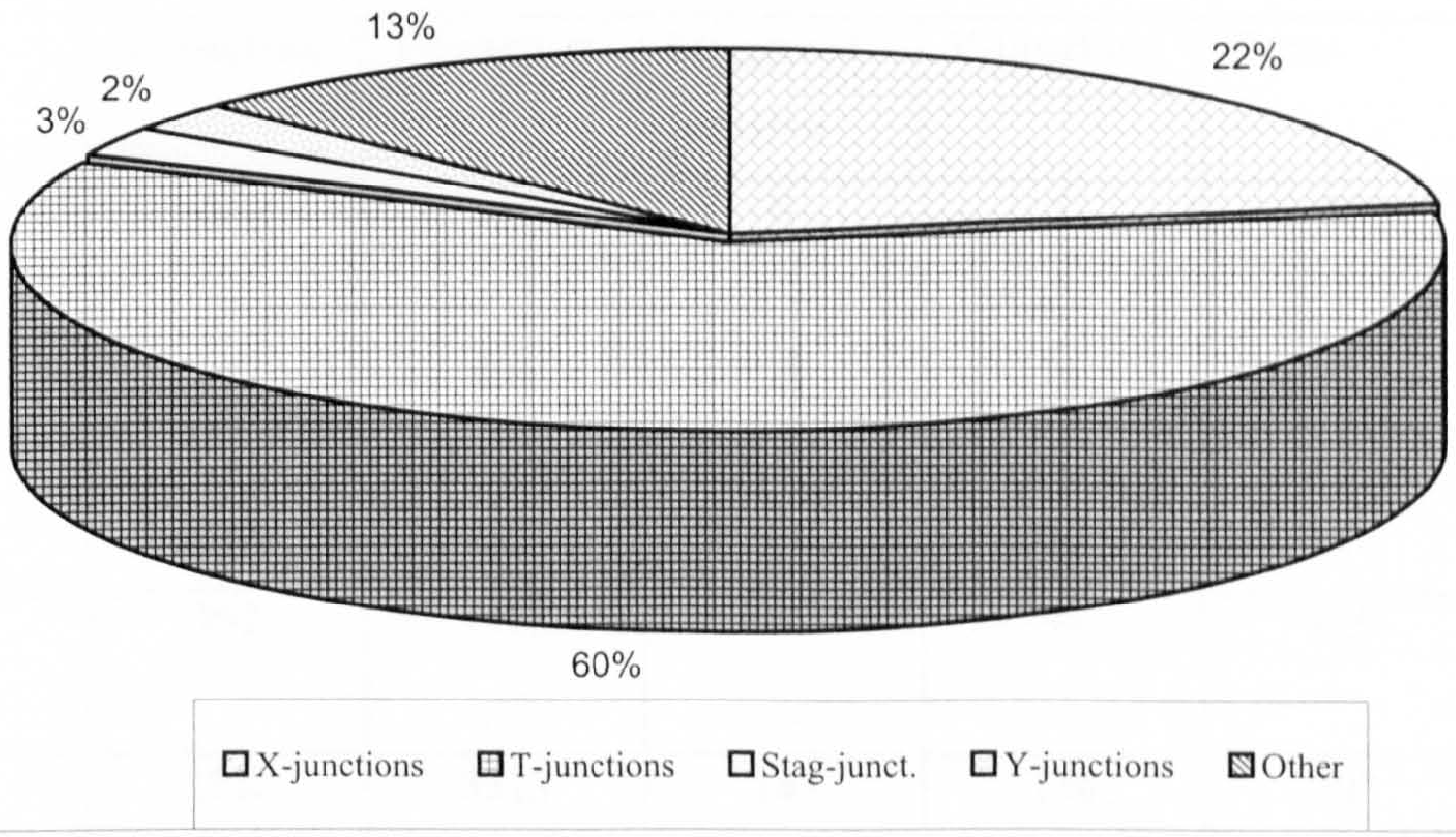


layout is shown in Figure 4.7. The total number of accidents at all such sites, in the three years 1996-1998, was 5519.

Clearly, and consistent with the earlier observation in section 4.2.3 of this report, X- and T-junctions accounted for almost three-quarters of all accidents occurring at urban junctions of all types, including signalised. The vast majority (more than 80 percent) of accidents at unsignalised junctions alone were also recorded at T- and X-junctions. Furthermore, of all accidents recorded at all T- and X-junctions, irrespective of the traffic control type, unsignalised T- and X-junctions accounted for 87 and 65 percent respectively.

This provides some justification for focussing on the two types of junction layout at the case- study and modelling stage. It is to be noted, however, that the predominance of these two junction types in the accident data may not necessarily mean that they are the most accident-prone, but it is quite likely to be so, because these are the most common types of junction layout. Other types of layout (e.g. Y-junction) may be rather few in number, or handle too little traffic to feature significantly in the accident data. In that case, the need to focus on X- and T-junctions becomes even more important.

Figure 4.7: Proportional representation of different types of unsignalised junction in accidents



4.3.1.2 Accident Severity

Table 4.4 gives the breakdown of accident severity by location and layout type. Comparing these with the figures in Table 4.2, it is noticed that, whilst unsignalised T-junctions accounted for 91 percent of fatal accidents at all types of T-junction, the corresponding X-junctions were responsible for 72 percent of fatal accidents at all X-junction. The severity ratios (proportion of fatal and severe injury accidents of the total for each junction type) were, however, almost the same for unsignalised as for all control types for the given junction layout. Overall, the severity ratio was slightly higher for unsignalised junctions (15 percent) than for all junctions (12.6 percent) but nearly two and-a-half times that for signalised junctions (6.3 percent) and four times that for roundabouts (4.0 per cent).

These severity ratios would appear consistent with the operational conditions at the different types of junction. Due to the priority arrangement at unsignalised junctions, drivers on the major roads would tend to take the right of way for granted and that leaves them unprepared for the situation where a minor road vehicle "unexpectedly" interferes with their movement. Collisions from such situations can have quite severe consequences.

Table 4.4. Accident severity by type of unsignalised junction

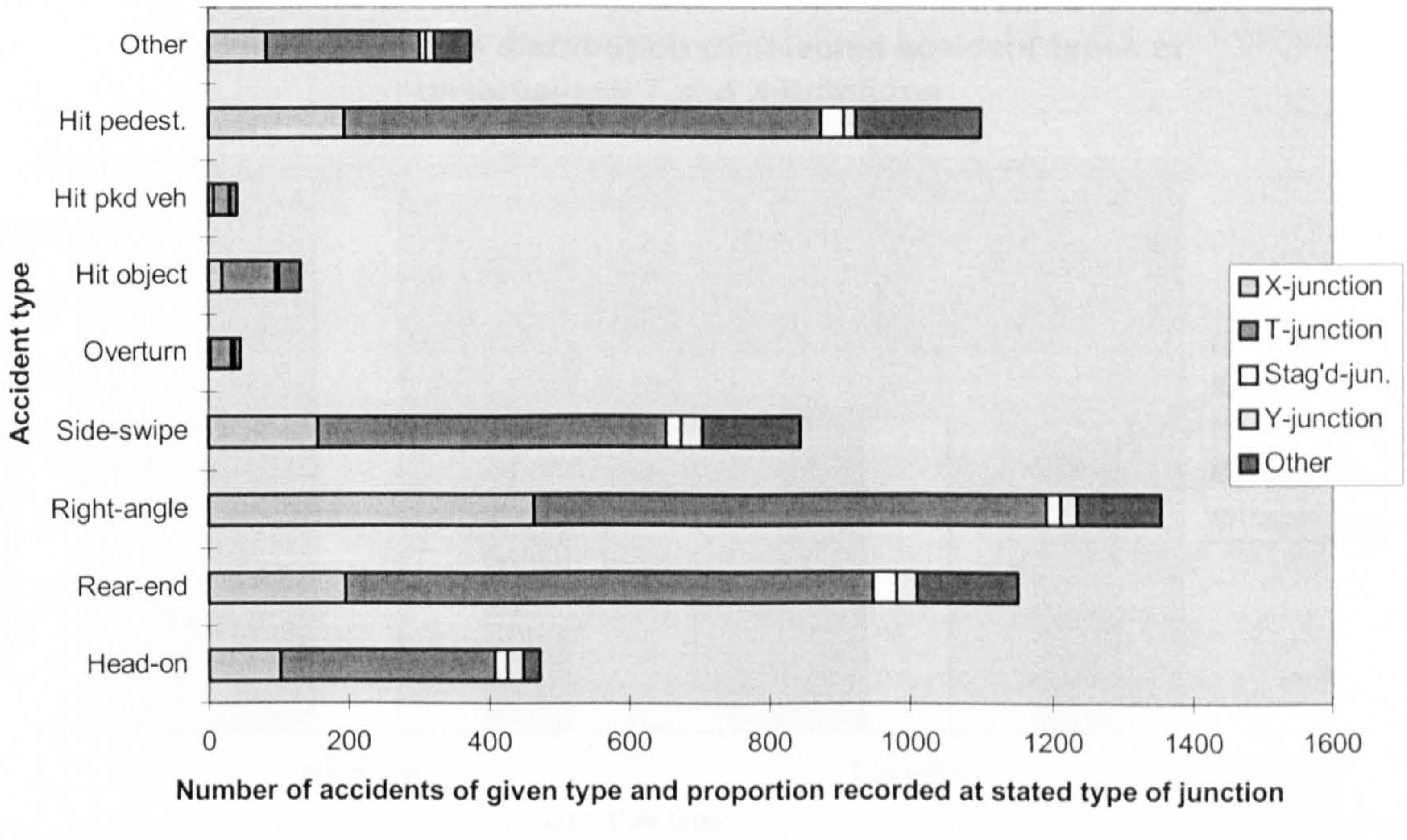
Accident Severity	Type of unsignalised junction					Total
	X-junction	T-junction	Staggered junction	Y-junction	Other	
Fatal	36	136	8	5	21	206
Severe Injury	122	404	15	11	72	624
Minor Injury	272	805	41	26	194	1338
Damage only	792	1968	77	94	420	3351
Total	1222	3313	141	136	707	5519

By contrast, most drivers approaching a roundabout, for example, know that they are supposed to give way to circulating traffic. As a result, they are more likely to exercise due caution on approach to the junction by slowing down considerably and, through that, limit the damage that might result in case of a collision. At roundabouts, therefore, the types of collision observed would be predominantly sideswipes and rear-end collisions in the damage-only category. The casualty statistics clearly support this rationalisation. For every 100 accidents, there were 57 casualties at unsignalised junctions, as opposed to 53 at all junctions and 26 at roundabouts.

4.3.1.3 Accident Types

Analysis of the accident types that occurred at unsignalised urban junctions (excluding roundabouts) revealed that the four most prominent, in terms of their proportional distribution, were right-angle, rear-end, pedestrian and side-swipe collisions, in that order. This is illustrated in Figure 4.8. Although the same accident types are also the most dominant in accidents at all types of junction, there is a noticeable difference in their relative proportions for each junction type.

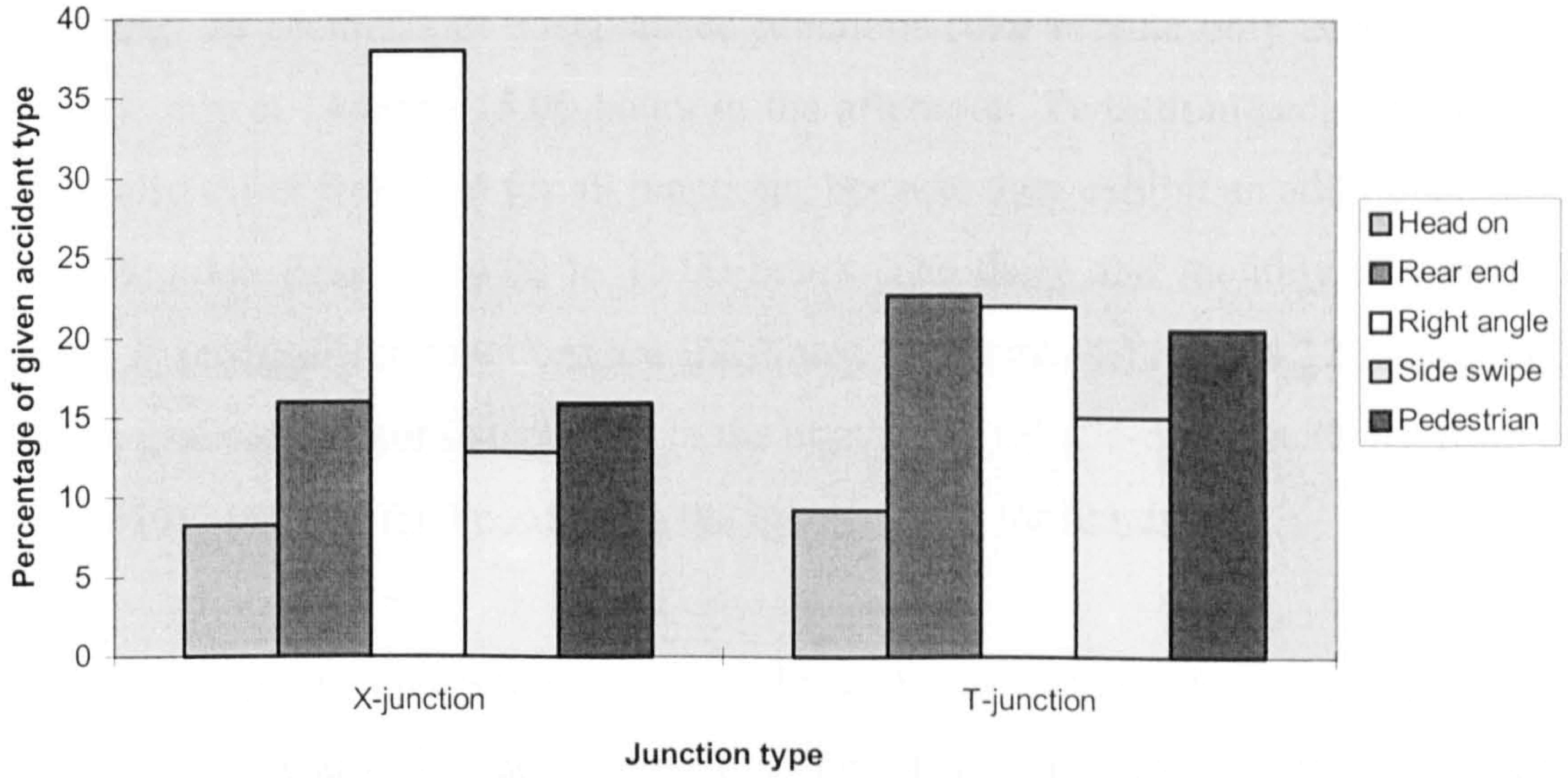
Figure 4.8 Accident type distribution at unsignalised urban junctions



Whereas in the general population of junctions right-angle, rear-end, side-swipes and pedestrian accidents are clearly differentiated by their proportional distribution, decreasing in that order, at unsignalised junctions pedestrian accidents and rear-end collisions are jointly the next most important (20 percent each), after right-angle collisions (24.6 per cent). This indicates that pedestrian accidents are probably more of a problem at unsignalised junctions than at the "average" type of junction.

Closer examination of the proportions of the different accident types within each junction category reveals some noticeable variations. For example, comparing the accident-type trends within X- and T-junctions, as illustrated in Figure 4.9, it is apparent that, whereas the main accident-types are more evenly distributed by proportion at T-junctions, right-angle collisions stand out quite clearly as the single most dominant accident type at X-junctions where there is clearly more opportunities for such collisions. This pattern of accident-type distribution at X-junctions would also be a reflection of the preponderance of accidents involving crossing traffic (i.e. traffic moving straight through the intersection from one arm to the other of the same road). Pedestrian accidents appear slightly more represented at T-junctions (20 per cent) than at X-junctions (16 per cent).

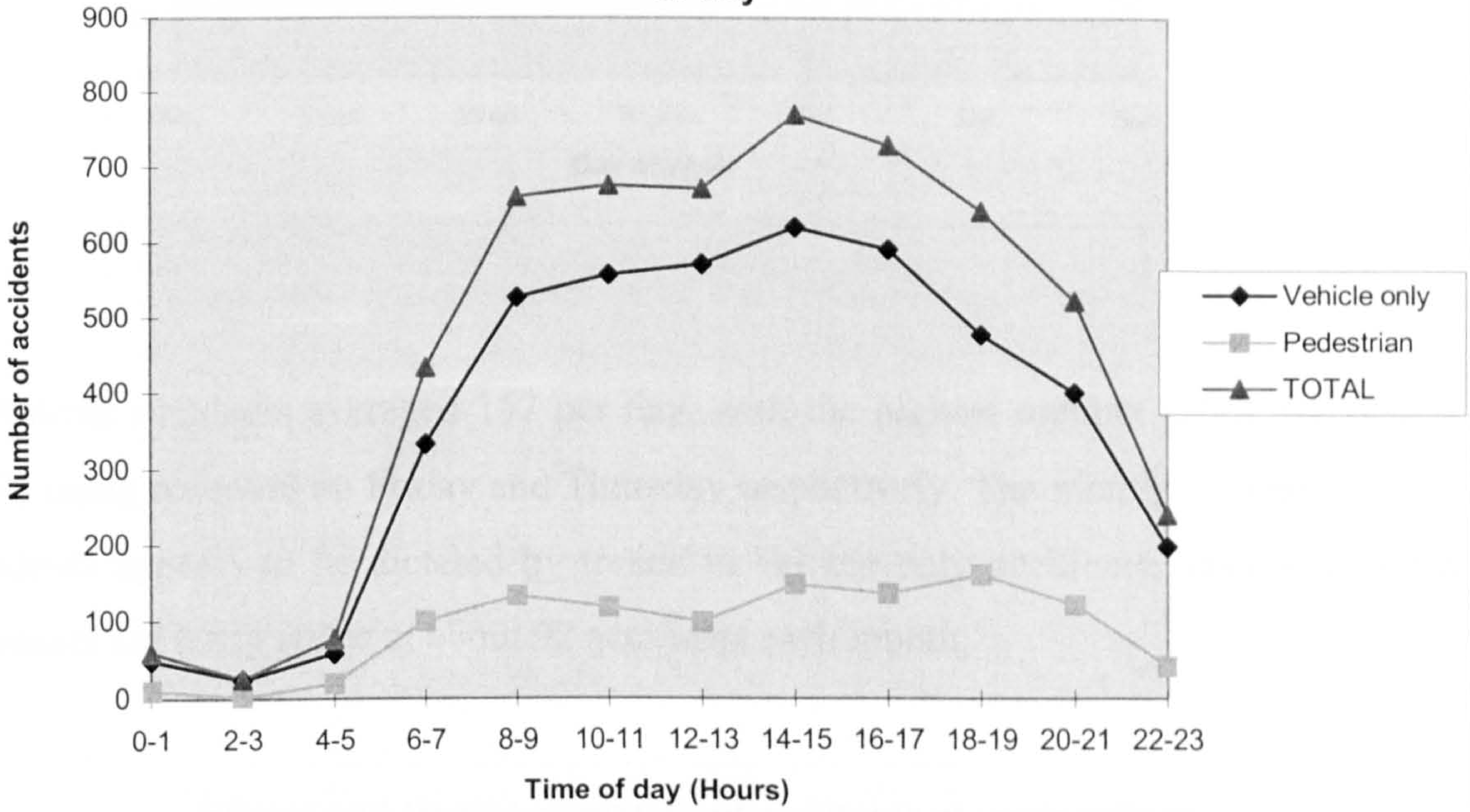
Figure 4.9 Relative distribution of selected accident types at unsignalised T and X-junctions



4.3.1.4 When Do Accidents Occur?

Figure 4.10 illustrates the distribution of accidents at unsignalised junctions according to the times of the day they occurred. Generally, individual accident types varied in a similar trend to that observed for accidents at all types of junction; however, overall accident numbers and vehicle-only accidents showed some noticeable difference.

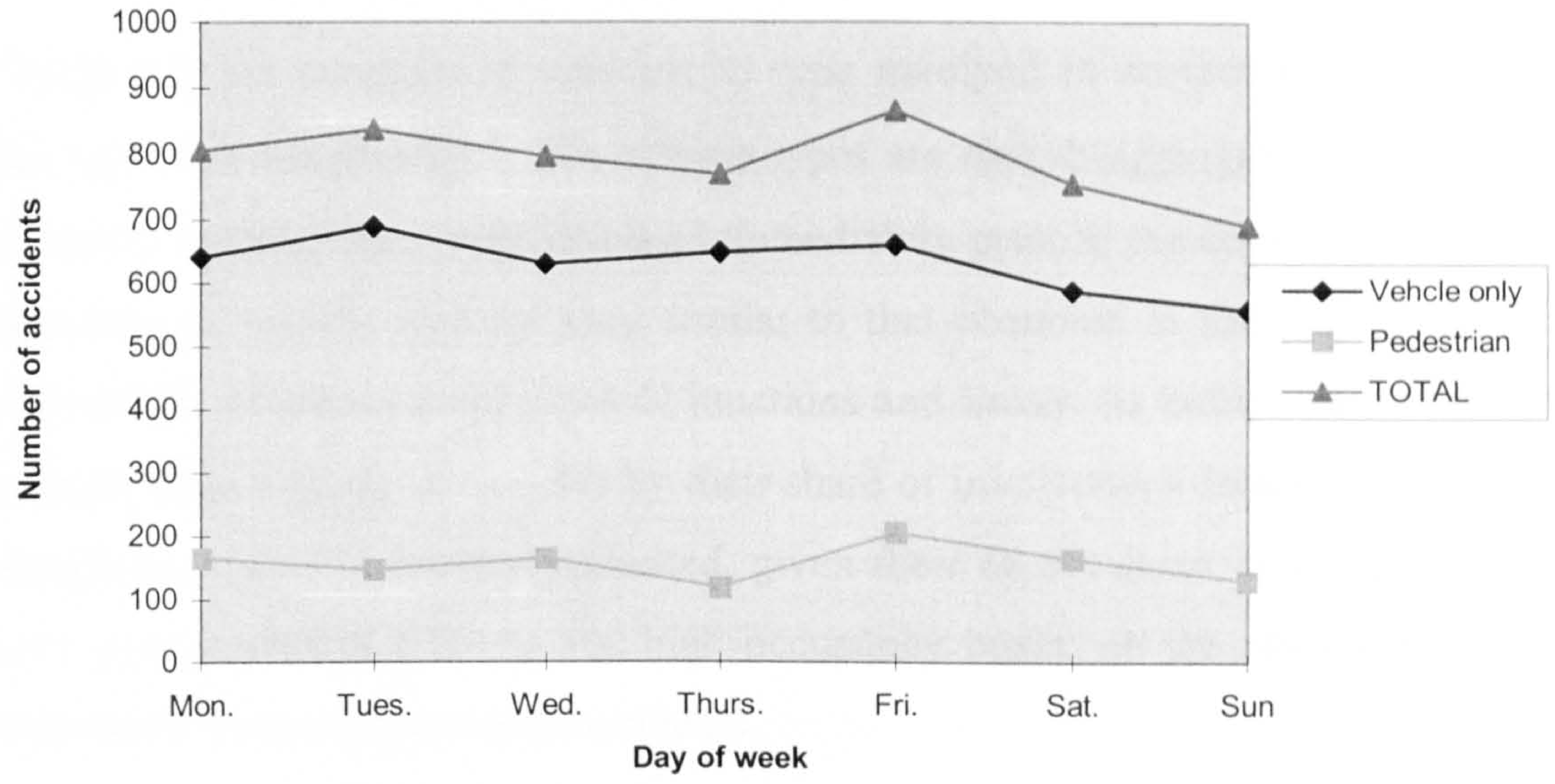
Figure 4.10 Distribution of accidents at unsignalised junctions by time of day



Unlike accidents at all junctions combined, which clearly exhibit peaks both morning and evening, all accidents at unsignalised junctions (like vehicle-only accidents) peak noticeably only at 14.00 to 15.00 hours in the afternoon. Pedestrian accident trends in this case also differ from that for all junctions, because they exhibit an additional, albeit minor, afternoon peak at 14.00 to 15.00 hours. The daily and monthly variations in accidents at unsignalised junctions are illustrated in Figures 4.11 and 4.12 respectively. There is a gradual and consistent drop in the number of vehicle-only accidents, from the highest (689) recorded for Tuesdays to the lowest (558) for Sundays.

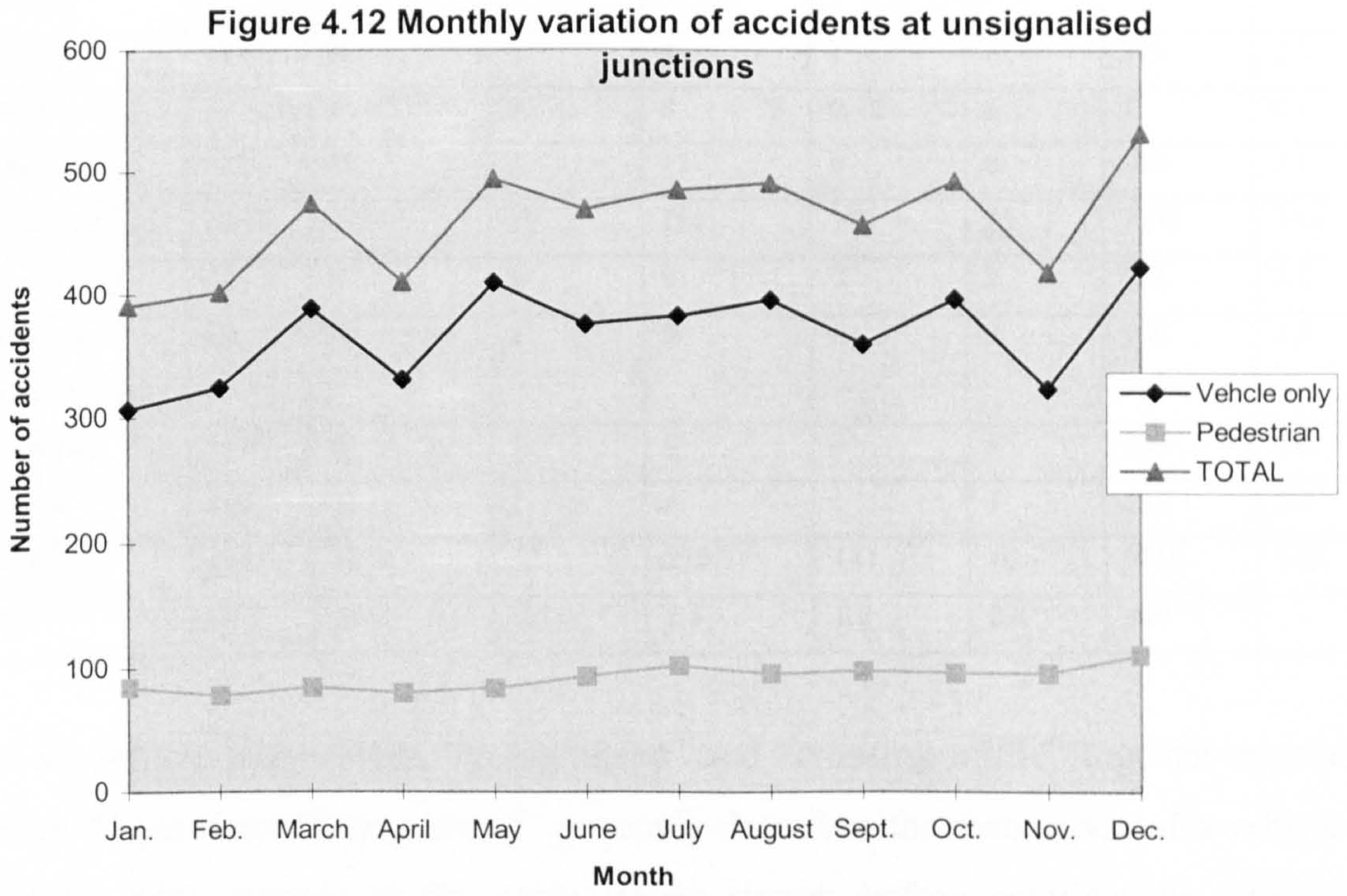
Whilst it is expected that Sundays would have the lowest accident numbers, due to considerably reduced traffic activity on this day, it is surprising that, notwithstanding the relatively comparable levels of traffic from Mondays through to Saturdays, accident numbers would generally decline in that order, as observed.

Figure 4.11 Daily variation in accidents at unsignalised junctions



Pedestrian accidents averaged 157 per day, with the highest number (206) and lowest (119) being recorded on Friday and Thursday respectively. The monthly variation in all accidents appears to be dictated by trends in vehicle-only accidents, since pedestrian accidents are fairly stable at about 92 accidents each month.

Figure 4.12 Monthly variation of accidents at unsignalised junctions



4.3.1.5 Vehicle-types and Vehicle-manoeuvres

In Table 4.5, the numbers of vehicles by type involved in accidents at unsignalised urban junctions are presented. The vehicle-types are also disaggregated by the type of manoeuvre in which they were involved immediately prior to the collision. The overall proportions of vehicle-type are very similar to that observed in the case of all urban accidents (i.e. accidents at all types of junctions and links). As before, cars constituted the single largest group of vehicles by their share of involvement in accidents (64.2%), although they are still under-represented, given their 68.8% share of vehicular traffic. Heavy goods vehicles (HGVs) and high occupancy buses, on the other hand, remain considerably over-represented in accidents.

Table 4.5. Vehicle-types and manoeuvres in unsignalised junction accidents

Vehicle Manoeuvre	Vehicle Type							
	Car	HGV+ Bus	Minibus	M/cycle	B/cycle	Other	TOTAL	%
Right-turn	145	62	1	4	4	3	219	2.3
Left-turn	455	195	4	11	11	2	678	7.0
U-turn	147	83	3	4	0	2	239	2.5
Cross Traffic	149	58	0	8	7	0	222	2.3
Merging	145	68	0	4	1	1	219	2.3
Diverging	5	4	0	0	0	0	9	0.1
Overtaking	118	74	3	15	0	0	210	2.1
Going ahead	4647	2224	39	185	113	25	7233	74.4
Reversing	49	67	0	0	0	2	118	1.2
Sudden Start/Stop	69	29	0	0	0	2	100	1.0
Parking	154	65	2	0	4	0	225	2.3
Other	159	75	1	4	1	3	243	2.5
TOTAL	6242	3004	53	235	141	40	9715	100
%	64.2	31.0	0.5	2.4	1.5	0.4	100	-

Of all vehicle manoeuvres, “going ahead” and ”crossing traffic” together represented about 77 per cent. “Going ahead” generally describes the manoeuvre of a vehicle that collides with another in the same traffic stream before entering the intersection. “Crossing traffic” on the other hand refers to colliding parties from the minor and major roads respectively whose paths cross each other. Thus, the vast majority of collisions involved vehicles either on the approaches to junctions or making a straight transition through the junction from one arm to the other of the same road. Vehicles executing one turning manoeuvre or another, at the time of accident, constituted only 14 per cent of all those involved in accidents.

4.3.2 Analysis of Case-study Junctions.

4.3.2.1 Accident rates and frequency

One of the main objectives of the case-study has been to compare the accident characteristics of different types of unsignalised junction. For this purpose, Table 4.6 provides summary information, such as the Average Annual Daily Traffic (AADT), the minor road's share of traffic and the accident frequency and rate for each junction type (see detailed breakdown in Appendix 4I).

Table 4.6 Traffic volume, accident frequency and rate by junction type

Junction type*	Number Of sites	AADT (vehicles/day)	Minor road's share of traffic (%)	Accident Frequency (accidents/site/ year)	Average number of accidents/year/ 10^6 vehicles entering the intersection
T-1	21	11,482 (1,386)	25.4 (2.3)	2.03 (0.49)**	0.66 (0.19)**
T-2	7	11,906 (1,724)	28.8 (3.3)	1.86 (0.59)	0.37 (0.11)
T-3	6	15,747 (3,176)	18.8 (5.9)	2.06 (0.57)	0.37 (0.11)
T-4	6	11,791 (1,262)	22.1 (8.3)	1.56 (0.92)	0.34 (0.16)
T-5	9	15,852 (2,297)	13.7 (3.4)	2.63 (1.02)	0.48 (0.13)
T-6	8	21,411 (2,973)	15.9 (3.5)	2.13 (0.61)	0.28 (0.09)
Average for T	-	**14,099** (1,969)	**21.6** (3.8)	**2.07** (0.66)	**0.48** (0.14)
X-1	14	11,764 (1,547)	35.6 (3.2)	2.33 (0.69)	0.54 (0.13)
X-2	11	18,901 (2,072)	16.0 (3.0)	3.03 (0.89)	0.48 (0.12)
X-3	9	18,386 (3,250)	33.0 (3.6)	1.48 (0.43)	0.22 (0.07)
Average for X	-	**15,826** (2,168)	**28.6** (3.2)	**2.33** (0.69)	**0.44** (0.11)

*See junction classification in Appendix 3II; **See Appendix 4II for statistical procedures for comparing means
Note: Figures in brackets are standard errors of the mean values shown

The lowest accident frequency (i.e. number of accidents recorded per year per site) for T-junctions is at junction type T-4 and the highest at type T-5. T-4 represents an intersection between a 4-lane dual carriageway with kerbed medians on the main approaches and a standard 2-lane single-carriageway. Left-turning manoeuvres are not possible at T-4 type junctions, because the kerbed median continues through the junction. T-5 is basically the same as T-4, except that at T-5 type junctions a break in the median allows left-turning manoeuvres, i.e. equivalent to the right-turn in the UK.

For X-junctions, X-2 and X-3 had the highest and lowest accident frequencies respectively. Whereas the difference between the two extreme values of accident frequency was not statistically significant (*t*-test) for T-junctions, at X-junctions it was just significant at the 5 per cent level. As far as accident frequency is concerned, therefore, there is little to choose between the different types of T-junction. The apparent variation in values is most likely due to random factors.

By contrast, however, it can be said that the typical X-3 junction has a significant tendency to record fewer accidents in any given year than any of the X-2 type. X-3 also records substantially fewer accidents than X-1. In statistical terms, the average T-junction also has about the same accident frequency as the corresponding X-junction. It needs to be noted, however, that accident frequency may not be the best indicator of safety at the different sites, since it does not take account of the intensity of use or the exposure to the risk of accident.

Probably, a relatively better basis for comparing the unsafety of junctions is the accident rate, which is defined as the average number of accidents recorded per million vehicles using the given type of junction in the same time period. In this regard, it can be seen that the trends are clearly different from that presented by accident frequency for the individual junction types, although overall accident rates also happen to be similar for T- and X-junctions.

T-1 has the worst accident rate (0.66 per million vehicles) and is considerably unsafer than T-2, T-3, T-4 and significantly more so than T-6. Although other factors may also be involved, this observation appears to underscore the safety benefits of using channelisation or carriageway dividers of some sort at junctions, the main features differentiating the rest of the T-junction types from T-1.

The marked difference in accident rate between junction types T-5 and T-6 also shows that a separate storage lane for vehicles turning left from the major road could also improve the safety status of the junction. In fact, T-6 is not only apparently much safer than T-5 and T-1 but, as the data shows, it also carries considerably more traffic and accommodates a higher proportion of minor road traffic than T-5 and almost double the traffic volume at T-1. T-6 type junctions, therefore, combine fairly well the twin attributes of lower potential for accidents and higher capacity, at least, within the limits of the range of traffic volumes and the splits between the major and minor arms of the junctions represented by the data.

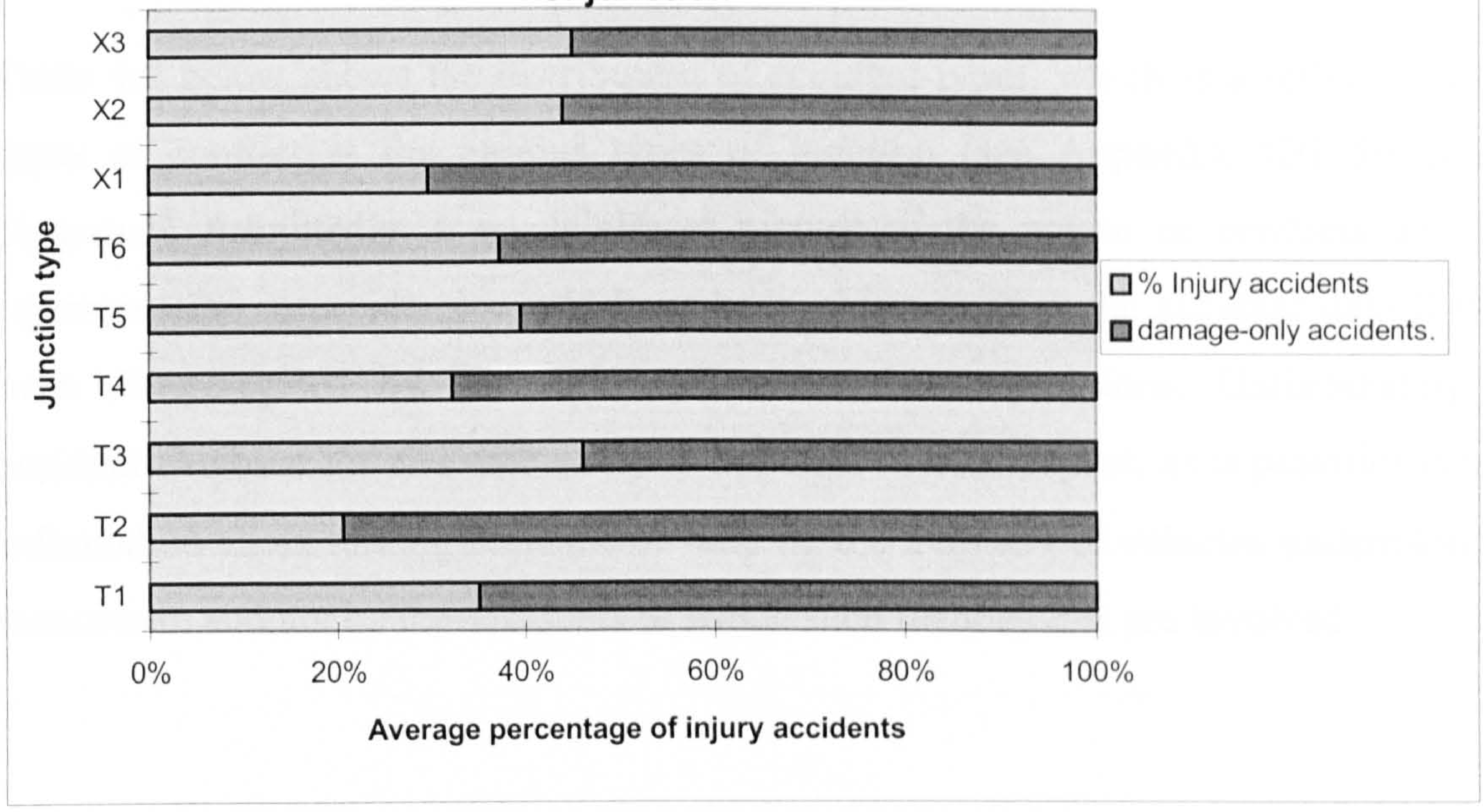
The difference in accident rate between junction types T-3 and T-5, notwithstanding the similar levels of traffic they handle, also probably gives a good account of channelisation on the minor road. This is consistent with what is generally expected, since the presence of kerbed islands on the minor road helps in organising turning movements of traffic and, by so doing, reduces conflicts and the chance of collisions at junctions.

Accident rates of junction types X-1 and X-2 are significantly higher than that of X-3; each of the former having more than twice the accident rate of the latter. Whilst being the least accident-prone, type X-3 junctions also carry twice the minor road proportion of traffic as X-2 and one and a half times the overall traffic volume of X-1. This would again underscore the potential benefits of having storage lanes for left-turning traffic on the major road.

4.3.2.2 Severity of accidents

Accident severity here is presented as the average percentage of injury (i.e. fatal, severe and minor injury) accidents in relation to all accidents recorded at the different junction types. As is evident from Figure 4.13, among the T-junctions types T-2 and T-3 have the lowest (20.5) and the highest (46.0) percentages respectively, of accidents involving injury. The difference between these two proportions is significant at 95 per cent confidence level. Speed may be an important factor here, since more than 70 percent of average vehicle spot-speeds on the major approaches to T-3 type junctions are above 50km/h, as against only 15 per cent at junction type T-2 (see Figure 3.2a for speed distribution).

Figure 4.13 Balance of injury and damage-only accidents by type of junction



However, although the same percentage of spot-speeds above 50km/h are recorded at T-3 junctions as at T-4, the latter still have significantly (at 5% level) less injury accidents by proportion than the former and both have a similar accident rate. The accident severity at T-3 and T-1 are also not significantly different. This probably suggests that, whilst speed might be influential in determining the severity of accidents, some measure of speed, other than just the nominal values may account largely for the level of injury accidents at any given site. Exploratory analysis of the relevant speed and accident data for X-junctions, for example, revealed that the standard deviation of junction approach spot-speeds of vehicles (x) correlated better with personal injury accidents (y) ($y = 0.031x^2 + 0.17x + 0.47$; $R^2 = 0.37$, n = 34) than other speed indicators, such as 85-th percentile and mean values.

Both junction types X-2 and X-3, have significantly higher accident severity than type X-1. Between the two of them, however, the difference is marginal. This might be expected, since the major arms of types X-2 and X-3 are both major dual-carriageway arterial roads with similar proportions (35%) of traffic speeds above 50km/h (see Figure 3.2b for speed distribution). By contrast, the single carriageway collector or distributor roads typical of junction type X-1 have more than 80 per cent of average spot-speeds below 40km/h.

4.3.2.3 Accidents by type of conflict

Table 4.7 below shows the distribution of accident-types, which is a reflection of the types of conflict at the various types of junction (see Appendix 4III for conflict diagrams). Admittedly, a much clearer picture of the nature of conflicts and their representation in accidents would have been obtained from the accident data if it had been disaggregated by the various flow-streams at junctions. Unfortunately, the accident database for this case-study is deficient in this respect, as it provides detailed information about turning movements only by the numbers of vehicles undertaking the manoeuvre and not by the accidents in which such manoeuvres are involved.

Table 4.7 Accident type distribution by junction type

T-Junctions

	Accident Type						
Junction type	Head-on	Rear- end	Side- wipe	Right-angle	Single vehicle	Pedestrian	Total
T-1	9	35	19	35	8	22	128
T-2	2	11	15	4	4	3	39
T-3	1	9	11	10	1	5	37
T-4	0	10	11	3	0	4	28
T-5	2	20	16	11	3	19	71
T-6	5	13	10	12	3	10	53
Total	19	98	82	75	19	63	356
Percentage	5.3	27.5	23.1	21.1	5.3	17.7	100

X-Junctions

Junction type	Head-on	Rear-end	Side-swipe	Right-angle	Single vehicle	Pedestrian	Total
X-1	5	16	18	36	4	19	98
X-2	9	24	13	26	5	23	100
X-3	2	10	3	14	3	8	40
Total	16	50	34	76	12	50	238
Percentage	6.7	21	14.3	32	5	21	100

On the other hand, although the information could have been extracted from the original accident report forms, this was not considered feasible due to the rather large number of forms involved. In the circumstances, therefore, it was necessary to rely on the accident types, which also give a good indication of the nature of conflicts.

It is clear from Table 4.7 that single vehicle accidents constitute only a small fraction (5%) of all accidents recorded at the case-study junctions. This confirms the expectation that accidents at junctions are predominantly due to conflicts between two or more vehicles, or between vehicles and pedestrians.

Overall, rear-end, side-swipe, right-angle collisions and pedestrian accidents are the four dominant accident types, in order of decreasing percentage at T-junctions, but the relative distribution within each type of T-junction differs markedly from this trend. Whereas rear-end collisions involve vehicles travelling in the same traffic stream, whether on the major or minor road, side-swipes usually involve merging and diverging manoeuvres. Right-angle collisions, on the other hand, predominantly involve the near-side major road vehicles who are moving straight through the junction from one arm to the other and left-turning vehicles from the minor road (see Appendix 4III).

Junction type T-1 appears to be the most susceptible to right-angle collisions amongst the T-junctions and this may be due, in part, to the potential for minor road vehicles to overshoot the position of the stop-line, accidentally or otherwise, into the path of through vehicles on the major road. The main accident types at this type of junction are right angle, rear-end, pedestrian and side swipes, in order of decreasing percentage. By comparison, the trends for T-5 and T-6, for example, are respectively, rear-end, pedestrian, side-swipe and right-angle and rear-end, right-angle, side-swipe and pedestrian in similar order.

The majority of pedestrian accidents were recorded at T-1 and T-5 type junctions and this would be largely attributable to the locations of these junctions (e.g. how close or far away they are from the CBD) and the level of pedestrian traffic on them. This is supported by the fact that, with the exception of T-6, junction types T-5 and T-1 recorded higher average peak hour pedestrian flows than the rest of the junctions. But the scale of pedestrian accidents at these sites could also be due to some site-specific features, which should become more apparent at the modelling stage when the relationships between site geometry, traffic variables and accidents are examined.

Relative to T-5, T-6 recorded a smaller average percentage of rear-end accidents, although the latter carries about 20 per cent more traffic and about twice the proportion of left-turning major road vehicles than the former. By these indicators, which may be closely related to the incidence of rear-end collisions, T-6 type junctions would have been expected to fare poorer in this respect than T-5. The observed outcome may be connected with the presence of a dedicated storage lane for left-turning major road traffic on T-6, which enables diverging traffic to leave the mainstream before slowing down to execute the turn.

The potential safety benefits of a separate left-turning storage lane on the major road, as obtains on T-6 junctions, may not be limited only to the reduction in incidence of rear-end accidents. By providing refuge for left-turning vehicles into and from the minor road, drivers are presented with the opportunity to wait for adequate safe gaps to leave or join the major traffic stream. This reduces the potential for conflict, and therefore accidents, between major and minor road traffic.

At X-junctions the distribution of accident types overall was right-angle, rear-end, pedestrian and side-swipe, in order of decreasing average percentage. Right-angle accidents stand out much more obviously here (it is consistently the most dominant at all the junction types) than with T-junctions. Such collisions predominantly involve vehicles making a straight transition through the junction from one arm to the other of the same road and the corresponding traffic stream on the other road, although other opportunities for right-angle collisions exist for left-turning vehicles as well. Junction type X-1 appears more particularly prone to right-angle collisions than the other junction types. This is even more evident when it is considered that half the sum of through minor and major road traffic, a proxy for the potential number of conflicts relevant to right angle collisions, is only 3,314 veh./day as compared to 7,051 veh./day for X-2 and 5,885 veh./day for X-3. Thus, although X-1 has potentially less exposure to this type of accident, it still manages to record a high proportion relative to the other types of junction. The general difficulty of clearly identifying the hierarchy of roads at such junctions, which is made worse by the absence of channelisation, may be a major factor in these accidents.

X-2 type junctions, on the other hand, indicate a higher potential for rear-end collisions relative to X-1 and X-3. These account for about 50 per cent of all rear-end collisions at X-junctions, although they evidently had a much smaller proportion (6.1%) of left-turning major road traffic, an important relevant traffic flow stream for rear-end collisions. X-3 and X-1 had 13.8 and 15 percent, respectively, of major road traffic making left-turn manoeuvres. Due to the absence of left-turning storage lanes for major road traffic at X-2 type junctions, it is quite likely that rear-end accidents would arise out of conflicts between cruising through traffic and slowing down left-turning traffic in the inner-lane of the major road. Pedestrian accidents are also most highly represented at X-2 junctions.

4.3.2.4 Accidents by type of junction control.

In this case-study, three types of unsignalised junction control were encountered, namely; "stop", "yield" or "give-way" and no control or "none". These control types were compiled based on the posted signs at each junction, therefore, no control or "none" represents the situation where no signs or road markings were present, although that does not necessarily mean that drivers were free to behave as they wished. By convention, at junctions where no specific rules are posted, traffic is expected to follow the rule of a roundabout, albeit invisible in this case. Doing a comparative assessment of the safety records of junctions with these different control types was an important part of meeting the objectives of the current thesis.

In Table 4.8 below, essential indicators have been presented to compare the unsafety of the control types as they operated at junctions of the type T-1. Isolating this group from other types of T-junctions, not only provides a more even-handed basis for the intended comparisons but, also an opportunity to see if there is any consistency or trend in traffic control practice. The general picture from Table 4.8 is that, as the level of control is tightened from "none" through "yield" to "stop", the nominal values of overall accident rate, injury accident rate and accident frequency consistently increase.

Table 4.8 Traffic and accident characteristics by type of control at junction type T-1

Junction control Type	Number of sites	AADT veh/day	Minor road's share of traffic (%)	Overall accident rate (accidents/10^6 vehicles)	Injury accident rate (accidents/10^6 vehicles)	Accident frequency (accidents./site/ year)
STOP	11	12,234 (2,133)*	22.9 (3.5)	0.89 (0.35)	0.26 (0.08)	2.51 (0.92)
YIELD	5	11,484 (1,758)	28.4 (5.4)	0.46 (0.06)	0.19 (0.03)	1.80 (0.23)
NONE	5	9,828 (3,354)	27.8 (1.5)	0.35 (0.15)	0.17 (0.09)	0.93 (0.29)
Overall total (average)	-	11482 (1,386)	25.4 (2.31)	0.66 (0.19)	0.22 (0.05)	1.97 (0.50)

* Figures in brackets are standard error of the mean values shown

Further to that, the differences in the overall accident rates and accident frequencies for the different controls were highly significant (at 1% level). On account of these two indicators, therefore, we can conclude that the unsafety situation at unsignalised junctions worsens with increasing level of control. In terms of accident rates, stop-controlled junctions are about twice and two and a half times as unsafe as "yield" and "no control" junctions, respectively. In any given year, stop-controlled junctions are also likely to record forty per cent more accidents than yield junctions and over two and half times more accidents than junctions at which there is no control. The difference in injury accident rate between no control and yield control junctions was however not statistically significant.

A contentious point that might be advanced, in defence of the apparently poorer safety record of tighter junction controls (e.g. stop control), is that the tightening itself may have been motivated by an existing bad accident situation at the site. It may also be said, that such sites carry more traffic relative to the junctions with more relaxed controls. Unfortunately, these points would tend rather to reinforce the case against adopting the tighter control as a safety intervention, because the situation remains unaffected (at best) after implementation. In fact, because accident rate, which is the main basis of comparison here, tends to be more favourable to high as opposed to low flow sites, the gulf in safety between stop controlled and other types of junction could actually be worse than portrayed here.

Nevertheless, it is important that reasonable caution is exercised in interpreting the above results. It is quite tempting, for example, to conclude that the safest junctions are those that have no control and, following that, suggest that we can improve safety at stop-controlled junctions by simply removing the controls! Such a view would be overly simplistic and could lead to even more disastrous consequences. Contemplating the replacement of stop with yield control, however, might be a more acceptable prospect, given the potential savings likely to accrue in respect of vehicle operation costs, in addition to the possible safety improvement as apparent in Table 4.8 (see also Section 2.2.1).

Above all, the results presented here must be interpreted within the context of the range of data covered and the comparative approach adopted. Decisions on safety interventions would have to be based on some notional "acceptable" threshold values of accidents, or accident rates, for each major type of junction and control type examined here, and options for improvement need not be limited to the junction types discussed. This latter point is examined further in Chapter 6, where decision criteria for accident blackspots are discussed.

It can also be observed from Table 4.8 that the level of control tends to increase with increasing AADT. Thus, the approach adopted to junction control, it appears, has been to implement stop control at the more highly trafficked junctions and, within that, probably giving preference to those with a much higher major road traffic relative to the minor road. The basis of this assertion is the fact that stop-controlled junctions recorded both the highest AADT and lowest minor road share of traffic. This might sound a prudent approach, since junctions of this nature (without any features on either road) are often formed by roads generally lower down the urban road hierarchy, which are not clearly distinguishable from each other by their geometric features.

The underlying rationale for implementing yield in preference to no control or *vice versa* is less obvious, except in the difference in AADT values for such sites. It appears though, that no control sites would usually have relatively low flows on both major and minor roads. It is also quite likely that, where the flow levels at sites with no control were comparable to others with either stop or yield signs, the non-provision of signing could have been more due to resource constraints of the responsible Road Department than to a deliberate decision not to actively control.

The same indicators as in Table 4.8 are presented in Table 4.9 for junction types T-2 to T-6. Similar trends obtain as for junction types T-1, as far as the relative safety records of the different types of control are concerned, although substantial differences can be seen between individual values of the key indicators in the two cases. Whereas accident frequency figures are essentially the same as those for T-1 type junctions, averaged over the different control types, all accident and injury accident rates of T-1 type junctions are between one and a half and two times those of T-2 to T-6 type junctions.

Table 4.9 Traffic and accident characteristics by type of control at T-2 to T-6 type junctions

Junction Control	Number of sites	AADT (vehicles/ day)	Minor road Traffic (%)	All accident Rate (accidents/ 10^6 vehicles)	Injury Accident rate (accidents/ 10^6 vehicles)	Accident Frequency (accidents/site /year)
STOP	16	16,995 *1868.9**	18.2 *2.96*	0.46 *0.09*	0.18 *0.04*	2.54 *0.62*
YIELD	17	13,380 *1,575.70*	19.5 *3.3*	0.33 *0.07*	0.1 *0.02*	1.84 *0.42*
NONE	3	15,942 *1,845.48*	25.2 *1.91*	0.2 *0.14*	0.06 *0.03*	1.11 *0.55*
Average (overall)	- -	15,200 *1,276.20*	19.4 *2.2*	0.37 *0.05*	0.13 *0.02*	2.09 *0.35*

*Figures in italics represent standard error of mean values

To confirm this, statistical tests have showed that, whilst the average accident frequency for T-2 to T-6 type junctions are the same as that for T-1 (difference not significant at 95 per cent confidence level), the differences between the average all accident and injury accident rates were highly significant. By implication, this means that, on average, T-junctions without features (i.e. some form of channelisation) are generally more than one-and-a-half times unsafer as those with features.

It is, however, slightly unexpected that junctions with features (i.e. some form of channelisation), mostly with dual-carriageways as the major roads, recorded less incidence of injury accident than those without features, because of the possibility of higher operating speeds on the former. A partial explanation of this trend may be that the much larger traffic volumes handled by junctions with features probably "dilute" their injury accident rate figures. Alternatively, as already observed elsewhere, the injury accidents may be more dependent on variability in traffic speeds than actual levels of speed.

Two intriguing aspects of the traffic characteristics of the T-2 to T-6 sites are that, first, those with no control recorded much higher traffic volumes and minor road's share of traffic than the yield controlled sites. Secondly, the least trafficked sites with features were not only yield controlled, but they also handled far more traffic than sites in the T-1 group, which would have qualified outright for stop control. Perhaps, the only plausible explanation for these observations is the possible element of arbitrariness in traffic control practice, in addition to obvious resource constraints, which mean that the road authorities are unable to implement traffic controls at all junctions in need of them at any one time.

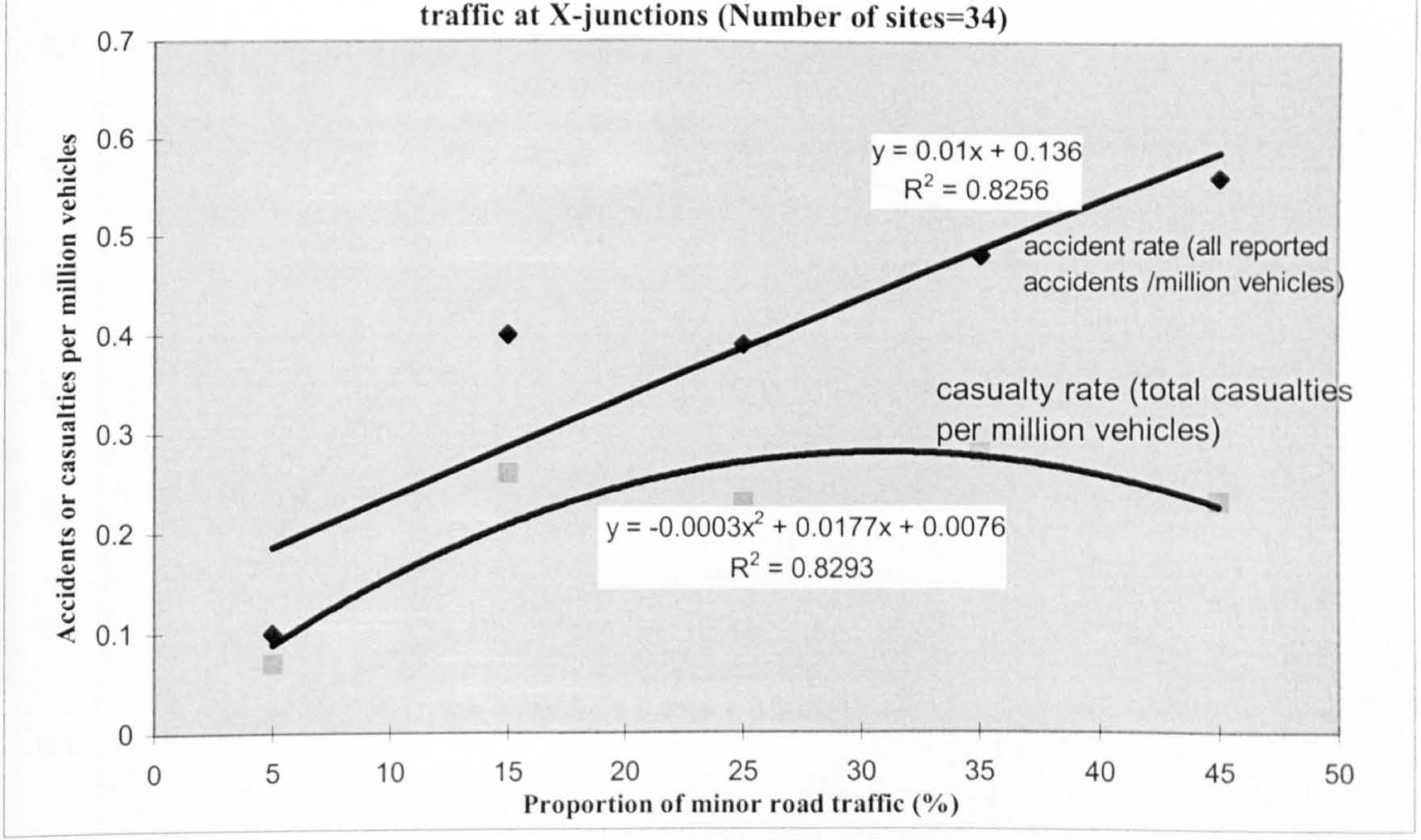
It was not possible to do similar comparisons of the accident records of the various unsignalised control types at X-junctions, because only 15 percent of the entire sample covered by the case-study were either yield control or the no control type. Generally speaking, therefore, it would be fair to say that all X-junctions are regulated by two-way stop control on the minor roads, irrespective of the AADT levels, or the relative split of traffic between the major and minor roads.

4.3.2.5 Safety implications of minor road traffic

The level of traffic on the minor road is one important parameter used as a guide for decisions on the type of control, or the need to upgrade unsignalised junctions, to achieve some set traffic management and safety objectives. Any consideration of the safety threshold limits for unsignalised junctions, therefore, has to include a close examination of the general relationship between minor road traffic and accidents. It is apparent from the discussions in the preceding sections that the proportion of junction traffic on the minor road clearly had a part to play in the differences in some safety indicators of the different types of junctions examined. To find out if there were any more general relationships, the minor road's share of traffic at each junction and the corresponding accident data were subjected to ordinary regression analysis. When the minor share of traffic was matched against overall accident rates and casualty rates across the spectrum of junction types, it was found that the relationship varied from none at all, for T-1, T-2, and X-3 junctions, through R^2=0.3-0.4, and R^2=0.5-0.7, for T-4, T-5, T-6, X-1 and T-3 and X-2 respectively (see Appendix 4IA-J for details of samples). Further exploration by aggregating the respective data for all T- and all X-junctions separately gave very good and quite plausible relationships.

As illustrated in Figure 4.14, for X-junctions, the relation between accident rate and the proportion of minor road traffic is a linear one. It shows that every 10 per cent increase in the minor road's share of traffic, leads to a 0.1 increase in accident rate (all reported accidents per million vehicles). The relation explains some 82.5 percent of the variation between the two parameters. The link between accident casualty rate and minor road proportion of traffic at X-junctions, on the other hand is described by a polynomial curve, which means that casualty rate (total casualties per million vehicles) increases with increasing proportion of traffic from the minor road, until it peaks at about 0.27 casualties per million vehicles, corresponding to 29.5 per cent for minor road traffic.

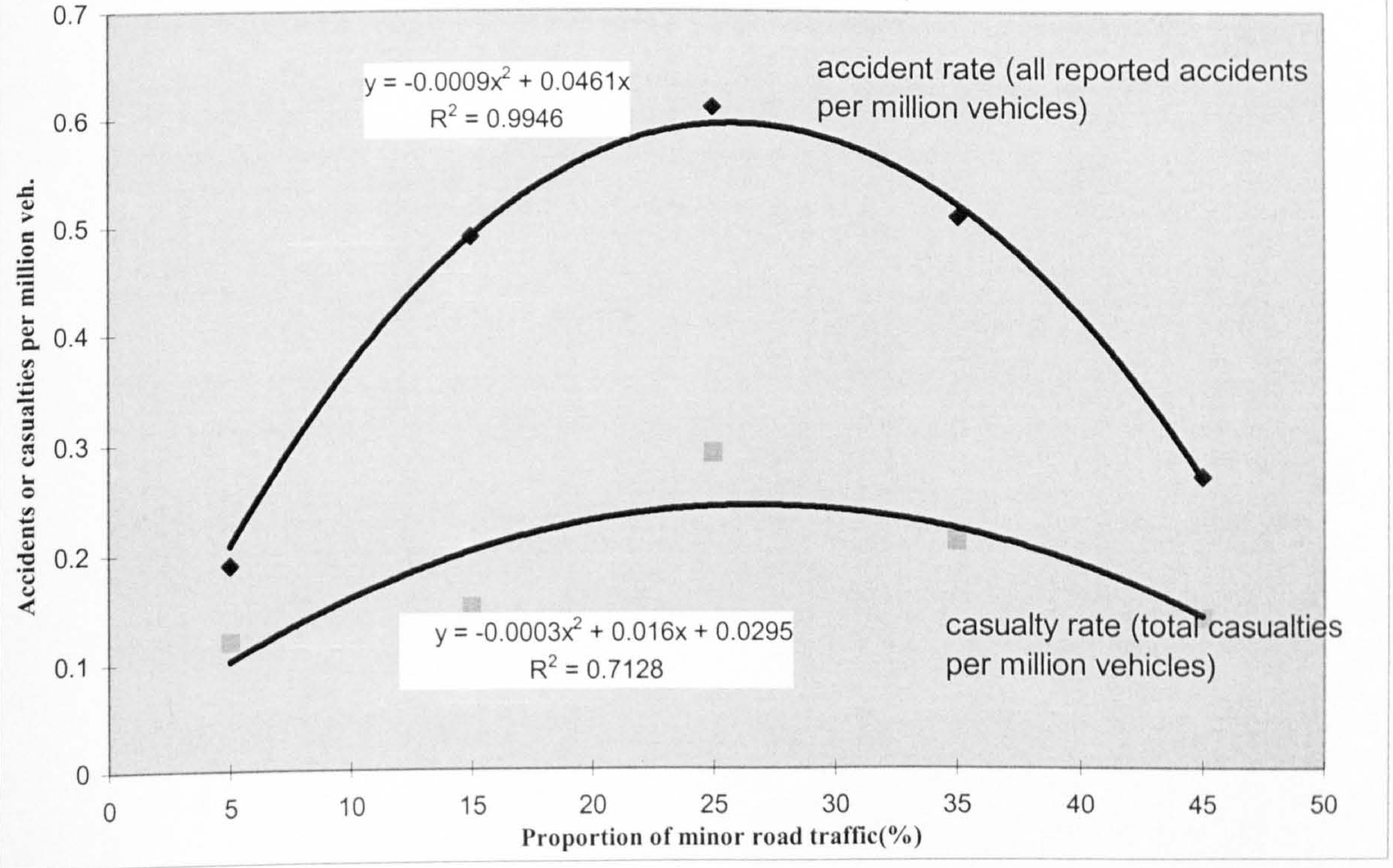
Figure 4.14 Variation of accident and casualty rates with minor road's share of traffic at X-junctions (Number of sites=34)



It is important to stress that accident rate cannot increase with minor road traffic without bounds. Thus, the trend observed must be understood within the limits of the data presented. The general relation is nonetheless quite plausible, because increasing traffic from the minor road will lead to increasing conflict at unsignalised junctions, and thereby, lead to a higher potential for accidents. It is also a realistic scenario to observe that, as the minor road traffic share increases so does the casualty rate. However, because casualty rate has a close relation with traffic speeds as well, it is expected that this will peak at a point and drop subsequently, as further increases in the share of minor road traffic leads to a general slow down of traffic on all arms of the junction. This critical turning point corresponds to 29.5 per cent for minor road traffic, as earlier stated.

At unsignalised T-junctions, the relation between minor road's share of traffic and casualty rate (see Figure 4.15) is similar to the one observed for X-junctions. The critical proportion of minor road traffic in this case is 26.7 per cent. The accident rate trend, however, is different. In this case, it follows a polynomial trend, similar to the casualty rate trend, and it peaks at 0.59 accidents per million vehicles for a minor road's traffic share of 25.6 percent. For unsignalised T-junctions, therefore, accident rates fall with casualty rates after both have peaked more or less at the same percentage of minor road traffic.

Fig. 4.15 Variation of accident and casualty rates with minor road's share of traffic at T-junctions (Number of sites=57)



It would appear that accident rate at T-junctions is more sensitive to increases in the minor road traffic than X-junctions, since the rate of increase or fall is much more rapid in the former case. The casualty trends on the other hand have similar gradients and only clearly differ in their turning point values. Finally, it is important to note that the regression relationships described above were obtained with a simplified form of the data. Only the averages of accident/casualty rate for five classes between 0.0% and 50.0%, and at intervals of 10% were plotted against the midpoints of the classes. Obviously, this raises queries about the relative weights of these points, since the distribution of junctions in the class intervals was not the same.

However, this was not a major concern, because the exact quantitative relationships themselves were not the main subject of interest. For the purpose of this study, it would have been satisfactory enough to identify any relationship, even if it was of a more qualitative nature. The main idea was to investigate evidence of any systematic relationship that further explained the differences in accident characteristics of the different junction types and hence buttressed the need to use the minor road's share of traffic as an explanatory variable for estimating accident prediction models. The relationships described, therefore, ought not to be taken literally.

The subject of the effect of minor road traffic on accident frequency is explored further in the next chapter of this thesis (Chapter 5), with the use of generalised linear models for accident prediction.

4.4 Conclusions

A total of 16,334 road traffic accidents, resulting in 10,493 casualties, were recorded in the two case-study cities, for the period 1996-1998 inclusive. In terms of severity, these accidents were split roughly in the ratio 1.0:3.0:6.0:13.0 respectively for fatal, severe injury, minor injury and damage only. The two most dominant urban accident types were pedestrian and rear-end collisions. Pedestrian accidents accounted for about 27 percent of all accidents and 70 percent of fatal accidents, which demonstrates their extreme vulnerability in urban traffic. Child pedestrians, especially girls under age 15 years, were particularly at risk. Most accidents took place in broad daylight and clear weather conditions but, for pedestrian accidents in particular, the twilight hours from 18.00 to 19.00 hours were crucial.

Overall urban accidents were almost equally split between links and junctions. This contrasts with the experience in industrialised countries (e.g. Sweden and UK), where about two-thirds of all accidents in built-up areas are at junctions. Two-thirds of all fatal accidents were recorded on links, resulting in an average of 1.8 fatalities per fatal accident. More than 60 percent of all junction accidents occurred at unsignalised locations, out of which 22 and 60 percent respectively were recorded at X- and T-junctions. Accidents at unsignalised junctions tended to have much more severe consequences than those occurring at other types of junction.

The predominant types of accident at unsignalised junctions were right-angle, rear-end and pedestrian collisions. Whereas the different accident types were more broadly represented at T-junctions, right-angle collisions, which involve, mostly, cross traffic, were clearly the most dominant at X-junctions. On the other hand, T-junctions appeared to have more pedestrian accidents. Of the vehicles involved in accidents at unsignalised junctions, cars constituted the largest group (64.2%) but heavy goods vehicles (HGVs) and high occupancy buses were those highly over-represented and apparently most accident-prone. The proportion of HGVs and high occupancy buses involved in accidents was nearly six times their percentage share of traffic. Most accidents involved two or more vehicles or vehicles and pedestrians and three-quarters of the vehicles involved were simply "going ahead" immediately prior to the collision. Unsignalised junction accidents, therefore, resulted largely from vehicle-vehicle or vehicle-pedestrian conflicts on the immediate approaches.

The case-study has enabled more quantitative comparisons to be undertaken of the levels of unsafety at a representative sample of unsignalised urban junctions, comprising six types of unsignalised T-junctions and three types of X-junctions, classified by the presence or otherwise of some features on either road. The main measure of unsafety was the accident, or casualty, rate per million vehicles. Generally, junctions without any features (i.e. some form of chanelisation) were 1.5 to 2.5 times more unsafe than those with features and this affirmed the basic need for channelisation, or divisional islands, on one or more approaches of the junction. For junctions with dual carriageway arterial roads, the presence of a dedicated left-turning storage lane for major road vehicles appeared to enhance safety as well as junction capacity. Stop-controlled junctions were also statistically significantly less safe than those with either yield or no control.

The minor road's share of traffic appeared to be one of the most influential factors of unsafety. Initial exploratory analysis using ordinary regression techniques showed that it had very high correlation with accident and casualty rates per million vehicles. These relationships, and those involving other accident factors identified in this Chapter, will be explored further and tested in the next stage of this thesis, in order to develop accident predictive models for unsignalised junctions, using Generalised Linear Interactive Modelling (GLIM) techniques.

CHAPTER 5

DEVELOPMENT OF ACCIDENT-PREDICTION MODELS

5.1 Introduction

The objective of modelling was to relate the observed average number of accidents in 3 years at unsignalised urban junctions to a range of explanatory variables largely identified from the analysis of accident characteristics presented in the preceding chapter of this thesis. The models so obtained would then provide a basis for assessing the impact of individual traffic or road features on accident potential, as well as a mechanism for predicting future site-specific mean accident frequency at selected types of junction in the presence of such features. In this study, the development of the accident-prediction models also constituted a major step towards outlining an alternative methodology for appraisal of accident potential using Empirical Bayesian statistical procedures.

Separate predictive models were developed for T- and X-junctions encompassing all accidents, all injury accidents and selected accident types, classified by their defining primary collision types, namely, head-on, rear-end, side-swipe, right-angle, single vehicle and pedestrian accidents. The models and the procedures adopted in their development are presented in this chapter.

5.2 The Independent/Explanatory Variables

A wide range of independent traffic and road variables was tested during the model development process. Most of such variables were identified as potentially influential determinants of accidents from the analysis of accident characteristics of unsignalised urban junctions presented in the previous chapter. Since the sample data analysed may not have revealed all the potentially important accident-dependent variables a number of other variables were also tested, although their effects may not have been all that apparent in the data analysed. The selection of the latter set of variables was guided as much by the findings from previous studies as it was informed by engineering judgement and intuition.

Undoubtedly, the most important accident-dependent variable tested was traffic volume, not least because it represents the exposure to accident, but also because traffic volume and composition give rise to conflicts and friction as a result of which accidents could occur. Different algebraic combinations of the Average Annual Daily Traffic (AADT), separated into various turning movements, were tested. The basic traffic flow streams are illustrated in Figures 5.1 and 5.2 respectively, for T- and X-junctions, whilst the respective flow functions are described in Tables 5.1 and 5.2. Traffic volume data for individual flow streams can be found in Appendix 5I and the full conflict diagrams for both types of junction are provided in Appendix 4III.

Figure 5.1 Vehicle and pedestrian flow Streams at T-junctions

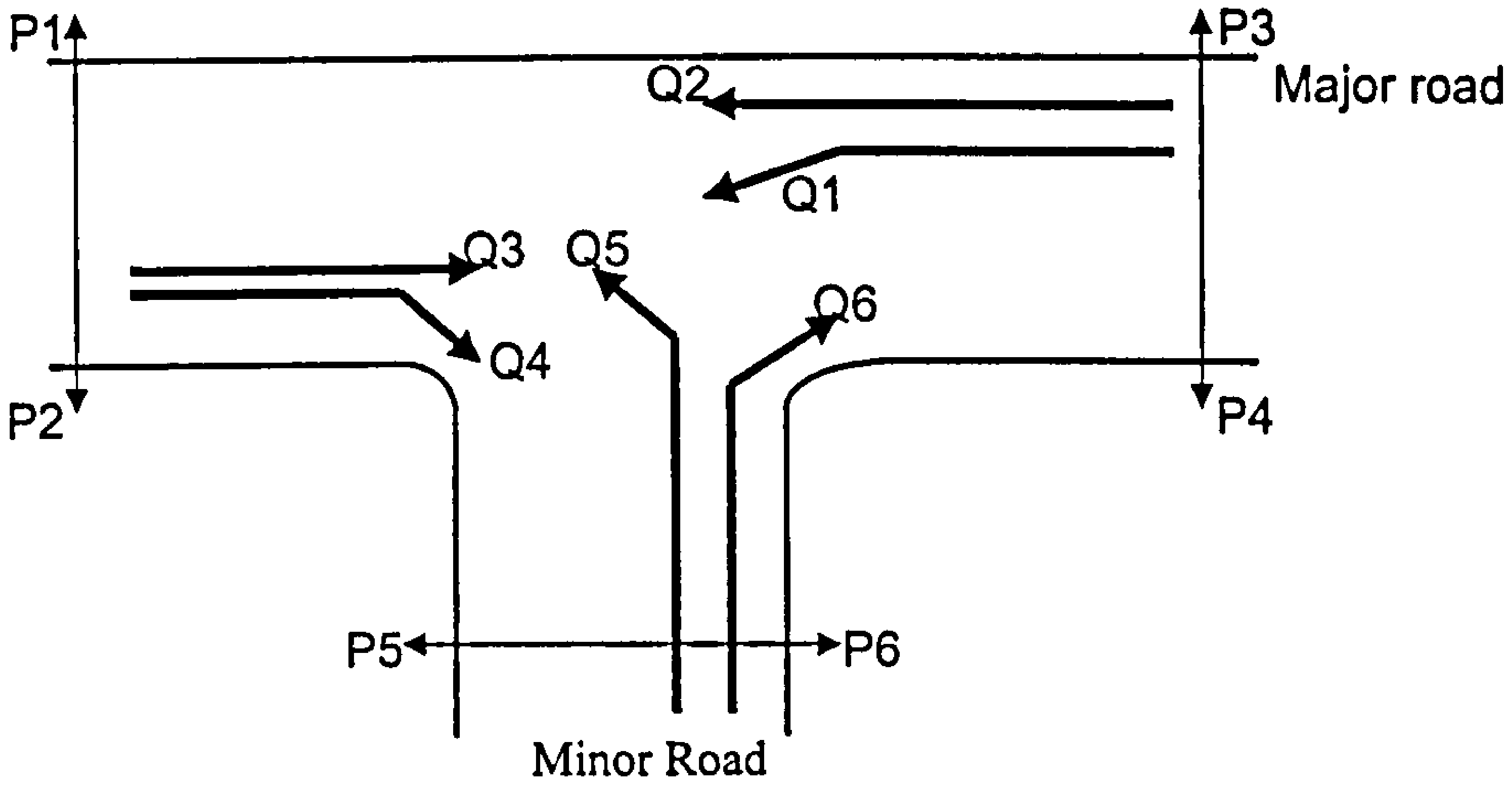


Figure 5.2 Vehicle and pedestrian flows at X-junctions

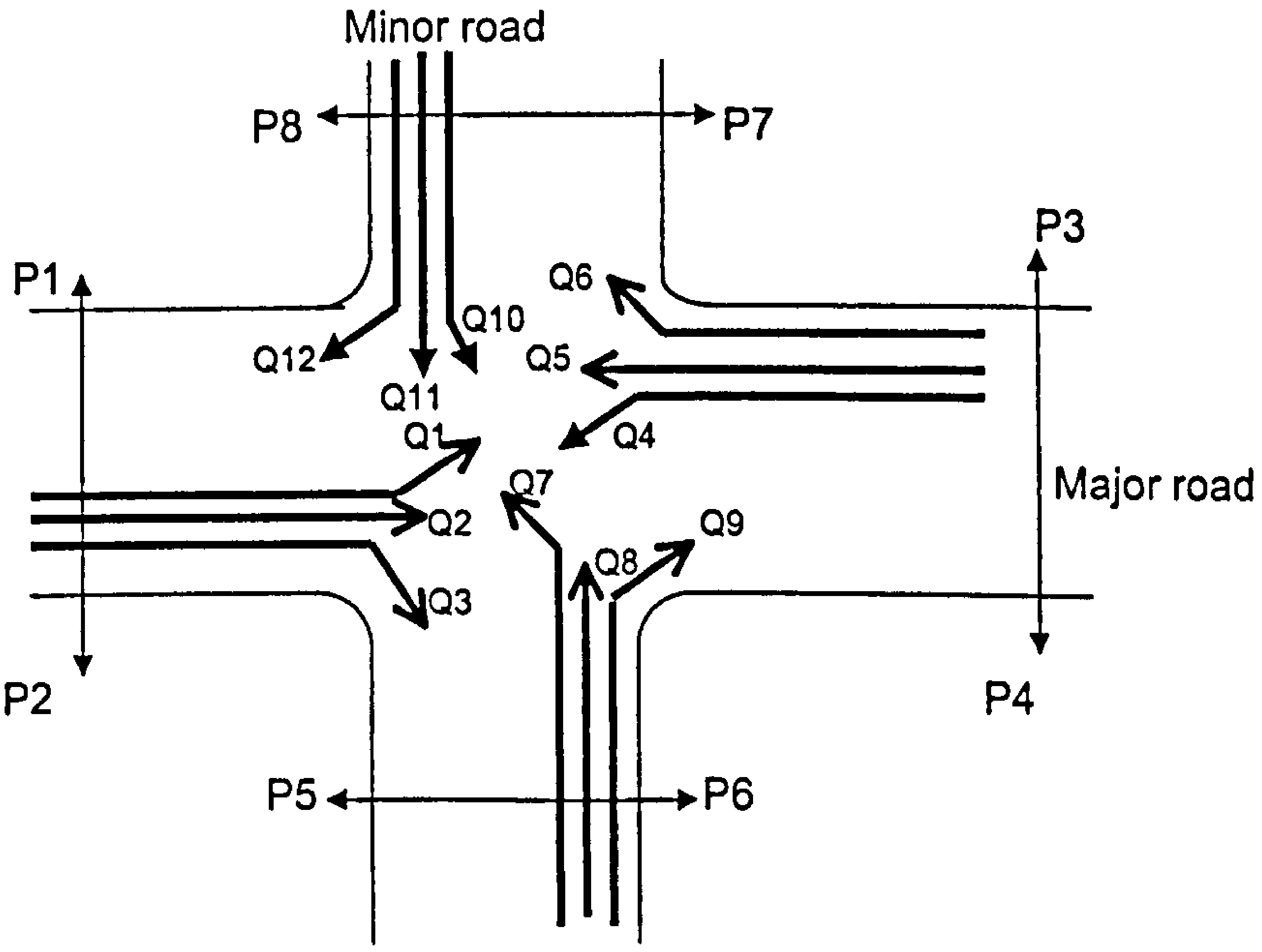


Table 5.1 Vehicle and pedestrian flow functions for T-junction accident models

VEHICLE FLOW FUNCTIONS	
Description	Equation
Total inflow	TINF = Q1+Q2+Q3+Q4+Q5+Q6
Major road inflow	MAJF = Q1+Q2+Q3+Q4
Minor road inflow	MINF = Q5+Q6
Minor road share of traffic	MRSH = MINF/TINF
Cross product flow	XPDF = MAJF*MINF
Crossing flow products	CFPD = (Q1*Q5)+(Q3*Q5)+(Q3*Q1)
Merging flow products	MEFP = (Q1*Q4)+(Q3*Q6)+(Q2*Q5)
Diverging flow products	DIFP = (Q1*Q2)+(Q3*Q4)+(Q5*Q6)
Encounter flows products	ENCP = CFPD+MEFP+DIFP
Proportion of Heavy goods vehicles	HGV = (No. of HGVs/TINF)*100%
Proportion of minor inflow turning left	PMIL = Q5/MINF
Proportion of major inflow turning left	PMAL = Q1/MAJF
VEHICLE AND PEDESTRIAN FLOW FUNCTIONS	
Total Pedestrian flow	PEDF = P1+P2+P3+P4+P5+P6
Sum of vehicle and pedestrian inflows	SVPF = TINF+PEDF
Product of vehicle and pedestrian inflows	PVFP = TINF*PEDF

Other traffic variables tested were the proportion of heavy goods vehicles as a percentage of the overall traffic inflow to the junction (HGV) and the standard deviation of the average vehicle spot speeds on the major approaches to the junction (SSD). The main features of the road environment of junctions were represented mostly by categorical variables (factors) classified into mutually exclusive subsets to reflect the presence, or absence, of the given feature. Thus, the type of traffic control (TCON) on the minor arms of the junction, for example, would be represented by three levels, denoted by the numbers 1, 2, 3 respectively for Stop, Yield and No controls.

Table 5.2 Vehicle and pedestrian flow functions for X-junction accident models

VEHICLE FLOW FUNCTIONS		
Description	Equation	
Major road inflow	MAJF =	Q1+Q2+Q3+Q4+Q5+Q6
Minor road inflow	MINF =	Q7+Q8+Q9+Q10+Q11+Q12
Total inflow	TINF =	MAJF+MINF
Minor road share of traffic	MRSH =	MINF/TINF
Cross product flow	**XPDF** =	MAJF*MINF
Product of sums of right angle flows	RAPD =	(Q2+Q5) * (Q11+Q8)
Sum of products of left turn from major and opposite ahead	TMAA =	Q1*Q5+Q4*Q2
Sum of products of left turn from minor and opposite ahead	TMIA =	Q7*Q11+Q8*Q10
Sum of products of left turn from major and previous ahead	TMAP =	Q1*Q11+Q4*Q8
Sum of products of left turn from minor and previous ahead	TMIP =	Q7*Q2+Q10*Q5
Sum of products of left turn and left turn	TLL =	Q1*Q10+Q1*Q4+Q1*Q7+Q10*Q4 +Q7*Q4+Q7*Q10
Crossing flow products	**CFPD** =	RAPD+TMAA+TMIA+TMAP+TMIP +TLL
Sum of merging major flow products	MMAJ =	Q7*Q5+Q9*Q2+Q12*Q5+Q10*Q2
Sum of merging minor flow products	MMIN =	Q1*Q8+Q3*Q11+Q4*Q11+Q6*Q8
Sum of merging flow products	**MEFP** =	MMAJ+MMIN
Sum of diverging major flow products	DMAJ =	Q2*(Q1+Q3)+Q5*(Q4+Q6)
Sum of diverging minor flow products	DMIN =	Q8*(Q7+Q9)+Q11*(Q10+Q12)
Sum of diverging flow products	**DFPD** =	DMAJ+DMIN
Sum of encounter flow products	**ENCP** =	CFPD+MEFP+DFPD
Proportion of Heavy goods vehicles	HGV =	(No. of HGVs/TINF)*100%
Proportion of minor inflow turning left	PMIL =	(Q7+Q10)/MINF
Proportion of major inflow turning left	PMAL =	(Q1+Q4)/MAJF
VEHICLE AND PEDESTRIAN FLOW FUNCTIONS		
Total Pedestrian flow	PEDF =	P1+P2+P3+P4+P5+P6
Sum of vehicle and pedestrian inflows	SVPF =	TINF+PEDF
Product of vehicle and pedestrian inflows	PVPF =	TINF*PEDF

On the other hand, levels 1 and 2 for the factor MED represented the presence and absence respectively of a median on the major road. Junction features, which were tested as continuous variables were the average width of medians on the major junction arms (MEDW) and the average width of the minor road at the neck of the junction (JNEC). These variables were measured in meters, the latter being used as a proxy for the radius of curvature of the entry kerb-lines. The road environment variables, which featured in the models, their levels and distribution in the modelling database are presented in Table 5.3 below. A detailed listing by junction-type is provided in Appendix 5II.

Table 5.3 Other Traffic and Road Variables and Factors for both T- and X-junctions

A. CATEGORICAL FACTORS

Symbol	Description	Levels	Number of sites with given features	
			T-junctions	X-junction
ZEX	Zebra crossing	1 = present	17	12
		2 = absent	40	22
ILM	Island on minor road, entry/exit divided on either side	1 = present	13	0
		2 = absent	44	34
ITM	Triangular island on minor, two-way entry/exit on either side	1 = present	7	0
		2 = absent	50	34
STL	Street lighting	1 = present	27	15
		2 = absent	30	19
LFT	Left-turning storage lane on major	1 = present	8	9
		2 = absent	49	25
TCON	Traffic control on minor	1 = stop	27	29
		2 = yield	22	4
		3 = none	8	1
MED	Median on major road	1 = present	17	20
		2 = absent	40	14
LANE	Number of lanes on major in each direction	1 = one	28	14
		2 = two	29	20

B. NON-CATEGORICAL VARIABLES

SSD	Average standard deviation of vehicles approach spot speeds (km/h)
JNEC	Average width of minor road at neck of junction (m)
MEDW	Average width of median on major arms (m)

5.3 Modelling Methodology

5.3.1 The Modelling Framework

In relating the number of observed accidents to traffic and road variables the Generalised Linear Models (GLM) framework was adopted. The advantage in doing this was that the theory of GLMs allowed the variation in the dependent variable to be separated into the systematic and random parts (McCullagh and Nelder, 1989). Consequently, it is possible to make structural and distributional assumptions which describe these two types of variations respectively (Kulmala, 1995). The structural assumption indicates that the expected value of the response variable can be related through a "link function" to a set of explanatory variables and their coefficients. On the other hand, random variation is described by a "random error term" associated with the model, which reflects the distributional properties of the response variable.

The ordinary linear model tackles both the distributional and structural assumptions together and assumes the response variable to be normally-distributed, quantitative and continuous and capable of taking any values. These run counter to the basic properties of accident counts, which are discrete, non-negative and generally governed by a non-stationary Poisson process (Jovanis and Chang, 1986). In addition, unlike least squares regression adopted in ordinary linear modelling, in the generalised linear models, parameter coefficients are estimated as maximum likelihood values, thus generating values of the parameters that are most likely to have given rise to the observed data. With this background, it became clear that the generalised linear modelling framework was a more appropriate basis for the current task of modelling accident frequency.

That accident counts at a given location are Poisson-distributed has been demonstrated and accepted by many researchers (e.g. Nicholson, 1986; Jovanis and Chang, 1985). According to the Poisson assumption, if Y is a random variable for the number of accidents at a specific location, and y the observation of this variable in a given time. Then for the mean of $Y=\Lambda$ and $\Lambda=\lambda$, Y is Poisson distributed with parameter λ such that, the probability of observing y accidents is given by the expression:

$$P(Y=y \mid \Lambda=\lambda) = e^{-\lambda} \lambda^{y}/y! \qquad \ldots\ldots\ldots\ldots\ldots\ldots \qquad (5.1)$$

with the expected value and variance of Y being:

$$E(Y|\Lambda=\lambda) = \lambda \qquad \text{and} \qquad Var(Y|\Lambda=\lambda) = \lambda \qquad \ldots\ldots\ldots\ldots\ldots\ldots \qquad (5.2)$$

Thus, the number of accidents occurring within any observed time interval is independent with an expectation λ that is a function of road and traffic variables characterising the site. The Poisson assumption, therefore, has the important constraint that the variance to mean ratio of the response variable is unity, since these two parameters are equal as in Equation 5.2. However, when dealing with cross-sectional accident data, such as the one under consideration, it is often realised that this variance to mean ratio constraint is violated, as the data is invariably "over-dispersed" (the variance is much greater than the mean).

According to Hauer (2001), over-dispersion is inherent in accident modelling databases and the "root cause" is between-site variation, which arises mainly from the fact that sites with the same "represented traits" (i.e. explanatory variables) have different means. If Λ follows the Gamma distribution, as is often assumed (e.g. Hauer *et al*, 1989; Kulmala, 1995), then the probability density function of the variable can be expressed as:

$$f_{\Lambda}(\lambda) = \frac{(\kappa/\mu)^{\kappa}\lambda^{\kappa-1}e^{-(\kappa/\mu)\lambda}}{\Gamma(\kappa)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots \qquad (5.3)$$

where κ is the shape parameter of the Gamma distribution that describes Λ, i.e. $\Lambda \sim \text{Gamma}(\kappa, \kappa/\mu)$, and μ is the expected value of Λ.

Subsequently, by applying the theorem of total probabilities and transformation of Equation 5.3, Kulmala (1995) showed that the point probability function of Y could be expressed as:

$$P(Y=y) = \int_0^{\infty}\frac{\lambda^{y}e^{-\lambda}}{y!}\frac{(\kappa/\mu)^{\kappa}\lambda^{\kappa-1}e^{-(\kappa/\mu)\lambda}}{\Gamma(\kappa)}\partial\lambda = \frac{\Gamma(\kappa+y)}{\Gamma(\kappa)y!}\left(\frac{\kappa}{\kappa+\mu}\right)^{\kappa}\left(\frac{\mu}{\kappa+\mu}\right)^{y} \qquad \ldots\ldots \qquad (5.4)$$

This equation (5.4) represents the Negative Binomial distribution with expected value and variance $E(Y) = \mu$, and $Var(Y) = \mu + (\mu^2/\kappa)$ respectively. Thus, the variance equals the expected value only when $\kappa \to \infty$, in which case the distribution degenerates to the

Poisson form. By adopting the Poisson distribution, therefore, it is implied that the expected value of accidents for different entities would be the same given the same represented traits. But as has been demonstrated by Hauer (2001), such an assumption is simplistic and not necessarily correct.

By contrast, the Negative Binomial distribution represents an extension of the Poisson distribution and allows the variance of the dependent variable to differ from the mean, as required. The Negative Binomial approach is therefore a more appropriate basis for handling over-dispersed data and was adopted for this study. The general approach, however, was always to start with a Poisson fit and establish the presence of over-dispersion before applying the Negative Binomial. As a result, in a few instances (e.g. in fitting models for specific accident types), the Poisson fit was retained since there was no obvious indication of over-dispersion. But the overwhelming majority of models were over-dispersed relative to the Poisson assumption. The statistical software Generalised Linear Interactive Modelling (NAG, 1993; NAG, 1996) was used to fit the models. The software is equipped with the exponential distributions and link functions required and has a special macro for fitting Negative Binomial models.

5.3.2 Functional Form of the Models

As became apparent from the review of literature on accident prediction modelling, different options have been explored by many authors in the past to relate accident frequencies to road and traffic variables, but opinions remain so varied that it is difficult to identify any clear-cut consensus. One of the reasons that has been cited for this diversity of views is the quality and type of data used for modelling. It does appear, therefore, that for each kind of database some exploratory examination may be required to determine the most appropriate functional forms. This is particularly important for the current study, since the type of database used appears uniquely different from those used in previous studies.

In this study, accidents and road and traffic data are obtained from a "typical" non-industrialised developing country with relatively low car ownership and a road and traffic environment that may be radically different from that of a typical industrialised country. Most reported previous studies have been carried out in industrialised countries. It was therefore expected that the key accident-dependent variables or their scale of contribution to accidents in this study would be different from those reported in the literature for similar studies.

Although the exact functional relationship between accident frequency and traffic flow variables is also still a subject of controversy, it has been reasonably well demonstrated (see relevant section of literature review) that, as a measure of exposure to accidents, this is probably the most important explanatory variable. Prediction models have, therefore, either been developed using only traffic flow as the sole explanatory variable, or to serve as the core of the model in cases where additional variables have been used. Being convinced of the propriety of this approach, this study was carried out similarly. Thus, the general form of the models developed in this study is:

$$E(\mu) = kQ^{\alpha} \exp (\Sigma\beta_j X_{ij}) \quad \text{..........................} \quad (5.5)$$

where $E(\mu)$ is the expected number of junction accidents (in 3 years),
Q– general traffic flow function, k, β_j, and α - the model parameters to be estimated
and X_{ij} - a vector of variables representing other traffic and road variables.

Consistent with the generalised linear modelling framework, Equation 5.5 assumes a linear form in the prediction mode, summing up the products of parameter values and their coefficients following a transformation, using a natural logarithmic link function. This general form of the model was used in recent studies published by the Transport Research Laboratory (TRL) of the United Kingdom (e.g. Layfield *et al.*, 1996). In this study, the extensive list of traffic flow functions listed in Section 5.2 were all tested either individually or in appropriate pairs in place of the general flow function in Equation (5.5) above.

This approach provided the opportunity to determine the most appropriate exposure function for each type of model, as it helped to identify the relevant contributory flows. Where a pair of traffic flow functions was used in a model (e.g. total traffic inflow in conjunction with the minor road's share of traffic), these functions were allowed to take different exponent values. Vehicular traffic flow values in the models were always in vehicles per 24 hours, whilst pedestrian flows reflected the absolute peak-hour counts. Other variables tested in the models were as presented in Section 5.2.

Separate sets of models were developed for all accidents, injury accidents and six types of accidents classified by their defining primary collision types, namely, head-on, rear-end, right-angle, side-swipe, single vehicle and pedestrian. Each set of models comprised "coarse" models, containing only traffic flow as the sole explanatory variable, and "comprehensive" models, which were extensions of the coarse models to include other road and traffic variables. These two types of model have slightly different practical applications, which are discussed later in this thesis. The rationale for developing separate models for specific accident-types was to identify at a more disaggregated level their particular contributory factors. Such information is useful for accident blackspot identification, since, at least in the conventional way, a clustering of any one or more of these different types of accident is usually the trigger to remedial action. Knowing the particular contributory factors would therefore enhance the manner of treatment.

Given that pedestrian accidents constituted about 50 per cent of all injury accidents in our modelling database, it was deemed necessary to constrain the coarse models for all injury accidents to include a pedestrian flow function in a manner that made them appear more logically plausible. For pedestrian accidents-only models the form of the pedestrian flow function was such that zero pedestrian flows will result in zero expected accidents.

5.3.3 Modelling Procedure

The general procedure that was adopted for determining the best fitting models is outlined in the flowchart in Figure 5.1. To identify the best flow-based models, different flow functions were initially tested individually or in appropriate combinations on the basis of a Poisson error structure. By this initial approach, it was possible to determine whether the fitted models were over-dispersed or not, following an assessment of the scaled deviance (SD) value and the degrees of freedom (DF). Over-dispersion was considered indicated if the SD was at least 1.5 times the DF i.e. SD>>DF (Lindsay, 1999). As expected, in most cases, the models were over-dispersed relative to the Poisson error structure and so the next logical step was to specify a Negative Binomial error structure and refit. At this stage, the over-dispersion parameter (κ) was set to be estimated automatically, by maximum likelihood, using the GLIM macro NEGBIN.

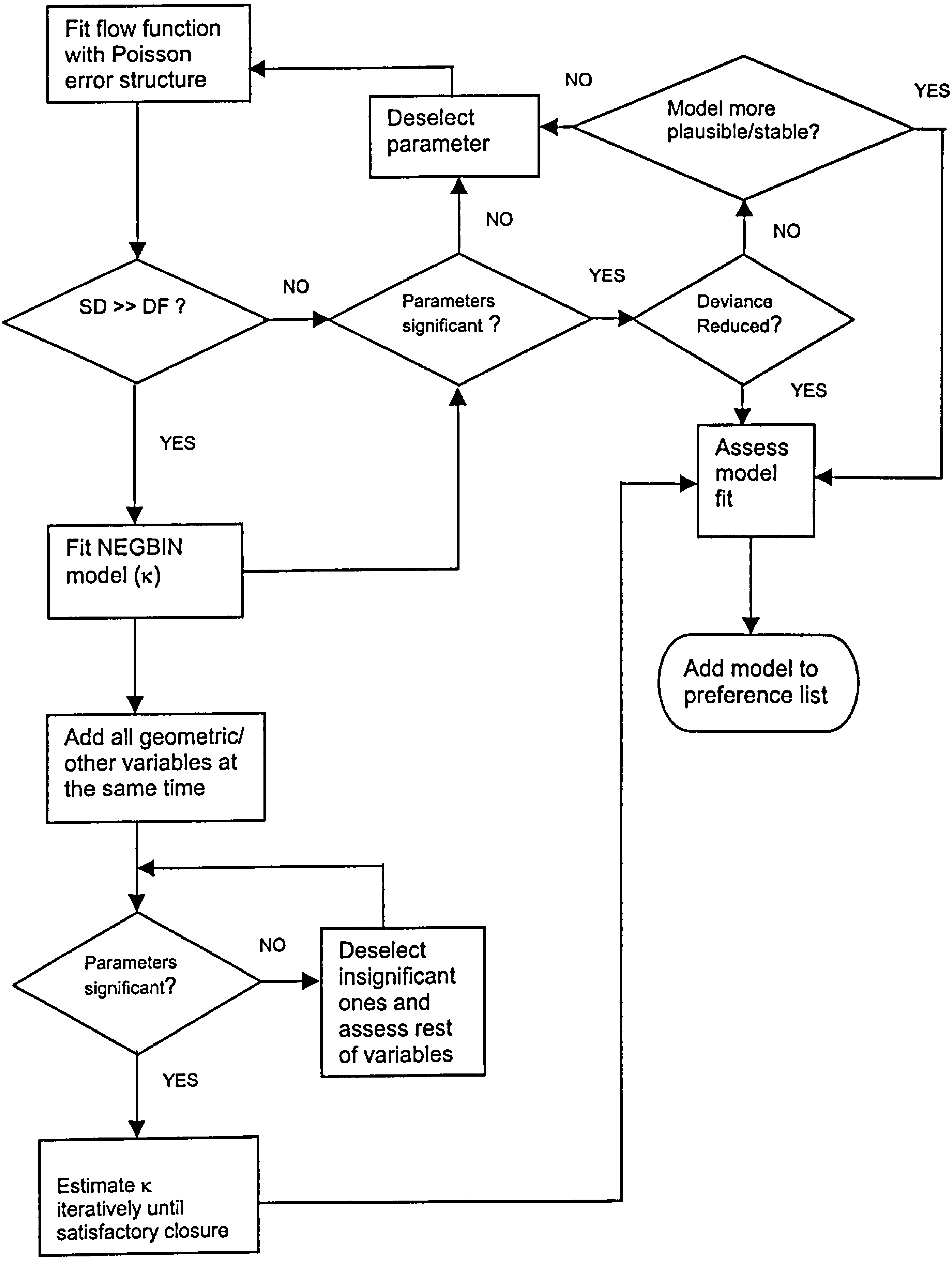


Figure 5.3 Flowchart for the development accident models

The model parameters were then assessed for their statistical significance and contribution to the reduction in deviance. Following a successful outcome of these assessments, parameters were accepted and the model's goodness-of-fit statistics (see section 5.4.2) calculated. This whole process resulted in the selection of the best 2 or 3 alternative flow-based models.

At the next level of modelling, the best flow-based models were each extended and tested, in turn, with the simultaneous addition of all other road and traffic variables. Starting with an initial value of the over-dispersion parameter equal to the one estimated during the first stage for the given flow-based model, the comprehensive model is fitted and then the individual parameters are assessed for their significance and contribution to the reduction in deviance.

Insignificant parameters were excluded one by one, starting with the most insignificant and the remaining variables refitted and reassessed until only the significant variables were left in the model. Subsequently, the final value of the over-dispersion parameter (κ) was estimated iteratively. Starting with the residuals produced by the initial fit, a new value of κ was estimated and the model refitted and the process was repeated until satisfactory closure (Hauer *et al*, 1989; Mountain *et al*, 1996). From this point, the model's goodness-of-fit statistics (see section 5.4) were calculated and the model was added to the list of alternative models.

It must be mentioned, however, that the above procedure was not always mechanically applied. Since the ultimate objective was to obtain logically plausible models that could be rationalised from an engineering perspective and not merely ensuring statistical efficiency, a few modifications were made along the way. The general rule was to include all parameters which were statistically significant in the models, however, other parameters, which were not statistically significant or did not contribute to the reduction in deviance to the expected level, were sometimes retained to enhance the stability and/or plausibility of the models. Also, because the models being sought were supposed to be causal in nature, a special effort was made to remove the potential effect of multi-collinearity among the explanatory variables.

Although multi-collinearity among explanatory variables does not jeopardise model estimation or performance, it does however make model interpretation difficult (Kulmala, 1995). A correlation matrix of all variables actually showed no particular pairs to be highly correlated (i.e. $R^2 \geq 0.65$). Multi-collinearity was, therefore, not ~~a~~ big problem in this study. All the same, a few variables that gave cause for concern, was re-specified to remove any lingering doubts about multi-collinearity. For example, an initial specification of a median on the major road as a two-level discrete factor, indicating the presence or absence of the feature appeared to correlate, albeit not strongly, with the number of lanes on the major road. For the avoidance of doubt and any potential effects of collinearity, the former parameter was re-specified as a continuous variable to represent the width of the median instead.

5.4 Model Evaluation

It is clear from the preceding section that, before coming out with the most appropriate and best fitting models, three types of objective assessments were always made, namely, tests of significance of individual parameters, their contribution to the reduction in deviance and the overall goodness-of-fit of the models. These assessments constituted the key basis for the acceptance or rejection of models, although they were sometimes moderated by some subjective decisions, informed by engineering judgement, where it was necessary to ensure the plausibility and/or stability of models. The specific objective criteria used are discussed below.

5.4.1 Assessment of Individual Model Parameters

Individual model parameters were generally assessed at two levels. The first test was to ensure that the estimated parameter coefficients were statistically significant. Thus, the ratio of the estimated coefficient to its standard error was required to pass the *t*-test at the 5 per cent level of significance. The other aspect was to examine whether a parameter's contribution to the reduction in deviance was significant. In other words, this was to assess whether the addition of the said parameter to the model increased the explanatory power of the model significantly.

According to McCullagh and Nelder (1989), the difference in scaled deviance between two nested models with degrees of freedom df_1 and df_2 will be distributed like χ^2 with

(df_1 - df_2) degrees freedom and can be used to assess the significance of adding one or more terms to a model. This procedure was applied and, at the required level of significance (5 per cent), the drop in deviance following the addition of one parameter should have been at least 3.84 (χ^2 with 1.0d.f.).

5.4.2 Explanatory Power of the Models

To describe how well the developed models fitted the data overall, two global goodness-of-fit measures were used. These measures were part of an extensive list developed by Fridstrom *et al* (1995) for generalised Poisson regression models, which give a measure of the percentage of systematic (explicable) variation in the response variable that is explained by the models. The measures, the log-likelihood ratio index (ρ^2) and the "Freeman-Tukey R^2" (based on the Freeman-Tukey transformation residuals), were applied in a similar way to the coefficient of determination (R^2), as used in ordinary least-squares regression.

The former is considered a "natural" choice for Poisson and Negative Binomial models and was easily calculated from the standard output of the NEGBIN fit in GLIM. The "Freeman-Tukey R^2" was also relatively easy to compute using the GLIM package but the other reason for selecting it was that it is acknowledged to be more robust than other similar measures of goodness-of-fit of models. The advantage in using both measures at the same time was to enable the assessment of models from alternative perspectives. These measures are presented in more detail below.

5.4.2.1 Log-likelihood Ratio Index (ρ^2)

This parameter is given by the expression:

$$\rho^2 = 1 - [LL(\beta) / LL(0)] \qquad \text{..........................} \quad (5.6)$$

where LL(β) is the log-likelihood value of the fitted model and LL(0) the corresponding value for the model in which only the constant term is used.

Both LL(β) and LL(0) are the result of the logarithmic transformation of the likelihood function of the Negative Binomial models, which is maximised to obtain the coefficient estimates for parameters in the models (McCullagh and Nelder, 1989). The value 2[LL(β) - LL(0)] is equivalent to the deviance value discussed in the previous section. By definition, therefore, ρ^2 represents the additional variation in accident frequency explained by the given model relative to the model with the constant term alone (the "null model").

5.4.2.2 The "Freeman-Tukey R^2" (R^2_{FT})

Using the Freeman-Tukey variance stabilising transformation (f_i) and the mean of its normal distribution function (ϕ_i) for a Poisson variable y_i with mean λ_i, Fridstrom *et al* (1995) provide the following expression in which the deviates ($e_i = f_i - \phi_i$) can be estimated from the corresponding residuals:

$$\hat{e}_i = \sqrt{y_i} + \sqrt{y_i + 1} - \sqrt{4\hat{y}_i + 1} \qquad \text{..........................} \qquad (5.7)$$

where, the fitted value is $\hat{y}$

Subsequently, the R^2_{FT} (Freeman-Tukey goodness-of-fit) measure is expressed as:

$$R^2_{FT} = \frac{\sum_i (f_i - \bar{f})^2 - \sum_i \hat{e}_i^2}{\sum_i (f_i - \bar{f})^2 - n} \qquad \text{........................} \qquad (5.8)$$

Equation (5.8) is the result of dividing the ordinary R^2 goodness-of-fit measure for the transformed variables by the maximally obtainable fit in a perfect Poisson model. Thus, the ratio provides a measure of the proportion of the systematic variation in accident frequency that is explained by the fitted model. Although this is one of many well-established measures of the global goodness-of-fit of accident prediction models, it is useful to bear in mind that the derivation is founded on the key property of the Poisson distribution which equates the variance to the mean. This means that the amount of expected random variation in the response variable is treated as though it was constant. This is important because the scope of random variation is variable and, according to Mountain *et al* (1996), is larger when the expected accidents are smaller.

5.5 Model Results and Interpretation

The model development procedures outlined in the preceding section were applied for selecting a range of suitable models for both X- and T-junctions. Because different exposure functions and variables were usually involved, it was not always possible to identify a single model as "the best". Therefore, as much as possible, a range of alternative "best" models for each accident category were identified and presented to enable comparison. Models developed covered separately all accidents, injury accidents and various accident types, classified by their defining primary collision types. In each case, two types of models have been presented in a two-stage process. At the first stage are the coarse (flow-based) models that contained traffic flow functions as the sole explanatory variable. The second stage involved full or comprehensive (flow-geometry-factors) models, which were basically extensions of the flow-based models to include the other most statistically significant and logically plausible traffic and road variables in the modelling database. See sample of GLIM modelling output in Appendix 5III.

5.5.1 X-junction Models

A total of 238 accidents were recorded for all the 34 X-junction sites included in the database for the study period 1996 to 1998 inclusive. The average number of accidents per junction was therefore 7.0. The best fitting models identified for X-junctions are presented in their linear form in Tables 5.4(a) & (b) for all accidents and all injury accidents respectively. The models for different collision-type accidents are presented in Tables 5.5(a) to (f).

5.5.1.1 All Accidents

For the coarse (flow-based) models (see Table 5.4a), it was observed that most of the main traffic flow functions described in Table 5.2 (see page 82) produced reasonably good statistical fit to the data. However, the three best fitting models in their exponential form were:

$$A = 1.59x10^{-3}\ TINF^{0.965}\ MRSH^{0.669} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (5.9)$$

$$A = 1.16x10^{-3}\ XPDF^{0.496} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (5.10)$$

$$A = 1.92x10^{-3}\ ENCP^{0.465} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (5.11)$$

where A is the 3 year accident frequency and the other parameters are as defined in Table 5.2.

Table 5.4a. Models for all Accidents at X-junctions (Total number of accidents=238; number of sites=34)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	1.946	0.179	10.872		LL(0) = -204.9**
Dispersion parameter	κ	*1.054*	*0.310*	*3.400*		
2. Flow-based models						
(a)	Lk	-6.444	2.834	-2.274	0.27	0.050
	LTINF	0.965	0.308	3.133		
	LMRSH	0.669	0.262	2.553		
Dispersion parameter	κ	*1.595*	*0.536*	*2.976*		
(b)	Lk	-6.758	2.695	-2.508	0.24	0.043
	LXPDF	0.496	0.155	3.200		
Dispersion parameter	κ	*1.518*	*0.503*	*3.018*		
(c)	Lk	-6.257	2.660	-2.352	0.21	0.040
	LENCP	0.465	0.152	3.059		
Dispersion parameter	κ	*1.472*	*0.483*	*3.048*		
3. Full Models						
(a)	Lk	-5.988	2.529	-2.368	0.89	0.198
	LTINF	0.453	0.293	1.546		
	LMRSH	0.949	0.319	2.975		
	LFT(2)	1.319	0.428	3.082		
	MEDW	0.335	0.174	1.925		
	HGV	0.185	0.076	2.434		
	JNEC	0.134	0.039	3.436		
Dispersion parameter	κ	*3.595*	-			
(b)	Lk	-9.419	2.230	-4.224	0.91	0.223
	LXPDF	0.370	0.132	2.803		
	STL(2)	0.580	0.239	2.427		
	LFT(2)	0.661	0.286	2.311		
	HGV	0.190	0.071	2.676		
	JNEC	0.134	0.036	3.722		
	SSD	0.100	0.042	2.381		
Dispersion parameter	κ	*4.650*	-			
(c)	Lk	-9.111	2.277	-4.001	0.89	0.215
	LENCP	0.349	0.134	2.604		
	STL(2)	0.640	0.246	2.602		
	HGV	0.183	0.073	2.507		
	JNEC	0.135	0.038	3.553		
	SSD	0.100	0.043	2.326		
	LFT(2)	0.666	0.295	2.258		
Dispersion parameter	κ	*4.250*	-			

*The prefix "L" indicates that the parameters are still in their logarithmic forms, e.g. LTINF = Log (TINF).

**LL(0) – Log-likelihood value for null model

On the whole, flow-functions involving interacting traffic streams like cross product flow (XPDF) and encounter flow products (ENCP) appeared to fit the data a good deal better than the relatively simple ones like total inflow (TINF) or major road flow (MAJF) and minor road flow (MINF).

Total inflow produced a considerably better fit only when specified alongside a flow-function reflecting the proportion of minor road traffic inflow as in Equation 5.9. Although these models were estimating total accidents, it was interesting to notice that the exposure variable for pedestrian accidents (PEDF) was not found to be significant. This probably had to do with the rather rough estimates of pedestrian flows used (only peak hourly counts of pedestrians was used) as well as the fact that pedestrian accidents comprised only 1 in 5 of all accidents at X-junctions. Thus, not surprisingly, the vehicle flow functions were dominant at this stage.

Since most variables with potentially significant impact on accidents are not included in the flow-based models, they may only be regarded as relatively coarse and rough estimators of accident frequency. That the selected models explained between 20-30 per cent of the systematic variation in accident frequency underscores the importance of traffic flow as a major determinant of accidents. It is evident from all the models that accident frequency generally increased at a decreasing rate with traffic flow. In model 5.9 accident frequency was almost proportional to total junction vehicle inflow (the exponent for this parameter was close to 1.0) at the same time as it followed the general trend with respect to the minor road's share of traffic. In order to determine causal models, as we set out to do under this study, an extensive list of other traffic variables and factors describing the junction environment and geometry had to be tested simultaneously with the best flow-based models.

The three alternative full (comprehensive) models obtained out of this process are also presented in their linear form in Table 5.4a. There is apparently not much to choose between these three models. All of them consistently produced very good *t*-statistics for individual parameters, at the same time as explaining about 90 per cent of the systematic variation in accident frequency. On account of the explanatory power and fewer degrees of freedom utilised, model 3b (see Table 5.4a) was the most preferred. In the exponential form, this model was:

$$A = 8.12x10^{-5} XPDF^{0.370} e^{(0.580STL(2)+0.661LFT(2)+0.190HGV+0.134JNEC+0.100SSD)} \ldots\ldots\ldots \quad (5.12)$$

where A is the 3 year accident frequency at X-junctions and parameters are as defined in Tables 5.2 and 5.3.

Apart from the traffic flow function, all the other variables, which appeared in this model, were consistently significant in most of the models developed for the number of accidents at X-junctions. These variables were, left turn lane on the major road (LFT), proportion of heavy goods vehicles and buses as a percentage of total traffic inflow (HGV) and the standard deviation of average spot speeds on the major approaches (SSD). The others were streetlights (STL) and the average width of the minor road at the neck of the junction (JNEC). Given their stability and consistency, these variables could be considered as representing causal rather than associative effects.

The preferred model (Equation 5.12) showed that, when the impact of the other variables was considered, the absence of dedicated left-turn lanes on the major road (LFT(2)) increased accident frequency by a factor of 1.94, whilst the absence of street lights (STL(2)) resulted in an increase of 1.79 times. Not surprisingly, the full models had a much better fit to the data than the flow-based models. By fitting the extra variables, the explanatory power of the models increased from between 20 and 30 per cent to about 90 percent.

Although the log-likelihood ratio values for the models appeared low, they nonetheless compare rather favourably with what has been widely reported in the literature (e.g. Jovanis and Chang, 1986; Abdel-Aty & Radwan, 2000). It is also useful to remember that the log-likelihood ratio statistic is measuring the extra amount of variation in accident frequency explained by the given model, relative to the model with only the constant term.

The deviance measure, proportion of systematic variation explained and the log-likelihood ratio statistics, as used above, are important tools that helped to identify generally good quality models that represented the key features of the overall data using as few parameters as possible. Important as they were, these measures indicated only the global (overall) fit of the models and might not necessarily have reflected a good local fit to all individual data points as well. It was necessary, therefore, to demonstrate further, at least for the preferred full model for all accidents, how well the model fitted the individual data points. This was done by plotting the standardised residuals from the model against their Normal ordered statistics. The information in the standardised residuals is identical to and has the same pattern as the raw residuals. However, because the values of the raw residuals would depend on the original units of measurement, large residuals could emerge solely because the original measured values were large. With a common scale, obtained through the standardisation, this source of confusion is removed and residuals lying outside plus or minus two standard deviation units from the mean, could be considered to fit poorly and coming from potentially extreme data ('O'Brian, 1992).

The transformed residuals have a mean value of 0 and standard deviation of 1.0 and the 95 per cent confidence interval would be plus or minus 2.0. Such a plot is part of the Macro Library of the GLIM package as a "Normal Q-Q plot" and is presented below, in Figure 5.4, for the selected full model for all accidents at X-junctions. The graph (Figure 5.4) amply demonstrates that the selected full model equally well fitted the individual points. All the standardised residuals were within the 95 per cent confidence interval of the normal order statistics. The other important piece of information from the plot is that the generalised Poisson assumption used in the modelling process was very appropriate. This is supported by the Filliben correlation coefficient of 0.95, evidence of a straight-line relationship between the Normal ordered statistics and the transformed residuals.

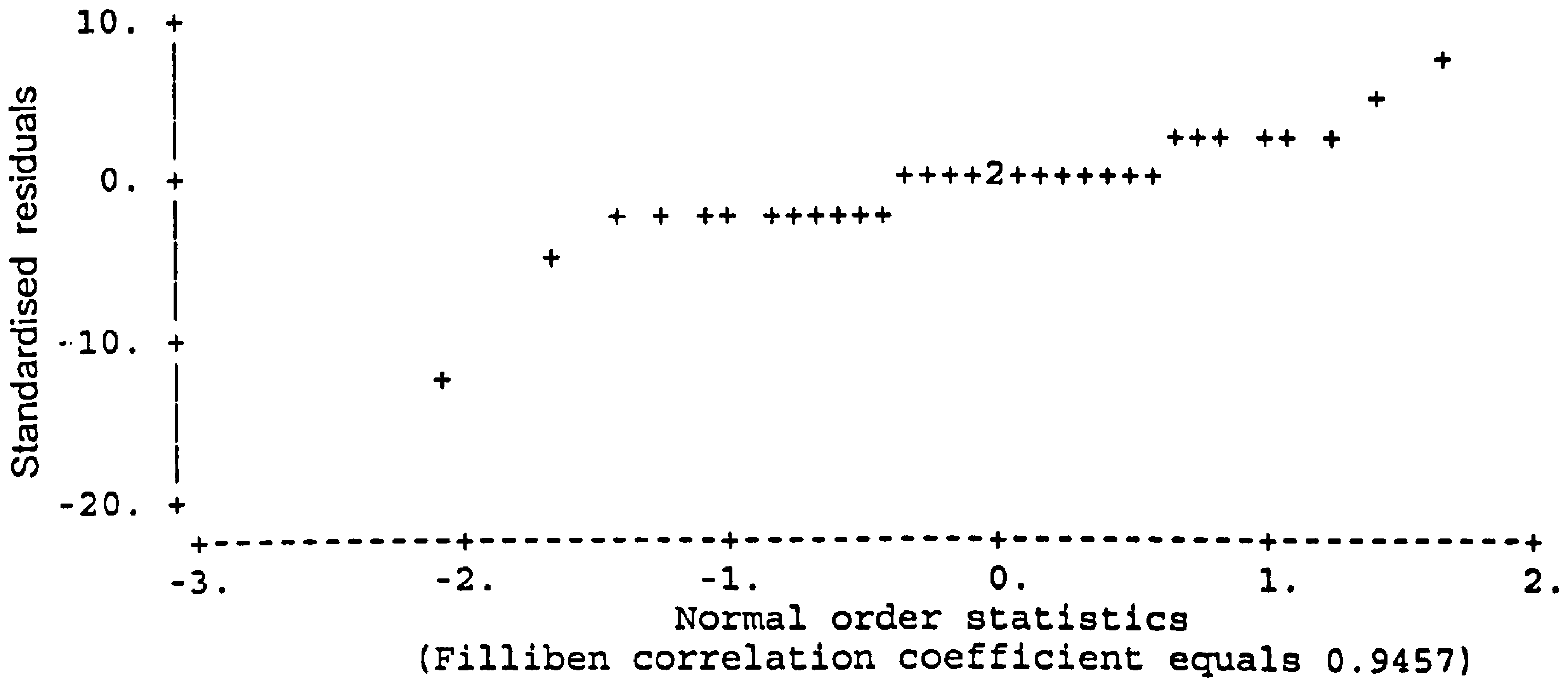


Figure 5.4 Normal Q-Q plot for selected full model for X-junctions

5.5.1.2 Injury Accidents

The three alternative flow-based best-fit models selected to estimate all injury accidents at X-junctions are presented in Table 5.4b in their linear form.

Table 5.4b Models for all Injury Accidents at X-junctions
(Total number of accidents=91; number of sites = 34)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	t-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	0.985	0.189	5.212	-	LL(0) = -146.1**
Dispersion parameter	κ	*1.185*	*0.454*	*2.610*		
2. Flow-based models						
(a)	Lk	-4.273	3.084	-1.386	0.40	0.041
	LXPDF	0.279	0.180	1.550		
	PEDF	0.00274	0.0013	2.104		
Dispersion parameter	κ	*2.070*	*1.010*	*2.050*		
(b)	Lk	-3.986	3.288	-1.212	0.39	0.044
	LTINF	0.533	0.362	1.472		
	LMRSH	0.400	0.292	1.370		
	PEDF	0.00284	0.00129	2.202		
Dispersion parameter	κ	*2.109*	*1.030*	*2.048*		
(c)	Lk	-3.632	3.062	1.186	0.38	0.037
	LENCP	0.240	0.178	1.348		
	PEDF	0.00277	0.00134	2.067		
Dispersion parameter	κ	*2.006*	*0.966*	*2.076*		
3. Full models						
(a)	Lk	-7.906	2.658	-2.974	0.90	0.177
	LXPDF	0.288	0.161	1.789		
	HGV	0.230	0.086	2.674		
	JNEC	0.100	0.047	2.128		
	SSD	0.136	0.052	2.615		
Dispersion parameter	κ	*4.50*				
(b)	Lk	-7.432	2.955	-2.515	0.87	0.164
	LSVPF	0.456	0.320	1.425		
	SSD	0.134	0.055	2.436		
	HGV	0.232	0.091	2.549		
	JNEC	0.110	0.049	2.245		
Dispersion parameter	κ	*3.25*				
(c)	Lk	-6.975	2.417	2.886	0.87	0.150
	LENCP	0.229	0.148	1.547		
	HGV	0.228	0.082	2.780		
	SSD	0.132	0.048	2.750		
	JNEC	0.106	0.045	2.356		
Dispersion parameter	κ	*6.50*				

*The prefix "L" indicates that the parameter is in its logarithmic form, e.g. LXPDF =Log (XPDF)
**LL(0) – Log-likelihood value for null model

These models were:

$$A = 0.014\,XPDF^{0.279}\,e^{0.00274PEDF} \qquad \text{..................} \qquad (5.13)$$

$$A = 0.019\,TINF^{0.533}\,MRSH^{0.400}\,e^{0.00284PEDF} \qquad \text{..................} \qquad (5.14)$$

$$A = 0.026\, ENCP^{0.240}\, e^{0.00277PEDF} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (5.15)$$

where, A is the 3 year injury accident frequency at X-junctions and other variables are as defined in Table 5.2.

This form of the models, i.e. forcing the inclusion of the pedestrian flow variable in the flow-based model, was chosen in preference to others with only vehicle flow functions. This was done in order to account fully for the exposure function for pedestrian accidents, which represented more than 50 per cent of all injury accidents at X-junctions. The adopted models provided the scope for accounting for pedestrian accidents, as well as other types of injury accidents which would result from vehicle-vehicle collisions only. The effect of constraining these models to include the pedestrian flow variables, however, was to reduce slightly the significance of the associated vehicle flow function. But this was not a great source of concern, since the models still predicted up to 40 percent of systematic variation in injury accident frequency.

The full models for all injury accidents (see section 3 of Table 5.4b) consistently included three, other explanatory variables, namely, SSD, JNEC and HGV. Although two of the three alternative models presented did not include a pedestrian flow function, it is thought that one of these additional explanatory variables could have been acting as a proxy for pedestrian accidents as well. As the parameter value SSD, for example, increases, it becomes more difficult for pedestrians to correctly judge the travelling speed of approaching vehicles. In such situations, pedestrian accidents are more likely. Therefore, the parameter's impact on injury accidents could be representing the risk of pedestrian accidents as well. The most preferred of the three alternative full models in its exponential form was:

$$A = 5.92x10^{-4}\, SVPF^{0.456}\, e^{(0.134SSD+0.232HGV+0.110JNEC)} \quad \ldots\ldots \quad (5.16)$$

where A is the 3 year injury accident frequency and
SVPF – the sum of total vehicle inflow (TINF) and pedestrian flow (PEDF)
across all the junction arms.

This model accounted for the pedestrian exposure variable (PEDF) and also explained just about as much systematic variation in injury accident frequency as the alternative models. On the whole, the full models, as in the case of models for all accidents, had much higher explanatory power than the flow-based models. Perhaps more interesting was the fact that the flow-based models for injury accidents had about twice the explanatory power of those for all accidents as measured by the proportion of systematic variation explained. This showed that the exposure variables were more influential in determining injury accident frequency than they were for all accidents, an indication that the flow functions in the former case might have been more "relevant" to the specific accident type. Relevant flows refer to the specific traffic streams to which the colliding parties in an accident belong and research experience shows that a clear identification of such flows can lead to improved model specification and estimation (Hauer *et al*, 1989).

5.5.1.3 Accidents by Collision-types

(a) Right-angle Collision Accidents

By definition, accidents of this nature primarily involved collisions between vehicles whose travel paths intersected at approximately right angles. Therefore, the relevant traffic streams in this case would be vehicles travelling straight through the junction from one arm to the other of the same road and the corresponding stream on the other road, together with the left turning flows. Reflecting this conflict scenario, the key vehicle flow functions, which fitted the data best, were those representing the sum of the products of left turning flows from the minor road and the far-side through flows on the major (TMIP). The other function was the "crossing flow products" (CFPD) – the sum of the products of all crossing vehicle streams.

These models, presented in their linear form in Table 5.5a, were:

$$A = 5.01x10^{-3}\ TMIP^{0.406} \quad \dots\dots\dots\dots\dots\dots\dots\dots \quad (5.17)$$

$$A = 3.20x10^{-4}\ CFPD^{0.523} \quad \dots\dots\dots\dots\dots\dots\dots\dots \quad (5.18)$$

where A is 3-year frequency of right angle collision accidents; other variables are as defined in Table 5.2.

Although model (5.17) predicted 5 per cent more of systematic variation in the response variable its log-likelihood ratio was less than that of model (5.18). The *t*-statistics of the parameters of the latter model were also much more significant than in the former.

Based on these considerations model (5.18) was preferred to (5.17). The main basis for this preference, however, was that the crossing flow products function included all the possible conflicting flows that would most likely have given rise to right-angle collisions.

For this reason, it appeared the more relevant flow function than the sum of products of left turn from minor and previous ahead (TMIP) function, even if the former function included "non-relevant" traffic streams as well. These non-relevant traffic streams could be seen as "contributory flows", in which case they influenced rather than participated directly in right-angle collisions. To illustrate, a right-turning vehicle from the major to the minor road, for example, would not form part of the relevant flows, because its path does not cross with another on the minor road. However, the visibility of through traffic on the major road from the vehicle waiting on the minor road to enter the junction may be obstructed by the right-turning major road vehicle and this may result in the former prematurely entering the junction and colliding with the latter.

Table 5.5a. Models for Right-angle Collision Accidents at X-junctions
(Total number of accidents = 76; number of sites=34)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	t-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	0.804	0.185	4.341	-	LL(0) =
Dispersion parameter	κ	*1.389*	*0.637*	*2.18*		-135.5**
2. Flow-based models						
(a)	Lk	-5.297	2.215	-2.391	0.38	0.052
	LTMIP	0.406	0.147	2.762		
Dispersion parameter	κ	*2.312*	*1.348*	*1.715*		
(b)	Lk	-8.047	2.635	-3.054	0.33	0.070
	LCFPD	0.523	0.155	3.377		
Dispersion parameter	κ	*2.595*	*1.519*	*1.708*		
3. Full models						
(a)	Lk	-8.827	2.294	-3.848	0.95	0.182
	LTMIP	0.430	0.150	2.868		
	JNEC	0.120	0.044	2.715		
	STL(2)	0.779	0.331	2.355		
	LFT(2)	0.717	0.372	1.930		
Dispersion parameter	κ	*4.120*	-			
(b)	Lk	-13.970	3.037	-4.600	0.93	0.193
	LCFPD	0.745	0.163	4.556		
	LFT(2)	1.027	0.392	2.621		
	STL(2)	0.832	0.327	2.540		
	SSD	0.144	0.059	2.432		
Dispersion parameter	κ	*4.790*	-			

*The prefix "L" indicates the natural logarithmic form of the variable, i.e LTMIP =Log(TMIP)

**LL(0) is the log-likelihood value of the null model

Thus, the crossing flow products function was seen as the more appropriate exposure function. Based on similar considerations, the full model involving the extension of model form (5.18) was selected as the better of the two alternatives presented in Table 5.5a. This model was:

$$A = 8.57x10^{-7}\ CFPD^{0.745}\ e^{(1.027LFT(2)+0.832STL(2)+0.144SSD)} \qquad \ldots\ldots\ldots\ldots\ldots(5.19)$$

where A is 3 year frequency of right angle collision accidents and other variables are as described in Table 5.2

In this model, the absence of a dedicated left-turn lane on the major road (LFT(2)) and streetlights (STL(2)) increased the expected frequency of right-angle collision accidents at X-junctions by a factor of 2.79 and 2.30 respectively. The streetlights factor (STL(2)) seemed to suggest that right-angle collisions at X-junctions would tend to occur during dark hours. It is also to be expected that, in the presence of dedicated left-turn lanes on the major roads, turning vehicles have the time and opportunity to wait and take advantage of safe gaps in conflicting traffic streams before executing the intended manoeuvre. In their absence, drivers might be tempted to make rash manoeuvres and get caught by the "opposite ahead" traffic.

The third additional variable in this model was SSD, representing the standard deviation of the average spot speeds of vehicles on the major approaches. This parameter is also positively correlated to the right-angle accident frequency. It could be doing so in two ways, first a large value of SSD means that there is wide variability in the arrival speeds of vehicles, making their correct anticipation difficult for drivers entering the junction from the minor road.

It also means that some vehicles on the major road may be approaching the junction at such high speeds that they may be unable to take avoiding action when another vehicle suddenly dashes out into their path from the minor road. The proportion of systematic variation in the expected frequency of right-angle accidents, explained by the preferred full model, was about three times that of the corresponding flow-based model. This shows the substantial contribution of the three additional variables to the model's predictive ability.

(b) Rear-end Collision Accidents

The best models obtained for this category of accidents were those that included the encounter flow products (ENCP) and diverging flow products (DFPD) functions as the main exposure variables. These models are presented in their linear form in Table 5.5b. The flow-based models were:

$A = 1.28x10^{-4}\ ENCP^{0.529}$ ....(5.20)

$A = 3.06x10^{-4}\ DFPD^{0.520}$ ....(5.21)

where A is the expected 3 year frequency of rear-end collision accidents.

Table 5.5b. Models for Rear-end Collision Accidents at X-junctions (Total number of accidents = 50; number of sites=34)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	0.386	0.186	2.075	-	LL(0) = -111.8**
Dispersion parameter	κ	*2.008*	*1.233*	*1.628*		
2. Flow-based models						
(a)	Lk	-8.966	3.138	-2.857	0.60	0.079
	LENCP	0.529	0.176	3.008		
Dispersion parameter	κ	*4.117*	*3.520*	*1.170*		
(b)	Lk	-8.091	2.840	2.849	0.58	0.080
	LDFPD	0.520	0.173	3.006		
Dispersion parameter	κ	*4.201*	*3.647*	*1.152*		
3. Full models						
(a)	Lk	-11.270	3.653	3.085	0.88	0.108
	LENCP	0.627	0.197	3.183		
	LFT(2)	0.752	0.437	1.721		
Dispersion parameter	κ	*4.20*	-			
(b)	Lk	-9.747	3.142	3.102	0.83	0.105
	LDFPD	0.590	0.184	3.205		
	LFT(2)	0.676	0.419	1.614		
Dispersion parameter	κ	*4.95*	-			

* The prefix "L" indicates the natural logarithmic form of the variable, i.e LENCP = Log (ENCP).

**LL(0) is the log-likelihood value of the null model

Both models were strikingly similar on both *t*-statistics for individual parameters and model goodness-of-fit measures. However, since DFPD is contained in the ENCP flow function (DFPD is one of three main flow functions summed up to obtain ENCP), the former was regarded as the more appropriate exposure function. The similarity of the model parameters confirmed that the other flow functions, which add up to DFPD to obtain ENCP, did not contribute much to the model's predictive ability. The appropriateness of the DFPD exposure function is also underscored by the fact that rear-end collisions can only occur between vehicles belonging to the same traffic stream.

The flow-based models for rear-end collision accidents predicted the highest proportion of systematic variation in the dependent variable than the corresponding models for any other accident type involving vehicle-vehicle collisions. Thus, rear-end collision accidents appeared clearly to be much more dependent on the exposure variable than other accident types. The full model based on the DFPD exposure function was also selected in preference to the one based on ENCP. This model was:

$$A = 5.85x10^{-5}\, DFPD^{\,0.590}\, e^{\,0.676LFT(2)} \qquad \text{........................(5.22)}$$

Of all the variables tested, none was significant at the 5 percent level. The variable representing the status of a left-turn lane on the major road was the most influential, having a relatively high *t*-ratio (1.72), at the same time as contributing to a meaningful drop in the scaled deviance. The model showed that when a left-turning lane was absent on the major road (LFT(2)), expected rear-end collision accident frequency was increased by a factor of 1.97. This was not unexpected, since braking or rapid deceleration by left-turning vehicles whilst still in the main traffic stream is a typical conflict scenario for rear-end collisions. When a left-turn lane is present on the main road, the turning vehicles are able to diverge from the mainstream before decelerating and this would tend to reduce the potential for rear-end collisions considerably, as evidenced by the model.

(c) Side-swipe Collision Accidents

The most influential vehicle flow functions for this category of accidents were the merging flow products (MEFP) and the cross product flow (XPDF), as shown in Table 5.5c. The flow-based models were:

$$A = 4.40x10^{-8}\, MEFP^{\,1.029} \qquad \text{.............. (5.23)}$$

$$A = 6.24x10^{-8}\, XPDF^{\,0.939} \qquad \text{..................(5.24)}$$

Model (5.23) had considerably better *t*-statistics for individual parameters and goodness-of-fit measures than model (5.24). It does show, therefore, that the merging flow products function was a better exposure variable for side-swipe collision accidents than the cross products of flow function. The full models for side-swipe collision accidents built on the above flow-based models included two additional variables, LFT(2) and JNEC, referring respectively to the absence of a left-turning lane on the major road and the average width of the minor road at the neck of the junction.

The preferred full model was:

$$A = 1.53x10^{-7}\,MEFP^{0.677}\,e^{(1.476LFT(2)+0.184JNEC)} \qquad \text{...............(5.25)}$$

where A is the expected 3 year frequency of side-swipe collision accidents at X-junctions.

Table 5.5c. Models for Side-swipe Collision Accidents at X-junctions
(Total number of accidents = 34, number of sites=34)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	5.87210^{-9}	0.3064	0	-	LL(0) = -91.92
Dispersion parameter	κ	*0.456*	*0.219*	*2.082*		
2. Flow-based models						
(a)	Lk	-16.940	5.576	-3.038	0.40	0.105
	LMEFP	1.029	0.336	3.063		
Dispersion parameter	κ	*0.890*	*0.518*	*1.718*		
(b)	Lk	-16.590	5.701	-2.910	0.16	0.086
	LXPDF	0.939	0.321	2.925		
Dispersion parameter	κ	*0.768*	*0.420*	*1.829*		
3. Full models						
(a)	Lk	-15.690	4.436	-3.537	(1.25)	0.241
	LMEFP	0.677	0.286	2.367		
	LFT(2)	1.476	0.640	2.306		
	JNEC	0.184	0.065	2.831		
Dispersion parameter	κ	*6.85*				
(b)	Lk	-15.79	4.718	-3.347	(1.20)	0.230
	LXPDF	0.631	0.285	2.214		
	LFT(2)	1.631	0.655	2.490		
	JNEC	0.183	0.067	2.731		
Dispersion parameter	κ	*5.75*				

* The prefix "L" indicates the natural logarithmic form of the variable, i.e LENCP = Log (ENCP).

**LL(0) is the log-likelihood value of the null model

The model indicates that the absence of a left-turn lane on the major road led to an increase in the expected frequency of side-swipe collision accidents by a factor 4.38. The need for junction tightening (reduction of, so-called, dead space) as a safety measure was also underscored by the positive correlation between the expected accidents and the width of the minor road at the neck of the junction. A wide junction entry width would encourage poor lane discipline and hence aggravate the potential of vehicles side-swiping each other.

Unexpectedly, the Freeman-Tukey goodness-of-fit value for both full models exceeded its expected maximum of 1.0. This was probably a consequence of the assumptions underlying the derivation of this statistic. The maximally obtainable model fit computed is determined by the amount of random variation (variance) in an assumed perfect Poisson model, which is constant and equal to the mean (see Fridstrom *et al*, 1995). The models specified above, however, are Negative Binomial, in which case the scope of random variation is variable, growing larger for smaller values of the expected variable (Mountain *et al*, 1996). The goodness-of-fit measure so calculated, therefore, could conceivably have exceeded 1.0.

Admittedly, it cannot be completely ruled out that this higher than expected goodness-of-fit value could also have been due to deficiencies in the estimated models. The possibility exists that the models could have misinterpreted part of the random variation as systematic, as a result of some spurious rather than causal correlation in the data. Cross-checking of both additional variables represented in the models, however, showed that they were all statistically significant and contributed to significant reductions in deviance. Therefore, if there was any spurious correlation, then it was not immediately obvious.

(d) Head-on Collision Accidents

As assessed by the ratio of scaled deviance to the degrees of freedom for the null model, accidents of this type were clearly not over-dispersed with respect to the Poisson distribution so as to warrant a Negative Binomial fit. The Poisson assumption, was therefore, applied. The best models that were fitted are presented in Table 5.5d. The cross product of flows (XPDF) and encounter flows (ENCP) exposure functions produced the more promising results for flow-based models. These models were:

$A = 1.87x10^{-3} XPDF^{0.317}$ ....(5.26)

$A = 3.47x10^{-3} ENCP^{0.280}$ ....(5.27)

where A is the estimated 3 year frequency of head-collision accidents

However, the *t*-statistics for the model parameters were in both cases marginal and their respective contributions to reduction in scaled deviance also fell well below the required value for 5 per cent level of significance. Subsequently, the χ^2-test was carried out for both models, since the deviance value follows the χ^2 distribution and it emerged that the null hypothesis (that these models had the same explanatory power as the model with the constant term only) could not be rejected. At 1.0 degree of freedom (the extra these models had over the null model), the critical χ^2 value is equal to 3.84, whereas the deviance change produced by the models were 1.61 and 1.35 respectively. As a result, these flow-based models were not considered reliable and are only indicative. It is apparent that the null model was the most credible in this case.

Table 5.5d. Models for Head-on Collision Accidents at X-junctions
(Total number of accidents = 16; number sites=34)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	-0.754	0.250	-3.016	-	SD=35.211 DF=33**
2. Flow-based models						
(a)	*Lk* *LXPDF*	*-6.280* *0.317*	*4.532* *0.257*	*-1.386* *1.232*	-	*SD=33.602* *DF=32*
(b)	*Lk* *LENCP*	*-5.663* *0.280*	*4.379* *0.247*	*-1.293* *1.132*	-	*SD=33.862* *DF=32*
3. Full models						
(a)	*Lk* *LXPDF* *SSD* *STL(2)*	*-12.410* *0.503* *0.331* *1.031*	*5.289* *0.262* *0.122* *0.619*	*-2.346* *1.920* *2.713* *1.666*	-	*SD=23.149* *DF=30*
(b)	*Lk* *LENCP* *SSD* *STL(2)*	*-12.320* *0.489* *0.332* *1.154*	*5.271* *0.257* *0.123* *0.647*	*-2.337* *1.903* *2.699* *1.784*	-	*SD=23.171* *DF=30*

* The prefix "L" indicates the natural logarithmic form of the variable, i.e LENCP = Log (ENCP).
**SD –scaled deviance of model fit; DF – degrees of freedom left after model fit

The full models explored appeared to produce a much better fit to the data. Two additional variables (SSD and STL) were consistently significant. The models are also presented in Table 5.5d. There was little to choose between the two alternatives, although the one based on the cross products flow function was slightly better on the amount of deviance reduced. This model was:

$$A = 4.08x10^{-6}\, XPDF^{\,0.503}\, e^{(0.331SSD+1.031STL(2))} \qquad \text{..............(5.28)}$$

where A is the estimated 3 year frequency of head-on collision accidents at X-junctions,

SSD – the standard deviation of average spot speeds on the major approaches and
STL(2) – parameter representing the absence of street lighting at the junction

The model showed that head-on collision accidents increased at decreasing rates with vehicular traffic and were also positively correlated to the standard deviation of average spot speeds on the major approaches to the junction. The absence of street lighting was reflected in an increase in the expected frequency of head-on collision accidents by a factor of 2.80. Due to the rather low accident frequency (less than 0.5 accidents per site) it is likely that the variation in the data is more random than systematic and therefore the estimated models (with the exception of the null model) together with the parameter effects cannot be considered reliable. The models are published only as an indication of what was attainable in the circumstances.

(e) Single Vehicle Accidents

This category of accidents was also under-dispersed and therefore modelled on the Poisson assumption. Of all the exposure variables tested, only one flow function was of any significance. This flow function was the ratio of the minor to major road traffic inflow. Although the *t*-statistic was marginal (1.431), the overall reduction in scaled deviance of 2.456 was the largest obtained for any flow function tested, albeit still not significant. The selected flow-based model was also merely indicative, since it did not have any more explanatory power than the null model. This model, presented in the linear form in Table 5.5e was:

$$A = 0.614\, MMR^{\,0.634} \qquad \text{.....................(5.29)}$$

where A is the expected single vehicle accident frequency at X-junctions and

MMR – the ratio of minor to major road traffic

In the extended model, only the variable representing the proportion of heavy goods vehicles as a percentage of total junction traffic (HGV) was significant. This model (also presented in Table 5.5e) was:

$$A = 0.035\,MMR^{0.873}\,e^{0.537HGV} \qquad \text{..................(5.30)}$$

With an extra two degrees of freedom and corresponding deviance drop of 11.139, this model was highly significant and had a much better explanatory power than the null model. The critical χ^2 value, at 2 degrees of freedom, is 9.21 at 1 per cent level of significance.

Table 5.5e. Models for Single-vehicle Collision Accidents at X-junctions
(Total number of accidents = 12; number of sites=34)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	-1.041	0.289	-3.608	-	SD=30.540 DF=33**
2. Flow-based model						
(a)	*Lk* *LMMR*	*-0.487* *0.634*	*0.428* *0.443*	*-1.138* *1.431*	-	*SD=28.080* *DF=32*
3. Full model						
(a)	*Lk* *LMMR* *HGV*	*-3.353* *0.873* *0.537*	*1.296* *0.462* *0.203*	*-2.587* *1.890* *2.645*	-	*SD=19.401* *DF=31*

* The prefix "L" indicates the natural logarithmic form of the variable, i.e LMMR = Log (MMR).
**SD –scaled deviance of model fit; DF – degrees of freedom left after model fit

According to the model, the frequency of single vehicle accidents increased with increasing proportion of heavy goods vehicles and buses at X-junctions. To have such influence, this group of vehicles must have been disproportionately involved in single vehicle accidents at X-junctions. That was not entirely surprising, since most single vehicle accidents are usually the result of mechanical failure or some vehicle defect of sorts. The particularly poor maintenance track record of heavy goods vehicles in Ghana was alluded to, in Section 4.2.5, as one primary reason for their disproportionate involvement in accidents in general.

Here again, a statement of caution is necessary about the reliability of the fitted models due to the rather low accident frequency (0.3 accidents per site). For a similar reason as cited in the preceding section for head-on collision accidents the null model here is also obviously the more reliable. The other models and estimated parameter effects are to be seen as only indicative.

It has been reported in sections of the literature that the traditional application of the poisson or negative binomial models (as was done under this study) may be inadequate for the purpose of modelling accident data with a preponderance of zero counts as in the present case. Some special approaches have therefore been suggested. Shankar *et al* (1997), for example, suggest that such data may be modelled better as a zero-altered probability process in which case the so-called zero-inflated poisson (ZIP) or negative binomial (ZINB) model structures could be explored. This approach was not pursued because a considerably much larger database than obtains under the current study would have been required to produce any useful results.

(f) Pedestrian Accidents

In order to obtain logically sound models, the exposure functions for all pedestrian accident models were constrained to include the pedestrian flow variable (PEDF) at the same level as the vehicle flow functions. The result of this constraint were models which predicted zero frequency of pedestrian accidents when either or both pedestrian and vehicle flow functions was zero. As always, the model parameters were also required at the same time to satisfy the statistical significance criteria as much as possible. After testing the broad range of variables in the database, the models presented in Table 5.5f were those that best met the set criteria.

The flow-based models selected were:

$$A = 0.092\, MRSH^{0.364}\, PEDF^{0.727} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5.31)$$

$$A = 9.81x10^{-4}\, PVPF^{0.519} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5.32)$$

where MRSH is the minor road's share of total junction vehicle inflow,
PEDF – the peak hour pedestrian flows across all junction arms and
PVPF – the product of total junction vehicle inflow and PEDF (i.e. TINF x PEDF)

The effect of specifying the pedestrian flow function alongside the vehicle flow function, as in model 5.27, was a substantial reduction in the significance (*t*-statistic) of the latter. By contrast, the pedestrian flow function was highly significant. This reflected the relative influence of the two exposure functions on the expected frequency of pedestrian accidents and it was hardly surprising that pedestrian exposure turned out to be the more important.

Despite predicting 10 per cent less of the systematic variation in the frequency of pedestrian accidents, model (5.32) had much better attributes overall than model (5.31). The parameters of the former model were highly significant and the model also produced a much better reduction in scaled deviance (-16.71 as against –13.0 for model (5.31)) despite using one less degree of freedom than model (5.31). Thus, between the two, model (5.32) was clearly the favourite.

Table 5.5f. Models for Pedestrian Accidents at X-junctions (Total number of accidents = 50; number of sites=34)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	0.386	0.222	1.739	-	LL(0) =
Dispersion parameter	κ	*0.998*	*0.492*	*2.028*		-113.4**
2. Flow-based models						
(a)	Lk	-2.388	0.899	-2.656	0.71	0.144
	LMRSH	0.364	0.330	1.103		
	LPEDF	0.727	0.166	4.380		
Dispersion parameter	κ	*3.544*	*2.987*	*1.186*		
(b)	Lk	-6.927	1.974	-3.509	0.61	0.103
	LPVPF	0.519	0.138	3.761		
Dispersion parameter	κ	*2.609*	*2.004*	*1.302*		
3. Full model						
(a)	Lk	-9.402	2.489	-3.777	0.81	0.156
	LPVPF	0.529	0.167	3.168		
	ZEX(2)	0.500	0.446	1.121		
	JNEC	0.0955	0.0585	1.632		
	STL(2)	0.538	0.432	1.245		
Dispersion parameter	κ	*2.410*	-			

* The prefix "L" indicates the natural logarithmic form of the variable, i.e LPEDF = Log (PEDF).

**LL(0) is the log-likelihood value of the null model

Only one full model, obtained by extending the exposure functions featured in the flow-based models above, proved satisfactory. This model is also presented in Table 5.5f. Most additional variables tested for the full models either did not pass the 5 per cent significance test or could not be logically connected with the incidence of pedestrian accidents and were dropped as a result. In the end, the variables retained were those that produced relatively better *t*-statistics, made meaningful contributions to the reduction in scaled deviance and above all, enhanced the general plausibility and stability of the

models. These variables represented the status of zebra crossings (ZEX) and streetlights (STL) and the average width of the minor road at the neck of the junction (JNEC).
The selected full model was:

$$A = 8.26x10^{-5}\, PVPF^{0.529}\, e^{(0.500ZEX(2)+0.538STL(2)+0.095JNEC)} \quad ....(5.33)$$

where ZEX(2) is a factor indicating the absence of marked zebra crossings in the vicinity of the junction and STL(2) the absence of street-lighting.

The model shows that the absence of marked zebra crossings in the vicinity of X-junctions tended to increase pedestrian accident frequency by a factor of 1.65, whilst the absence of streetlights led to a 1.71 fold increase. The implication of this is that marked zebra crossings and streetlights at the junctions in the modelling database generally reduced the potential for pedestrian accidents.

5.5.2 T-junctions Models

Similar procedures for model development as those used for X-junctions were applied for selecting the best accident models for T-junctions. Thus, alternative models were estimated separately for all accidents, injury accidents and the various accident types, as defined by the primary collisions involved. These models are presented in Tables 5.6a & b and 5.7a-f and are discussed below.

5.5.2.1 All Accident Models

354 accidents were recorded at all the 57 T-junction sites in the database for the period 1996-1998 inclusive. This translated into an average 3-year accident frequency per junction of 6.21. As was the case with the "all accident" models for X-junctions, most of the large variety of vehicle flow functions tested for T-junctions yielded statistically significant fits to the data. The pedestrian flow function (PEDF) was again not significant when combined in the appropriate form with the vehicle flow functions. The models, which were selected are presented in Table 5.6a. The flow-based models were:

$$A = 5.09x10^{-4}\, XPDF^{0.552} \quad .... (5.34)$$

$$A = 6.37x10^{-4}\, MAJF^{0.501}\, MINF^{0.583} \quad .... (5.35)$$

$$A = 7.99x10^{-4}\ TINF^{1.032}\ MRSH^{0.505} \qquad \text{................} \qquad (5.36)$$

where A is the expected 3-year accident frequency at T-junctions, XPDF – the product of the major (MAJF) and minor (MINF) road daily in flows, TINF – the total 24-hour vehicle inflow to the junction, and MRSH – the minor road's share of total junction traffic

Table 5.6a. Models for all Accidents at T-junctions
(Total number of accidents = 354; number of sites = 57)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	1.826	0.131	13.918	-	LL(0) = -330.3**
Dispersion parameter	κ	*1.218*	*0.298*	*4.089*		
2. Flow-based models						
(a)	Lk	-7.583	1.837	-4.128	0.37	0.063
	LXPDF	0.552	0.108	5.102		
Dispersion parameter	κ	*2.154*	*0.631*	*3.414*		
(b)	Lk	-7.358	1.957	-3.760	0.37	0.064
	LMAJF	0.501	0.184	2.720		
	LMINF	0.583	0.141	4.146		
Dispersion parameter	κ	*2.159*	*0.633*	*3.412*		
(c)	Lk	-7.132	2.068	-3.449	0.33	0.059
	LTINF	1.032	0.226	4.564		
	LMRSH	0.505	0.149	3.385		
Dispersion parameter	κ	*2.065*	*0.596*	*3.465*		
3. Flow- geometry-factors						
(a)	Lk	-7.158	1.881	-3.805	0.50	0.096
	LMAJF	0.573	0.198	2.894		
	LMINF	0.480	0.132	3.636		
	SSD	0.0691	0.0360	1.919		
	TCON(2)	-0.480	0.224	-2.143		
	TCON(3)	-0.953	0.338	-2.820		
	MEDW	-0.166	0.082	-2.024		
Dispersion parameter	κ	*3.008*	*0.972*	*3.095*		
(b)	Lk	-6.897	1.695	-4.069	0.49	0.096
	LXPDF	0.514	0.098	5.245		
	SSD	0.0694	0.0358	1.939		
	TCON(2)	-0.465	0.223	-2.085		
	TCON(3)	-0.952	0.338	-2.817		
	MEDW	-0.151	0.0703	-2.148		
Dispersion parameter	κ	*2.996*	*0.967*	*3.098*		
(c)	Lk	-6.962	2.001	-3.479	0.46	0.091
	LTINF	1.001	0.216	4.634		
	LMRSH	0.390	0.148	2.635		
	SSD	0.0677	0.0367	1.845		
	TCON(2)	-0.493	0.230	-2.143		
	TCON(3)	-0.971	0.342	-2.839		
	MEDW	-0.160	0.084	-1.905		
Dispersion parameter	κ	*2.829*	*0.895*	*3.161*		

* The prefix "L" indicates the natural logarithmic form of the variable, i.e LXPDF = Log (XPDF).
**LL(0) is the log-likelihood value of the null model

These models mean that the expected total accident frequency at T-junctions increased approximately as a function of the square root of the vehicle exposure functions XPDF, MAJF, MINF and MRSH. The exception was total junction vehicle inflow (TINF), to which the expected accident frequency was virtually proportional. The exponent value for this function, as in model (5.36), did not differ substantially from 1.0.

Of the three alternative models, the one based on the cross product flow function (Equation 5.34) was the most preferred, because it used one less degree of freedom than the others and still managed to produce one of the highest proportion of systematic variation explained (37 per cent). The model's log-likelihood ratio statistic was also relatively high. The alternative full models involving extensions of the flow-based models shared similar characteristics as the core flow-based models. Thus, based on similar considerations as before, the full model built, on the cross product of flows exposure function, emerged as the preferred one. This model was:

$$A = 1.01x10^{-3}\,XPDF^{0.514}\,e^{(0.0694SSD-0.465TCON(2)-0.952TCON(3)-0.151MEDW)} \qquad \text{......(5.37)}$$

where A is the expected 3-year frequency of accidents at T-junctions,
TCON(2) - parameter representing traffic control level 2 (i.e.YIELD) on the minor road,
TCON(3) – level 3 of traffic control on the minor road (i.e. no control),
MEDW – average width of the median on the major road and
SSD- standard deviation of average spot speeds on the major approaches to the junction

It is significant to observe that two of the three additional variables included in the model, i.e. traffic control on the minor road and the average width of the median on the major, had negative signs to their parameter estimates. This means that the said parameters were negatively correlated to the expected accident frequency at T-junctions, in which case the presence of the stated traffic control type and increasing values of MEDW would lead to less accident frequency. The specific effects of traffic control as captured in the model was that, when the type of control at the minor road was TCON(2), which represented the YIELD sign, the accident frequency reduced by a factor of 0.63. On the other hand, TCON(3) (i.e. no control) on the minor road was associated with a reduction in accident frequency by a factor of 0.39.

These effects were relative to level 1 of traffic control (TCON(1)), which represented STOP control at the minor road in the modelling database. Thus, earlier observations made in Section 4.3.2.4 of this thesis, which discussed the relative safety records of the three types of control appear to have been partly confirmed. Junctions which had YIELD or "no control" were adjudged by the model as having a better safety record than those with STOP control. However, whereas the model estimated that YIELD-controlled junctions had a far better potential for accident reduction (more than one and a half times better) than "no control", the reverse was true in Section 4.3.2.4 when simple accident rates and accident frequency were compared. The model, therefore, does curb the temptation to conclude (or imply, as in Section 4.3.2.4) that the best form of junction control, from a safety perspective, is "no control" and total reliance on the discretion of drivers.

The confounding question about the safety record of STOP control however remains unanswered. The model confirmed that, at least as far as the modelling database was concerned, STOP control was associated with the worst impact on accident potential at T-junctions. It may as well be that the level of control at the particular junctions might have been stepped up to STOP control in response to a bad accident situation in the first place. But since, as is apparent, the intervention did not appear to have improved the situation, it is entirely appropriate to question the effectiveness of the STOP control as an accident remedial measure.

This is an important concern that touches at the heart of long-established codes of practice, as set out in safety warrants, which until now, have taken for granted the relative safety benefits of increasing the level of control at unsignalised junctions. The impact of the other parameters on accident frequency in the model appeared fairly straightforward and logical. It is not incomprehensible, for example, that, the width of the median on the major road would be related to fewer accidents, considering junctions of equivalent traffic with and without the median.

On the other hand, large values of SSD would suggest wide variability and extremes in vehicles' approach speeds, leading to less predictability and poor mutual anticipation between drivers. This atmosphere would breed more conflicts and potentially lead to more accidents. The proportion of systematic variation in accident frequency explained by the full models were only about 10 per cent more than their corresponding flow-based models and generally only about half the percentages achieved for all accident models for X-junctions. This was most probably due to the fewer additional parameters accepted on account of their significance into the full models for T-junctions. Also, the contribution of the individual parameters to the reduction in model deviance, although statistically significant, was generally less than the levels attained for X-junctions. It is not exactly clear why this happened, besides suggesting that it could have something to do with consistency in the database. Nonetheless, the 50 per cent proportion of systematic variation explained by the full models was still good by most standards reported in the literature.

The plot of standardised residuals and their normal order statistics, in Figure 5.5 below, demonstrated further the quality of the selected full model for accident frequency at T-junctions. It shows how well the model fitted individual data points in the database. All but one of the 57 data points fell within the range plus or minus 2.0, the 95 per cent confidence interval of the normal order statistics. This is evidence of a well-fitting model. The fit to a straight line was also very close, given the Filliben correlation coefficient value of 0.87, so the use of a generalised Poisson assumption as a basis for developing the models was equally well supported.

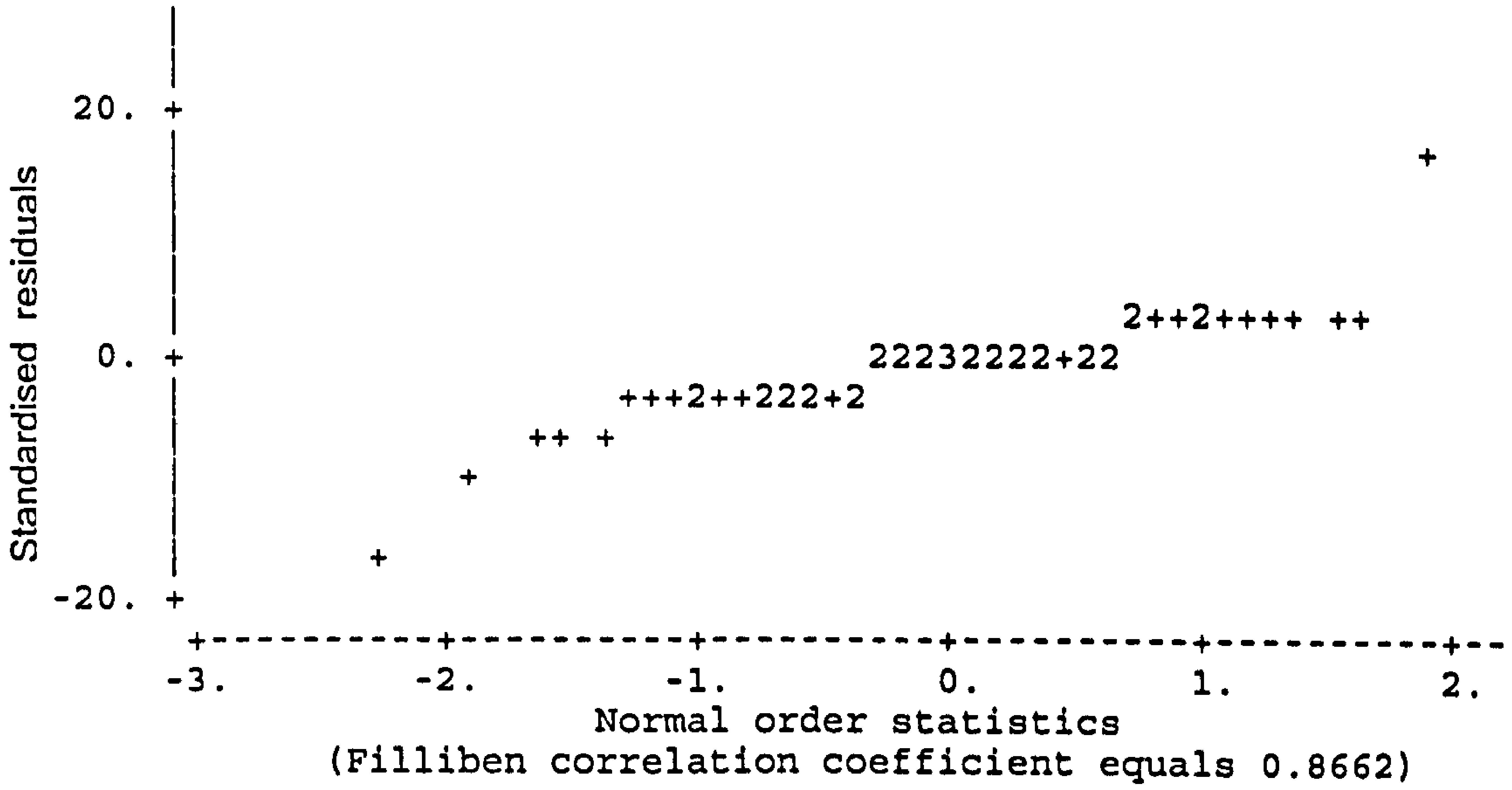


Figure 5.5 Normal Q-Q plot for selected full model for T-junctions

5.5.2.2 Injury Accidents

Accidents in this category were those in which there were any type of injury to the victims, including minor injury requiring only first aid, severe injury resulting in long-term hospitalisation and death. A total of 126 such accidents occurred during the study period 1996-1998 inclusive at the 57 junction sites in the database. Thus, the injury accident frequency per junction was 2.2 and half of all injury accidents involved at least one pedestrian.

In order to take account of the large proportion of pedestrian accidents involved, the general form of the flow-based models for injury accidents at T-junctions was specified such that it included both pedestrian and vehicle exposure functions. This was done in a manner that made the prediction of injury accidents resulting only from vehicle-vehicle collisions possible, even where pedestrian injuries were theoretically zero. From a broad range of vehicle and pedestrian flow combinations tested, the best three alternative flow-based models obtained were:

$$A = 1.12x10^{-3} XPDF^{0.430} e^{0.00303PEDF} \qquad \text{..................(5.38)}$$

$$A = 2.96x10^{-3} ENCP^{0.370} e^{0.00351PEDF} \qquad \text{.................. (5.39)}$$

$$A = 9.05x10^{-3} MAJF^{0.479} MINF^{0.398} e^{0.00304PEDF} \qquad \text{.................. (5.40)}$$

where A is the expected 3-year frequency of injury accidents at T-junctions,
ENCP – the sum of encounter flow products and XPDF, PEDF,
MINF and MAJF as previously defined.

The models are presented in Table 5.6b in their linear form. All three alternative models produced very high proportions of systematic variation explained for injury accident frequency, about one and a half times those obtained by the corresponding flow-based models for X-junctions and "all accidents" models for T-junctions. This implied that, at T-junctions, injury accidents were much more dependent on exposure variables than at X- junctions. It also confirmed an earlier observation that the exposure functions were more influential in predicting injury accidents than all accidents at any given type of junction.

The flow-based model represented by Equation (5.38) was clearly the most preferred on account of the fewer degrees of freedom expended and the generally better *t*-statistics of individual model parameters and global goodness-of-fit measures for the model as a whole. The selected full models for injury accidents at T-junctions are also presented in

Table 5.6b. Only two additional variables were significant enough to be included in these models. The variables were the average standard deviation of vehicle spot speeds on the major approaches (SSD) and the level of traffic control on the minor road (TCON). The pedestrian exposure variable (PEDF) was not significant at this stage and did not therefore feature separately as an explanatory variable. It featured as an integral part of the combined exposure function SVPF. However, as can be seen in Table 5.6b, the full model based on the latter exposure function performed poorly in relation to the alternative models, although it appeared more logically constituted than the others.

Table 5.6b. Models for Injury Accidents at T-junctions
(Total number of accidents = 126; number of sites = 57)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	0.793	0.131	6.074	-	LL(0) =
Dispersion parameter	κ	*1.923*	*0.757*	*2.540*		-223.7**
2. Flow-based models						
(a)	Lk	-6.796	2.285	-2.974	0.63	0.098
	LXPDF	0.430	0.137	3.144		
	PEDF	0.003027	0.001725	1.755		
Dispersion parameter	κ	*3.080*	-			
(b)	Lk	-5.821	2.066	-2.818	0.59	0.093
	LENCP	0.370	0.123	3.005		
	PEDF	0.003509	0.001438	2.440		
Dispersion parameter	κ	*6.966*	*6.112*	*1.140*		
(c)	Lk	-7.007	2.448	2.862	0.64	0.097
	LMAJF	0.479	0.221	2.168		
	LMINF	0.398	0.172	2.318		
	PEDF	0.003038	0.001756	1.730		
Dispersion parameter	κ	*2.902*	-			
3. Full models						
(a)	Lk	-7.852	2.192	-3.582	0.71	0.111
	LXPDF	0.490	0.126	3.901		
	SSD	0.0844	0.0445	1.898		
	TCON(3)	-0.765	0.428	-1.789		
Dispersion parameter	κ	*3.24*	-			
(b)	Lk	-7.728	2.391	-3.232	0.70	0.110
	LMAJF	0.464	0.221	2.103		
	LMINF	0.503	0.161	3.124		
	SSD	0.08535	0.04570	1.868		
	TCON(3)	-0.767	0.435	-1.764		
Dispersion parameter	κ	*2.995*	-			
(c)	Lk	-6.332	2.151	-2.944	0.47	0.084
	LSVPF	0.726	0.224	3.240		
	SSD	0.0719	0.040	1.798		
	TCON(3)	-0.811	0.412	-1.970		
Dispersion parameter	κ	*4.809*	*3.046*	*1.579*		

* The prefix "L" indicates the natural logarithmic form of the variable, i.e LXPDF = Log (XPDF).

**LL(0) is the log-likelihood value of the null model

The models in which the pedestrian exposure variable was not explicitly represented were accepted, partly because of their far superior goodness-of-fit measures and, also, because they included the parameter SSD. Because of the operational environment the parameter value (SSD) characterised, it was presumed that it could well be accounting in part for the risk of pedestrian accidents in the models. This presumption seemed to gain support from the fact that estimates of the parameter value in the models in question were more significant than in the model with the combined pedestrian and vehicle flow function.

The levels of traffic control in the models were again negatively correlated to injury accident frequency and, as before, it is to be appreciated that their estimated impacts were relative to TCON(1) or STOP control, which was not explicitly featured. Therefore, TCON(2), or YIELD control, and TCON(3), or no control, were adjudged to be associated with less accident potential than STOP control.

The full injury accident models explained only an average of 7 per cent more systematic variation in the response variable than the respective flow-based models and as much as 20 per cent less than corresponding models for X-junctions. It is probably also noteworthy that no junction geometry variable was represented in the full models for T-junctions. All these would go to emphasise the point that injury accidents at T-junctions were far more dependent on traffic factors than geometry, or the road environment. Of the alternative full models presented in Table 5.6b, the preferred one was:

$$A = 3.89x10^{-4}\, XPDF^{\,0.490}\, e^{(0.0844SSD-0.765TCON(3))} \qquad \text{.............(5.41)}$$

The effect of traffic control as captured by the preferred full model was such that, relative to STOP control, T-junctions which had no control at all (TCON(3)) were associated with a reduction in injury accident potential by a factor of 0.46. Interestingly, the expected reduction in accident potential associated with YIELD-control (i.e. TCON(2)) was estimated to be more than one and a half times that of junctions with no control. This is reassuring because it showed that, from a safety perspective at least some form of junction control may still be better than no control at all. The YIELD control parameter (TCON(2)) was, however, not retained in the full model because the *t*-statistic value for the estimate fell well short of the required significance level.

The results also provide reasonable grounds for a radical re-appraisal of the rationale for implementing STOP controls at T-junctions. Since the presumed safety benefits of implementing this most restrictive form of unsignalised junction control do not appear to materialise, it might make sense to explore the effectiveness of replacing it with YIELD control. At least three potential advantages will accrue as a result. Junction control will become more flexible whilst delays to traffic associated with the mandatory STOP control would be minimised, together with the attendant adverse impact on the environment.

The need for such re-appraisal has been underscored in the works of Polus (1985), Ronald and James (1988) and Lum and Parker (1982). These authors studied the impact on safety of increasing the level of junction control through replacement of YIELD signs by STOP or implementation of four-way STOP controls at unsignalised X-junctions. They observed that, whilst such measures may result in the redistribution of accidents at the given site, they did not meet the desired objective of reducing the overall accident frequency. Consequently, they concluded that the measures were merely restrictive and not universally justified by the operational and environmental impacts resulting from their use.

5.5.2.3 Accidents by Collision-types

(a) Right-angle Collision Accidents

The models, which were selected as most suitable for this group of accidents, are presented in Table 5.7a. In the flow-based models, exposure functions based on different combinations of the major (MAJF) and minor road flows (MINF) produced the best results. The first exposure variable (XPDF) was a product of the two flows and constrained to have the same exponent. In the other exposure function, the constraint on the exponent was removed and the flow variables were allowed to take separate exponent values. The flow-based models were:

$$A = 6.93x10^{-4}\, XPDF^{0.444} \qquad \text{.................(5.42)}$$

$$A = 4.41x10^{-4} MAJF^{0.536} MINF^{0.392} \qquad \text{.................}(5.43)$$

where A is the expected 3-year frequency of right-angle collision accidents at T-junctions.

Table 5.7a. Models for Right-angle Collision Accidents at T-junctions (Total number of accidents = 52; number of sites=57)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	0.274	0.151	1.817	-	LL(0) = -178.8**
Dispersion parameter	κ	*1.851*	*0.979*	*1.891*		
2. Flow-based models						
(a)	Lk	-7.275	2.468	-2.948	0.43	0.050
	LXPDF	0.444	0.144	3.083		
Dispersion parameter	κ	*3.079*	*2.136*	*1.441*		
(b)	Lk	-7.726	2.660	-2.905	0.46	0.051
	LMAJF	0.536	0.247	2.170		
	LMINF	0.392	0.183	2.142		
Dispersion parameter	κ	*3.095*	*2.151*	*1.439*		
3. Full models						
(a)	Lk	-7.144	2.624	-2.723	0.95	0.119
	LXPDF	0.415	0.145	2.854		
	MEDW	-0.161	0.107	-1.507		
	ITM(2)	0.844	0.623	1.356		
	TCON(3)	-1.764	0.760	-2.321		
Dispersion parameter	κ	*3.080*	-			
(b)	Lk	-8.570	3.007	-2.850	0.98	0.124
	LMAJF	0.684	0.310	2.208		
	LMINF	0.293	0.188	1.559		
	MEDW	-0.222	0.124	-1.795		
	ITM(2)	0.815	0.628	1.297		
	TCON(3)	-1.768	0.758	-2.332		
Dispersion parameter	κ	*3.100*	-			

* The prefix "L" indicates the natural logarithmic form of the variable, i.e LXPDF = Log (XPDF).

**LL(0) is the log-likelihood value of the null model

The global goodness-of-fit measures for both models were similar but the one based on the cross products of flow function (XPDF) was marginally preferable, on account of the fewer degrees of freedom used.

The alternative full models included three other explanatory variables, representing the average width of the median on the major road (MEDW), the status/type of island on the minor road (ITM) and the level of traffic control (TCON). The models are also presented in Table 5.7a. TCON(3) or no control and MEDW were all negatively correlated to the expected frequency of right-angle collision accidents. ITM(2), representing the absence of a triangular island with dual-directional traffic flow on either side on the minor road, was associated with an increase in the frequency of right-angle collision accidents, hence the positive sign attached to this parameter in the model. Although the latter parameter's *t*-statistic did not meet the required level for significance, it was deemed prudent to retain it in the model due to the substantial reduction in deviance it contributed. Perhaps, more importantly, the parameter also ensured the stability of the full model (i.e. its presence in the model enhanced the significance of the other parameter estimates and without it these parameters were less significant).

The preferred full model in exponential form was:

$$A = 7.89x10^{-4}\, XPDF^{\,0.415}\, e^{(0.844ITM(2)-0.161MEDW-1.764TCON(3))} \quad \ldots\ldots. \quad (5.44)$$

Thus, the estimated effects of the additional variables were such that the absence of a triangular island on the minor road (ITM(2)) was associated with an increase in right-angle accident frequency by a factor of 2.33, whilst no control (TCON(3)) on the minor road reduced it 0.17 times.

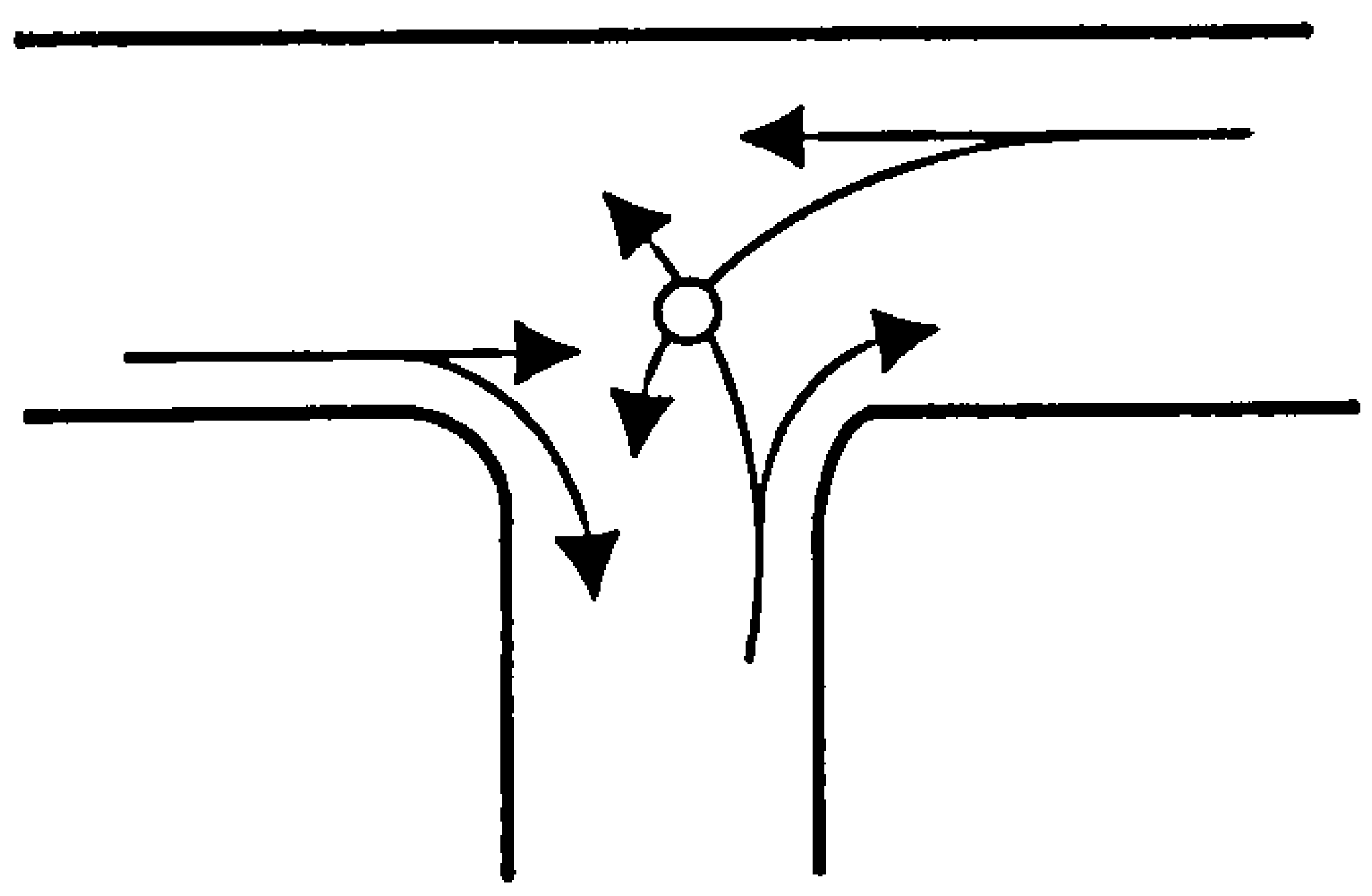


Figure 5.6a.

Illustration of major conflict in the absence triangular island on minor road (ITM(2)).

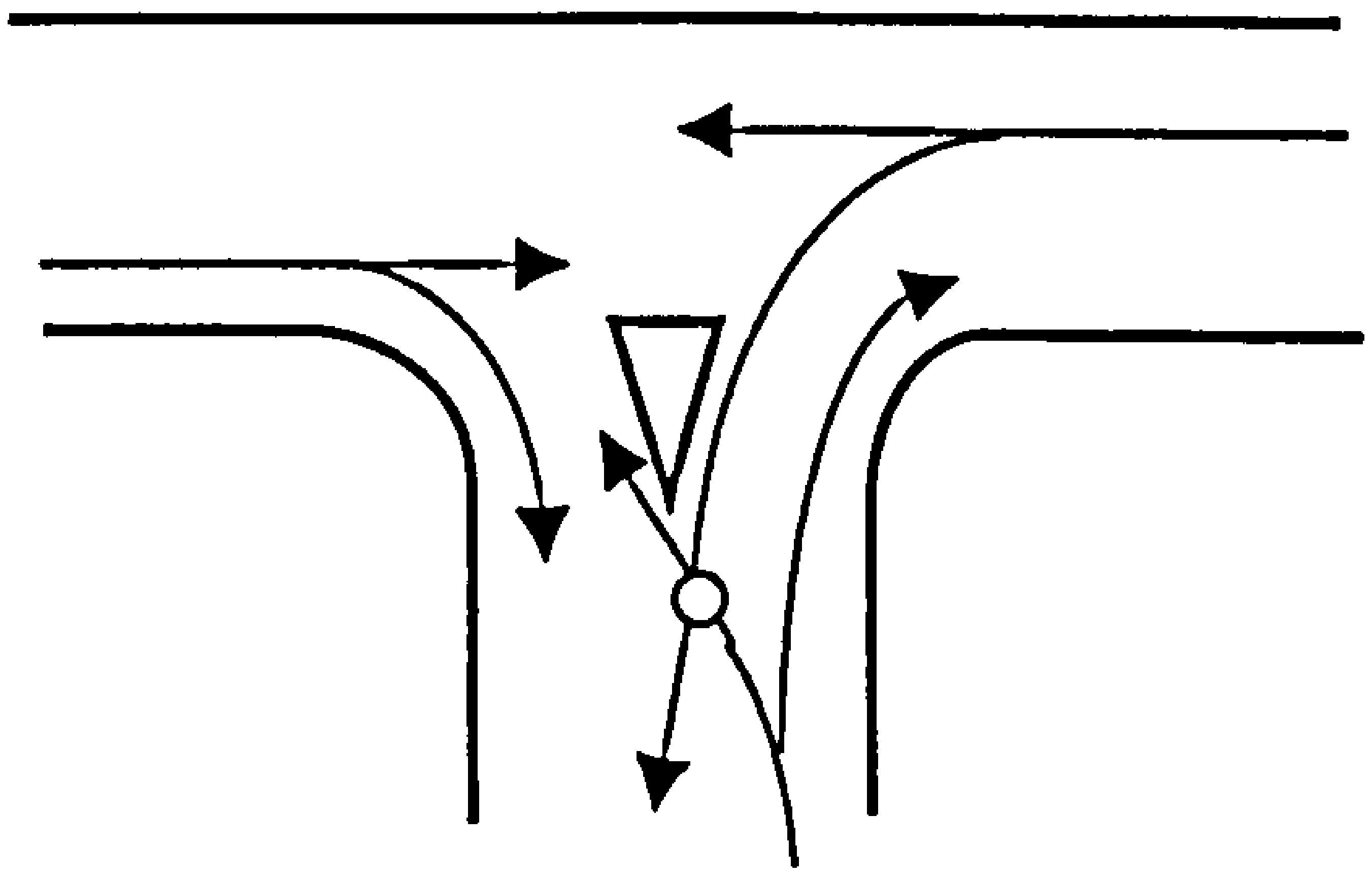


Figure 5.6b

Illustration of major conflict in the presence of triangular island on minor road (i.e. "Bennett junction")

The effect of the absence of a triangular island on the minor road (ITM(2)) is best illustrated by Figures 5.6a & b. The conflict between left-turning vehicles from both major and minor roads is one of the key conflicts that result in right-angle collisions at T-junctions. As shown in Figure 5.6a, the conflict point between the two left turns occurs on the major road. The risk of collision between vehicles in the two streams is therefore high, given the higher traffic volume and speeds on the major road. The situation is further aggravated because the left-turning minor road vehicle has to concentrate on the approaching major through traffic on the near-side and yet remain aware of the left-turning from major traffic in order to identify and accept safe gaps. In the event that the driver pays too much attention to the major road traffic approaching on the near-side, he/she becomes more vulnerable to a right-angle collision type accident.

On the other hand, when the island is present on the minor road, as shown in Figure 5.6b (i.e. Bennett junction), the conflict point of interest can be displaced onto the minor road. As a result, the collision does not only become less likely but it also changes character as a sideswipe, due to the acute angle at which the traffic streams now meet. Also, on approach to the major road this time, the left-turning minor road vehicle has only the near-side approaching major traffic to worry about, hence the chance of misjudgement and getting involved in a right-angle type of collision is minimised. In the light of the foregoing, it is understandable that in the prediction model, the situation depicted in Figure 5.6a will be associated with higher frequencies of right-angle collisions than Figure 5.6b.

How increasing width of the median on the major road (MEDW) could be associated with reduction in the incidence of right-angle collisions, as captured by the model was, however, less understood. Perhaps, the gap between wide medians in the central area of the junction could be providing safe refuge for left-turning vehicles to transit before completing the difficult manoeuvre. In that case, decision making is simplified and less likely to lead to collisions since the left-turning manoeuvre (a relevant flow for right-angle collisions) is accomplished in a two-stage process, in which the driver needs only to identify safe gaps in one traffic stream at a time.

(b) Rear-end Collision Accidents

Rear-end collisions were the predominant type of accident at T-junctions. They constituted just over a quarter (28 per cent) of all accidents reported for all the case-study junctions during the period 1996-1998 inclusive and an average of 1.7 per junction. The cross products of flow (XPDF) and the merging flow products (MEFP) were the most significant exposure functions and led to the following flow-based models:

$$A = 2.47x10^{-5} XPDF^{0.652} \qquad \text{.....................(5.45)}$$

$$A = 3.75x10^{-5} MEFP^{0.658} \qquad \text{.....................(5.46)}$$

These models are presented in their linear form in Table 5.7b. On average, the proportion of systematic variation explained by them was about half the percentage obtained for corresponding models for X-junctions. It means that, despite the higher frequency per junction at T-junctions than X-junctions, rear-end collisions at the T-junctions in the database were still more subject to random factors. As can be seen from the same table, the full models also compared similarly with the corresponding ones for X-junctions. The additional variable in the full models in this case was the factor ZEX(2), which represented the absence of designated zebra crossings at the junction sites.

Table 5.7b. Models for Rear-end Collision Accidents at T-junctions (Total number of accidents = 98; number of sites=57)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	t-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model *Dispersion parameter*	Lk κ	0.542 *0.808*	0.179 *0.245*	3.032 *3.298*	-	LL(0) = -203.4**
2. Flow-based models						
(a) *Dispersion parameter*	Lk LXPDF κ	-10.61 0.652 *1.220*	2.929 0.711 *0.423*	-3.622 3.812 *2.883*	0.34	0.067
(b) *Dispersion parameter*	Lk LMEFP κ	-10.19 0.658 *1.186*	2.835 0.174 *0.406*	-3.594 3.791 *2.923*	0.30	0.064
3. Full models						
(a) *Dispersion parameter*	Lk LMEFP ZEX(2) κ	-11.80 0.713 0.922 *1.437*	2.847 0.170 0.383 *0.524*	-4.145 4.194 2.407 *2.742*	0.40	0.092
(b) *Dispersion parameter*	Lk LXPDF ZEX(2) κ	-12.44 0.716 0.962 *1.531*	2.952 0.168 0.393 *0.578*	-4.214 4.262 2.532 *2.649*	0.48	0.097

* The prefix "L" indicates the natural logarithmic form of the variable, i.e. LXPDF = Log (XPDF).

**LL(0) is the log-likelihood value of the null model

Although the connection between this variable and rear-end collisions appears slightly tenuous, it proved far more significant in all respects than other variables, which otherwise would have been expected to be more directly connected with rear-end collisions. For example, variables such as those representing the proportion of heavy goods vehicles in traffic (HGV) and the absence of a left-turning lane on the major road (LFT(2)) were estimated with negative and positive coefficients respectively in the tested models. However, the parameter estimates and contribution of LFT(2) and HGV to the reduction in scaled deviance were always very marginal. It was also observed that inclusion of these otherwise more plausible variables in the full models led to the improbable situation that the proportion of systematic variation explained by the full models became less than that explained by the flow-based models. This meant that the additional variables were contributing more uncertainty to the models than they helped to explain the data. Because of these observations the variables were eventually dropped from the models in favour of ZEX(2).

The preferred full model was:

$$A = 3.96x10^{-6} XPDF^{0.716} e^{0.962ZEX(2)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(5.47)$$

The model shows that in the absence of designated zebra crossings at T-junctions the expected frequency of rear-end collision type accidents was increased by a factor of 2.62. How this manifested itself in practice was not entirely clear but it is imaginable that the absence of designated crossing areas at junctions can lead to pedestrians crossing the arms of the junction haphazardly, when and where they choose. This, in turn, is likely to result in unpredictable stopping or rapid deceleration of lead vehicles when pedestrians are encountered unexpectedly, thereby increasing the potential for rear-end collisions.

(c) Side-swipe Collision Accidents

Side-swipe collisions were the next most common accident type after rear-end collisions at T-junctions, with an average frequency of 1.44 per junction in the three-year period 1996-1998. Alternative models that best described the relationship between the frequency of these accidents and the relevant road and traffic variables are presented in Table 5.7c. The selected flow-based models were built separately upon the merging flow products (MEFP) and encounter flow products (ENCP) traffic exposure functions. In their exponential form, the models were:

$$A = 1.33x10^{-3}\, MEFP^{0.431} \qquad \text{.....................(5.48)}$$

$$A = 1.72x10^{-3}\, ENCP^{0.395} \qquad \text{.....................(5.49)}$$

where A is the expected 3-year frequency of side-swipe collision accidents
at T-junctions

Of the two models, the one based on the merging flow products (MEFP) function was by far the better one. The parameter estimates were more significant and it explained a higher proportion (11 per cent) of systematic variation. This exposure function was also only one of three that constituted the encounter flow products (ENCP). The MEFP function was therefore more relevant to the accident type and the full model based on it clearly more preferable to the alternative.

Table 5.7c. Models for Side-swipe Collision Accidents at T-junctions (Total number of accidents = 82; number of sites=57)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	0.364	0.176	2.063	-	LL(0) = -188.1**
Dispersion parameter	κ	*0.929*	*0.370*	*2.511*		
2. Flow-based model						
(a)	Lk	-6.622	2.746	-2.412	0.11	0.031
	LMEFP	0.431	0.169	2.550		
Dispersion parameter	κ	*1.229*	*0.555*	*2.212*		
(b)	Lk	-6.363	2.988	-2.130	0.08	0.024
	LENCP	0.395	0.175	2.255		
Dispersion parameter	κ	*1.155*	*0.507*	*2.276*		
3. Full models						
(a)	Lk	-7.518	2.944	-2.554	0.30	0.049
	LDIFP	0.482	0.176	2.739		
	ITM(2)	-0.475	0.443	-1.072		
	ZEX(2)	0.742	0.389	1.907		
Dispersion parameter	κ	*1.604*	*0.854*	*1.878*		
(b)	Lk	-7.678	3.088	-2.486	0.28	0.047
	LENCP	0.465	0.176	2.642		
	ITM(2)	-0.462	0.448	1.031		
	ZEX(2)	0.690	0.385	1.792		
Dispersion parameter	κ	*1.537*	*0.795*	*1.933*		

* The prefix "L" indicates the natural logarithmic form of the variable, i.e LMEFP = Log (MEFP).
**LL(0) is the log-likelihood value of the null model

The selected full models however were based on the extension of the encounter flow products function (ENCP), on the one hand, and the diverging flow products (DIFP), on the other. The most promising additional variables that featured represented the status of designated zebra crossings (ZEX) at the site and the peculiar triangular island on the minor road (ITM). In each case, T-junction sites without marked zebra crossings (ZEX(2)) were associated with an increase in the frequency of side-swipe collisions, whilst the absence of the triangular island on the minor road contributed to a reduction in the accident frequency.

Here again, it is not exactly clear how the absence of marked zebra crossings at the junctions could have impacted on the incidence of side-swipe collisions. The connection could be a tenuous and indirect one, similar to the circumstances under which the same variable was thought to be impacting on rear-end collisions, as argued in the preceding section. However, it is quite likely, also, that the variable was merely masking another factor or combination of factors, more directly connected to the particular accident type, but which turned out to be insignificant when tested for inclusion in the models. Such a situation could have arisen either because the important factor or factors were not properly represented in the modelling database or inadvertently left out altogether during the data collection exercise.

Having said the above, it is important to note that the parameter (ZEX) was finally accepted into the models for good reasons. The estimate of its coefficient was significant and it contributed even more significantly to the reduction in scaled deviance. The presence of the variable in the model also enhanced the model's stability substantially by improving upon the significance of the other parameters. On the other hand the parameter (ITM(2)) was also retained, notwithstanding its relatively poor *t*-statistic, because, in addition to the reduction in deviance, it was particularly influential for the significance of the traffic flow function (DIFP). The preferred full model in exponential form was:

$$A = 5.43x10^{-4}\, DIFP^{\,0.482}\, e^{(0.742ZEX(2)-0.475ITM(2))} \qquad \text{...........(5.50)}$$

The diverging flow products function (DIFP) is pertinent in this case because it involves lane changing, a situation which leads to side-swipe collisions, particularly, at junctions with two-lane approaches. It is also apparent from the full model that the absence of marked zebra crossings (ZEX(2)) at T-junctions increased the frequency of side-swipe collision accidents by a factor of 2.1. On the other hand, junctions without the triangular island on the minor road (ITM(2)) were associated with a reduction in the accident frequency by a factor of 0.62 (see Equation 5.50). The latter point is partly illustrated in Figure 5.6b, where the presence of the special type of island transforms the character of at least one potential right-angle conflict point on the major road into a potential side-swipe conflict on the minor road. In addition, the two-directional traffic flow on either side of the island substantially increases the chance of close encounters between entering and exiting vehicles on the minor road and, hence the potential for side-swipe collisions. With these in mind, it appears understandable that the absence of this type of island on the minor road would be associated with a reduction in the frequency of side-swipe collisions, as estimated by the models. However, the low *t*-statistic for the estimate of this parameter in the full model means that the estimate is less precise than desired and its impact as described above cannot, therefore, be taken for granted.

(d) Head-on Collision Accidents

Since there was no evidence of over-dispersion in the data, models for this category of accident were built on the assumption of a Poisson error distribution. The selected models are presented in Table 5.7d. The most significant exposure functions were cross products of flow (XPDF) and encounter flow products (ENCP). On the basis of these functions, the flow-based models were:

$$A = 2.24x10^{-6}\, XPDF^{0.695} \qquad \text{...................(5.51)}$$

$$A = 5.03x10^{-6}\, ENCP^{0.648} \qquad \text{...................(5.52)}$$

where A is the expected 3-year frequency of head-on collision accidents

The χ^2 goodness of fit was used to assess the overall quality of the models. Both models, on account of the amount of scale deviance reduced, were highly significant (at the 1 per cent level). The critical χ^2 value at the 1 per cent level of significance for 1 degree of freedom is 6.535, whilst the respective values of scaled deviance reduced by the models in Equations (5.51) and (5.52), were 8.317 and 6.91. Both models, therefore, had a much better explanatory power than the null model. Despite meeting the statistical requirements these models still need to be treated with caution due to the rather low average accident frequency (0.3 accidents per site) on which they are based. The preponderance of zero accident counts for many sites in the database means that the data may be subject to considerable random variation and the estimates are likely to be much less precise than appears. Therefore, as in similar situations encountered earlier in this thesis, it was determined that the null or grand mean model is likely to be the more reliable one.

The results from fitting the extended or full models were even less promising. Although the full models also appeared to have much better fit to the data than the null model, the χ^2 tests revealed that they were not significant improvements over the flow-based models. Again, the only reason these models are published here is to give an indication of the best that was attainable in the circumstances after testing nearly all the variables in the database.

Table 5.7d. Models for Head-on Collision Accidents at T-junctions (Total number of accidents = 19; number of sites=57)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	-1.099	0.229	-4.793	-	SD=47.292 DF=56**
2. Flow-based models						
(a)	*Lk* *LXPDF*	*-13.01* *0.695*	*4.475* *0.256*	*-2.907* *2.712*	-	*SD=38.975* *DF=55*
(b)	*Lk* *LENCP*	*-12.20* *0.648*	*4.482* *0.257*	*2.722* *2.521*	-	*SD=40.382* *DF=55*
3. Full models						
(a)	*Lk* *LXPDF* *STL(2)*	*-15.99* *0.839* *0.869*	*5.004* *0.281* *0.495*	*-3.195* *2.987* *1.755*	-	*SD=35.792* *DF=54*
(b)	*Lk* *LTINF* *STL(2)* *MEDW*	*-17.16* *1.654* *0.977* *-0.270*	*5.586* *0.574* *0.509* *0.197*	*-3.072* *2.882* *1.919* *-1.371*	-	*SD=36.864* *DF=53*

*The prefix "L" indicates the natural logarithmic form of the variable, i.e. LXPDF=Log(XPDF)

** SD is model scaled deviance and DF is the residual degrees of freedom

The obtained full models are also listed in Table 5.7d. Additional variables which were relatively most influential were STL(2) and MEDW, representing the absence of street-lighting at the junction sites and the presence/width of a median on the major road respectively. The streetlights factor was consistent in both models, whilst the influence of a median was only reflected in one model. Whilst the absence of streetlights was associated with an increase in the frequency of head on collisions, the presence/width of the median on the major road tended to reduce it. For illustration the better one of the two full models was:

$$A = 1.14X10^{-7} XPDF^{0.839} e^{0.869STL(2)} \qquad \text{..................(5.53)}$$

(e) Single Vehicle Accidents

The data for single vehicle accidents were under-dispersed and were therefore fitted with the Poisson error distribution. However, the exercise did not produce any statistically significant flow-based models. None of the models listed in Table 5.7e represented a significant improvement over the null model. The models are simply indicative of the best estimates that were obtained. This outcome of the modelling exercise suggested that single vehicle accidents at T-junctions were essentially random and unpredictable by nature. In the circumstances, therefore, the grand mean of accident frequency across all junctions (i.e. null model) provided the best and only basis on which to estimate the frequency of single vehicle accidents at T-junctions.

Table 5.7e. Models for Single-vehicle Collision Accidents at T-junctions (Total number of accidents = 19; number of sites=57)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	-1.099	0.229	-4.793		SD=51.112 DF=56
2. Flow-based model						
(a)	*Lk* *LXPDF*	*-5.642* *0.268*	*3.922* *0.229*	*-1.439* *1.169*	-	*SD=49.698* *DF=55*
3. Full model						
(a)	*Lk* *LXPDF* *STL(2)*	*-7.356* *0.349* *0.618*	*4.214* *0.241* *0.491*	*-1.746* *1.444* *1.258*	-	*SD=48.063* *DF=54*

*The prefix "L" indicates the natural logarithmic form of the variable, i.e. LXPDF=Log(XPDF)

** SD is model scaled deviance and DF is the residual degrees of freedom

(f) Pedestrian Accidents

As was done for pedestrian accident models for X-junctions, the model forms tested here were required to include exposure functions that accounted for both vehicle and pedestrian flows in a logically plausible manner. Thus, different vehicle flow functions were individually combined with the pedestrian flow in various ways and tested. The most significant results were obtained when the exposure variable involved the total vehicle inflow to the junction (TINF) and the pedestrian flow (PEDF), specified side by side or as a combined function. The models obtained are presented in Table 5.7f. In their exponential form, the flow-based models were:

$$A = 6.79x10^{-4}\, PVPF^{\,0.544} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5.54)$$

$$A = 2.02x10^{-3}\, TINF^{\,0.399}\, PEDF^{\,0.614} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5.55)$$

where A is the estimated 3-year frequency of pedestrian accidents at T-junctions and PVPF – a combined vehicle and pedestrian exposure function (=TINFxPEDF)

Table 5.7f. Models for Pedestrian Accidents at T-junctions (Total number of accidents = 63; number of sites=57)

Model Description	Model Terms*	Estimated Coefficient	Standard Error of Estimate	*t*-statistic	Freeman-Tukey R^2	Log-Likelihood ratio (ρ^2)
1. Null model	Lk	0.100	0.180	0.555	-	LL(0) =
Dispersion parameter	κ	*1.053*	*0.492*	*2.140*		-166.0**
2. Flow-based models						
(a)	Lk	-7.295	1.965	-3.712	0.78	0.078
	LPVPF	0.544	0.143	3.804		
Dispersion parameter	κ	*2.611*	*2.027*	*1.288*		
(b)	Lk	-6.204	2.853	-2.175	0.82	0.080
	LTINF	0.399	0.310	1.287		
	LPEDF	0.614	0.194	3.165		
Dispersion parameter	κ	*2.639*	*2.054*	*1.285*		
3. Full models						
(a)	Lk	-8.409	2.088	-4.027	0.92	0.090
	LPVPF	0.607	0.147	4.129		
	STL(2)	0.470	0.324	1.451		
Dispersion parameter	κ	*2.847*	*2.287*	*1.245*		
(b)	Lk	-8.498	3.317	-2.561	0.92	0.090
	LTINF	0.618	0.351	1.761		
	LPEDF	0.603	0.195	3.092		
	STL(2)	0.475	0.353	1.346		
Dispersion parameter	κ	*2.846*	*2.286*	*1.245*		

* The prefix "L" indicates the natural logarithmic form of the variable, i.e. LPVPF = Log (PVPF).

**LL(0) is the log-likelihood value of the null model

Like the corresponding models for X-junctions, these models predicted a very large proportion of the systematic variation in the frequency of pedestrian accidents. This would reinforce the point made earlier to the effect that pedestrian accident frequency was more dependent on traffic exposure function than other road or traffic variables. Consistent with this observation, most additional variables tested for the full models produced insignificant parameter estimates and very small contributions to the reduction in model scaled deviance.

The only variable of any consequence was the one representing the status of street lighting at the junction (STL). Although the parameter estimate was just short of the value required for significance at the 5 per cent level, it still produced the single largest reduction in scaled deviance. For this reason, the variable was accepted into the model to enhance its plausibility. The two alternative full models (see Table 5.7f) had very similar characteristics, except that the model based on the combined pedestrian and vehicle exposure function used one less degree of freedom. This model was:

$$A = 2.23x10^{-3}\, PVPF^{0.607}\, e^{0.470STL(2)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots..(5.56)$$

where STL(2) is a factor representing the absence of street lighting at the junction and other variables are as previously defined.

The absence of street lighting at T-junctions (STL(2)) was estimated by the model to be associated with an increase in pedestrian accident frequency at T-junctions by a factor of 1.6. A similar effect was identified in the models for pedestrian accidents at X-junctions.

5.6 Conclusion

Prediction models have been developed relating the 3-year accident frequency at unsignalised T- and X-junctions to various road and traffic variables. The models were of two types, the first (flow-based) based solely on the traffic exposure function, whilst the second (full models) were extensions of the best exposure functions to include other significant road and traffic variables. Models were developed separately for all accidents, injury accidents and other accident types categorised by the defining collision types involved, namely, head-on, rear-end, sides-wipe and right-angle collisions and pedestrian accidents.

Generally, traffic exposure functions such as the cross products of flow (XPDF) and the sum of encounter flow products (ENCP) produced much better fit to the accident data than simpler flow functions like the total traffic inflow (TINF). Two goodness-of-fit measures were mainly used to assess the overall quality of the models. The Freeman-Tukey R^2 presented the proportion of systematic variation in the dependent variable explained by the models, whilst the Log-likelihood ratio statistic (ρ^2) was used to determine how much more explanatory power the fitted model had over the model with only the constant term. In isolated cases, where the accident data were under-dispersed (for some selected accident types), the latter type of model evaluation was carried out using the χ^2 test.

On average, flow-based models for T-junctions had about one-and-a-half times more "proportion explained" than those obtained for X-junctions. It would appear, therefore, that the exposure variables were much more influential determinants of accident frequency at T-junctions than at X-junctions. Fewer additional variables made it into the full models for T-junctions than for X-junctions, leading to a reversal of the trend in the proportion of systematic variation explained in the full models. Within each junction group (i.e. X- or T-junctions), flow-based models for the various types of accident defined by the primary collision also produced higher "proportion explained" than the corresponding models for all accidents or injury accidents. This trend was largely attributed to the fact that, at the more disaggregate level, it was easier to identify the more appropriate exposure functions relevant to the particular collision type.

The three most consistent additional variables that featured in the extended accident models for X-junctions were street lighting and dedicated left–turning lanes, as well as the average standard deviation of approach spot speeds of vehicles on the major road. Those for T-junctions were level of traffic control, average width of the median on the major road and the average standard deviation of vehicle approach spot speeds on the major road. The absence of street lighting and dedicated left-turning lanes and the average standard deviation of vehicle approach spot speeds were all positively correlated with accident frequency.

Interestingly, whilst the average width of the median on the major road was associated with an increase in accident frequency at X-junctions, it had the opposite effect at T-junctions. Also, the accident potential of T-junctions that had YIELD or no control was adjudged to be much lower than sites controlled by STOP control. This apparently confirmed the earlier finding, in Section 4.3.2.4, regarding the relative accident potential of junctions with the different levels of control.

For the individual accident types defined by the primary collisions, the additional variables captured in the respective full models differed in type as well as their nature of influence on accident frequency. For example, whereas the absence of a dedicated left- turning storage lane on the major road was most influential in increasing the frequency of side-swipe accidents at X-junctions, the most influential additional variable for side- swipes at T-junctions was the triangular island on the minor road. The absence of the triangular island on the minor road reduced the incidence of side-swipes at T-junctions by a factor of 0.62, whilst at the same time increasing right-angle collisions by 2.33 times. The absence of left-turn storage lanes on the major road also increased the frequency of rear-end collisions at X-junctions two-fold.

Given the large variety of variables tested in the model estimation process, the quality of the models obtained and the consistency of the additional variables, it can be concluded that the full models developed represented causal rather than associative relationships. The models can be used subsequently, therefore, for the reliable prediction of accident frequency associated with the junction types and features described. In the ensuing chapter, the estimated models are used to obtain more refined estimates of site-specific accident potential, as part of a new procedure for safety appraisal and accident "blackspot" identification and ranking.

CHAPTER 6

EMPIRICAL BAYESIAN ESTIMATION OF ACCIDENT POTENTIAL AND DEVELOPMENT OF REVISED "BLACKSPOT" DECISION CRITERIA

6.1 Introduction

In the preceding chapters, the accident records for selected junctions in a case study were analysed. As a result of this analysis, some key traffic and road features associated with the incidence of accidents were identified and subsequently tested, as part of a wide range of explanatory variables to develop accident prediction models for two families of junctions, namely T- and X-junctions. Thus, apart from the observed accident counts for each specific junction, the model predictions provided yet another, even more useful, indicator of accident potential. In this chapter, it is argued that the two types of indicators of accident potential have both advantages and disadvantages that make them potentially unsuitable to be used individually, although they both contain important clues to obtaining the best estimate of site-specific accident potential. The Empirical Bayesian (EB) method has been outlined, by which the two kinds of clues are combined to produce more refined estimates of the accident potential for specific sites. On the basis of these refined (EB) estimates, new improved criteria for accident "blackspot" identification and ranking have also been outlined.

6.2 Empirical Bayesian (EB) Estimation of Accident Potential

6.2.1 The General Principle

The accident potential, or "unsafety", of any site is defined as the long-term average number of accidents at the site, if the design, traffic flows, road environment and all other features of the site were to remain constant over a long period of time (Kulmala, 1995; Hauer, 1992). Knowledge of the accident potential at any road location would facilitate important decisions that are taken regularly by the road authorities. These decisions relate to determining whether a particular site is unsafe enough to require some remedial action and, where some intervention has been implemented, to know by how much, if any, the level of safety has been improved. The level of improvement can then help in the identification of which measures are effective and which amount to a relative waste of resources.

However, since it is practically impossible to keep all site conditions constant over the short-term, let alone the long-term, it means that accident potential (unsafety) remains an expectation that has to be estimated. Thus, use of the observed accident frequency to represent the accident potential, as is often done, is erroneous and amounts to oversimplification, not least because accident counts are subject to both random variation and the regression-to-mean phenomenon. Hauer (1992) suggested that the accident history of a site could be seen as only one of two important clues, which can be used for a more realistic and accurate estimation of accident potential. The accident frequency has the important attribute that it reflects conditions that may be specific to the site under investigation and which are likely to affect safety in an unknown manner.

The second clue that contains information about the accident potential of a site is what Hauer (1992) described as "the traits". These are key characteristics of the site that connect it with others in a family or reference population. For a road location, such as a junction, these could be the layout, other geometric variables, traffic volumes etc. They enable reasonable estimates (inference) of the accident potential of the given location to be made if the unsafety of other junctions with similar traits were to be known. The accuracy of such estimates would however depend on the level of definition of the reference population that shares the given traits and that, in turn, depends on the availability of data and the inevitably subjective judgement about which traits are important and which are not.

The most common basis for such inference is usually the average accident counts or accident rates across the reference population. However, it has been observed (e.g. Mountain *et al*, 1996) that, when well-fitting prediction models are used to estimate the expected accidents, the quality of the estimates tend to be much better than using accident counts or accident rate. But even the prediction models would be associated with some degree of unexplained site-to-site variations, since it is not possible that all the factors that influence accidents at each site would be included in the model. As a consequence, sites with similar explanatory variables or traits would still have different underlying mean accident frequency (Mountain *et al*, 1996).

It is apparent therefore that the best estimate of unsafety of the location would be one that combines the two key clues of "traits" and accident history. The theoretical framework for doing this is the Empirical Bayesian (EB) procedure, which has been described by a number of authors (e.g. Abbess *et al*, 1981; Hauer and Persaud, 1987; Hauer, 1992), as follows:

Let x be the number of accidents recorded for a junction in the given time period (eg. 3 years) for which we want to estimate its accident potential. Let also Λ be the junction's accident potential (unsafety) and $E(\Lambda)$ and $Var(\Lambda)$ the mean and variance respectively, of the Λs of junctions in the same family or reference population as the junction of interest. Following this, if x follows the Poisson distribution and the Λs in the reference population can be described by a Gamma probability density function, then the best estimator (Empirical Bayes estimate) of Λ for the specific junction is given by:

$$EB = \alpha E(\Lambda) + (1-\alpha)x \quad \text{.................} \quad (6.1)$$

where $\alpha = E(\Lambda)/[E(\Lambda)+ \; Var(\Lambda)] = 1/[1+(E(\Lambda)/\kappa)]$ .... (6.2)

κ is the overdispersion parameter estimated from the model fitting process

In deriving the above relationships, Hauer (1992) observed that the following equalities were assumed; $E(x)=E(\Lambda)$ and,

$$Var(x)=E(\Lambda)+Var(\Lambda).$$

Thus, the *EB* estimate is a weighted combination of the observed accident counts (x) and what is known about the average unsafety across the family of junctions to which the given junction belongs ($E(\Lambda)$). The weight α is always between 0 and 1 and, naturally, depends on the accident record and how different the unsafety of the junction is from the family average. When $Var(\Lambda) >> E(\Lambda)$, α approaches zero and $EB \cong x$, i.e. the family of junctions is so diverse that what is known about the average exerts little influence on the junction-specific estimate. Conversely, when $Var(\Lambda) << E(\Lambda)$, α approaches unity and $EB \cong E(\Lambda)$, and the family is said to be homogenous enough for each junction's unsafety to be inferred from the average, hence little weight is put on the individual junction accident history. Generally, the period for which the accident record is available should be the same to which $Var(\Lambda)$ and $E(\Lambda)$ pertain. In the context of this thesis, this period is 3 years. The EB estimate is recommended because it increases the precision of the estimate of site-specific accident potential beyond what is normally possible when only the accident records are used. In addition, the EB estimate automatically accounts for the regression-to-mean (Hauer, 1992).

The most widely used method for estimating $E(\Lambda)$ and $Var(\Lambda)$ is described as the "method of sample moments". It derives its name from the use of the calculated sample mean and variance to represent $E(\Lambda)$ and $Var(\Lambda)$ respectively. A detailed discussion of the method is outside the scope of this thesis but may be found in Hauer (1992) and Hauer and Persaud (1987). Suffice it to say, however, that the authors identified three main drawbacks to this method. First, it requires rather large samples to produce good estimates. Secondly, with the large samples, the range of traits describing the entities also widens and it becomes difficult to identify adequate reference populations. Thirdly, the method deals best with traits that are discrete in nature but is unable to account properly for continuous variables.

The other method, which remains largely unexplored by practising engineers in road safety, but which is highly recommended by Hauer and Persaud (1987) and Mountain *et al* (1996), is the option of estimating $E(\Lambda)$ and $Var(\Lambda)$ from multivariate regression models. In fact, $E(\Lambda)$ is precisely the sort of parameter that the accident prediction models in the preceding chapter of this thesis are estimating. The variable $Var(\Lambda)$ can also be estimated by the squared residuals obtained from the model fits. Alternatively, Hauer and Persaud (1987) provide the following relationship for calculating it:

$$Var(\Lambda) = [E(\Lambda)]^2 / \kappa \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (6.3)$$

The variance of the *EB* estimate is also given by:

$$Var(EB) = \; [E(\Lambda)/(\kappa+E(\Lambda))]^2 \times (\kappa+x) = (1-\alpha)\,EB \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (6.4)$$

The main advantages in using this method are that the multivariate regression models provide estimates of the reference population mean accident potential and variance that exactly match many traits, whilst at the same time dealing comfortably with traits of a continuous nature. The other point is that this method does not require a large reference population for any combination of traits (Hauer 1992).

Despite these advantages, the integration of accident prediction model estimates with the Empirical Bayesian procedure to produce refined estimates of site-specific accident potential is still uncommon. A major hindrance has often been the absence of good prediction models. Having developed the models in Chapter 5.0, a key objective of this study has been to demonstrate how the EB method could be applied to produce refined estimates of accident potential for the junctions in the case-study and, following that, outline a new procedure for accident blackspot identification and ranking.

6.2.2 Worked Examples

(a) Using all Accident Model for X-junctions

Consider a typical X-junction of type X-1 (see Appendix 3II) located in an urban area, with average daily traffic inflow of 2,200 from the major road and 1,793 from the minor. In three consecutive years, the junction recorded a total of 8 accidents. Assuming that 6.5 per cent of the total junction traffic are heavy goods vehicles, whilst the average standard deviation of vehicle approach spot speeds on the major road is 11km/h. What will be the *EB* refined estimate of the junction's accident potential, if the measured average width of the minor road at the neck of the junction, is 13.9m? Assume also, that the junction area has no street lighting.

The question is answered in the following steps:

Step1: Calculate the average accident potential for junctions of this kind (E(Λ)).
This is done, by making use of the accident prediction model (full model) estimated in Chapter 5.0. Thus, using the full model for X-junctions (see Equation 5.12) the estimate is given by:
$E(\Lambda) = 8.12x10^{-5}\, XPDF^{0.370}\, e^{(0.580STL(2)+0.661LFT(2)+0.190HGV+0.134JNEC+0.100SSD)}$
where XPDF = MAJFxMINF = 2,200x1,793 vehicles/day ,

STL(2) = 1, i.e. no street lighting; LFT(2) = 1, i.e. left turn lanes on major road, HGV=6.5%, JNEC = 13.9m and SSD = 11km/h. Hence,

$E(\Lambda) = 8.12\text{x}10^{-5}\ (2200\text{x}1793)^{0.37}\ e^{(0.58\text{x}1+0.661\text{x}1+0.19\text{x}6.5+0.134\text{x}13.9+0.1\text{x}11)}$

=5.15accidents/3yrs

<u>Step 2:</u> Calculate the "weight" (α)

The weight is needed to combine the observed accident count of 8 in 3years with the estimated average of 5.15 for this kind of junction. It is done, by using Equation (6.2). Thus, $\alpha = 1/\ [1+(5.15/4.65)] = 0.474$. Note that the overdispersion parameter (κ) is 4.65 for the given accident model (see Table 5.4a).

<u>Step 3:</u> Calculate the *EB* Refined value of Accident Potential

The *EB* refined estimate of the expected accidents (accident potential) at the junction is calculated, using Equation (6.1) as follows:

$EB = \alpha E(\Lambda) + (1-\alpha)x$ = 0.474x5.15+0.526x8 = **6.65** accidents/3years

That *EB* estimate (6.65accidents/3years) is between the average for similar sites (5.15accidents/3years) and the observed accident count for this junction (8.0) underscores the significance of the mechanism for combining the two estimates. The EB procedure "pulls" the accident count towards the average and, by so doing, accounts for the regression-to-mean bias. The standard deviation of the refined estimate is given by:

$\sigma_{EB} = \sqrt{\{[(1-\alpha)\ EB\}} = \pm\sqrt{(0.526\text{x}6.65)} = \pm 1.87$ accidents in 3years.

Therefore, the junction's accident potential after the EB refinement is **6.65± 1.87 accidents in 3years.**

(b) Using all Accident Model for T-junctions

Suppose the junction, whose refined accident potential is required, has the features of junction type T-5 (see Appendix 3II). If this junction recorded 11 accidents in three consecutive years and the daily major and minor road traffic inflow are 8095 and 1225 respectively, what will be the refined estimate of the accident potential for the period?

Assume that the minor road is STOP-controlled, whilst the average width of the median on the major road is 3.5m and the average standard deviation of vehicle spot speeds on the major road is 8.5km/h.

Step1: Calculate the average accident potential for junctions of this kind (E(Λ)).
The relevant prediction model is as in Equation (5.37):

$$E(\Lambda)= 1.01x10^{-3}\, XPDF^{\,0.514}\, e^{(0.0694SSD-0.465TCON(2)-0.952TCON(3)-0.151MEDW)}$$

In this case, *XPDF = MAJFxMINF*; SSD = 8.5km/h; MEDW = 3.5m; since the traffic control on the minor road is STOP (i.e TCON(1)), it means that TCON(2)= 0; TCON(3)= 0;
The overdispersion parameter for the model (κ) is 2.996 (see Table 5.6a)
Therefore,

$$\begin{aligned} E(\Lambda) &= 1.01x10^{-3}\, XPDF^{\,0.514}\, e^{(0.0694SSD-0.465TCON(2)-0.952TCON(3)-0.151MEDW)} \\ &= 1.01x10^{-3}\, (8095x1225)^{\,0.514}\, e^{(0.0694x8.5\,-\,0.151x3.5)} \\ &= 1.01x10^{-3}\, x3945.71\, x1.063 = 4.24\ accidents/3years \end{aligned}$$

Step 2: Calculate the "weight" (α)
$\alpha = 1/[1+(4.24/2.996)] = 0.414$

Step 3: Calculate the EB Refined value of Accident Potential
EB = 0.414x4.24+0.586x11 = **8.20 accidents/3years**
The standard deviation for the estimate is $\sigma_{EB} = \sqrt{}(0.586x8.20) = 2.19$ accidents/3years. Therefore, precisely speaking, the EB refined accident potential of the junction is **8.20±2.19 accidents/3years.**

Apart from simply providing the best estimate of the accident potential of a given site, the Empirical Bayesian refinement also presents an important opportunity to improve the quality of "before and after" studies. In typical "before and after" studies, inferences are made about the effectiveness of accident remedial measures on the basis of comparison of accidents observed at the sites in question in equivalent periods before and after implementation. Such simple comparisons have been shown to be misplaced and resulting in erroneous, often inflated, conclusions about the effectiveness of measures. The valid comparison requires that accidents after implementation are compared with accidents that "would have occurred, had the measure not been implemented "(Hauer and Lovell, 1986).

The reason is that sites selected for remedial treatment are often selected because of their high accident numbers and therefore subject to the regression-to-mean phenomenon. The Empirical Bayesian procedure enables the unbiased estimation of the accidents that would have occurred had the measure not been implemented by satisfactorily accounting for the regression-to-mean effect. Thus, to be able to make more credible inferences about the effectiveness of measures, it is suggested that the accident count after implementation is compared with the Empirical Bayesian estimate of the expected before accidents in an equivalent period.

6.3 Bayesian Methodology for Identification of "Blackspots"

The general rationale for seeking to identify accident blackspots lies in the understanding that if the unsafety record of any site is "unusually bad" then there must be an underlying cause. By identifying such sites, the road agencies can diagnose the problem and carry out the most cost-effective remedial action. The identification process is, therefore, an important diagnostic tool that needs to be handled well to deliver the right results. To this end, a radically different technique for identifying and ranking accident blackspots, which is more accurate and reliable than current methods, is presented in this section of the thesis.

As previously discussed under the section on review of the relevant literature, accident-prone locations ("blackspots") in the road network in Ghana are currently determined solely on account of the total number of accidents recorded during a 1 to 3 year period. With this approach, a list of road locations is periodically compiled in a ranked order and the site with the highest number of recorded accidents in the given period is assumed to be the one in most urgent need of attention. The method is simple to use but has significant disadvantages. It tends to be biased and arbitrary, because there is often no reference "norm" against which the accident numbers for various sites are compared.

As a result, the list of accident-prone locations can usually be almost as long as there are sites with any accident records and therefore unmanageable. It also does not account for any measure of exposure or site-specific conditions and tends to be biased towards the selection of sites with high vehicle flows. The approach is akin to the use of annual accident total (AAT) by many local authorities in the United Kingdom, as reported by Maher and Mountain (1988).

Another commonly used technique, which is clearly an improvement on the use of accident counts, is the "rate and number" method (Hauer and Persaud, 1983). In this case, the criterion of accident-proneness is the average accident rate (per million vehicles and/or vehicle-kilometres). Thus, a site is considered hazardous when the accident rate over some given period of time exceeds a "norm" (e.g. the mean accident rate over all sites in an area) plus a multiple of the related standard deviation. The multiple used would depend on the desired degree of confidence (e.g. 2 standard deviations for 95 per cent confidence interval). This technique at least accounts for exposure and uses confidence limits, thereby conceding some element of uncertainty with the rates used.

However, this method has the tendency to select sites with low flows and in cases where accidents are weighted according to their severity, the method tends also to give undue prominence to relatively more random and rare high severity accidents. The predominant use of "regional" or "area" accident characteristics by this technique, as a reference level for determining "above-average" accident history, can also be improved if the site of interest is compared instead with others sharing similar underlying characteristics (traits).

Due to the now well-known tendency of accident counts to fluctuate randomly in successive periods, irrespective of site conditions, none of the techniques of blackspot identification mentioned above can be trusted to deliver truly deviant sites, in terms of their unsafety. The accident counts by themselves are likely to reflect significant random and fleeting effects that may not necessarily be related to the underlying unsafety or accident potential of the site. The more appropriate criterion of deviancy must, therefore, be the *expected* accident count, which is the long-term average of observed accidents at the site.

On the other hand, this random variable can be estimated only within some limits of precision and that is where the Empirical Bayesian (EB) techniques, introduced in the previous section, become useful. Apart from providing a coherent and more logical framework for combining important "clues" to produce the best estimate of unsafety, the EB procedure also provides the opportunity to identify hazardous sites, on the basis of a probability that the accident potential or unsafety exceeds a given norm. Such probabilistic identification methods differ qualitatively and quantitatively from the confidence-based methods currently used (Higle and Witkowski, 1988).

The EB technique proposed, here, followed the original work of Higle and Witkowski (1988) but differed in three important respects. The procedure used by Higle and Witkowski (1988) involved three steps. In the first step, they aggregated the accident histories across a number of sites within a defined *region,* to produce a gross estimate of the probability distribution of *accident rates* across the region. They then used the regional distribution and the accident history, at individual sites, to obtain a refined estimation of the probability distribution associated with the accident rate at each particular site. With this collection of refined distributions, it was then possible to assess the probability that any given site is hazardous.

A similar procedure was applied here but, instead of aggregating sites by a defined area, the sites in this study were combined according to their shared characteristics. And, since like was mixed with like in these defined "families" of junctions, the first difference from the Higle and Witkowski (1988) approach is that better and more consistent estimates would be obtained than using the regional or area groupings.

Secondly, instead of accident rates, the estimated expected accidents from prediction models were used here. In this way, apart from including exposure to accidents, other significant accident-dependent variables were accounted for. The third difference is that the distribution parameters for expected accidents within the family of junctions were calculated from the model estimate and its variance, following the lead of Rodriguez and Sayed (1999), in contrast to the sample mean and variance used by Higle and Witkowski (1988).

Thus, the entire procedure proposed is, as follows:

<u>Step 1</u>: Determine the probability density function of expected accidents across the family of junctions (i.e. T- or X-junctions). This is the *prior* distribution i.e. the assumed distribution before the site-specific accident data become available. It is known that this will generally follow the Gamma distribution of the form:

$$f_{PR}(\lambda) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda} \qquad \ldots\ldots\ldots\ldots \qquad (6.5)$$

where $f_{PR}(\lambda)$ is the probability density function of expected accidents across
across the family of junctions, α and β are the parameters of the distribution

Thus, the first step essentially involves estimating the parameters α and β to define the distribution. This is done, using the estimates of mean expected accidents ($E(\Lambda)$) and the variance $Var(\Lambda)$ from the appropriate GLIM full model for all accidents, as follows:

$$\beta = E(\Lambda)/Var(\Lambda) = \kappa/E(\Lambda) \text{ and } \alpha = \beta \, x \, E(\Lambda) = \kappa \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad (6.6)$$

where κ is the overdispersion parameter from the Negative Binomial model fit

<u>Step 2:</u> Determine the *posterior* distribution. This is the site-specific probability density function resulting from combining the observed accidents for each site (a_i) with the gross estimate of the probability distribution across the family of junctions ($f_{PR}(\lambda)$). These density functions ($f_i(\lambda| a_i)$ are obtained, using Bayes' theorem, as:

$$f_i(\lambda| a_i) \propto f(a_i|\lambda) f_{PR}(\lambda) \qquad \ldots\ldots\ldots\ldots\ldots\ldots \qquad (6.7)$$

They also follow the Gamma distribution but are defined by new parameters calculated from the EB refined estimates of unsafety and its variance (see Equations (6.1) and (6.4)), as follows:

$$\beta_l = EB/Var(EB) = \kappa/E(\Lambda) + 1 \text{ and } \alpha_l = \beta_l \, x \, EB = \kappa + a \qquad \ldots\ldots\ldots\ldots \qquad (6.8)$$

where a is the observed number of accidents at the given site.

Thus, the overall probability density function of the *posterior* distribution is:

$$f_{POS}(\lambda) = \frac{[\kappa / E(\Lambda) + 1]^{(\kappa + a)} \lambda^{\kappa + a - 1} e^{-[\kappa / E(\Lambda) + 1]\lambda}}{\Gamma(\kappa + a)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots \qquad (6.9)$$

<u>Step 3:</u> Using the collection of posterior density functions, test if a given site is a blackspot. Given an upper limit on the "acceptable" expected accidents of λ_{CR}, the site is deemed to be a blackspot if there is a significant probability that λ_i exceeds λ_{CR}, In other words:

$$P(\lambda_i > \lambda_{CR} \mid a_i) > \delta \qquad \text{....................} \quad (6.10)$$

where δ is a predetermined tolerance level (usually 0.95).

Alternatively, this can be expressed as:

$$[1 - \int_0^{P_{50}} \frac{\{\kappa / E(\Lambda) + 1\}^{(\kappa+a)} \lambda^{(\kappa+a-1)} e^{-\{\kappa/E(\Lambda)+1\}\lambda}}{\Gamma(\kappa + a)} \partial\lambda] \geq \delta \qquad \text{...........} \quad (6.11)$$

In this context, the 50-th percentile (P_{50}) value of the expected accidents across the family of junctions was proposed as the λ_{CR}. This represents the maximum level of expected accidents at 50 per cent of junctions and it appeared to make sense, therefore, to investigate those junctions whose accident potential is above it. Thus, λ_{CR} was calculated as P_{50} from the prior distribution, such that:

$$\int_0^{P_{50}} \frac{[\kappa / E(\Lambda)]^{\kappa} \lambda^{\kappa-1} e^{-[\kappa/E(\Lambda)]\lambda}}{\Gamma(\kappa)} \partial\lambda = 0.50 \qquad \text{.....................} \quad (6.12)$$

The equation represents an incomplete Gamma function and had to be solved by approximate methods of estimation, using the *GAMMAINV* computation in *MS Excel.* What was required was the inverse value of the cumulative distribution ($\lambda = \lambda_{CR}$), given the percentile probability (0.50). Using the data from the worked example on T-junctions (see Section 6.2.2b), λ_{CR} was computed as 3.78 accidents/3-years. For the X-junction example this was 4.79 accidents/3-years.

Thus, when the appropriate parameter values from the worked example on the T-junction are substituted in Equation (11) the result is, as follows:

$$1 - \int_0^{3.78} \frac{\{2.996/4.24 + 1\}^{(2.996+11)} \lambda^{(2.996+11-1)} e^{-\{2.996/4.24+1\}\lambda}}{\Gamma(2.996+11)} \partial\lambda = 0.993$$

This shows that the probability of the 11 accidents observed in three years at the T-junction exceeding the P_{50} value of expected accidents at the site (=3.78 accidents/3years) is 99.3 per cent. Since this is more than the 95 per cent considered significant, it can be concluded that this T-junction is indeed a blackspot.

Similarly, with $\kappa = 4.65$, $E(\Lambda) = 5.15$ accidents/3years the 8 accidents observed in 3 years at the X-junction in the worked example exceeded the junction's P_{50} value (= 4.79 accidents/3years) with a probability of 84.4 per cent. In this case, the junction could not be said to be a blackspot, because the probability was less than 95 per cent.

6.4 Using Decision Curves (Nomographs) for Blackspot Identification

The Bayesian procedure for blackspot identification described above undoubtedly involves some quite demanding mathematical calculations. Therefore, if it is to stand any chance of being applied, which is one of the goals of this research project, then the process needs to be made much simpler. Consequently, it was decided to translate the decision process typified by Equation (6.11) into nomographs, a language the average traffic or maintenance engineer understands very well and would be comfortable with. The results are presented in Figures 6.1 and 6.2. To obtain the curves, Equation (6.11) was solved iteratively for the observed accident frequency that produced the desired significance level. The *GAMMADIST* facility in *MS Excel* was used for the computations.

To illustrate their use, consider a T-junction for which 15 accidents in 3 years are predicted, using the full model for all accidents. Then, for this particular junction, as shown in Figure 6.1, at least 21 accidents need to be observed in the same time period, for it to be considered a blackspot at the 95 per cent confidence level. At the higher (99 per cent) confidence level, the number of observed accidents required would be 24.

The curves are presented for the two levels of confidence for purposes of comparison. Normally, the 95 per cent confidence level should be statistically satisfactory for the decisions required.

Figure 6.1 Blackspot Decision Nomograph for T-junctions

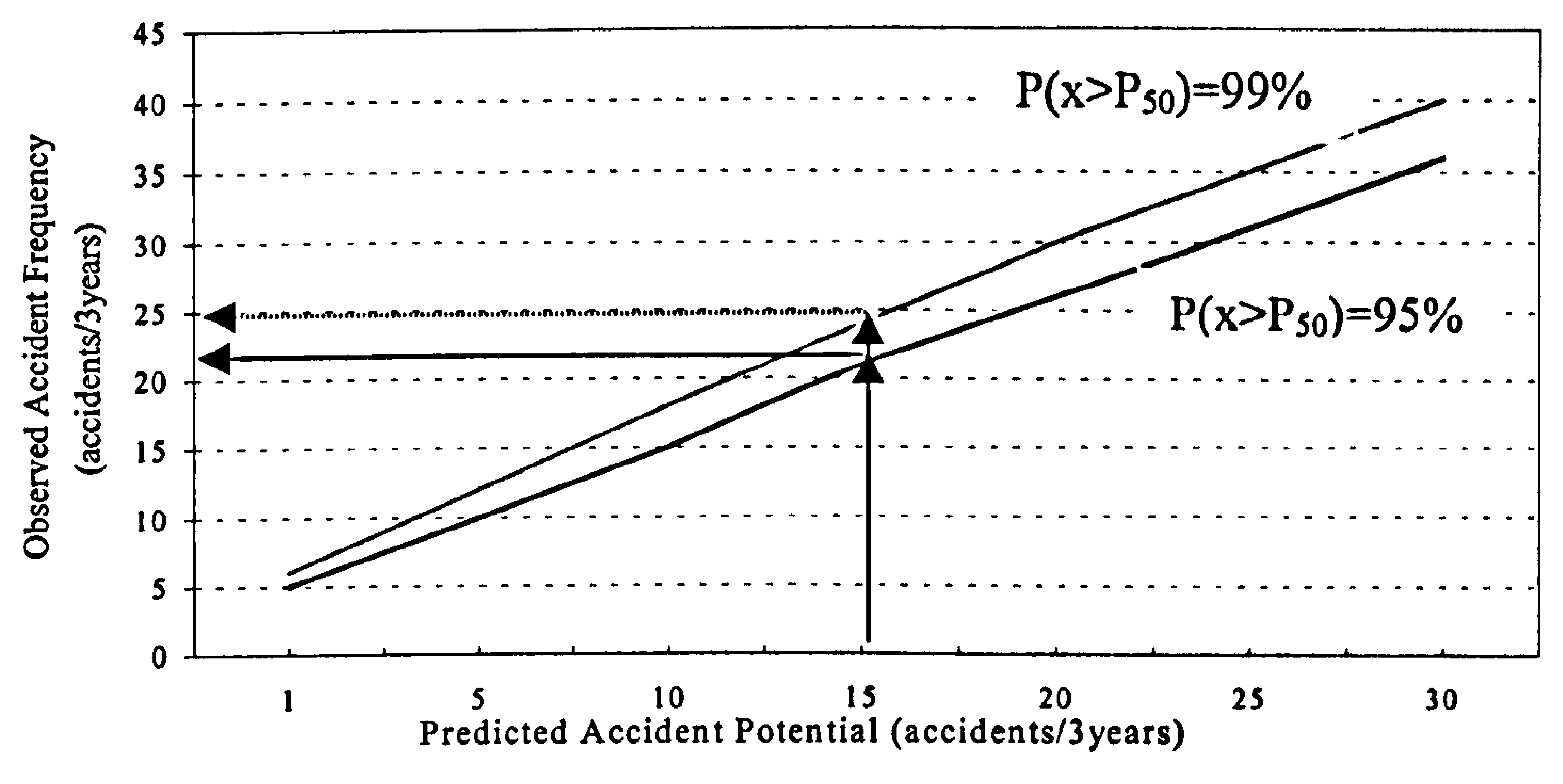
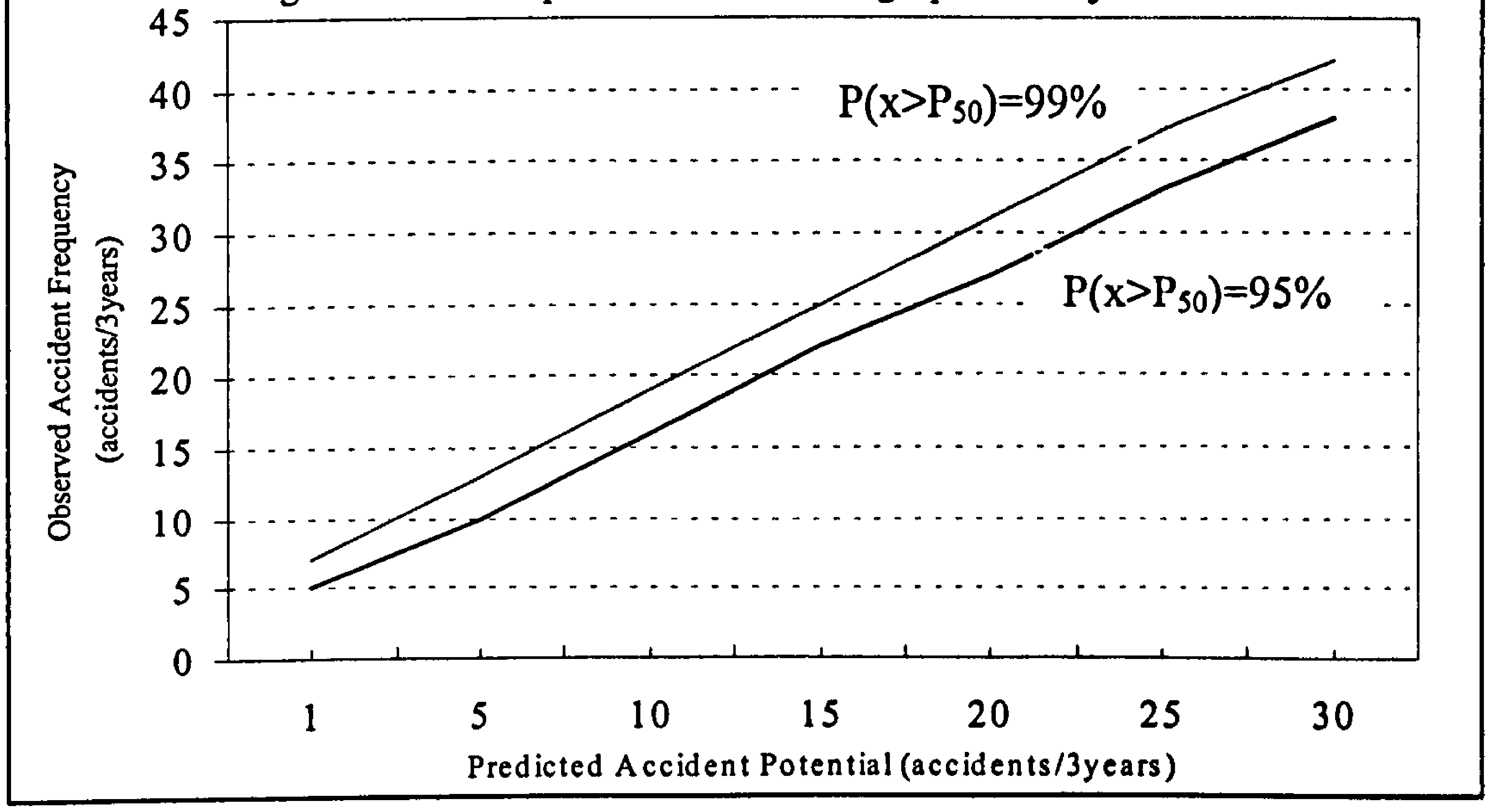


Figure 6.2 Blackspot Decision Nomograph for X-junctions



6.5 Revised Criteria for Ranking Blackspots for Treatment

It is inevitable that, even with the most rigorous procedures for identification or classification, the road authorities will always end up with a substantial number of junctions that would qualify as blackspots at any particular point in time. What a good identification process does is to ensure that all the sites which need attention are captured, whilst leaving out unworthy ones, even if these are characterised by some fleeting random escalations in accident frequency. After that, the next step is to decide in what order to tackle the sites, since it is practically impossible to work on all of them at the same time, due to perennial resource limitations. Consequently, a reliable mechanism is required to enable the authorities to rank the list of blackspots in some order of priority for subsequent attention, in a way that will ensure efficient utilisation of resources.

The ranking criteria most commonly used currently often depend on, or are closely related to, the method used in identifying the blackspots. For example, where the annual accident total (AAT), or some variant thereof is used for blackspot identification, the sites are simply listed in descending order, with the one having the highest accident number, or rate, being ranked first. Although this approach is still in widespread use (it is the current practice in Ghana and has been reported in Maher and Mountain (1988) as used by most UK highway authorities), it has significant undesirable attributes. It is usually biased in favour of high or low flow sites, depending on whether the accident number or rate approach is used.

Another disadvantage is that the criterion is unable to separate random and fleeting high trends in accident numbers from those associated with the underlying safety of the site. Hence, it is highly susceptible to giving high priority ranking to sites, which would probably not have qualified as blackspots in the first place, if more precise procedures had been used. Priority lists based on this criterion, therefore, cannot be trusted, since they do not necessarily reflect the true scale of the underlying accident problem at the sites. Lastly, the use of such lists, compiled in this way, gives no indication of the potential benefits or the relative difficulty or ease of carrying out appropriate remedial intervention.

The use of aggregate weighted accident numbers (Equivalent Accident Number (EAN)) is another ranking criterion based on observed accident counts. In this case, the observed accident total is separated by severity, typically into property damage, injury and fatal accidents. Each accident is then assigned a weight according to its severity (e.g. TRL (1991) recommend the following weights: 1 for each property damage accident, 3 for an injury accident and 12 for a fatal accident). The weights are each multiplied by the number of accidents in the relevant severity group and aggregated for all accidents at the blackspot. Thereafter, the sites are ranked in descending order of their aggregate weighting (EAN). This method is an improvement on the use of raw accident totals, in particular because, through the weights attached to each accident type by severity, it indirectly provides an indication of the potential savings in accident costs that will accrue from carrying out a remedial measure.

The drawback of this method, however, is that it still depends on accident counts and that makes it susceptible to regression-to-mean effects. The relatively heavy weight it attaches to fatal accidents, in particular, also aggravates this susceptibility to random and rare events that are not related to the underlying unsafety of a site. For example, a site with only one fatal accident, which may have occurred "by chance", will be considered more dangerous and ranked higher than a site with ten property damage accidents, which might be due to systematic underlying factors all capable of remedy.

McGuigan (1981) proposed an alternative and improved criterion, called the Potential for Accident Reduction *(PAR)*. This is calculated as the difference between the observed accident frequency (Y_i) and the expected accidents (m_i) for each site (i.e. $Y_i - m_i$). In the author's opinion, this difference represents the maximum number of accidents that any remedial intervention at the site could practically hope to reduce. The merit in this approach is the admission that not all accidents may be treatable and its use of the expected accidents as the baseline (the "norm", as it were) reduces the arbitrariness associated with criteria based solely on accident counts, which may be undergoing regression-to-mean effect.

However, Maher and Mountain (1988) observed that the *PAR* method is, by no means, without fault. In their opinion, the part use of observed accidents (Y_i) means that part of the *PAR* is still due to random variation, which no treatment can affect and there is also no indication as to which of the changeable characteristics at a site would need treatment. The other criticism of the *PAR*, as proposed by McGuigan (1981), is that the regression equations used to estimate (m_i) are rather basic, since they rely on only traffic flow and may not be accurate enough.

In this study, an alternative criterion based on the general concept of the *PAR* but devoid of the latter's identified shortcomings is presented. It is proposed, therefore, to call this criterion the Amended Potential Accident Reduction *(APAR)*. This is given by the expression:

$$APAR = (EB - m_i) / m_i \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (6.13)$$

where EB is the Empirical Bayes refined estimate of accident potential at the site and

m_i the expected accidents, estimated by the appropriate prediction model

The numerator in Equation (6.13) ($EB - m_i$) preserves the original concept of the *PAR*. It represents the difference between what is the best estimate of the accident potential at the site, considering both the accident history and the traits, and gives a good indication of the margin of potential reduction in accidents to be achieved by the most effective intervention that retains the unsignalised status of the junction. Arguably, the concept of "most effective intervention" could also be seen in terms of the *safest possible design.* In that case potential remedial measures for the particular site may include options outside the scope of unsignalised junctions.

Thus one could think of implementing a standard rotary intersection design, for example, in place of a stop-controlled junction with above average expected accidents. The focus of this study however is on low-cost remedial measures for unsignalised junctions, hence the use of the expected accidents for the "average" unsignalised junction as the baseline for computing the potential accident reduction. It is significant that in this case Y_i, as in the *PAR*, is replaced by *EB,* which is not trivial as the use of *EB* means that the random variation associated with the *PAR* has been accounted for.

The difference ($EB - m_i$) could, by itself, serve as a criterion for ranking. It does appear as a logical criterion for the potential cost-effectiveness (i.e. the maximum reduction in accidents/casualties for money spent) of the chosen measure and it should provide better results than the *PAR*. To improve further upon the overall quality of the estimates relative to *PAR*, m_i is to be obtained from the prediction of the appropriate full model, as opposed to the use of flow-based model predictions in the *PAR* approach. Thus, other parameters (site characteristics) which have a causal relationship with accidents and the scale and type of their influence become more apparent (in the form of the full model). Consideration may be given to altering such variables as part of the remedial intervention.

The *APAR* is proposed as a ratio, relative to the expected accidents, in order to reduce the refined margins of all potential reductions to a common scale to facilitate a more even comparison (see Equation 6.13). This ratio format is consistent with the general mode of expression of the effectiveness of measures. Thus, the *APAR* value is also an indicator of the potential effectiveness of a remedial intervention, since it shows by what factor of the expected accidents at a blackspot a reduction can be achieved. By so doing, it reflects the general attractiveness or potential effectiveness of tackling each site. In Table 6.1 below, a comparison of the *PAR* and *APAR* ranking orders is presented for six T-junction sites in the study sample, which were identified as blackspots, using the criteria set in Section 6.4.

Although the number of sites in this list may not be really sufficient (a good indication, perhaps, of how effective the criteria are) to enable a thorough comparison, some patterns are nonetheless apparent from Table 6.1 and worthy of note. It can be seen, for instance, that the *PAR* ranking-order tends to follow the order of the accident totals. This is easily explained by the fact that the accident totals themselves are directly used in the computation. The two sites in the list that recorded distinctively high accident numbers had the same rank orders by *PAR* and *APAR*. However, for the remaining four sites, which were relatively less "extreme" blackspots, particularly in terms their observed accidents, the rank-orders were quite different. This is where the difference between the two criteria manifests itself most clearly.

Table 6.1 Rank-Order of Blackspots for T-junctions, using *APAR* and *PAR* Criteria

Junction Name	Observed accidents (Y_i)	Predicted accidents (m_i)	*PAR* = (Y_i-m_i)	Bayesian estimate (*EB*)	$(EB\text{-}m_i)$	*APAR* = $\frac{(EB\text{-}m_i)}{m_i}$	Rank number	
							APAR	*PAR*
(1) Abooma/Coastal	32	6.38	**25.62**	23.80	17.42	**2.73**	*1*	*1*
(2) Timber Gardens	13	9.18	**3.82**	12.05	2.87	**0.31**	*4*	*5*
(3) Coastal Rd./1st Jn.	10	6.31	**3.69**	8.82	2.51	**0.40**	*3*	*6*
(4) Neoplan/Abrepo	18	13.48	**4.52**	17.19	3.71	**0.28**	*6*	*3*
(5) New Road/Makro	32	17.09	**14.91**	29.76	12.67	**0.74**	*2*	*2*
(6) Darkman/M'way	16	11.49	**4.51**	15.05	3.56	**0.30**	*5*	*4*

Site 3, for example, was ranked 6th by the *PAR*, because it had the lowest margin of expected reduction (3.69 accidents/3years). However, when all the potential margins of reduction are refined and assessed, relative to the expected accidents (as in *APAR*), this site is elevated in importance and becomes 3rd in the *APAR* priority list. By contrast, site 4 experiences a reduced priority rating from 3rd to 6th, when the criterion is changed from *PAR* to *APAR*, despite having a much larger absolute margin of potential accident reduction than site 3. The least that one can say about these patterns is that the two criteria give qualitatively different ranking outcomes.

The advantage in using the *APAR* lies in the fact that it produces more reliable estimates of the margins of potential accident reduction and reduces these margins to a common baseline, to enhance even comparison of sites. As Table 6.1 would show, it appears that the *APAR* may be particularly useful for prioritising between less "extreme" blackspots. This should prove an important attribute, since, in practice, it is usually such "middle-ranking" types of blackspot that are most prevalent and also difficult to prioritise using observed accident numbers or *PAR*.

The processes of "blackspot" identification and ranking outlined above are intended to produce, as efficiently and precisely as possible, a refined list of sites with accident problems that are "treatable". By definition, therefore, sites appear in the prioritised list in order of "treatability", which at this stage is judged by the magnitude of *APAR* or ($EB\text{-}m_i$). In order to identify the specific "treatable" accident problem it will be necessary to carry out detailed analysis at the individual sites. In this connection a clustering or dominance of specific accidents types is usually the clue to the problem and the solution. The intensity of the clustering or dominance of specific accident types would generally determine whether the site is a hard or easy to treat one. Thus, important as it is, the proper ranking of sites is not the solution to "blackspots" but only an initial step towards the diagnosis and solution.

It is important to note that the use of Equivalent Accident Number (EAN) and *APAR* to rank sites are not necessarily mutually exclusive. Depending on the priorities of the local road agency, in particular if the emphasis is on casualty/injury reduction, the two criteria could be employed together. In that case it would be advisable that the EAN is computed for the accident types in clusters and not for all accidents at the site in order to reduce the otherwise undue influence of the occasional high severity accident that has no roots in the "treatable" problem.

6.6 Conclusion

Until now the unsafety or accident potential of different road locations has been assessed usually solely from their accident history. However, since by definition this is an unknown variable that can only be estimated, this approach has been criticised as fundamentally misleading and inaccurate by many authors. In this chapter, the Empirical Bayesian procedure for estimation of site-specific accident potential has been presented as a much superior alternative that automatically accounts for the regression-to-mean effects inherent in observed accident data. The main inputs for such estimates are the observed accident counts of the particular site and the expected accidents at sites with similar characteristics as the one under study. A key feature of this study has been the demonstration of how accident prediction model estimates can be incorporated into the Bayesian procedure, to improve further on the quality of the estimates and extend its applicability to relatively smaller reference populations.

The unique ability of the Bayesian analysis to treat the accident potential, at a particular site, as a random variable was also utilised to outline new and improved criteria for accident blackspot identification and ranking. To start with, a probability distribution of expected accidents across a family of junctions with shared characteristics (e.g. T-junctions) was estimated from the accident prediction models. This distribution was then used, in conjunction with the accident history at a particular site, to obtain a refined estimation of the probability distribution associated with the accident potential at that particular site. With the collection of refined distributions, it was then possible to assess if there was a significant probability that a site's accident potential exceeded a predetermined "norm" to qualify as a blackspot. To remove the computational difficulties associated with this process and to encourage its adoption by the traffic authorities in Ghana, decision curves, or nomographs, were developed for the determination of blackspots for both T- and X-junctions. This approach represents a complete revision of and improvement upon the criteria currently in use.

A new basis (criterion) for the ranking of accident blackspots for treatment has also been presented. The criterion proposed is the Amended Potential Accident Reduction (*APAR*). The main concept is an extension of the Potential Accident Reduction (*PAR*), as originally proposed by McGuigan(1981), but the computation parameters have been revised with the aim of producing more refined estimates and, hence, overcoming some of the shortcomings associated with the *PAR*. Unlike the *PAR*, the *APAR* was proposed as a ratio to reduce the refined potential accident reductions to a common baseline, to enable more equitable comparisons of the potential effectiveness of intervention measures at all blackspots.

CHAPTER 7
CONCLUSIONS AND RECOMMENDATIONS

This study was undertaken with the main intention of developing suitable accident prediction models as an integral part of the process of outlining a more proactive and efficient methodology for appraising accident potential at unsignalised urban junctions in Ghana. Following a thorough review of the relevant literature, field studies were carried out in a designated case-study area, during which a wide range of road and traffic data was collected. The case-study involved 57 T-junctions, comprising 6 types distinguished by the presence, or otherwise, of some important site features, and 34 X-junctions of 3 types. From the detailed analysis of the accumulated data presented in the preceding parts of this report, the following conclusions and recommendations appear to be warranted.

7.1 Conclusions

(i) The review of the literature showed that most studies on the evaluation of the accident potential at unsignalised urban junctions were of the "before and after" type. The reported results of comparisons of the accident potential of different levels of unsignalised junction control between each other and signalised control remain largely inconclusive and contradictory. In particular, significant questions have been raised about the assumed safety merits of increased level of junction control, as recommended by many existing safety warrants. Differences in the type and volume of data sets and the failure of most of the reported studies to account for the regression-to-mean phenomenon are some of the main reasons cited for the inconsistent results.

Most reported accident prediction modelling has concentrated on the development of coarse, as opposed to causal or full models, for rural or urban signalised junctions. The few that have tackled comprehensive modelling have been based on data from industrialised countries and a large majority was pursued as an end in itself, rather than as a means to an end.

(ii) A total of 16,334 road traffic accidents, resulting in 10,493 casualties, were recorded in the case-study cities during the three-year study period 1996 to 1998. These accidents were broadly-speaking split in their distribution evenly between link sections and junctions. This was not quite as expected, since junctions are generally perceived as more accident-prone than links, given the greater potential for conflict from intersecting traffic streams. Unsignalised junction accidents accounted for more than 60 per cent of all junction accidents and roughly 80 per cent of this proportion was shared between T- and X-junctions. Accidents at unsignalised junctions tended to have much more severe outcomes than those occurring at other types of junction.

The predominant accident-types at unsignalised junctions, classified by the defining primary collision-type, were right-angle, rear-end and pedestrian accidents. Whereas the different collision-types were more evenly represented at T-junctions, right-angle collisions alone, which involved mostly cross traffic, were the most dominant at X-junctions. On the other hand, T-junctions appeared to have more pedestrian accidents. Heavy Goods Vehicles (HGVs) and buses were much more likely to be involved in accidents at unsignalised junctions than any other category of vehicle. Their proportional involvement in accidents was nearly six times their share of traffic. Significantly, about three out of four accident vehicle-manoeuvres were simply "going ahead" immediately prior to the collision. This means that most accidents took place on the immediate approaches to junctions or between vehicles making a straight transition from one arm to the opposite one as at X-junctions.

(iii) The case-study enabled a more quantitative evaluation of unsafety or accident potential at a representative sample of unsignalised junctions, comprising six types of T-junction and three types of X-junction, classified by the presence (or otherwise) of some features (channelisation or divisional islands) on either arms. The main measure of unsafety was the accident rate per million vehicles. Generally, junctions without any features were 1.5 to 2.5 times more unsafe than those with features and this appeared to affirm the basic need for channelisation or divisional islands on either one or both approaches of the junction. For junctions on dual carriageway arterial roads, the presence of a dedicated storage lane for left-turning major road vehicles appeared to enhance overall safety as well as traffic flow. It was, however, slightly more intriguing that the incidence of injury accidents on such junctions (with dual carriageway arterial roads) was less than at junctions without features, given the generally higher operating speeds on the former. The minor road's share of traffic appeared to be one of the most influential factors for unsafety. Using ordinary regression techniques, it was demonstrated that the minor road's share of traffic and accident or casualty rate were systematically connected.

Due to restrictions in the study sample (i.e. nearly all X-junctions were controlled by stop signs), comparison of the accident potential associated with different types of junction control was carried out only for T-junctions. The general finding was that stop-controlled junctions were associated with higher levels of unsafety than yield-controlled junctions or junctions without any form of control at all. This was an important observation, if controversial, because it reinforces questions that have been raised in the literature regarding the safety merits of progressive increases in the level of control at unsignalised junctions. Overall, the difference between both the accident rate and accident frequency at T-junctions and X-junctions was not statistically significant. This implied that the two types of junction layout, within the limits of the case-study data, had similar accident potential or unsafety.

(iv) Prediction models have been developed relating the 3-year accident frequency at unsignalised T- and X-junctions to various road and traffic variables. The models were of two types, the first (flow-based) were based solely on the traffic exposure function, whilst the second (full models) were extensions of the best exposure functions to include other significant road and traffic variables. Models were developed separately for all accidents, injury accidents and other accident types categorised by the defining collision types involved, namely, head-on, rear-end, side-swipe and right-angle collisions and pedestrian accidents.

Generally, traffic exposure functions such as the cross products of flow (XPDF) and the sum of encounter flow products (ENCP) produced much better fits to the accident data than simpler flow functions like the total traffic inflow (TINF). On average, flow-based models for T-junctions had about one-and-a-half times more "proportion explained" than corresponding models for X-junctions. This means that the exposure variables were much more influential determinants of accident frequency at T-junctions than at X-junctions. Fewer additional variables proved significant in the full models for T-junctions leading to higher values of proportion explained for the X-junction full models.

Within each junction group (T- or X-junctions), flow-based models for the various types of accident defined by the primary collision also produced higher "proportion explained" than the corresponding models for all accidents or injury accidents. This trend was largely attributed to the fact that, at the more disaggregate level, it was easier to identify the more appropriate exposure functions relevant to the particular collision type.

The three additional variables that featured most consistently in the extended accident models for X-junctions were street lighting, dedicated left–turning lanes and the average standard deviation of approach spot speeds of vehicles on the major road. Those for T-junctions were the level of traffic control, the average width of the median on the major road and the average standard deviation of vehicle approach spot speeds on the major road. The absences of street lighting and dedicated left-turning lanes and the average standard deviation of vehicle approach spot speeds were all positively correlated with accident frequency. For the individual accident types defined by the primary collisions, the additional variables captured in the corresponding full models differed in type, as well as the nature of their influence on accident frequency.

Interestingly, whilst the average width of the median on the major road was associated with an increase in accident frequency at X-junctions, it had the opposite effect at T-junctions. Also, the accident potential of T-junctions that had YIELD or no control was adjudged to be much lower than at STOP-controlled sites. This apparently confirmed the earlier finding, in Section 4.3.2.4, regarding the relative accident potential of junctions with the different levels of control.

Given the large variety of variables tested in the model estimation process, the quality of the obtained models and the consistency of the additional variables, it can be concluded that the full models developed represented causal rather than associative relationships. The models can subsequently, therefore, be used for reliable prediction of accident frequency associated with the junction types and features described.

(v) Until now the unsafety, or accident potential, of road locations has been assessed usually solely from their accident history. But this approach has been criticised as fundamentally misleading and inaccurate by many authors. The Empirical Bayesian procedure for estimation of site-specific accident potential has been presented as a much superior alternative that automatically accounts for the regression-to-mean effects inherent in observed accident data. This estimate is produced from a uniquely weighted combination of the observed accident counts of the particular site and the expected accidents for sites with characteristics similar to those of the one under study. A key feature of this study was the demonstration of the framework for integrating accident model predictions with the Empirical Bayesian procedure, to improve further on the quality of the estimates of accident potential and to extend the applicability of the procedure to relatively smaller reference populations.

The unique ability of the Bayesian analysis, to treat the accident potential at a particular site as a random variable, was also utilised to outline new and improved criteria for accident blackspot identification and ranking. These are probabilistic criteria, based on the evaluation of an incomplete gamma function. To remove the computational difficulties associated with the process and to encourage its adoption by the traffic authorities in Ghana, decision curves, or nomographs, have been developed for the determination of blackspots for both T- and X-junctions at specified confidence levels. This approach represents a radical departure from and improvement upon the criteria currently in use.

A new basis (criterion) for the ranking of accident blackspots for treatment has also been presented. The criterion proposed is the Amended Potential Accident Reduction (*APAR*). The main concept was an extension of the Potential Accident Reduction (*PAR*), as originally proposed by McGuigan(1981), but the computation parameters have been revised, with the aim of producing more refined estimates, and hence overcoming some of the shortcomings associated with the *PAR*. Unlike the *PAR*, the *APAR* is proposed as a ratio to reduce the refined potential accident reductions to a common baseline, so as to enable more equitable comparisons of the potential effectiveness of intervention measures at all blackspots.

On the whole, the use of the Empirical Bayesian procedures to produce refined estimates of accident potential at unsignalised junctions, using inputs from the full accident prediction models and the accident counts represents a unique approach that should lead to more accurate and efficient safety evaluation. The extension of this methodology to produce revised criteria for accident blackspot identification and ranking, is also bound to improve the scientific basis and cost-effectiveness of remedial interventions.

7.2 RECOMMENDATIONS

(i) The new procedures outlined in this study, insofar as they represent an improved basis for appraising and quantifying of accident potential and its determining variables, require urgent adoption. This could give an important boost to the overall national accident reduction effort. The accident prediction models developed, when used either by themselves, or as part of the Empirical Bayesian procedure, will be useful in a variety of important ways, including:

- assessing the unsafety implications of individual junction features, since the magnitude and direction of their impact on accident frequency has now been quantified;
- auditing and making a comparison of design/safety schemes before detailed design is done;
- monitoring and evaluation of accident remedial schemes, or the safety effects of traffic management measures; and
- accident prediction to facilitate decisions based on COBA.

(ii) In order to continue to improve upon the methodology and sustain its use into the future, some further work is recommended, as follows:

- to computerise the accident prediction models and estimation procedures to facilitate their use;
- to carry out a similar but more extensive study involving a larger database, with improved quality and broader range of independent variables. This should either confirm or reject the effects of individual junction features in the various prediction models and would give a useful indication as to how the size of the data-base is likely to affect the accuracy or reliability of prediction models. A much larger database should also enable the use and verification of the zero-inflated approach to the modelling of accident data with a preponderance of zero counts;
- to review or validate the prediction models periodically, since they cannot be valid for all time; and
- to develop separate prediction models for other types of road locations, such as link sections on urban roads and trunk roads.
- to explore the possibility of developing prediction models based on vehicle manoeuvre or by separate junction arms, if the data permits. Although this approach has been reported in parts of the literature as giving a better picture of the unsafety situation at junctions than models based on initial impact or collision type, it was not possible to pursue it in this study due to data limitations.

It is hoped that carrying out the above recommendations would consolidate and entrench the use of this new methodology of unsafety appraisal, as part of standard practice by the road authorities, and contribute significantly to bringing about a much-needed reduction in the incidence of road traffic accidents in Ghana and elsewhere.

REFERENCES

Abbess, C., Jarret, D. and Wright, C.C. (1981): Accidents at Blackspots: Estimating the Effectiveness of Remedial Treatments, with Special Reference to the Regression-to-Mean Effect. *Traffic Engineering & Control*, 22 (10), pp535-542.

Abdel-Aty, M. and Radwan, E. (2000): Modelling Traffic Accident Occurrence and Involvement. *Accident Analysis and Prevention* 32 (5), pp633-642

Aitkin, M., Anderson, D., Francis, B. and Hinde, J. (1989): *Statistical Modelling in GLIM.* Oxford: Oxford Statistical Science Series 4, Oxford Science Publications. 374 p. ISBN 0-19-852204-5

Almqvist, S. and Hyden, C. (1994): Methods for assessing traffic safety in Developing Countries. *Building Issues*, 6(1). Center for Habitat Studies, University of Lund, Lund, Sweden.

Amis, G. (1996): An Application of Generalised Linear Modelling to the Analysis of Traffic Accidents. *Traffic Engineering & Control*, 37 (12), pp691-696.

Baruya, B., Finch, D. and Wells, P. (1999): Mastering the Speed Safety Problem. *Traffic Engineering & Control*, 40 (2), pp58-60.

Ben-Akiva, M., Ceder, A., Cheng, L-h. and Liss, C.M. (2000): A Methodology for Estimating Traffic Safety Improvements at Intersections. *Journal of Advanced Transportation*, 33 (3), pp273-293

Bonneson, J. A. and McCoy, P. T. (1993): Estimation of Safety at Two-way Stop-controlled Intersections on Rural Highways. *Transportation Research Record 1401*, Transportation Research Board, National Research Council, Washington D. C., pp83-89.

Building and Road Research Institute (1999): Identification and Analysis of Accident Blackspots on Urban Road Network – Inception Report, Department of Urban Roads, Ministry of Roads and Transport, Ghana.

Building and Road Research Institute (1999): Road Accidents in Ghana: Statistics 1988-1993. Ministry of Roads and Transport, Ghana

Building and Road Research Institute (1998): Analysis of Accident Blackspots and Design of Remedial Measures for Trunk Road Network – Final Report, Ghana Highway Authority, Ministry of Roads and Transport, Ghana.

Chadda, H. S. and Parker, E. C. (1983): Multi-way Stop Signs – Have we gone too far? *ITE Journal 53*, pp19-21

David, N.A. and Norman, J.R. (1975): *Motor Vehicle Accidents in Relation to Geometric and Traffic Features of Highway Intersections.* FHWA, U.S. Department of Transportation

Department of Transport (1981): *Cost-Benefit Analysis Manual (COBA 9).* HMSO, London

Department of Transportation (1981): *Highway Safety Evaluation Procedural Guide.* FHWA, Washington

Fridstrom, L., Ifver, J., Ingebrigtsen, S., Kulmala, R. and Thomsen, L. K. (1995): Measuring the Contribution of Randomness, Exposure, Weather and Daylight to the Variation in Road Accident Counts. *Accident Analysis & Prevention*, 27 (1), pp1-20

Frith, W. J. and Dery, M. N., (1987): Intersection Control by Stop and Giveway Signs – The Conclusions of Polus. *Accident Analysis & Prevention*, 19 (3), pp237-241

Frith, W. J. and Harte, D.S. (1986): The Safety Implications of Some Control Changes at Urban Intersections. *Accident Analysis & Prevention*, 18 (3), pp183-192

Garber, N.J. and Hoel, L.A. (1988): *Traffic and Highway Engineering.* West Publishing Company, New York, pp84-97

Ghee, C., Silcock, D., Astrop, A. and Jacobs,G. (1997): Socio-economic aspects of Road Accidents in Developing Countries. TRL Report 247, pp29

Glauz, W.D., Bauer, K.M. and Migletz, D.J.(1985): Expected Traffic Conflict Rates and their use in Predicting Accidents. *Transportation Research Record 1026*, TRB, National Research Council, Washington D.C., pp1-12.

Glauz, W.D. and Migletz, D.J.(1980): Application of Traffic Conflict Analysis at Intersections. *NCHRP Report 219*, TRB, National Research Council, Washington D.C., pp109.

Hakkert, A.S. and Mahalel, D. (1978): Estimating the number of Accidents at Intersections from the knowledge of Traffic Flows from the Approaches. *Accident Analysis and Prevention*, **10** (1), pp69-79

Hall, R.D. and Surl, R.A.J. (1981): Accidents at Four-arm Roundabouts and Dual-carriageway Junctions – Some Preliminary Findings. *Traffic Engineering and Control*, 22(6), pp339-344

Hanna, J.T., Flynn, T.E, and Tyler, W.L. (1976): Characteristics of Intersection Accidents in Rural Municipalities. *Transportation Research Record 601*, TRB, National Research Council, Washington D.C., pp79-82

Hauer, E. (2001): Overdispersion in Modelling Accidents on Road Sections and in Empirical Bayes Estimation. *Accident Analysis and Prevention* 33(6), pp799-808

Hauer, E. (1995): On Exposure and Accident Rate. *Traffic Engineering & Control*, 36 (3), pp134-138

Hauer, E. (1992): Empirical Bayes Approach to the Estimation of "Unsafety": The Multivariate Regression Method. *Accident Analysis & Prevention*, 24 (5), pp457-477

Hauer, E. and Lovell, J. (1986): New Directions for Learning about Safety Effects of Measures. *Transportation Research Record 1068,* Transportation Research Board, National Research Council, Washington D.C, pp96-107.

Hauer E., Ng, J. C. N. and Lovell J., (1989): Estimation of Safety at Signalised Intersections. *Transportation Research Record 1185*, Transportation Research Board, National Research Council, Washington D. C., pp48-61

Hauer, E. and Persaud, B. N. (1987): How to Estimate the Safety of Rail-Highway Grade Crossings and the Safety Effects of Warning Devices. *Transportation Research Record 1114*, Transportation Research Board, National Research Council, Washington D.C, pp131-139.

Hauer, E. and Persaud, B. N. (1983): A Common Bias in Before-and-After Accident Comparisons and its Estimation. *Transportation Research Record 905,* Transportation Research Board, National Research Council, Washington D. C., pp164-174.

Highway Capacity Manual (1997): *Special Report 209*. Transportation Research Board, National Research Council, Washington, D. C.

Higle, J. L. and Witkowski, J. M. (1988): Bayesian Identification of Hazardous Locations. *Transportation Research Record 1185*, Transportation Research Board, National Research Council, Washington D. C., pp24-31.

Hills, B., Elliot, G. and Clarke, D. (1994): Microcomputer Accident Analysis Package *v5.0 (MAAPfive) User Guide*. Transport Research Laboratory, Overseas Centre, Crowthorne, Berks, UK

Hills, B. L. and Jacobs, G. D. (1981): The Application of Road Safety Countermeasures in Developing Countries, *Traffic Engineering & Control*, 22 (8/9), pp464-468

Hyden, C. (1987): The Development of a Method for Traffic Safety Evaluation: Swedish Traffic Conflicts Technique. *Bulletin 70*, Department of Traffic Planning and Engineering, University of Lund, Lund, Sweden.

Hyden, C. and Almqvist, S. (1995): Traffic Safety Assessments Based on Traffic Conflicts: Field Studies in Kingston, Jamaica. *Working Report No. 7136.* Department of Traffic Planning and Engineering, University of Lund, Lund, Sweden.

Institute of Transport Economics (1977): Proceedings from the First Workshop on Traffic Conflicts. Oslo, Norway, pp142

Institute of Transportation Engineers (1982): Transportation and Traffic Engineering Handbook, Second Edition, Prentice-Hall International, London, pp717-722

Jaadan, K. S. and Nicholson, A. J. (1992): Relationships Between Road Accidents and Traffic Flows in an Urban Network, *Traffic Engineering & Control*, 33 (9), pp507-511.

Jovanis, P.P. and Chang, H-L (1986): Modelling the Relationship of Accidents to Miles Travelled, *Transportation Research Record 1068*, Transportation Research Board, pp42-51

King, G.F.and Goldblatt, R.B. (1986): Relationship of Accident Patterns to Type of Intersection Control, *Transportation Research Record 540.* Transportation Research Board, National Research Council. Washington D.C., pp1-12.

Kulmala, R., (1995): Safety at Rural Three- and Four-arm Junctions, Development and Application of Accident Prediction Models. Espo 1995, Technical Research Centre of Finland, *VTT 233*, 104p

Kulmala, R., (1994): Measuring the Safety Effects of Road Measures at Junctions. *Accident Analysis & Prevention*, 26 (6), pp781-794

Lalani, N. and Walker, D. (1981): Correlating Accidents and Volumes at Intersections and on Urban Arterial Street Segments, *Traffic Engineering & Control*, 22(6), pp359-363.

Lau, M. Y. K. and May, A. D. (1986): *Accident Prediction Models for Signalised Intersections: Working Paper.* Institute of Transportation Studies, University of California, Berkeley, 105p

Layfield, R. E., Summersgill, I., Hall, R. D. and Chatterjee, K. (1996): Accidents at Urban Priority Crossroads and Staggered Junctions, *TRL Report 185,* Transport and Road Research Laboratory, Crowthorne. 120p

Leong, H.J.W.(1973): Relationship between Accidents and Traffic Volumes at Urban Intersections, *Australian Road Research*, 5(3), pp72-90

Lindsay, J. K (1999): On the use of Corrections for Overdispersion, *Journal of Royal Statistical Society (Applied Statistics), Part C,* 48(4), Blackwell Publishers, pp553-561.

Lovell, J. and Hauer, E. (1986): The Safety Effects of Conversion to All-way Stop Control, *Transportation Research Record 1068.* TRB, National Research Council, Washington D.C., pp103-107.

Lum, H. S. and Parker, M. R. (1982): Intersection Control and Accident Experience in Rural Michigan, *Public Roads 46,* 13p.

Lum, H. S. and Stockton, W. R. (1982): Stop Sign, Versus Yield Sign, *Transportation Research Record 881.* Transportation Research Board, National Research Council, Washington D. C., pp29-33.

Maher, M. J. (1987): Accident Migration – A Statistical Explanation? *Traffic Engineering & Control,* 28 (9), pp480-483.

Maher, M. J. and Mountain, L. J. (1988): The Identification of Accident Blackspots: A Comparison of Current Methods, *Accident Analysis & Prevention,* 20(2), pp143-151.

Maher, M. J. and Summersgill, L. (1996): A Comprehensive Methodology for the Fitting of Predictive Accident Models, *Accident Analysis & Prevention,* 28 (3), pp281-296.

Malaterre, G. and Muhlrad, N. (1980): Conflicts and Accidents as Tools for a Safety Diagnosis, Proceedings of 2nd International Traffic Conflict Technique Workshop, *TRRL Supplementary Report 557*, pp43-63.

Manual on Uniform Traffic Control Devices (1978), U.S. Department of Transportation, Federal Highway Administration, Washington, D.C

Maycock, G. and Hall, R.D. (1984): Accidents at Four-arm Roundabouts, *TRRL Report LR 1120,* Transport and Road Research Laboratory, Crowthorne.

McCullagh, P. and Nelder, J. A. (1989): *Generalized Linear Models: Monographs on Statistics and Applied Probability 37*, Chapman & Hall, London.

McGuigan, D.R.D. (1978): Traffic Signals and Road Accidents. *Traffic Engineering & Control*, 19(8/9), pp420.

McGuigan, D.R.D. (1981): The use of Relationships between Road Accidents and Traffic Flow in "Blackspot" Identification. *Traffic Engineering & Control*, 22(8/9), pp448-453.

Miaou, S. and Lum, H. (1993): Modelling Vehicle Accident and Highway Geometric Design Relationships, *Accident Analysis & Prevention*, **25** (6), pp689-709.

Milton, J. and Mannering, F. (1998): The Relationship among Highway Geometrics, Traffic-related Elements and Motor-Vehicle Accident Frequencies. *Transportation* **25**, pp395-413

Mountain, L., Maher, M. and Fawaz, B. (1998): Improved Estimates of the Safety Effects of Accident Remedial Schemes. *Traffic Engineering & Control*, 39 (10), pp554-558.

Mountain, L. and Fawaz, B. (1996): Estimating Accidents at Junctions Using Routinely Available Input Data. *Traffic Engineering & Control*, 37 (11), pp624-628.

Mountain, L., Fawaz, B. and Jarret, D. (1996): Accident Prediction Models for Roads with Minor Junctions, *Accident Analysis & Prevention*, 28 (6), pp695-707.

Mountain, L., Fawaz, B. and Jarret, D. (1995): The Influence of Minor Junctions on Link Accident Frequencies. *Traffic Engineering & Control*, 36 (12), pp673-679.

Mountain, L. Fawaz, B. and Sineng, L. (1992a): The Assessment of Changes in Accident Frequencies on Link Segments: A Comparison of Four Methods. *Traffic Engineering & Control*, 33 (7/8), pp429-434.

Mountain, L., Fawaz, B., and Sineng, L. (1992b): The Assessment of Changes in Accident Frequencies at Treated Intersections: A Comparison of Four Methods. *Traffic Engineering & Control*, 33 (2), pp85-87.

Nicholson, A. J. (1986): The Randomness of Accident Counts, *Accident Analysis & Prevention*, 18 (3), pp193-198.

Numerical Algorithms Group (1996): *GLIM 4* Macro Library Manual, Release 2.0, Royal Statistical Society.

Numerical Algorithms Group (1993): *GLIM 4*: The Statistical System for Generalised Linear Interactive Modelling. Clarendon Press, Oxford.

'O'Brian, L (1992): Introduction to Quantitative Geography: Measurement, Methods and Generalised Linear Models. Chapman and Hall, New York, pp202-266

Perkins, S.R. and Harris, J.I. (1968): Traffic Conflict Characteristics - Accident Potential at Intersections. *Highway Research Record 225*, HRB, National Research Council, Washington D.C., pp35-43

Persaud, B. N. (1988): Do Traffic Signals Affect Safety? Some Methodological Issues, *Transportation Research Record 1185*. Transportation Research Board, National Research Council, Washington D. C., pp37-47.

Persaud, B. N. (1986): Safety Migration, the Influence of Traffic Volumes and Other Issues in Evaluating Safety Effectiveness – Some Findings on Conversion of Intersections to Multiway Stop Control, *Transportation Research Record 1068*. Transportation Research Board, National Research Council, Washington D. C. pp108-114.

Persaud, B.N. and Hauer, E. (1984): Comparison of Two Methods for Debiasing Before and After Studies, *Transportation Research Record 975*, TRB, National Research Council, Washington D.C., pp43-49

Pickering, D., Hall, R.D. and Grimmer, M. (1986): Accidents at Rural T-junctions, *TRRL Report RR65*, Transport and Road Research Laboratory, Crowthorne.

Polus, A. (1985): Driver Behaviour and Accident Records at Unsignalised Urban Intersections, *Accident Analysis & Prevention*, 17 (1), pp25-32.

Rodriguez, L. F. and Sayed, T (1999): Accident Prediction Models for Urban Unsignalised Intersections in British Columbia, *Proceedings of 78th Annual General Meeting of Transportation Research Board*, January, 10-14, 1999, Washington D.C.

Ronald, W. E. and James, A. B. (1988): Field Evaluation of Two-way Versus Four-way Stop Sign Control at Low-Volume Intersections in Residential Areas. *Transportation Research Record 1160*, Traffic Control Devices. Transportation Research Board, National Research Council, Washington D. C. pp7-13.

Rosenbaum, M. J. (1983): A Review of Research Related to the Safety of Stop Versus Yield Sign Traffic Control, *Public Roads 47*, pp77-81.

Salifu, M. (1998): Driver Behaviour at Uncontrolled Pedestrian Crossings in Kumasi, *Journal of Building and Road Research*, 6(1&2), pp25-27

Salifu, M. (1998): Introduction to Driver Training and Licensing in Ghana, *International Association of Traffic and Safety Sciences (IATSS) Research*, 21(1), pp104-105

Salifu, M. and Mock, C. (1998): Pedestrian Injuries in Kumasi – Results of an Epidemiologic Survey, *The Ghana Engineer*, 18(1), pp23-27

Salifu, M. (1996): Urban Pedestrian Accidents in Ghana, *International Association of Traffic and Safety Sciences (IATSS) Research,* 20(1), pp131-139

Salifu, M., Djokoto, S. and Nyarko-Marfo, K. (1996): Speeds and Speed Limits on Urban Arterial Roads, *The Ghana Engineer*, 15(1), pp27-35

Shankar, V., Milton, J. and Mannering, F. (1997): Modelling Accident Frequencies as Zero-Altered Probability Processes: An Empirical Inquiry, *Accident Analysis and Prevention*, 29(6), pp829-837

Summersgill, I., Kennedy, J. V. and Baynes, D. (1996): Accidents at Three-arm Priority Junctions on Urban Single-carriageway Roads, *TRL Report 184.* Transport Research Laboratory, Crowthorne

Tanner, J.C. (1953): Accidents at Rural 3-way Junctions, *Journal of Institution of Highway Engineers*, 2(11), pp56-67

Transport Research Laboratory (1991): Towards Safer Roads in Developing Countries, A Guide to Planners and Engineers. Overseas Development Administration, United Kingdom

Upchurch, J. E. (1983): Guidelines for Use of Sign Control at Intersections to Reduce Energy Consumption, *ITE Journal 53*, pp22-34.

Walpole, R.E. (1982): Introduction to Statistics, 3rd Edition. Macmillan Publishers, London

Worsey, G. (1985): Predicting Urban Accident Rates from Road and Traffic Characteristics, *ITE Journal*, pp16-22

Wright, C. C., Abbess, C. R. and Jarret, D. F. (1988): Estimating the Regression-to-mean Effect Associated with Road Accident Blackspot Treatment: Towards a More Realistic Approach, *Accident Analysis & Prevention,* 20 (3), pp199-214

Wright, C.C. and Boyle, A. J. (1987): Road Accident Causation and Engineering Treatment: A Review of Some Current Issues. *Traffic Engineering & Control*, 28 (9), pp475-479.

APPENDIX 3I

Sample of Accident Report Form

1 REPORT NUMBER /　2 YEAR　3 REGION　TOWN (if urban)

GHANA POLICE SERVICE

ROAD ACCIDENT REPORT

4 POLICE STATION

☐ URBAN:
☐ RURAL ______ KM FROM ______ TOWARDS ______
(TOWN) (TOWN)

NAME OF ROAD/STREET/OTHER
☐ MAJOR ROAD ☐ MINOR ROAD

☐ INTERSECTION WITH ______ (ROAD/STREET)
☐ NON INTERSECTION: BETWEEN ______ AND ______
(ROAD/STREET) (ROAD/STREET)

5 No of vehicles involved ______
6 No of vehicles damaged ______

Severity of injury	drivers	passengers	pedestrians
Killed	7.	8	11
Injured	9	10	12

DATE 13 day | 14 month | year

15 DAY OF WEEK

TIME (24hrs) 16 hour 17 mins

18 ACCIDENT SEVERITY
F. Fatal　I. inj not hospitalised
H. inj & hospitalised　D. damage only

19 WEATHER VISIBILITY
1. clear
2. fog/mist
3. rain
4. dust/smoke
5. dazzle
6. other ______

20 LIGHT CONDITIONS
1. day
2. dawn/dusk no street lights
3. dawn/dusk street lights on
4. dawn dusk street lights off
5. night no street lights
6. night street lights off
7. night street lights on

21 ROAD DESCRIPTION
1. straight and flat
2. curve only
3. incline only
4. curve and incline
5. bridge (name river) ______
6. croad

22 TRAFFIC MOVEMENT
1. one way
2. two way

23 ROAD SEPARATION
1. central reserve
2. No central reserve

24 ROAD SURFACE TYPE
1. tar good
2. tar few potholes
3. tar many potholes
4. gravel
5. earth few potholes
6. earth many potholes

25 ROAD WIDTH ______ metres

26 SHOULDER WIDTH ______ metres

27 SHOULDER
1. tarred
2. untarred
3. no shoulder
4. shoulder overgrown

28 SURFACE CONDITION
1. dry
2. wet
3. muddy
4. flooded
5. loose gravel

29 Bad road edge
☐ Yes ☐ No

30 LOCATION TYPE
1. not at junction
2. ┼
3. ┬
4. ┴┬
5. Y
6. ○
7. R/way crossing
8. other

31 TRAFFIC CONTROL
1. none
2. centreline only
3. pedest. crossing
4. school crossing
5. police / city guard
6. traffic signals
7. stop sign
8. give way
9. other

32 HIT & RUN
1. not hit & run
2. yes hit & run

33 COLLISION TYPE
1. head on
2. rear end
3. right angle
4. side swipe
5. Overturned
6. hit object on road
7. hit object off road
8. hit parked veh
9. hit pedestrian
10. other

34 ROADWORKS
1. not at roadworks
2. at roadworks

35 ACCIDENT ATTENDED
1. attended by police
2. reported at station
3. report after 24 hours or more

36 MAJOR OFFENDER
veh. No.

37 COMPLETE FOR HQ OFFICE USE ONLY

OWNER'S NAME　VEHICLE 1.
OWNER'S ADDRESS
MOTOR INSURANCE TYPE
POLICY NUMBER
PLACE ISSUED　Expiry Date
ROAD WORTHINESS CERT. ☐ Yes ☐ No　Place of issue　Cert. number　Expiry Date
38 MAKE　39 MODEL　40 VEH. AGE　41 REGION OF REGISTRATION
REGIST NO.

42 VEHICLE TYPE
1　5
2　7
3　8
4　9 other
5　? unknown

43 OWNERSHIP/USAGE
1. govt. veh　6. commercial
2. company　7. hire car
3. private　8. police/military
4. taxi　9. emergency veh.
5. bus　10. other

44 VEHICLE MANOEUVRE
1. right turn
2. left turn
3. U turn
4. cross traffic
5. merging
6. diverging
7. overtaking
8. going ahead
9. reversing
10. sudden start
11. sudden stop
12. parked off road
13. parked on road
14. other ______

45 VEHICLE DAMAGE
CIRCLE DAMAGE TO VEHICLE 1
4
2　6 ROOF　3
5
1. no damage
7. underside
8. multiple
9. damage no details
? unknown

SKETCH DAMAGE TO BIKES, TRACTORS, TRAILERS, ETC.

46 NOSE TO TAIL
1. No
2. yes front veh.
3. yes rear veh.
4. yes middle veh.
? unknown

47 LOADING
1. OK load
2. overloaded
3. insecure load
4. protruding load
5. other improper load

48 LIGHTING DEFECTS
1. none　4. brake lights
2. headlights　5. indicators
3. rearlights　6. multiple

49 OTHER DEFECTS
1. none　2. brakes　3. steering　4. tyres　5. suspension　6. rollbars　7. multiple　8. other

DRIVER'S NAME　DRIVER 1　50 SEX　51 AGE　52 NAT.
DRIVER'S ADDRESS　PHONE

53 DRIVER INJURY
F fatal
H inj. & hospitalised
I inj. not hospitalised
O no injury

54 INJURY TYPE
Insert number from diagram below ______

55 LICENCE No
CLASS
RESTRICTION
EXPIRY DATE
56 PLACE OF ISSUE

57 LICENCE STATUS
1. FULL LICENCE
2. PROVISIONAL LICENCE
3. LEARNERS PERMIT
4. UNLICENCED

Driver's Profession

58 DRIVING EXPERIENCE ______ YEARS

59 DRINK/DRIVING
1. not suspected
2. suspected
3. tested & positive
4. tested & negative
?. unknown

60 DRIVER ERROR
1. none　7. improper o/taking
2. inexperience　8. improper turning
3. inattentive　9. fatigued/asleep
4. too fast　10. loss of control
5. too slow　11. other
6. no signal

TYPE OF INJURY
0 Nil
9 multiple
1 2 3 4 5 6 7 8

OWNER'S NAME　VEHICLE 2
OWNER'S ADDRESS
MOTOR INSURANCE TYPE
POLICY NUMBER
PLACED ISSUED　Expiry Date
ROAD WORTHINESS ☐ Yes ☐ No　Place of issue　Expiry Date
38 MAKE　39 MODEL　40 VEH. AGE　41 REGION OF REGISTRATION
REGIST. NO.

42 VEHICLE TYPE
1　5
2　7
3　8
4　9 Other
5　? unknown

43 OWNERSHIP/USAGE
1. govt. veh　6. commercial
2. company　7. hire car
3. private　8. police/military
4. taxi　9. Emergency veh.
5. bus　10. other

44 VEHICLE MANOEUVRE
1. right turn
2. left turn
3. U turn
4. cross traffic
5. merging
6. diverging
7. overtaking
8. going ahead
9. reversing
10. sudden start
11. sudden stop
12. parked off road
13. parked on road
14. other

45 VEHICLE DAMAGE
CIRCLE DAMAGE TO VEHICLE 2
4
2　6 ROOF　3
5
1. no damage
7. underside
8. multiple
9. damage no details
? unknown

46 NOSE TO TAIL
1. No
2. yes front veh.
3. yes rear veh.
4. yes middle veh.
? unknown

47 LOADING
1. OK load
2. overloaded
3. insecure load
4. protruding load
5. other improper load

48 LIGHTING DEFECTS
1. none　4. brake lights
2. headlights　5. indicators
3. rearlights　6. multiple

49 OTHER DEFECTS
1. none　2. brakes　3. steering　4. tyres　5. suspension　6. rollbars　7. multiple　8. other

DRIVER'S NAME　DRIVER 2　50 SEX　51 AGE　52 NAT.
DRIVER'S ADDRESS　PHONE

53 DRIVER INJURY
F fatal
H inj & hospitalised
I inj not hospitalised
O no injury

54 INJURY TYPE
Insert number from diagram below ______

55 LICENCE NO:
CLASS
RESTRICTION
EXPIRY DATE
56 PLACE OF ISSUE

57. LICENCE STATUS
1. FULL LICENCE
2. PROVISIONAL LICENCE
3. LEARNERS PERMIT
4. UNLICENCED

Driver's profession

58. DRIVING EXPERIENCE ______ YEARS

59. DRINK/DRIVING
1. not suspected
2. suspected
3. tested & positive
4. tested & negative
? unknown

60. DRIVER ERROR
1. none　7. improper o/taking
2. inexperience　8. improper turning
3. inattentive　9. fatigued/asleep
4. too fast　10. loss of control
5. too slow　11. other
6. no signal

61 ☐☐　62 ☐☐　63 ☐☐　OFFENCES COMMITTED (IF ANY) FOR HQ. OFFICE USE ONLY　61 ☐☐　62 ☐☐　63 ☐☐

APPENDIX 3I (Continued)

NAMES AND ADDRESSES

PASSENGER CASUALITIES

PASSENGERS	VEH NO. 64	SEX 65	AGE 66	INJURY SEV 67	INJURY TYPE 68	POSIT 69	LIQUOR 70	ACTION 71
1.								
2.								
3.								
4.								

PEDESTRIAN CASUALTIES

PEDESTRIANS	SEX 72	AGE 73	SEV. 74	TYPE 75	ACTION 76	LOC. 77	SCHOOL 78
1.							
2.							
3.							

67 74 **INJURY SEVERITY**

- F Fatal
- H hospitalised
- I injured but not hospitalised

68 75 **TYPE OF INJURY**

6 multiple

69 **PASSENGER POSITION**

1. front seat
2. rear seat
3. m/cycle passenger
4. bus passenger

Truck/utility

5. inside
6. outside sitting
7. outside standing
8. other ______

70 **LIQUOR**

1. not suspected
2. suspected
3. unknown

71 **PASSENGER ACTION**

1. boarding
2. alighting/jumping
3. falling from vehicle
4. other ______
9. unknown

76 **PEDESTRIAN ACTION**

1. none
2. crossing road
3. walking along road
4. walking along edge
5. playing on road
6. on footpath
7. other ______
9. unknown

77 **PEDESTRIAN LOCATION**

1. on pedest, crossing
2. within 50m of pedest, crossing
3. on central refuge
4. in-road centre
5. on footpath/verge
6. other ______
9. unknown

78 **SCHOOL PUPILS**

1. adult-not school pupil
2. child not school pupil
3. pupil on school journey
4. pupil not on school journey
9. unknown

FOR HQ OFFICE USE ONLY

79	80	81	82 TYPE	83 TOWN/VILL	84 km POST	85 100 m	86 MAPSER	87 MAP CODE

88 X CO-ORDINATE	89 Y CO-ORDINATE	90 ROUTE NUMBER	91 NODE 1	92 NODE 2	93 DIRECTION

NAMES ADDRESSES-PHONES **WITNESSES**

INDEPENDENT WITNESS ? ☐ YES ☐ NO

INDEPENDENT WITNESS ? ☐ YES ☐ NO

INDEPENDENT WITNESS? ☐ YES ☐ NO

INDEPENDENT WITNESS ? ☐ YES ☐ NO

INDEPENDENT WITNESS ? ☐ YES ☐ NO

WHAT CAUSED THE ACCIDENT?

DRIVER 1 SAID

DRIVER 2 SAID

______________________ SAID

SKETCH OF ACCIDENT SCENE:
MARK ROAD NAMES, DIRECTIONS, VEHICLE POSITION, SIGNS, SIGNALS, STREET LIGHTS ETC.

POLICE DESCRIPTION OF ACCIDENT:

SITE LOCATION SKETCH

show location of
site in relation to
prominent buildings
landmarks bridges etc.
indicate distance
from such prominent
landmark etc.

INVESTIGATING OFFICER'S NAME RANK NUMBER

DATE SUBMITTED

REVIEWING OFFICER'S NAME RANK NUMBER

DATE

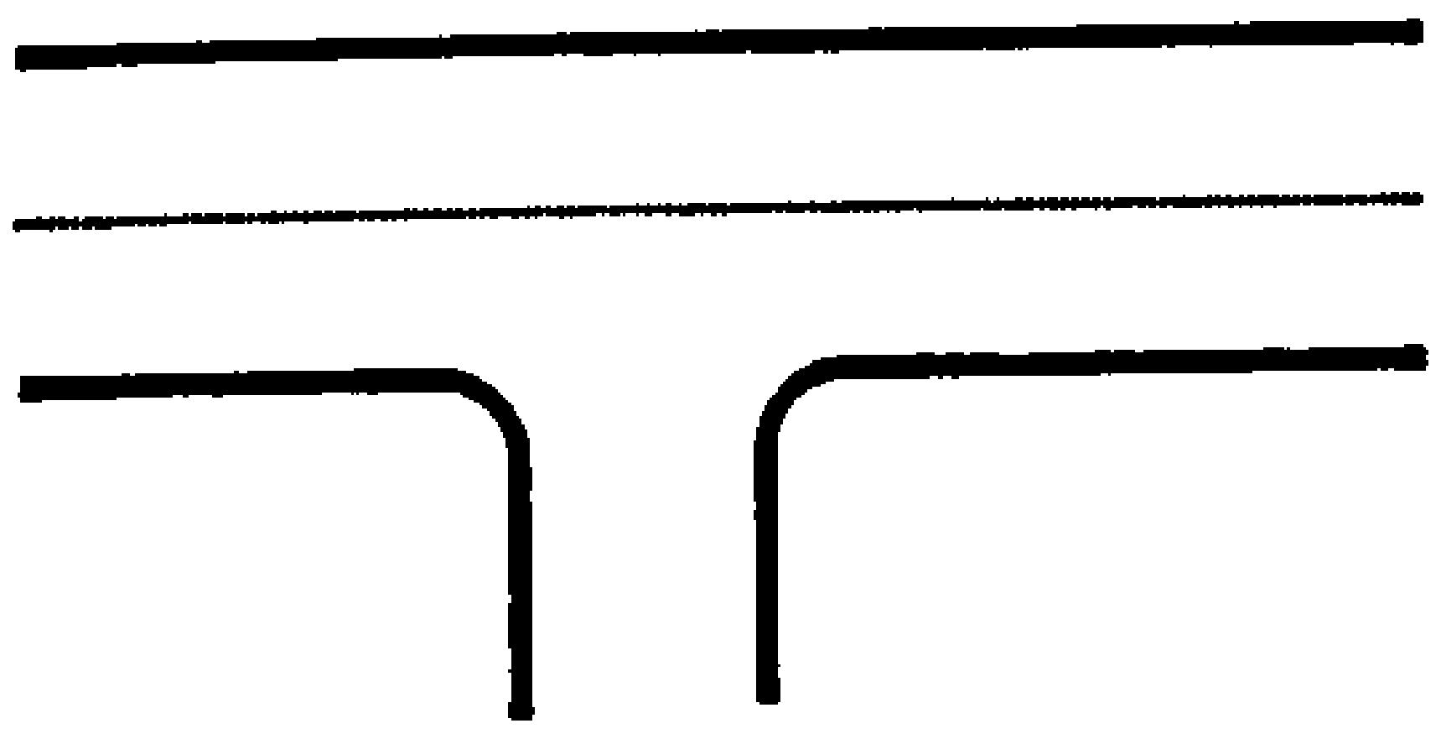
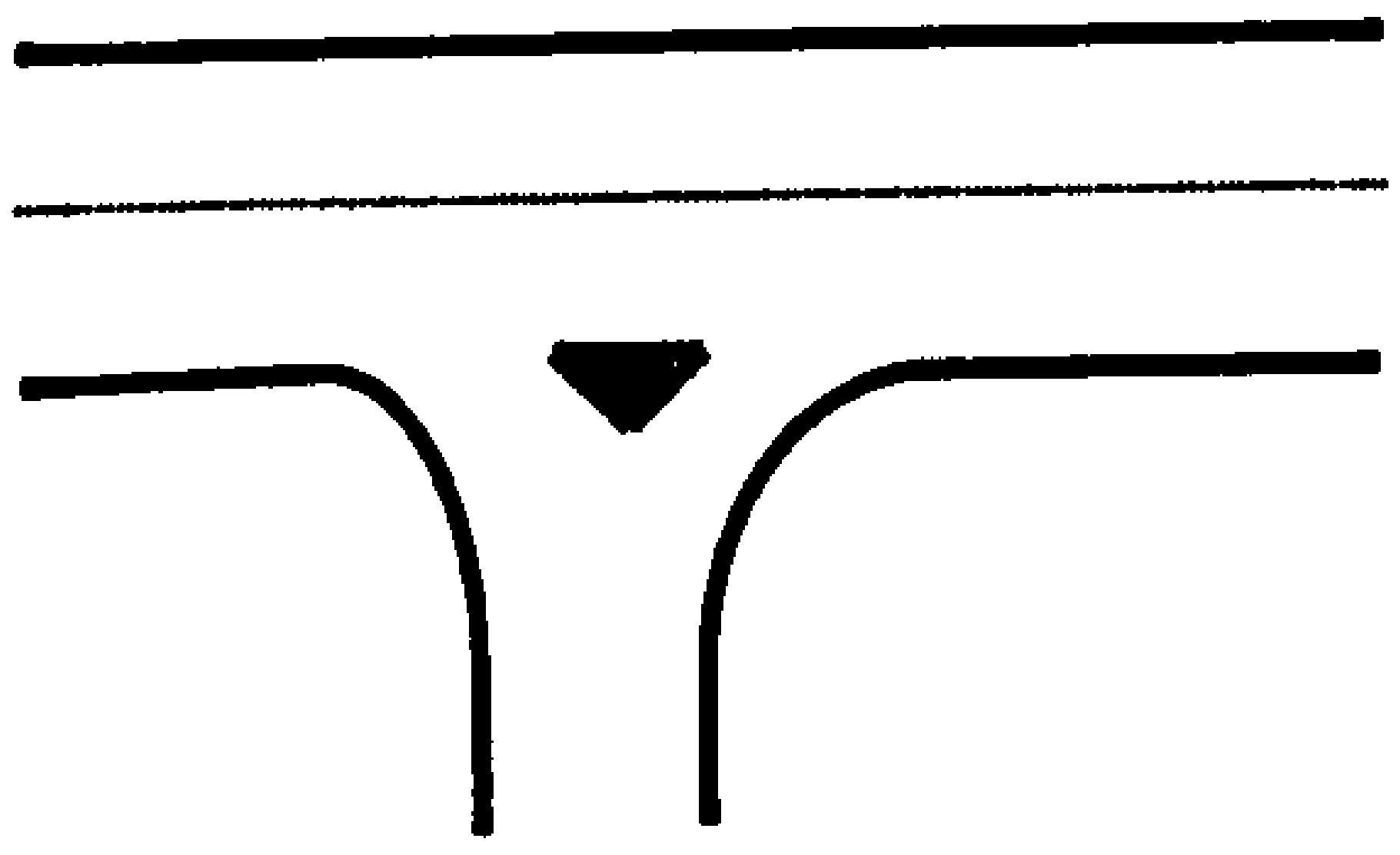
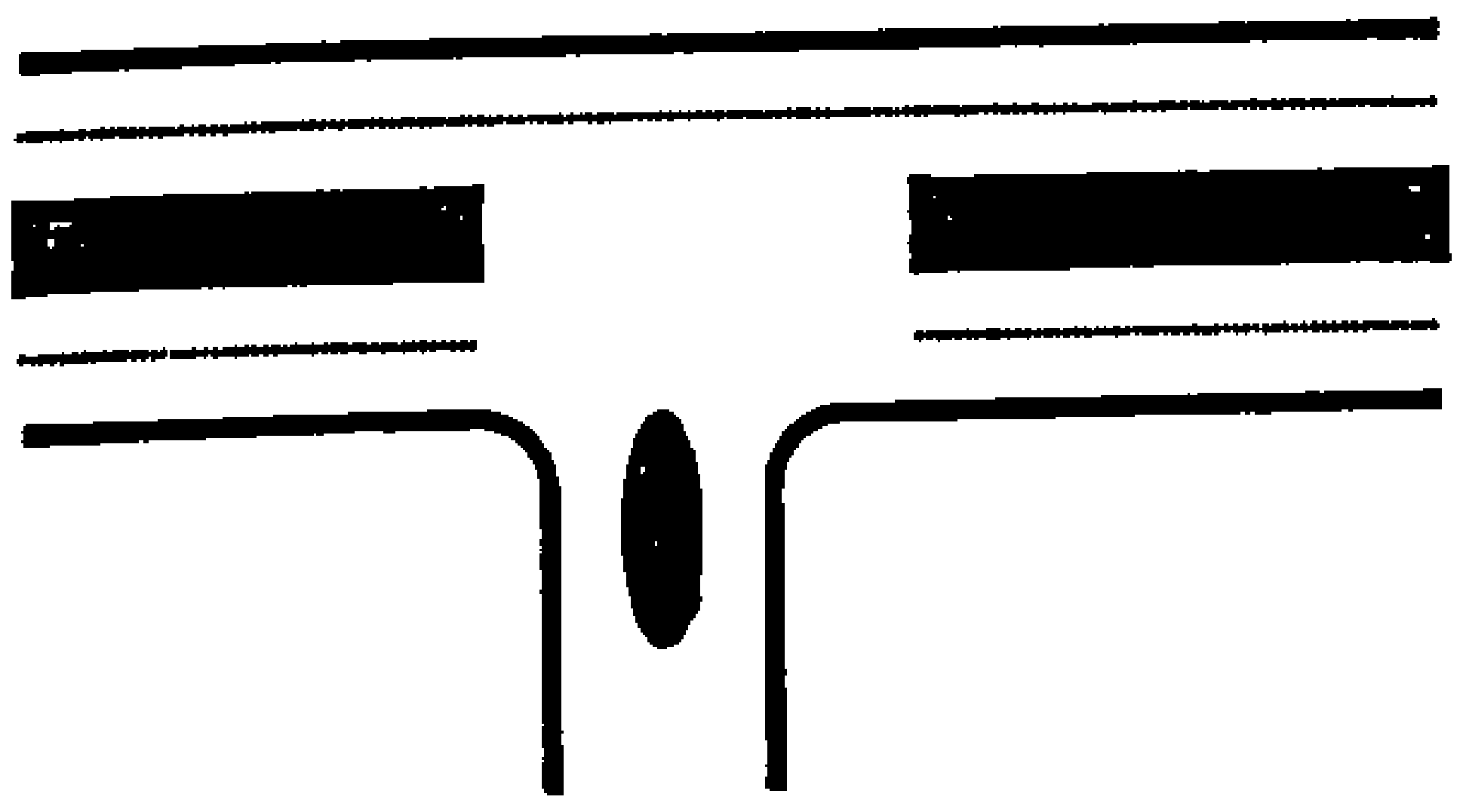
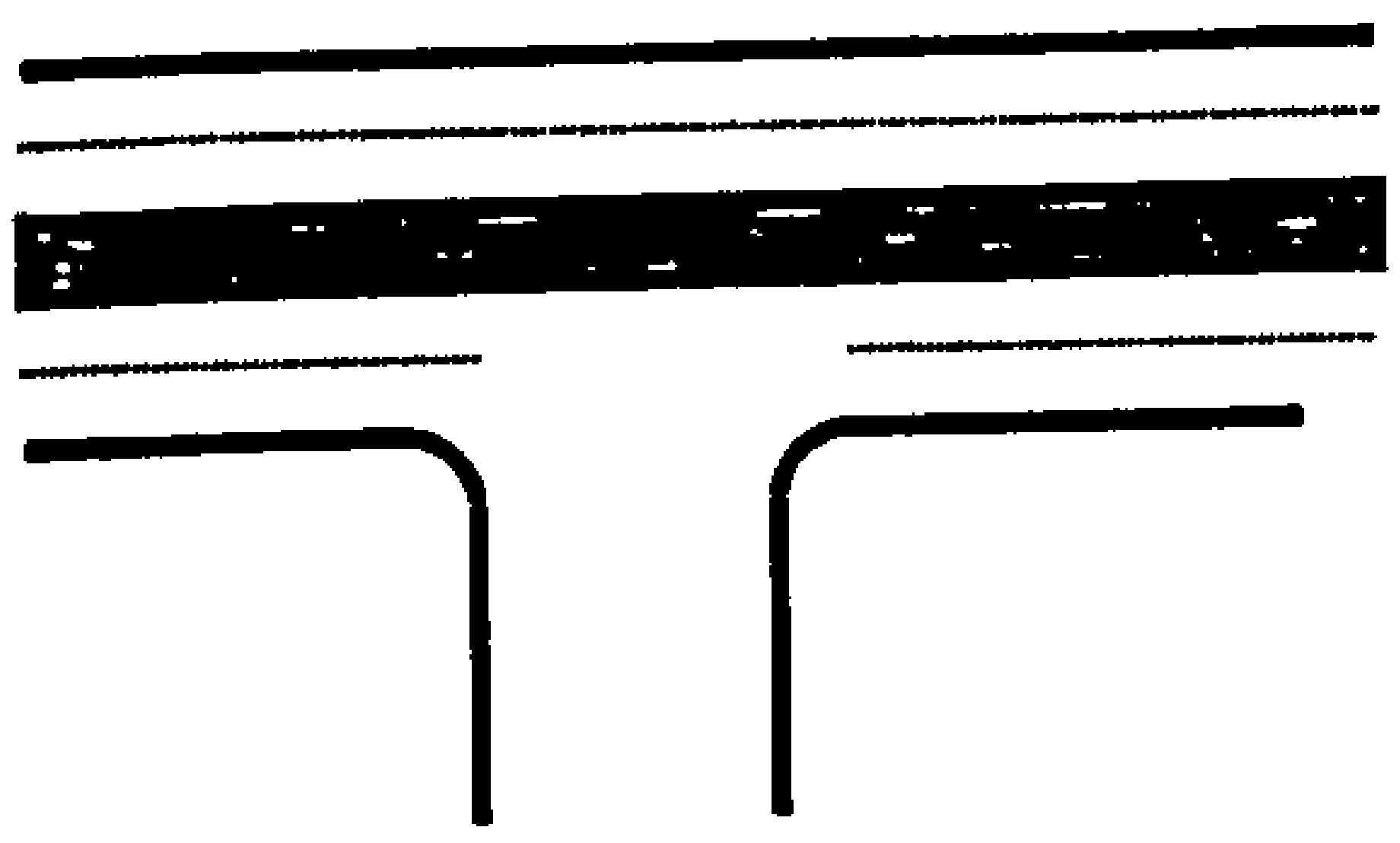
ACTION PROPOSED SECTION

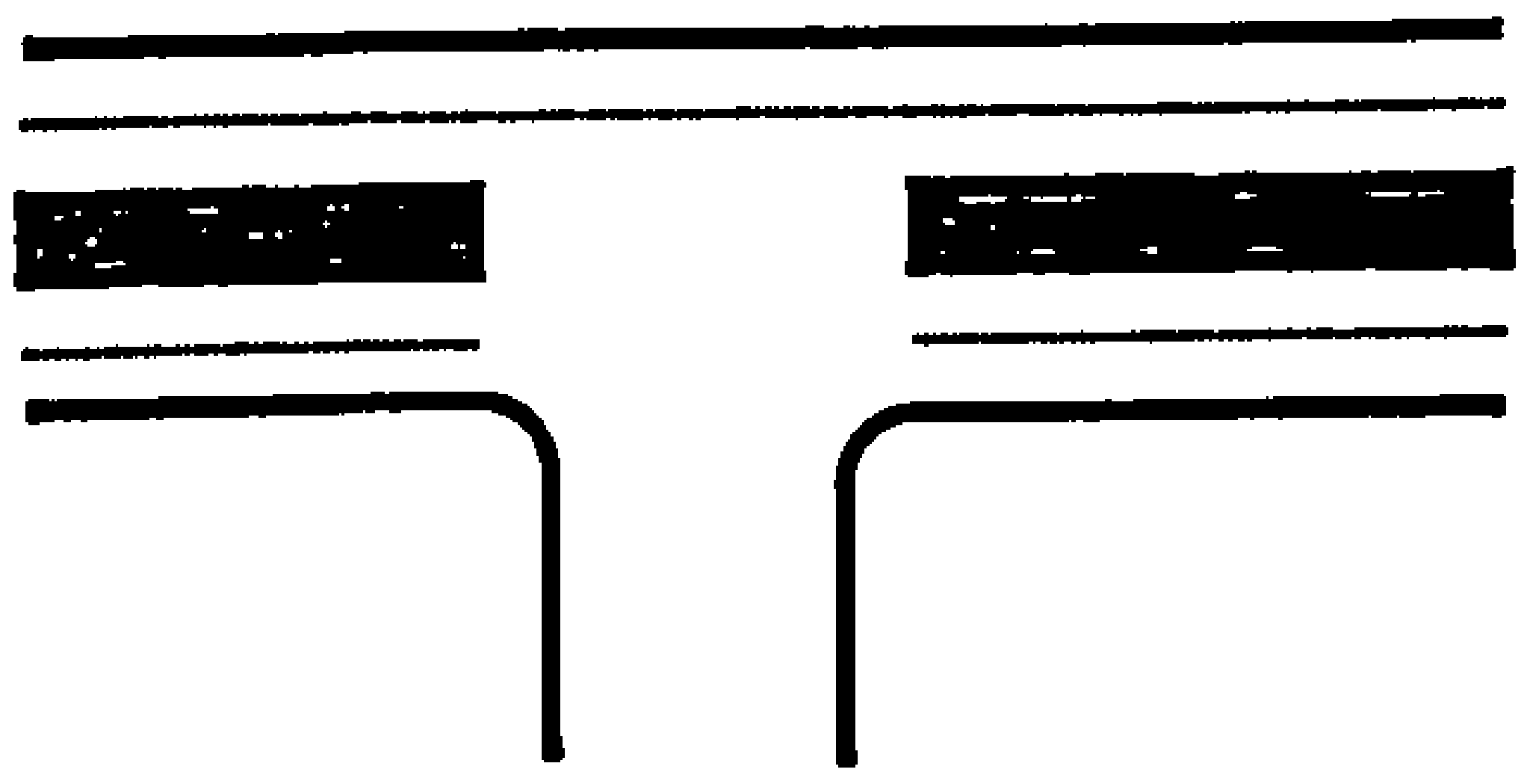
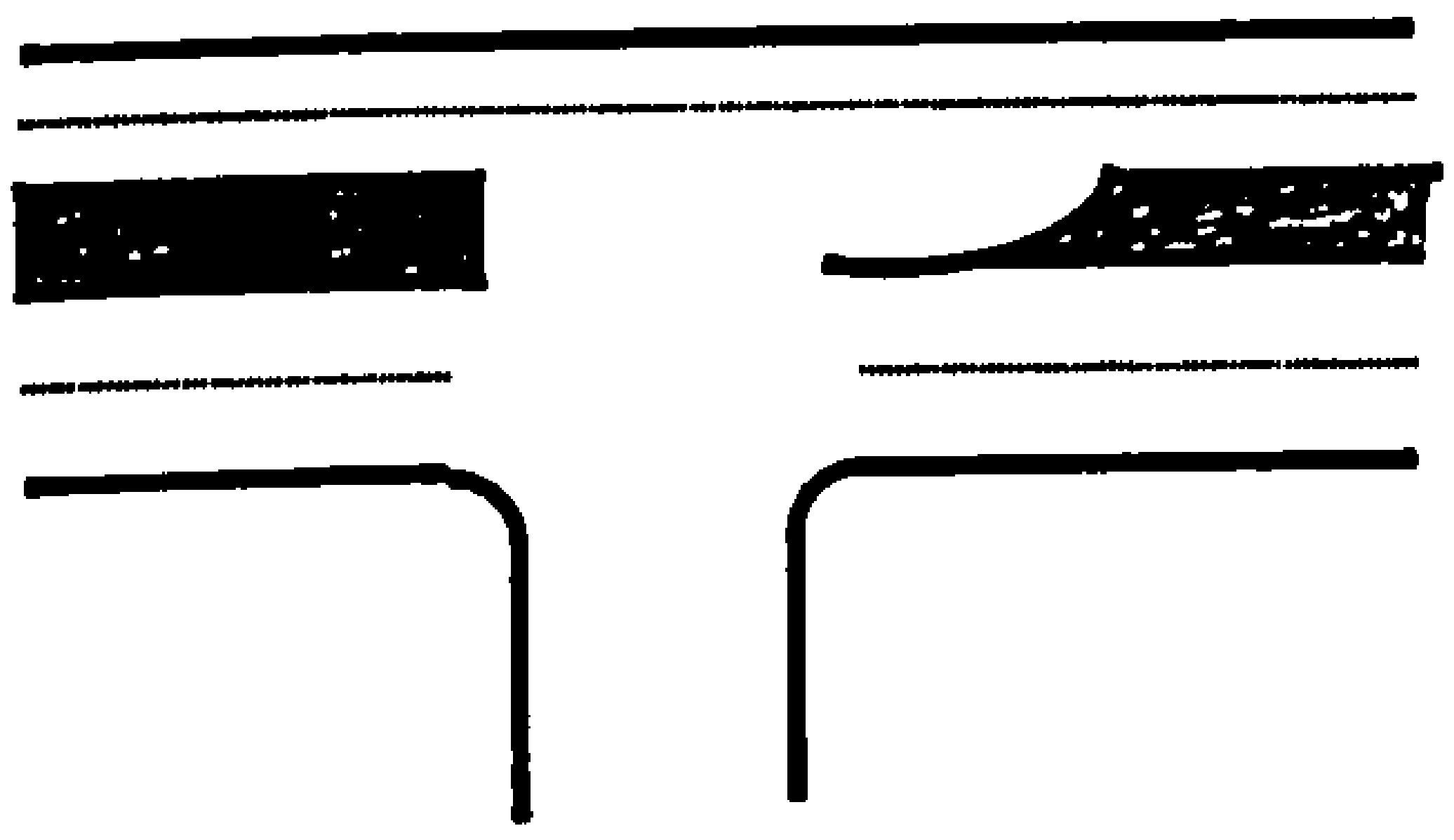
CONFIRMED/VARIED

APPENDIX 3II

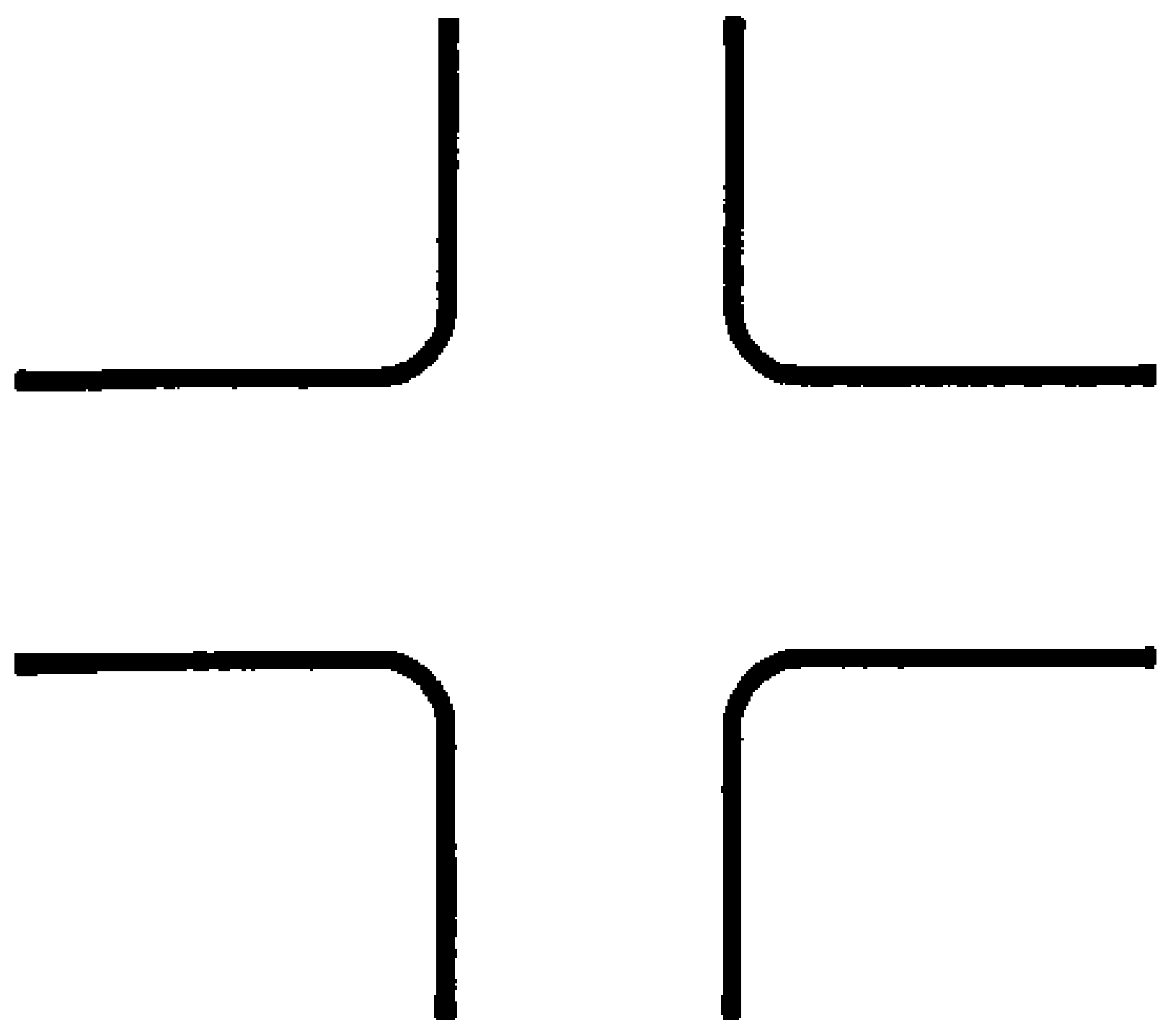
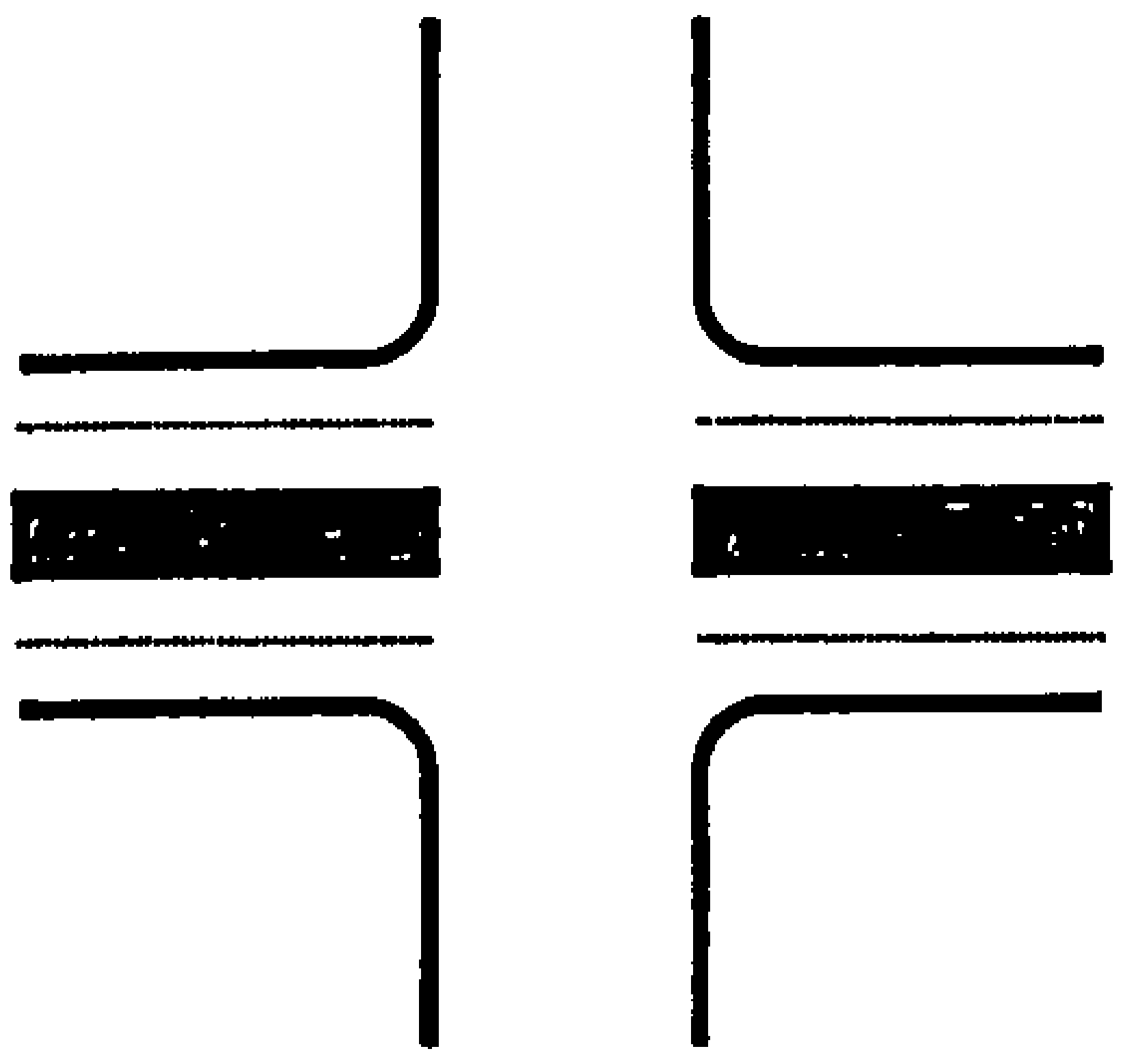
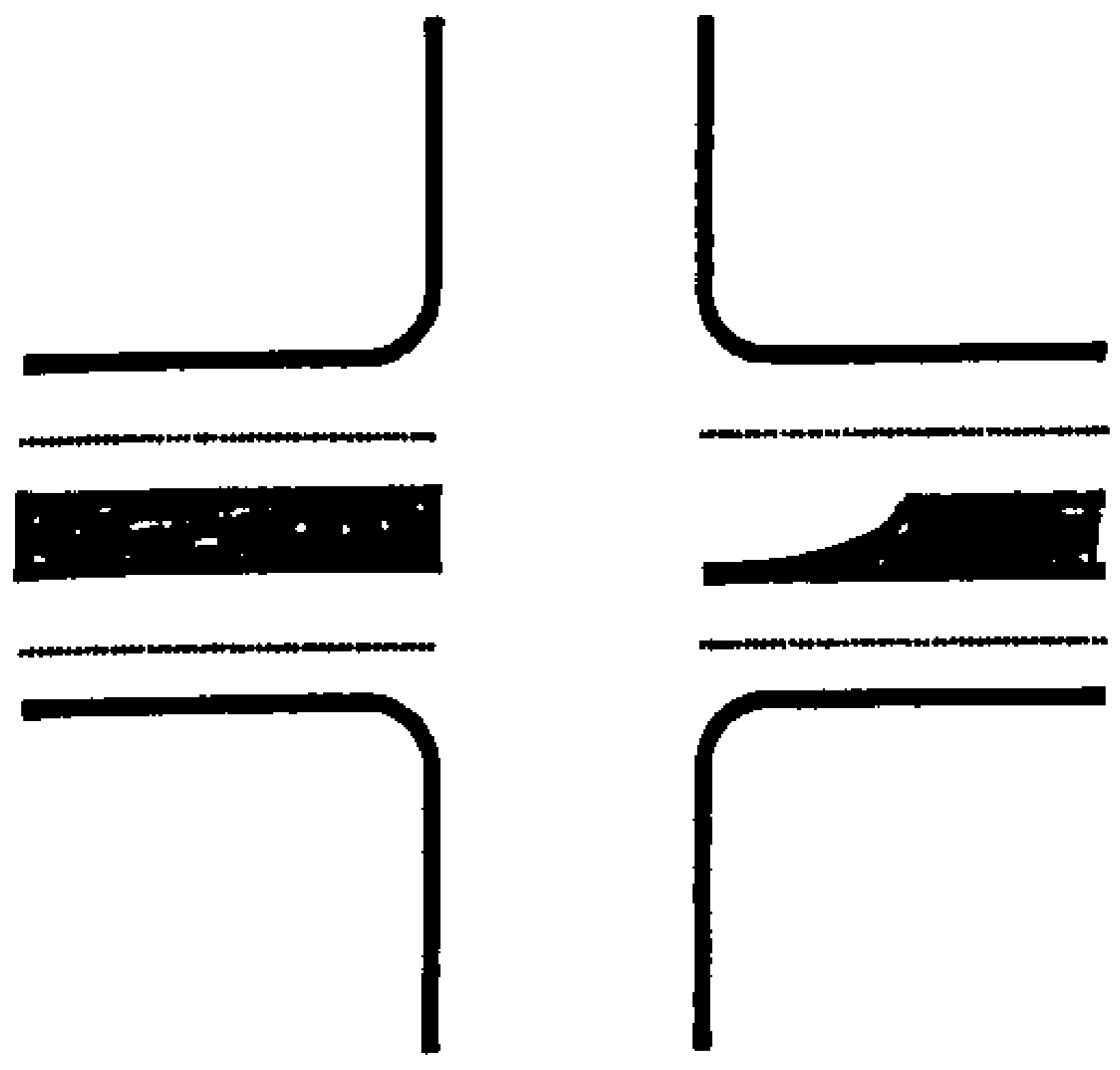
TYPOLOGY OF JUNCTIONS

T-JUNCTIONS

	Major road	Minor Road
T-1 	No features	No features
T-2 ("Bennett Junction") 	No features	Island, with two-way traffic on both sides of island
T-3 	Kerbed medians, with two lanes in each direction	Island, with one-way traffic on either side of island
T-4 	Kerbed median strip, left turn not possible	No features, left turn not possible

	Major Road	Minor Road
T-5 	Kerbed medians, two approach lanes, left turn to and from minor road possible.	No features
T-6 	Kerbed medians, two approach lanes, left turn to and from minor road possible, dedicated storage lane for left-turn.	No features

X-JUNCTIONS

	Major Road	Minor Road
X1 	No features	No features
X2 	Kerbed medians, two approach lanes	No features
X3 	Kerbed medians, two approach lanes, at least one dedicated left-turn storage lane	No features

APPENDIX 4I
Breakdown of Traffic Volumes, Accident Frequencies/Rates by Junction Sites

Table 4IA

Junction-type / name T-1	AADT (veh/day)	Cumulative Traffic carried (1996-1998) (x 10^6veh)	Minor road's share of traffic (%)	Peak hour pedestrian flows across all arms of intersection (peds/h)	All Accidents		Injury Accidents		Pedestrian accidents		Accident casualties	
					(number)	(accidents per 10^6veh.)	(PIA)	(PIA per 10^6veh)	(number)	(number / 10^6veh)	(casualties)	(casualties / 10^6veh)
1. Dadeban/Industrial	10,662	11.67	28.0	26	6	0.51	4	0.34	1	0.08	6	0.51
2. Kwashieman/Sakamana	5,125	5.61	27.3	32	0	0	0	0	0	0	0	0
3. Coastal Rd./Second Junct.	6,970	7.63	26.6	38	6	0.79	1	0.13	1	0.13	1	0.13
4. Coastal Rd./Third Junction	8,948	25.16	3.7	33	1	0.04	1	0.04	0	0	1	0.04
5. Kasapreko/Coastal	8498	9.30	21.0	27	5	0.54	2	0.22	0	0	4	0.43
6. Abooma/Coastal	11,183	7.86	19.0	21	32	4.07	5	0.64	2	0.25	7	0.89
7. Chemu/Banana Inn	6,720	22.5	10.8	33	0	0	0	0	0	0	0	0
8. Darkuman/Link A	7,867	8.61	30.3	22	5	0.58	2	0.23	1	0.12	3	0.35
9. Darkuman/Bubiashie	9,138	10.00	22.9	42	5	0.50	2	0.20	2	0.20	2	0.20
10. Darkuman/Sakaman	7,176	12.24	30.3	58	0	0	0	0	0	0	0	0
11. Chemu/Ed. Mondlana	4,361	4.77	25.3	26	4	0.84	2	0.42	1	0.21	2	0.42
12. AkukorFoto/Dansoman	4,964	5.43	25.2	41	3	0.55	2	0.37	0	0	2	0.37
13. Secretariat/Kinbu	6,550	7.17	18.8	29	7	0.98	1	0.14	0	0	1	0.14
14. Indece Ave/BNI	22,981	9.80	21.4	21	15	1.53	8	0.82	4	0.41	17	1.73
15. Aboabo/Asawasi	13,001	14.24	45.3	202	8	0.56	4	0.28	3	0.21	4	0.28
16. Aboabu/Bus Stop	9,040	9.90	39.7	189	5	0.51	1	0.10	1	0.10	1	0.10
17. Kwadaso Estates Junction	20,171	7.36	23.4	70	7	0.95	3	0.41	2	0.27	6	0.82
18. Police Depot Jn(Edwenasi)	13,083	14.30	19.6	69	2	0.14	1	0.07	1	0.07	1	0.07
19. Ridge Police Stn Junction	21,605	23.60	33.4	30	5	0.21	0	0	0	0	0	0
20. Edwenasi Jn. (Police Dep)	25,348	27.70	48.3	157	8	0.29	3	0.11	2	0.07	4	0.14
21. High School Junction	17,741	19.43	13.1	102	4	0.21	3	0.15	1	0.05	5	0.26
TOTAL	**241,132**	**264.28**	**533.4**	**1268**	**128**	**13.8**	**45**	**4.67**	**22**	**2.17**	**67**	**6.88**
AVERAGE	**11,482**	**12.58**	**25.4**	**61**	**6.10**	**0.66**	**2.14**	**0.22**	**1.05**	**0.10**	**3.19**	**0.33**
STDEV	**6,351**	**6.97**	**10.6**	**55**	**6.85**	**0.87**	**1.96**	**0.22**	**1.12**	**0.11**	**3.84**	**0.41**

Table 4IB

Junction-type / name T-2	AADT (veh/day)	Cumulative traffic carried (1996-1998) (x10^6 veh.)	Minor road's share of traffic (%)	Peak hour pedestrian flows across all arms of intersection (peds/h)	All Accidents		Injury Accidents		Pedestrian Accidents		Accident casualties	
					(number)	(accidents/ 10^6 veh.)	(PIA)	(PIA per 10^{6}veh)	(number)	(number / 10^{6}veh)	(casualties)	(casualties / 10^{6}veh)
1. Timber Gardens	16,853	18.45	28.5	83	13	0.70	4	0.22	2	0.11	5	0.27
2. High street/Dodoo	9,657	10.57	25.0	22	5	0.47	1	0.09	0	0	1	0.09
3. Alajo/Nsawam Rd.	16,144	17.68	18.0	58	9	0.51	0	0	0	0	0	0
4. Agric Jn./Kwadaso	10,628	11.64	28.3	144	7	0.60	2	0.17	1	0.08	2	017
5. Regional Admin. Junction	5,773	6.32	23.4	13	0	0	0	0	0	0	0	0
6. Briscoe Junction	13,125	14.37	32.1	34	5	0.35	1	0.07	0	0	1	0.07
7. Raintree Ave./Pine Avenue	5,490	6.01	46.0	8	0	0	0	0	0	0	0	0
TOTAL	77,670	85.04	201.3	362	39	2.63	8	0.55	3	0.19	9	0.60
AVERAGE	11,096	12.15	28.8	52	5.57	0.37	1.14	0.08	0.43	0.03	1.29	0.08
STDEV	4,561	4.99	8.8	49	4.68	0.28	1.46	0.09	0.78	0.05	1.80	0.10

Table 4IC

Junction-type / name T-3	AADT (veh/day)	Cumulative traffic carried (1996-1998) (x 10^6 veh.)	Minor road's share of traffic (%)	Peak hour pedestrian flows across all arms of intersection (peds/h)	All Accidents		Injury Accidents		Pedestrian Accidents		Accident Casualties	
					(number)	(accidents / 10^{6}veh)	(PIA)	(PIA per 10^{6}veh)	(number)	(number / 10^6 veh)	(casualties)	(casualties / 10^{6}veh)
1. Coastal Rd./First Junction	10,696	11.71	34.5	24	10	0.85	5	0.43	2	0.17	6	0.51
2. Old Winneba/Ring Rd. Ext.	6,677	7.31	39.2	102	3	0.41	3	0.41	3	0.41	3	0.41
3. Ebankese/ Castle Rd.	9,661	10.58	12.1	26	0	0	0	0	0	0	0	0
4. CPC/ Roman Girls	18,769	20.55	8.3	48	7	0.34	3	0.14	0	0	3	0.14
5. Mmrom Jn./ Suame	23,623	25.87	4.0	67	6	0.23	2	0.08	0	0	0	0
6. Alabar Rd./Suame	25,058	27.44	14.5	20	11	0.40	4	0.14	0	0	0	0
TOTAL	94,484	103.46	112.6	287	37	2.63	17	1.20	5	0.58	12	1.06
AVERAGE	15,747	17.24	18.77	49	6.17	0.37	2.83	0.20	0.83	0.10	2	0.18
STDEV	7,780	8.52	14.53	32	4.17	0.28	1.72	0.18	1.33	0.17	2.45	0.23

Table 4ID

Junction-type / name T-4	AADT (veh/day)	Cumulative traffic carried (1996-1998) (x10^6 veh.)	Minor road's share of traffic (%)	Peak hour ped. Flows across all arms of intersection (peds/h)	All Accidents		Injury Accidents		Pedestrian Accidents		Accident casualties	
					(number)	(accidents / 10^6 veh)	(PIA)	(PIA per 10^6 veh)	(number)	(number / 10^6 veh)	(casualties)	(casualties / 10^6 veh)
1. Neoplan/Abrepo	15,793	17.29	33.7	207	18	1.04	5	0.29	3	0.17	6	0.35
2. Labadi/ Giffard	15,066	16.49	40.5	27	0	0	0	0	0	0	0	0
3. Labone/ Ring Rd.	7,663	8.39	46.7	25	4	0.48	2	0.24	1	0.12	2	0.24
4. Ring Rd./ N.Ridge	11,089	12.14	4.0	22	0	0	0	0	0	0	0	0
5. Goldhouse/Alliance	11,066	12.12	4.5	20	3	0.25	1	0.08	0	0	1	0.08
6 Abelenkpe/ Eng. C	10,069	11.03	3.5	20	3	0.27	1	0.09	0	0	2	0.18
TOTAL	70,746	77.46	132.9	323	28	2.04	9	0.70	4	0.29	11	0.85
AVERAGE	11,791	12.91	22.15	54	4.67	0.34	1.5	0.12	0.67	0.05	1.83	0.14
STDEV	3,091	3.38	20.30	75	6.74	0.39	1.87	0.12	1.21	0.08	2.23	0.14

Table 4IE

Junction-type / name T-5	AADT (veh/day)	Cumulative traffic carried (1996-1998) (x 10^6 veh)	Minor road's share of traffic (%)	Peak hour ped. Flows across all arms of intersection (peds/h)	All Accidents		Injury Accidents		Pedestrian Accidents		Accident casualties	
					(number)	(accidents / 10^{6}veh)	(PIA)	(PIA per 10^{6}veh)	(number)	(number / 10^{6}veh)	(casualties)	(casualties / 10^{6}veh)
1. Sawaaba Jn.	20,914	22.90	9.1	274	7	0.30	4	0.17	2	0.09	4	0.17
2. New Road Maakro	20,580	22.53	27.3	315	32	1.42	11	0.49	7	0.31	12	0.53
3. Kaase Jn/Ahodwo	11,354	12.43	33.0	168	5	0.40	2	0.16	2	0.16	2	0.16
4. Magazine/Maakro	19,615	21.15	6.9	67	8	0.39	5	0.24	4	0.19	7	0.33
5. Offinso/Suame PO	14,993	16.42	11.0	97	4	0.24	2	0.12	2	0.12	3	0.18
6. Mizpa school Jun.	25,821	28.27	1.8	40	5	0.18	2	0.07	0	0	3	0.11
7. Ring Rd East/Osu	16,639	18.22	6.7	24	2	0.11	1	0.05	0	0	2	0.11
8. Akukorfoto/Oblogo	3,434	3.76	14.0	81	3	0.80	1	0.26	2	0.53	3	0.80
9. 7th Avenue/Castle	9,320	10.20	13.1	25	5	0.49	0	0	0	0	0	0
TOTAL	142,670	155.88	122.9	1091	71	4.33	28	1.56	19	1.40	36	2.39
AVERAGE	15,852	17.32	13.7	121	7.89	0.48	3.11	0.17	2.11	0.15	4.0	0.26
STDEV	6,892	7.52	10.1	108	9.23	0.40	3.33	0.15	2.26	0.17	3.53	0.25

Table 4IF

Junction-type / name T-6	AADT (veh/day)	Cumulative traffic carried (1996-1998) (x10^6 veh.)	Minor road's share of traffic (%)	Peak hour ped. Flows across all arms of intersection (peds/h)	All Acidents		Injury Accidents		Pedestrian Accidents		Accident casualties	
					(number)	(accidents / 10^{6}veh)	(PIA)	(PIA per 10^{6}veh)	(number)	(number / 10^{6}veh)	(casualties)	(casualties / 10^{6}veh)
1. Darkuman/M'way	18,776	20.56	23.2	34	16	0.78	4	0.19	0	0	6	0.29
2. Mukose/Abeka	7,115	7.79	21.8	19	0	0	0	0	0	0	0	0
3. 28th Feb./Secretar.	15,478	16.95	21.9	91	8	0.47	4	0.23	3	0.18	4	0.23
4. Indece./28th Feb.	17,006	18.62	29.6	85	5	0.27	2	0.11	1	0.05	3	0.16
5. Club 600 Junction	30,004	32.85	7.7	148	9	0.27	6	0.18	4	0.12	6	0.18
6. 24th Feb./ STC	25,700	28.14	2.9	38	0	0	0	0	0	0	0	0
7. Suame/ Jubilee Jn.	24,530	26.86	15.6	71	8	0.30	0	0	0	0	0	0
8. Poku Transport Jn.	32,680	35.78	4.7	164	5	0.14	3	0.08	2	0.05	3	0.08
TOTAL	171,289	187.55	127.4	650	51	2.23	19	0.79	10	0.40	22	0.94
AVERAGE	21411	23.44	15.92	81	6.38	0.28	2.38	0.10	1.25	0.05	2.75	0.12
STDEV	8408	9.20	9.80	53	5.21	0.26	2.26	0.10	1.58	0.07	2.55	0.11

Table 4IG

Junction-type / name X-1	AADT (veh/day)	Cumulative traffic carried (1996-1998) (x10^6 veh)	Minor road's share of traffic (%)	Peak hour ped. Flows across all arms of intersection (peds/h)	All Accidents		Injury Accidents		Pedestrian Accidents		Accident casualties	
					(number)	(accidents / 10^6 veh)	(PIA)	(PIA per 10^6veh)	(number)	(number / 10^6veh)	(casualties)	(casualties / 10^6veh)
1. Nungua/Coastal	15,399	16.86	45.3	22	4	0.24	1	0.06	0	0	1	0.06
2. Kwash Mkt/Saka	3,993	4.37	44.9	24	5	1.14	2	0.46	1	0.23	3	0.69
3. Ed.Mond/Kwash	10,419	11.41	14.2	37	5	0.44	1	0.09	1	0.09	1	0.09
4. AkuoM/Ed.Mond	8,150	8.92	40.2	18	0	0	0	0	0	0	0	0
5. Eseefio/MangoT	3,416	3.74	44.4	29	4	1.07	2	0.53	1	0.27	2	0.53
6. Teshie/Tsuibleo	18,030	19.74	26.8	40	15	0.76	3	0.15	2	0.10	4	0.20
7. M'wyExt/Kwash	16,541	18.11	44.2	80	29	1.60	10	0.55	6	0.33	11	0.61
8. Gidibar/Burma	11,371	12.45	30.9	251	7	0.56	3	0.24	3	0.24	3	0.24
9. Asawase Market	24,320	26.63	46.1	213	14	0.52	3	0.11	2	0.07	6	0.22
10. Ahinboboano	16,479	18.04	33.8	408	5	0.28	1	0.05	0	0	4	0.22
11. Adum//Chardukof	7,513	8.23	13.0	168	0	0	0	0	0	0	0	0
12. Aboabo Station	11,149	12.21	48.6	248	7	0.57	3	0.24	3	0.24	3	0.24
13. Aboabo/Angloga	9,607	10.52	23.4	36	0	0	0	0	0	0	0	0
14. Anyidado W'shop	8,309	9.09	42.0	21	3	0.33	0	0	0	0	0	0
TOTAL	164,696	180.32	497.8	1595	98	7.51	29	2.48	19	1.57	38	3.10
AVERAGE	11,764	12.88	35.6	114	7	0.54	2.07	0.18	1.36	0.11	2.71	0.22
STDEV	5,787	6.34	12.1	123	7.80	0.47	2.58	0.20	1.74	0.12	3.02	0.23

Table 4IH

Junction-type / name X-2	AADT (veh/day)	Cumulative traffic carried (1996-1998) (x10^6 veh.)	Minor road's share of traffic (%)	Peak hour ped. flows across all arms of intersection (peds/h)	All Accidents		Injury Accidents		Pedestrian Accidents		Accident casualties	
					(number)	(accidents / 10^6veh)	(PIA)	(PIA per 10^6veh)	(number)	(number / 10^6veh)	(casualties)	(casualties / 10^6veh)
1. Pink Panter	12,726	13.93	12.7	106	12	0.86	5	0.36	3	0.21	10	0.72
2. Okess Junction	17,471	19.13	21.2	30	8	0.42	2	0.10	0	0	14	0.73
3. New Rd/Maakro	24,276	26.58	28.6	315	32	1.20	11	0.41	7	0.26	12	0.45
4. Kumaca Junct.	26,531	29.05	14.7	504	15	0.52	8	0.27	4	0.14	9	0.31
5. Asafo/FNT	31,072	34.02	3.4	27	1	0.03	1	0.03	0	0	1	0.03
6. Airport/Buok.Ext	20,425	22.42	6.2	30	1	0.04	0	0	0	0	0	0
7. Coastal/Chanel5	9,747	10.67	34.7	92	12	1.12	8	0.75	5	0.47	9	0.84
8. Ta'di Rd/ LBK	16,293	17.84	12.5	26	5	0.28	2	0.11	1	0.06	2	0.11
9. NimaRA/New T.	9,623	10.50	8.8	65	3	0.28	1	0.09	1	0.09	2	0.19
10. Kanda/N.Ridge	17,039	18.66	8.5	25	4	0.21	2	0.11	1	0.05	3	0.16
11. M'wyll/Achimot	22,710	24.87	24.9	33	7	0.28	4	0.16	1	0.04	6	0.24
TOTAL	207,913	227.67	176.2	1253	100	5.24	44	2.39	23	1.32	68	3.78
AVERAGE	18,901	20.69	16.0	114	9.09	0.48	4.0	0.22	2.09	0.12	6.18	0.34
STDEV	6,873	7.53	10.0	155	8.90	0.41	3.58	0.22	2.34	0.14	4.85	0.30

Table 4IJ

Junction-type / name X-3	AADT (veh/day)	Cumulative traffic carried (1996-1998) ($x10^6$ veh)	Minor road's share of traffic (%)	Peak hour pedestrian flows across all arms of intersection (peds/h)	All Accidents		Injury Accidents		Pedestrian Accidents		Accident casualties	
					(number)	(casualties / 10^6veh)	(PIA)	(PIA per 10^6veh)	(number)	(number / 10^6veh)	(casualties)	(casualties / 10^6 veh)
1. Spintex/Lashibi	13,240	14.50	41.4	20	4	0.27	1	0.07	0	0	3	0.21
2. Secret./Dodoo	13,644	14.94	41.0	25	3	0.20	0	0	0	0	0	0
3. Oblogo/Sab.Zon	7,284	8.00	35.0	33	1	0.12	1	0.12	1	0.12	1	0.12
4. ForeignAf/Secret	5,536	6.06	45.8	21	0	0	0	0	0	0	0	0
5. ZionSt/Hansen	13,944	15.27	41.5	135	11	0.72	5	0.33	3	0.20	5	0.33
6. TopHigh/Bomso	28,919	31.67	14.5	239	9	0.28	7	0.22	2	0.06	8	0.25
7. KN Ave/Graphic	32,239	34.21	23.8	279	5	0.15	2	0.06	2	0.06	4	0.12
8. Giffard/ 2nd Circ.	26,739	29.28	21.5	24	0	0	0	0	0	0	0	0
9. Awoshie/M'wyIII	23,928	26.20	32.2	32	7	0.27	2	0.08	0	0	2	0.08
TOTAL	165473	180.13	296.7	808	40	2.01	18	0.88	8	0.44	23	1.11
AVERAGE	18386	20.01	33.0	90	4.44	0.22	2	0.10	0.89	0.05	2.55	0.12
STDEV	9749	10.48	10.9	103	3.94	0.21	2.45	0.11	1.17	0.07	2.74	0.12

APPENDIX 4II

Procedure for Statistical Comparison of Mean Accident Frequencies and Rates of Different Junction Types

The tool that was used to compare the sample mean accident frequencies and rates of the different junction-types was the *MS Excel* analysis tool for "*t*-Test: Two-Sample Assuming Unequal Variances". This *t*-test form assumes that the variances of both ranges of data (i.e. any two sets of junctions to be compared) are unequal. For this reason, it is referred to as a heteroscedastic *t*-test. It is most appropriate for determining whether two sample means are equal and usually applied on small samples (n<30) as is the case under consideration.

The test statistic value *t* is determined as follows:

$$t = \frac{\bar{x} - \bar{y} - \Delta_0}{\sqrt{\frac{S_1^2}{m} + \frac{S_2^2}{n}}}$$

where $\bar{x}, \bar{y}$ are the respective mean values being tested,

Δ_0 - the hypothesised difference between the means (= 0), and

S_1, S_2 and m and n – the respective sample standard deviations and sizes.

On the other hand, the degrees of freedom (*df*) is given by the equation:

$$df = \frac{\left(\frac{s_1^2}{m} + \frac{s_2^2}{n}\right)^2}{\frac{(s_1^2 / m)^2}{m - 1} + \frac{(s_2^2 / n)^2}{n - 1}}$$

Because the result of the calculation of the degrees of freedom would usually not be an integer, the calculation is programmed to use the nearest integer to obtain a critical value from the *t* table. The significance level applied in all the tests was 5 per cent. All that is required to perform the test is to specify the range of the input variables. Below are tables showing the sample pairings compared and the results as well as sample outputs of the analysis.

(a) Comparison of Accident Rates (see Table 4.6)

Table 4IIA Sample pairs and results of the *t*-tests of mean accident rates between junction-types

JUNCTION-TYPE (Compared sample)	JUNCTION-TYPE (Reference sample)					
	T-1	T-2	T-3	T-4	T-5	T-6
T-1	######	NS	NS*	NS*	NS	S
T-2	NS	######	NS	NS	NS	NS
T-3	NS*	NS	#######	NS*	NS	NS
T-4	NS*	NS	NS*	#######	NS*	NS
T-5	NS	NS	NS	NS*	########	NS
T-6	S	NS*	NS*	NS*	NS	########

##########	X-1	X-2	X-3
X-1	##########	NS	S
X-2	NS	###########	S
X-3	S	S	##########

LEGEND: NS – difference not significant, S- significant, NS* - just short of one-tail significance

Sample output from *MS Excel*

T-5 vs. T-6 (Comparison of Mean Accident Rates)
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.481111	0.27875
Variance	0.164686	0.066155
Observations	9	8
Hypothesized Mean Difference	0	
Df	14	
T Stat	1.241505	
P(T<=t) one-tail	0.117409	
T Critical one-tail	1.761309	
P(T<=t) two-tail	0.234818	
T Critical two-tail	2.144789	

X-1 vs. X-3 (Comparison of Mean Accident Rates)
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.536428571	0.223333
Variance	0.223147802	0.046325
Observations	14	9
Hypothesized Mean Difference	0	
Df	19	
T Stat	2.156133996	
P(T<=t) one-tail	0.022050184	
T Critical one-tail	1.729131327	
P(T<=t) two-tail	0.044100368	
T Critical two-tail	2.093024705	

X vs. T (Comparison of Mean Accident Rates Overall)
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.434117647	0.478246
Variance	0.166788592	0.354904
Observations	34	57
Hypothesized Mean Difference	0	
Df	87	
T Stat	-0.418242949	
P(T<=t) one-tail	0.338400044	
T Critical one-tail	1.662556315	
P(T<=t) two-tail	0.676800087	
T Critical two-tail	1.987609721	

(b) Comparison of Accident Frequencies (see Table 4.6)

Table 4IIB Sample pairs and results of the *t*-tests of mean accident frequencies between junction-types

JUNCTION-TYPE (Compared sample)	JUNCTION-TYPE (Reference sample)					
	T-1	T-2	T-3	T-4	T-5	T-6
T-1	######	NS	NS	NS	NS	NS
T-2	NS	######	NS	NS	NS	NS
T-3	NS	NS	#######	NS	NS	NS
T-4	NS	NS	NS	#######	NS	NS
T-5	NS	NS	NS	NS	########	
T-6	NS	NS	NS	NS	NS	########

##########	X-1	X-2	X-3
X-1	##########	NS	NS
X-2	NS	###########	S
X-3	NS	S	##########

LEGEND: NS – difference not significant, S- significant

Sample output from *MS Excel*

T-1 vs.T-4 (Comparison of mean accident frequencies)
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	2.032380952	1.555
Variance	5.213129048	5.05215
Observations	21	6
Hypothesized Mean Difference	0	
Df	8	
t Stat	0.457191562	
P(T<=t) one-tail	0.329846363	
t Critical one-tail	1.85954832	
P(T<=t) two-tail	0.659692727	
t Critical two-tail	2.306005626	

X-1 vs. X-2 (Comparison of mean accident frequencies)
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	2.333571429	3.03
Variance	6.757101648	8.81924
Observations	14	11
Hypothesized Mean Difference	0	
Df	20	
t Stat	-0.614506619	
P(T<=t) one-tail	0.272904325	
t Critical one-tail	1.724718004	
P(T<=t) two-tail	0.54580865	
t Critical two-tail	2.085962478	

X vs. T (Comparison of mean accident frequencies overall)
t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	2.333235294	2.070702
Variance	6.113071034	4.55976
Observations	34	57
Hypothesized Mean Difference	0	
Df	62	
t Stat	0.515076703	
P(T<=t) one-tail	0.304165511	
t Critical one-tail	1.669804988	
P(T<=t) two-tail	0.608331023	
t Critical two-tail	1.99896931	

(c) Testing Differences in Proportions of Injury Accidents

To test the statistical significance of the differences between the proportions of accidents constituting injury accidents at the different junction-types as shown in Figure 4.13, the following procedure was adopted after Walpole (1982):

Step 1: State the null hypothesis: H_o: $p_1 = p_2$, where, p_1 and p_2 are the two population proportions of the same attribute (injury accidents) under investigation.

Step 2: State the alternative hypothesis: H_1: Alternatives are $p_1 < p_2$, $p_1 > p_2$, or $p_1 \neq p_2$

Step 3: Choose a level of significance equal to α.

Step 4: Then the critical region is defined as:
$z < - z_\alpha$ for the alternative $p_1 < p_2$,

$z > z_\alpha$ for the alternative $p_1 > p_2$,

$z < -z_{\alpha/2}$ and $z > z_{\alpha/2}$ for the alternative $p_1 \neq p_2$.

Step 5: Compute $\hat{p}_1 = x_1 / n_1$, $\hat{p}_2 = x_2 / n_2$, $\hat{p} = (x_1 + x_2) / (n_1 + n_2)$, $\hat{p}$ is the pooled estimate of the proportion, and then, find z:

$$z = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}\hat{q}\left[(1/n_1) + (1/n_2)\right]}}, \quad \hat{q} = 1 - \hat{p}$$

Decision: Reject H_o if z falls in the critical region; otherwise, accept.

Worked Example:

Testing the difference in the proportions of injury accidents at junction types T-3 and T-1, as illustrated in Figure 4.13.

H_o: $p_{T\text{-}3} = p_{T\text{-}1}$, H_1: $p_{T\text{-}3} > p_{T\text{-}1}$, $\alpha = 0.05$, therefore, critical region is $z > 1.645$

The computations:

$$\hat{p}_{T-3} = \frac{x_{T-3}}{n_{T-3}}; \ \hat{p}_{T-1} = \frac{x_{T-1}}{n_{T-1}}; \ \hat{p} = \frac{x_{T-3} + x_{T-1}}{n_{T-3} + n_{T-1}},$$

$$\hat{p}_{T-3} = 0.46; \ \hat{p}_{T-1} = 0.35; \ n_{T-3} = 37; \ n_{T-1} = 128; \ \hat{p} = \frac{17 + 45}{37 + 128} = 0.37;$$

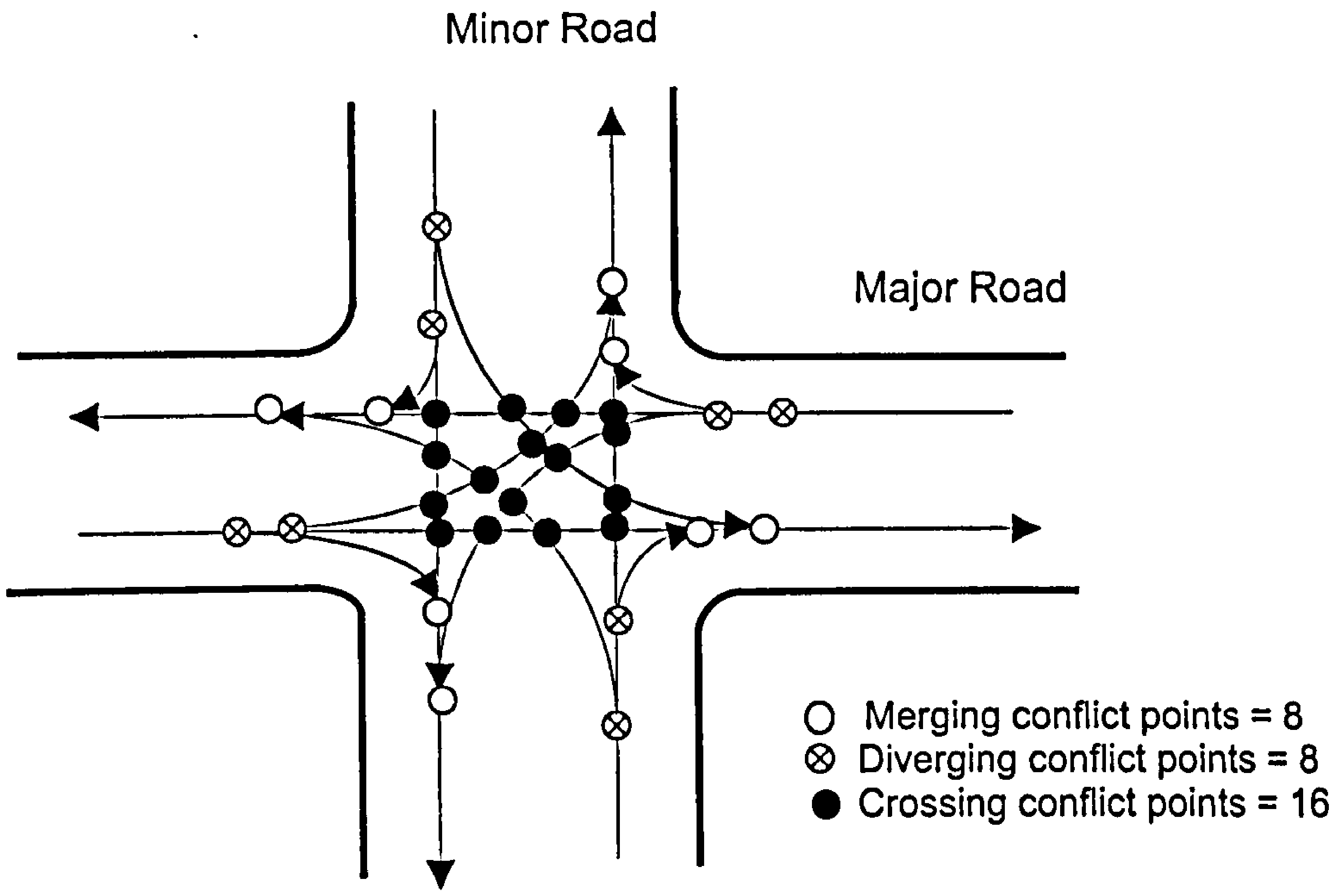
$$\text{Therefore } z = \frac{0.46 - 0.35}{\sqrt{(0.37)(0.63)\left[\left(\frac{1}{37}\right) + \left(\frac{1}{128}\right)\right]}} = 1.22$$

Decision:

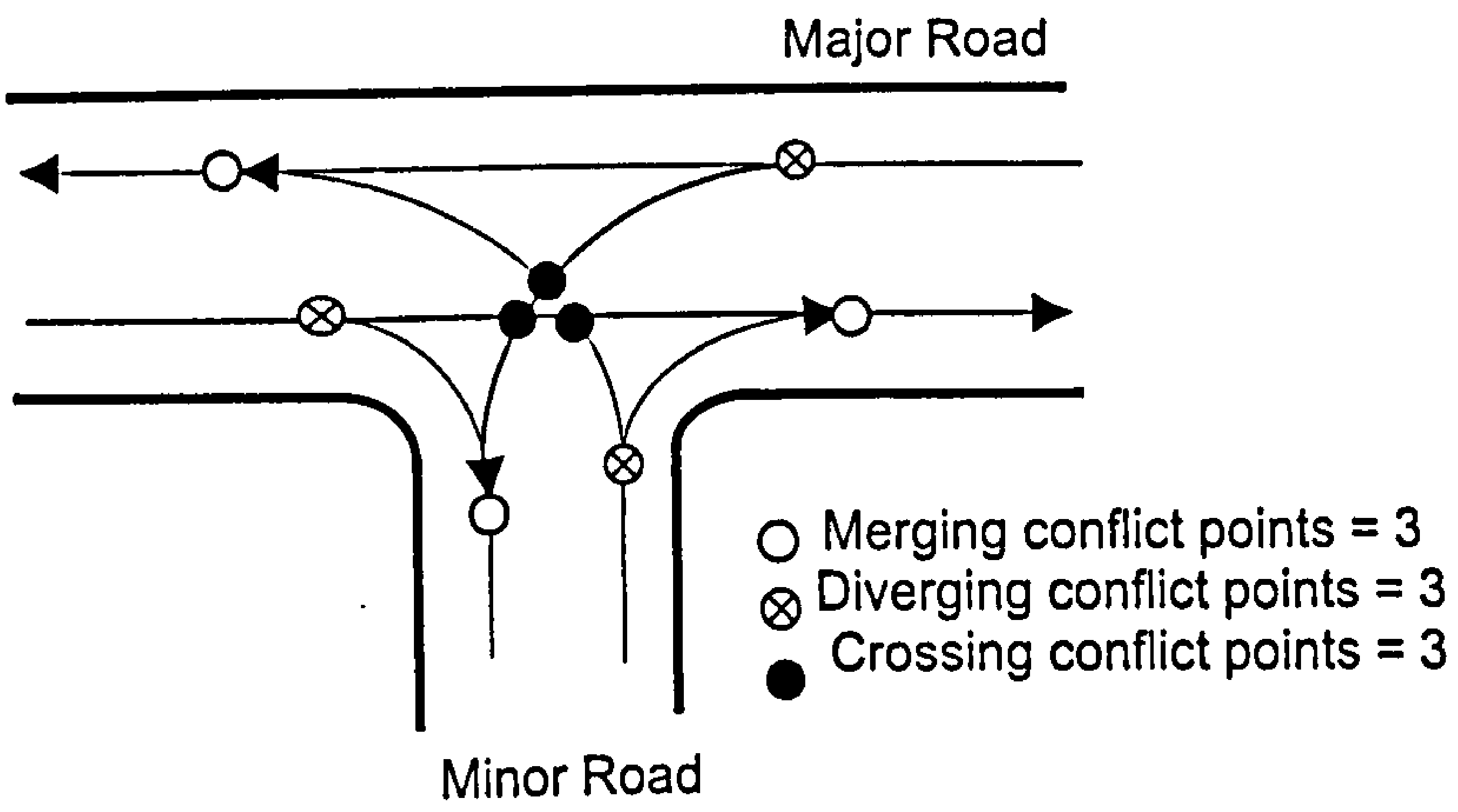
Since z =1.22 is < 1.645 (z critical) then the null hypothesis (H_o) cannot be rejected. Hence, it is concluded that the difference in the proportions of injury accidents at junction types T-3 and T-1 is not significant.

APPENDIX 4III
Conflict Points at Unsignalised Junctions

(A) X-junctions



(B) T-junctions



APPENDIX 5I

Traffic Volumes by Flow Streams and Junction Sites

Table 5IA

JUNCTION	AVERAGE ANNUAL DAILY TRAFFIC (AADT)											% of	% of
TYPE AND NAME	MAJOR ROAD TRAFFIC* (vehicles/day)					MINOR ROAD TRAFFIC (vehicles/day)					GRAND TOTAL	HGVs	Trotros
T-1	Left	Straight		Right	TOTAL	Left	Straight		Right	TOTAL	(veh./day)	maj/min	maj/min
	Q1	Q2	Q3	Q4		Q5	-	-	Q6				
1. Dadeban/Industrial	358	3990	2048	1281	7677	1921	-	-	1064	2985	10662	9 / 4	33 / 22
2. Kwashieman/Sakaman	769	1485	438	1034	3726	626	-	-	773	1399	5125	2 / 3	31 / 18
3. Coastal Rd./ 2nd Junct.	108	1980	2563	461	5112	637	-	-	1221	1858	6970	2 / 3	18 / 24
4. Coastal Rd/3rd Junct.	1073	3321	3611	613	8617	65	-	-	266	331	8948	4 / 5	29 / 12
5. Kasapreko/Coastal	630	3303	1563	120	6716	1069	-	-	713	1782	8498	3 / 2	31 / 19
6. Abooma/Coastal	519	3564	3517	1458	9058	837	-	-	1288	2125	11183	1 / 3	29 / 17
7. Chemu/Banana Inn	1575	801	2265	1353	5994	136	-	-	590	726	6720	2 / 2	23 / 22
8. Darkuman/ Link A	933	1733	1467	1348	5481	1541	-	-	845	2386	7867	3 / 6	24/ 20
9. Darkuman/Bubiashie	641	2994	2295	1112	7042	1041	-	-	1055	2096	9138	5/ 3	22 / 18
10 Darkuman/Sakaman	704	1865	1593	840	5002	802	-	-	1372	2174	7176	7 / 4	23 / 22
11 Chemu/Ed.Mondlana	318	1299	1188	453	3258	647	-	-	429	1103	4361	3 / 2	31 / 21
12 Akukorfoto/Dansoman	389	1585	1391	348	3713	473	-	-	778	1251	4964	2 / 5	22 / 24
13 Secretariat/Kinbu	269	1556	2801	693	5319	396	-	-	835	1231	6550	5 / 3	17/ 28
14. Indece Ave/BNI	179	9116	8196	572	18063	2779	-	-	2139	4918	22981	7 / 4	16/ 13
15. Aboabo/Asawase	1024	813	954	4320	7111	4656	-	-	1234	5890	13001	5/ 4	17 / 22
16. Aboabo/Bus stop	1938	174	236	3105	5453	1478	-	-	2112	3590	9040	6 / 4	24 / 26
17. Kwadaso Est.Junction	226	10183	4386	656	15451	4350	-	-	372	4720	20171	5 / 4	9 / 8
18. Police Dep.Jn(Edwenase)	4036	2236	1420	2827	10519	1057	-	-	1507	2564	13083	4 / 7	22 / 13
19. Ridge Police stn Junction	715	5352	6701	1621	14389	6230	-	-	986	7216	21605	4 / 4	15 / 8
20. Edwenasi Jn.(Police Dep)	1253	5756	4782	1300	13091	6558	-	-	5699	12257	25348	6 / 3	4 / 10
21. High School Junction	1885	5162	5446	2920	15413	554	-	-	1774	2328	17741	5 / 2	24 / 20
TOTAL	**19542**	**68268**	**58861**	**28435**	**176205**	**37853**	-	-	**27052**	**64905**	**241110**	-	-
AVERAGE	**931**	**3251**	**2803**	**1354**	**8338**	**1803**	-	-	**1288**	**3092**	**11482**	-	-
STDEV	**888**	**2630**	**2085**	**1078**	**4427**	**1959**	-	-	**1134**	**2733**	**6350**	-	-

*See traffic flow streams in Figure 5.1

Table 5IB

JUNCTION	AVERAGE ANNUAL DAILY TRAFFIC (AADT)											% of	% of
TYPE AND NAME	MAJOR ROAD TRAFFIC* (vehicles/day)					MINOR ROAD TRAFFIC (vehicles/day)					GRAND TOTAL	HGVs	Trotros
T-2	Left	Straight		Right	TOTAL	Left	Straight		Right	TOTAL	(veh./day)	maj/min	maj/min
	Q1	Q2	Q3	Q4		Q5	-	-	Q6				
1. Timber Gardens	242	4897	4452	2468	12059	4247	-	-	547	4794	16853	11 / 9	33 / 16
2. High Street/Dodoo	913	2177	2704	1451	7245	913	-	-	1499	2412	9657	3 / 2	18 / 13
3. Alajo/Nsawam Rd	989	6138	4954	1162	13243	1130	-	-	1771	2901	16144	13 / 7	24 / 18
4. Agric Junction/ Kwadaso	973	2158	3780	711	7622	1085	-	-	1921	3006	10628	15 / 7	32 / 30
5. Regional Admin. Junction	236	1437	1769	981	4423	938	-	-	412	1350	5773	13 / 6	5 / 5
6. Briscoe Junction	1816	2578	2965	1547	8906	2824	-	-	1395	4219	13125	16 / 12	31 / 18
7. Raintree Ave./Pine Ave	1939	444	376	154	2913	97	-	-	2480	2577	5490	13 / 6	5 / 5
TOTAL	7108	19829	21000	8474	56411	11234	-	-	10025	21259	77670	-	-
AVERAGE	1015	2833	3000	1211	8059	1605	-	-	1432	3037	11096	-	-
STDEV	672	1991	1582	727	3745	1424	-	-	740	1151	4561	-	-
T-3	Q1	Q3	Q2	Q4		Q5	-	-	Q6				
1. Coastal Rd./1st Junction	1290	2276	1935	1501	7002	1935	-	-	1759	3694	10696	8 / 3	22 / 12
2. Old Winneba /Ring Rd. Ext.	933	678	2152	297	4060	614	-	-	2003	2617	6677	9 / 7	21 / 18
3. Ebankese /Castle	543	4193	2944	814	8494	624	-	-	543	1167	9661	3 / 2	16 / 8
4. CPC /Roman Girls	788	9855	6333	242	17218	547	-	-	1004	1551	18769	9 / 6	7 / 11
5. Mmrom Jn./Suame	275	10664	11513	215	22667	514	-	-	442	956	23623	8 / 10	34 / 19
6. Alabar Rd./Suame	2475	9445	9062	430	21412	311	-	-	3335	3646	25058	9 / 12	22 / 13
TOTAL	6304	37111	33939	3499	80853	4545	-	-	9086	13631	94484	-	-
AVERAGE	1051	6185	5656	583	13475	757	-	-	1514	2272	15747	-	-
STDEV	778	4330	3996	501	7961	588	-	-	1092	1225	7780	-	-

*See traffic flow streams in Figure 5.1

Table 5IC

JUNCTION	AVERAGE ANNUAL DAILY TRAFFIC (AADT)											% of	% of
TYPE AND NAME	MAJOR ROAD TRAFFIC* (vehicles/day)					MINOR ROAD TRAFFIC (vehicles/day)					GRAND TOTAL	HGVs	Trotros
T-4	Left	Straight		Right	TOTAL	Left	Straight		Right	TOTAL	(veh./day)	maj/min	maj/min
	Q1	Q2	Q3	Q4		Q5	-	-	Q6				
1. Neoplan / Abrepo	-	-	8293	2171	10464	-	-	-	5329	5329	15793	7 / 6	14 / 17
2. Labadi / Giffard Rd.	-	-	5821	3142	8963	-	-	-	6103	6103	15066	4 / 3	18 / 12
3. Labone / Ring Rd.	-	-	2895	1186	4081	-	-	-	3582	3582	7663	5 / 3	13 / 16
4. Ring Rd. /N. Ridge	-	-	10089	558	10647	-	-	-	442	442	11089	3 / 2	14 / 13
5. Goldhouse / Alliance	-	-	10203	362	10565	-	-	-	501	501	11066	5 / 3	17 / 4
6. Abelenkpe/ Engineers Cent	-	-	9419	298	9717	-	-	-	352	352	10069	3 / 1	18 / 2
TOTAL	-	-	46720	7717	54437	-	-	-	16309	16309	70746	-	-
AVERAGE	-	-	7787	1286	9073	-	-	-	2718	2718	11791	-	-
STDEV	-	-	2893	1149	2529	-	-	-	2635	2635	3091	-	-
T-5	Q1	Q2	Q3	Q4		Q5	-	-	Q6				
1. Sawaaba Junction	2038	9009	7240	718	19005	461	-	-	1448	1909	20914	3 / 5	8 / 23
2. New Rd./ Maakro	241	4975	4596	5148	14960	4884	-	-	736	5620	20580	8 / 6	31 / 9
3. Kaase / Ahodwo	1491	3678	2205	238	7612	311	-	-	3431	3742	11354	9 / 7	14 / 11
4. Magazine / Maakro	659	8794	8198	608	18259	862	-	-	494	1356	19615	12 / 8	27 / 13
5. Offinso Rd./Suame PO	961	5561	6305	513	13340	461	-	-	1192	1653	14993	11 / 5	29 / 23
6. Mizpa School Junction	131	12431	12533	261	25356	320	-	-	145	465	25821	7 / 2	32 / 13
7. Ring Rd. East/ Osu	782	8086	5741	980	15589	490	-	-	560	1050	16639	4 / 2	27 / 19
8. Akukorfoto/ Oblogo	292	1065	1190	407	2954	188	-	-	292	480	3434	4 / 3	28 / 13
9. 7th Avenue / Castle Rd	341	3372	3523	859	8095	341	-	-	884	1225	9320	2 / 1	23 / 8
TOTAL	6936	56971	51531	9732	125170	8318	-	-	9182	17500	142670	-	-
AVERAGE	771	6330	5726	1081	13908	924	-	-	1020	1944	15852	-	-
STDEV	640	3526	3431	1546	6834	1497	-	-	994	1689	6892	-	-

*See traffic flow streams in Figure 5.1

Table 5ID

JUNCTION TYPE AND NAME	AVERAGE ANNUAL DAILY TRAFFIC (AADT)											% of HGVs	% of Trotros
	MAJOR ROAD TRAFFIC* (vehicles/day)					MINOR ROAD TRAFFIC (vehicles/day)					GRAND TOTAL		
T-6	Left	Straight		Right	TOTAL	Left	Straight		Right	TOTAL	(veh./day)	maj/min	maj/min
	Q1	Q2	Q3	Q4		Q5	-	-	Q6				
1. Drakuman/Motorway	1721	6203	3570	2928	14422	1721	-	-	2633	4354	18776	13 / 10	23 / 25
2. Mukose / Abeka	487	2036	2198	845	5566	487	-	-	1062	1549	7115	5 / 2	22 / 18
3. 28th Feb./Secretariat Rd.	949	5927	2723	2489	12088	1996	-	-	1394	3390	15478	4 / 3	27 / 21
4. Indece / 28th February	2243	4387	5139	197	11966	690	-	-	4350	5040	17006	5 / 3	22 / 14
5. Club 600 Junction	6335	13448	7615	287	27685	287	-	-	2032	2319	30004	11 / 23	37 / 21
6. 24th February/ STC	425	11689	11850	989	24953	540	-	-	207	747	25700	8 / 5	19 / 36
7. Suame / Jubilee Junction	2189	8706	8619	1188	20702	1001	-	-	2827	3828	24530	8 / 9	31 / 9
8. Poku Transport Junction	726	15207	13290	1917	31140	1017	-	-	523	1540	32680	9 / 7	17 / 37
TOTAL	15075	67603	55004	10840	148522	7739	-	-	15028	22767	171289	-	-
AVERAGE	1884	8450	6876	1355	18565	967	-	-	1879	2846	21411	-	-
STDEV	1940	4633	4184	998	8931	606	-	-	1370	1532	8408	-	-

*See traffic flow streams in Figure 5.1

Table 5IE

JUNCTION	AVERAGE ANNUAL DAILY TRAFFIC (AADT)															% of	% of
TYPE AND NAME	MAJOR ROAD TRAFFIC* (vehicles/day)							MINOR ROAD TRAFFIC (vehicles/day)							GRAND TOTAL	HGVs	Trotros
X-I	Q1	Q2	Q3	Q4	Q5	Q6	TOTAL	Q7	Q8	Q9	Q10	Q11	Q12	TOTAL	(veh./day)	maj/min	maj/min
1. Nungua/Coastal	270	2535	1279	1291	2383	657	8415	2277	516	1338	1022	798	1033	6984	15399	6 / 2	13 / 8
2. Kwash.Mkt/Saka	104	771	261	115	594	355	2200	125	271	250	146	719	282	1793	3993	9 / 4	17 / 22
3. Edmund./Kwash	723	3918	1084	494	2150	570	8939	196	205	331	148	148	452	1480	10419	8 / 3	23 / 18
4. Aku Om./Ed.Mon	312	1218	479	177	1853	833	4872	343	291	906	624	614	500	3278	8150	3 / 2	19 / 5
5. Eseefio/M.Tree	379	263	516	185	302	253	1898	175	263	156	253	126	545	1518	3416	3 / 2	21 / 10
6. Teshie/Tsuibleo	370	3893	224	415	7517	774	13193	280	101	247	1167	652	2390	4837	18030	7 / 4	22 / 16
7. M'wy Ext/Kwash	1224	3288	519	1187	1928	1088	9234	298	3190	544	791	1038	1446	7307	16541	10 / 5	21 / 23
8. Gidibar/Burma	2107	2226	130	98	2150	1140	7851	174	576	152	1185	1129	304	3520	11371	7 / 5	11 / 14
9. Asawase Market	1547	3680	223	1371	3047	3247	13115	1031	3469	2801	434	3071	399	11205	24320	2 / 5	15 / 5
10. Ahinboboano	148	2227	3351	128	2011	3036	10901	335	2306	49	335	2464	89	5578	16479	2 / 8	20 / 9
11. Adum/Charduk.	281	2954	67	292	2852	90	6536	157	67	124	79	247	303	977	7513	3 / 2	18 / 12
12. Aboabo Station	340	328	177	189	2522	2169	5725	303	1892	530	303	593	1803	5424	11149	5 / 4	17 / 22
13. Aboabo/Anglog.	266	2873	181	1703	2178	162	7363	361	95	1455	133	86	114	2244	9607	9 / 5	19 / 17
14. Anyidado W'shp	88	2305	118	15	2268	36	4830	447	702	126	670	1437	97	3479	8309	9 / 3	13 / 2
TOTAL	8159	32479	8609	7660	33755	14410	105072	6502	13944	9009	7290	13122	9757	59624	164696	-	-
AVERAGE	583	2320	615	547	2411	1029	7505	464	996	644	521	937	697	4259	11764	-	-
STDEV	611	1253	867	576	1649	1052	3499	567	1196	768	392	879	709	2864	5787	-	-

*See vehicle flow streams in Figure 5.2

Table 5IF

JUNCTION	AVERAGE ANNUAL DAILY TRAFFIC (AADT)															% of	% of
TYPE AND NAME	MAJOR ROAD TRAFFIC* (vehicles/day)							MINOR ROAD TRAFFIC (vehicles/day)							GRAND TOTAL	HGVs	Trotros
X-2	Q1	Q2	Q3	Q4	Q5	Q6	TOTAL	Q7	Q8	Q9	Q10	Q11	Q12	TOTAL	(veh./day)	maj/min	maj/min
1. Pink Panter	187	5205	748	166	4477	322	11105	197	322	187	582	125	208	1621	12726	8 / 1	4 / 9
2. Okess Junction	1843	5341	55	99	5703	735	13776	120	208	340	1261	154	1612	3695	17471	4 / 5	19 / 23
3. New Rd/Maakro	287	5651	117	196	5221	5847	17319	131	144	209	5351	287	835	6957	24276	8 / 6	31 / 9
4. Kumaca Jun.	2207	8788	564	1565	8929	564	22617	654	629	1437	359	514	321	3914	26531	7 / 5	10 / 22
5. Asafo/ FNT	139	15905	83	70	13734	83	30014	126	195	278	111	139	209	1058	31072	4 / 2	23 / 13
6. Airport/Buokrom	137	9049	289	365	9110	213	19163	137	213	319	76	61	456	1262	20425	11 / 7	9 / 7
7. Coastal/Chanel5	211	1938	1139	446	2490	141	6365	1033	211	752	270	505	611	3382	9747	12 / 3	24 / 27
8. T'adi Rd/ LBK	922	5203	1073	1055	5239	771	14263	372	186	576	222	248	426	2030	16293	13 / 2	22 / 18
9. Nima RA/New T.	182	3753	299	86	4266	192	8778	139	21	246	75	118	246	845	9623	8 / 4	25 / 27
10. Kanda/N.Ridge	206	7426	119	97	7610	130	15588	184	108	271	76	260	552	1451	17039	6 / 2	18 / 11
11. M'wyll/Achimot	259	8539	591	49	6371	1245	17054	345	160	222	764	345	3820	5656	22710	7 / 3	20 / 13
TOTAL	6580	76798	5077	4194	73150	10243	176042	3438	2397	4837	9147	2756	9296	31871	207913	-	-
AVERAGE	598	6982	462	381	6650	931	16004	313	218	440	832	251	845	2897	18901	-	-
STDEV	743	3694	393	489	3083	1670	6558	289	155	373	1543	153	1065	2018	6873	-	-

*See vehicle flow streams in Figure 5.2

Table 5IG

JUNCTION TYPE AND NAME	AVERAGE ANNUAL DAILY TRAFFIC (AADT)															% of HGVs maj/min	% of Trotros maj/min
	MAJOR ROAD TRAFFIC* (vehicles/day)							MINOR ROAD TRAFFIC (vehicles/day)							GRAND TOTAL (veh./day)		
X-3	Q1	Q2	Q3	Q4	Q5	Q6	TOTAL	Q7	Q8	Q9	Q10	Q11	Q12	TOTAL			
1. Spintex/Lashibi	585	1702	1297	1085	1957	978	7604	2425	191	1765	245	872	138	5636	13240	9 / 5	21 / 13
2. Secret/Dodoo	1047	2390	739	510	1061	2296	8043	349	753	658	954	1101	1786	5601	13644	3 / 2	25 / 28
3. Oblogo/S.Zongo	536	1331	598	712	1197	361	4735	144	475	702	279	361	588	2549	7284	4 / 3	29 / 22
4. Foreign Af/Secret	585	752	355	282	512	512	2998	470	616	146	262	386	658	2538	5536	3 / 2	28 / 20
5. Zion St./Hansen	376	3762	351	451	2684	527	8151	828	1781	614	401	1266	903	5793	13944	5 / 3	26 / 23
6. Top High/Bomso	1771	9610	1902	203	10758	465	24709	2279	232	131	261	218	1089	4210	28919	6 / 3	31 / 16
7. KN Ave/Graphic	1277	10795	639	516	10771	577	24575	160	2874	957	393	2948	332	7664	32239	4 / 5	21 / 8
8. Giffard/ 2nd Circ.	1461	7686	1981	1310	6766	1775	20979	682	1115	477	920	1624	942	5760	26739	3 / 1	21 / 16
9. Awoshie/ M'wyIII	2141	5281	938	1407	4567	1886	16220	459	3089	775	408	2437	540	7708	23928	9 / 5	27 / 21
TOTAL	9779	43309	8800	6476	40273	9377	118014	7796	11126	6225	4123	11213	6976	47459	165473	-	-
AVERAGE	1087	4812	978	720	4475	1042	13113	866	1236	692	458	1246	775	5273	18386	-	-
STDEV	619	3751	619	443	4062	740	8592	871	1102	487	279	949	484	1885	9749	-	-

* See traffic flow streams in Figure 5.2

APPENDIX 5II

Additional Explanatory Variables for Models Tested

Table 5IIA

Name and type of site	Vehicle approach speed on major road (km/h)			Minor road width at neck of of junction (m)	Approach Lanes on major road		Major road width of median (m)	Traffic signs on approach to junction		Designated Pedestrian Crossing? YES/NO	Street lighting? YES/NO
T-1	Mean	85%-ile	STDEV		#	Width (m)		Major	Minor		
1. Dadeban/Industrial	25.1	30	4.1	13.2	1	4.0	0	T-junct.	Stop	No	Yes
2. Kwashieman/Sakamana	29.8	31.2	3.8	18.6	1	4.0	0	T-junct	Nil	No	No
3. Coastal Rd./Second Junct.	22	24	1.8	19.0	1	4.0	0	Nil	Stop	No	No
4. Coastal Rd./Third Junction	43.3	51.3	9.7	18.5	1	4.0	0	Nil	Stop	No	No
5. Kasapreko/Coastal	22.7	24	1.3	15.2	1	4.0	0	T-junct	Yield	No	No
6. Abooma/Coastal	22.6	24.1	1.9	18.5	1	4.0	0	T-junct	Stop	No	No
7. Chemu/Banana Inn	40.1	46.3	6.8	17.5	1	3.8	0	T-junct	Stop	No	No
8. Darkuman/Link A	40.4	46.3	8.5	18.0	1	3.8	0	Nil	Stop	No	No
9. Darkuman/Bubiashie	50.5	53	2.4	19.0	1	3.8	0	Nil	Yield	No	No
10. Darkuman/Sakaman	48	53	7.6	20.1	1	5.0	0	T-junct	Stop	No	No
11. Chemu/Ed. Mondlana	45.9	52.4	6.2	18.4	1	3.8	0	Nil	Nil	No	No
12. AkukorFoto/Dansoman	34.1	47.4	11.8	18.5	1	4.0	0	Nil	Nil	No	No
13. Secretariat/Kinbu	38	50.5	10.7	21.0	1	3.7	0	nil	Stop	No	No
14. Indece Ave/BNI	54.7	57	2.7	16.5	1	5.0	0	T-junct	Stop	No	Yes
15. Aboabo/Asawasi	35.4	42.1	5.5	20.1	1	3.6	0	Nil	Yield	No	No
16. Aboabu/Bus Stop	34.7	42.1	6.8	24.2	1	4.0	0	T-junct	Yield	No	No
17. Kwadaso Estates Junction	41.1	47	4.7	18.3	1	3.5	0	Nil	Stop	No	No
18. Police Depot Jn(Edwenasi)	34.2	38.6	6.1	29.7	1	4.5	0	Nil	Nil	Yes	Yes
19. Ridge Police Stn Junction	46.6	51.1	3.7	30.1	1	4.8	0	Nil	Nil	No	Yes
20. Edwenasi Jn. (Police Dep)	44.4	48.1	4.5	25.6	1	3.5	0	Nil	Stop	Yes	Yes
21. High School Junction	44	52.2	6.8	16.4	1	4.0	0	T-junct	Yield	Yes	No

Table 5IIB

Name and type of site	Vehicle approach speed on major road (km/h)			Minor road width at neck of junction (m)	Major road width of Median (m)	Lanes on Major road		Dimensions of island on minor road (m)		Traffic signs on approach to junction		Designated Pedestrian Crossing? YES/NO	Street lighting? YES/NO
T-2	Mean	85%-ile	STDEV			#	width (m)	width (m)	Length (m)	major	minor		
1. Timber Gardens	43	49	5.7	8.5	0	1	4.0	3.5	4.0	T-junct.	yield	yes ·	NO
2. High street/Dodoo	34.2	45	8.1	8.0	0	1	4.0	2.5	5.0	nil	nil	no	YES
3. Alajo/Nsawam Rd.	47	51	5.4	8.8	0	1	4.0	20	25	nil	yield	no	YES
4. Agric Jn./Kwadaso	39.3	49	9	8.8	0	1	4.0	14.5	22	T-junct	yield	no	NO
5. Regional Admin. Junction	51.3	53	1.4	8.0	0	1	3.5	25	15	T-junct	yield	no	YES
6. Briscoe Junction	42.9	47.1	5.3	21.9	0	1	4.5	20	11.5	T-junct	yield	no	NO
7. Raintree Ave./Pine Avenue	47.3	49.2	2.1	15.6	0	1	4.5	18	12.6	nil	nil	no	NO

Table 5IIC

Name and type of site	Vehicle approach speed on major road (km/h)			Minor road width at neck of junction	Approach lanes on major road		Width of median islands (m)		Traffic signs on approach to junction		Designated pedestrian crossing? YES/NO	Street lighting? YES/NO
T-3	Mean	85%-ile	STDEV	(m)	#	Width (m)	major road	minor road	major road	minor road		
1. Coastal Rd./First Junction	35.1	40	6.1	15.2	2	2.5	3.0	1.0	T-junct	stop	No	No
2. Old Winneba/Ring Rd. Ext.	51.9	58.1	4.6	8.8	2	4.0	4.3	2.0	T-junct	stop	Yes	No
3. Ebankese/ Castle Rd.	53	55.1	2	9.0	2	3.5	3.9	1.8	T-junct	yield	Yes	Yes
4. CPC/ Roman Girls	55.9	61.3	6.6	17.1	2	3.5	1.6	1.5	T-junct	yield	No	Yes
5. Mmrom Jn./ Suame	47	52	4.6	12.6	2	3.6	1.6	1.4	T-junct	yield	No	Yes
6. Alabar Rd./Suame	53.3	60.1	6.2	15.6	2	3.6	2.1	1.5	Nil	yield	NO	Yes

Table 5IID

Name and type of site	Vehicle approach speed on major Road (km/m)			Minor road width at neck of junction (m)	Approach lanes on major road		Major road width of median (m)	Traffic signs on approach to junction		Designated Pedestrian crossing? YES/NO	Street lighting? YES/NO
T-4	Mean	85%-ile	STDEV		#	width (m)		major	minor		
1. Ncoplan/Abrepo	38.7	50.6	11.5	24.4	2	3.8	0	T-junct	yield	no	yes
2. Labadi/ Giffard	50.4	53.1	2.5	20.5	2	3.5	0	T-junct	yield	no	yes
3. Labone/ Ring Rd	54.2	58	4.8	20.2	2	3.5	0	T-junct	yield	no	yes
4. Ring Rd./ N.Ridge	51.9	55	2.2	15.5	2	3.8	0	T-junct	yield	no	yes
5. Goldhouse/Alliance	48.8	52	2.4	14.6	2	3.5	0	T-junct	yield	no	yes
6 Abelenkpe/ Eng. C	54	58.2	3.9	15.0	2	3.5	0	T-junct	yield	no	yes

Table 5IIE

Name and type of site	Vehicle approach speed on major Road (km/h)			Minor road Width at neck of junction (m)	Approach lanes on major road		Major road width of median (m)	Traffic signs on approach to junction		Designated pedestrian crossing? YES/NO	Street lighting? YES/NO
T-5	Mean	85%-ile	STDEV		#	width (m)		major	minor		
1. Sawaaba Jn.	48.9	55.2	8.1	22.1	2	4.3	2.8	T-junct	stop	yes	yes
2. New Road Maakro	43.3	53.1	9.1	20.6	2	5.5	1.8	Nil	stop	no	yes
3. Kaase Jn/Ahodwo	40.4	45.4	4.9	30.3	2	3.8	2.1	T-junct	stop	yes	no
4. Magazine/Maakro	52.8	62	8	28.6	2	4.0	2.2	T-junct	yield	no	yes
5. Offinso/Suame PO	40.2	44.3	3.9	18.8	2	4.0	2.5	t-junct	stop	yes	yes
6. Mizpa school Jun.	68.5	78	11.6	20.2	2	4.0	4.5	Nil	stop	yes	yes
7. Ring Rd East/Osu	54.4	57.1	3.1	17.5	2	3.5	5.5	Nil	stop	nil	yes
8. Akukorfoto/Oblogo	42	44	2.1	18.5	2	3.5	2.5	Nil	stop	yes	no
9. 7th Avenue/Castle	39	47.2	8.5	16.0	2	3.8	3.5	T-junct	stop	yes	no

Table 5IIF

Name and type of site	Vehicle approach speed on major road (km/h)			Minor road width at neck of junction (m)	Lanes on major road		Major road width of median (m)	Traffic signs on approach to junction		Designated pedestrian crossing? YES/NO	Street lighting? YES/NO
T-6	Mean	85%-ile	STDEV		#	width(m)		Major	Minor		
1. Darkuman/M'way	32	36	3.8	25.4	2	3.8	1.0	Nil	Stop	no	no
2. Mukose/Abeka	31.6	33	1.3	13.5	2	3.0	1.8	Nil	yield	no	no
3. 28th Feb./Secretar.	48.2	51	2.2	15.8	2	3.5	1.9	Nil	stop	yes	no
4. Indece./28th Feb.	52.3	56.1	5.8	16.1	2	3.8	1.9	T-junct	stop	yes	no
5. Club 600 Junction	50.8	55	4.8	12.7	2	4.0	2.4	T-junct	stop	yes	no
6. 24th Feb./ STC	51.6	55.1	3.5	15.6	2	3.8	3.9	T-junct	stop	yes	yes
7. Suame/ Jubilee Jn.	47.6	50.2	3.7	15.2	2	3.8	3.5	T-junct	stop	yes	yes
8. Poku Transport Jn.	60.1	71.2	9.6	28.2	2	4.0	3.9	T-junct	nil	no	yes

Table 5IIG

Junction-type and name X-1	Vehicle approach speed on major road (km/h)			Average entry width at neck of junction (m)		Average width of approach lanes (m)		Traffic signs on approach to junction		Designated pedestrian crossing? YES/NO	Street lighting? YES/NO
	Mean	85%-ile	STDEV	Major	Minor	major	minor	major	minor		
1. Nungua/Coastal	33.5	36.1	5.4	13.6	12.8	4.0	4.0	nil	yield	no	no
2. Kwash Mkt/Saka	38.3	51.2	11	18.7	13.9	4.0	4.0	nil	nil	no	no
3. Ed.Mond/Kwash	27.7	31.3	4.6	20.1	16.8	4.0	3.5	nil	yield	no	no
4. AkuoM/Ed.Mond	25.8	28	2.9	14.8	12.5	4.0	3.5	X-junct	stop	yes	no
5. Eseefio/MangoT	40.3	49.3	9.8	18.0	17.2	4.0	3.6	X-junct	stop	no	no
6. Teshie/Tsuibleo	32.2	38.3	6.8	22.1	19.8	4.0	3.5	yield	stop	no	no
7. M'wyExt/Kwash	30.2	48	14	20.6	22.7	4.5	3.8	X-junct	stop	no	no
8. Gidibar/Burma	38	43.2	5.2	13.6	10.5	4.2	4.0	X-junct	stop	no	no
9. Asawase Market	32.7	41	6.9	28.4	23.4	4.6	4.5	X-junct	stop	yes	no
10. Ahinboboano	31.5	39.1	6.5	17.5	14.6	3.8	4.8	yield	stop	no	no
11. Adum//Chardukof	28.1	32.4	8.1	18.7	13.8	4.2	3.5	yield	stop	yes	yes
12. Aboabo Station	25.9	31	3.9	20.1	16.2	3.8	3.8	X-junct	stop	yes	no
13. Aboabo/Angloga	35.2	40.1	4.8	20.2	17.0	4.0	3.8	X-junct	stop	yes	yes
14. Anyidado W'shop	40	45.1	4.9	15.0	12.6	4.0	3.5	X-junct	stop	no	yes

Table 5IIH

Junction-type and name	Vehicle approach speed on major road (km/h)			Average entry Width at neck of Junction (m)		Average width of approach lanes (m)		Major road width of median (m)	Traffic signs on approach to junction		Designated Pedestrian Crossing.?	Street Lighting?
X-2	mean	85%ile	STDEV	Major	Minor	Major	minor		major	minor	YES/NO	YES/NO
1. Pink Panter	52.3	63.1	11.9	12.5	21.8	3.8	3.5	2.3	X-junct	stop	no	Yes
2. OKESS Junction	43.5	47.1	3.3	10.2	18.3	3.8	3.0	1.9	nil	yield	no	No
3. New Road /Maakro	46.7	56.1	8.9	15.3	20.8	4.5	4.0	1.8	X-junct	stop	no	Yes
4. Kumaca Junction	46.4	57.0	8.5	13.5	21.8	3.7	3.0	3.0	X-junct	stop	yes	Yes
5. Asafo / FNT	52.1	55.0	2.2	10.1	11.5	4.5	2.5	2.1	nil	stop	no	Yes
6. Airport / Buokrom Ext.	48.7	51.0	2.1	10.8	10.9	4.5	3.0	2.1	X-junct	stop	no	Yes
7. Coastal / Channel 5	45.4	56.3	9.7	12.6	13.8	4.0	3.5	1.6	X-junct	stop	no	No
8. Ta'di Rd / LBK	57.8	63.0	5.8	13.2	18.4	3.7	3.0	1.9	X-junct	yield	yes	Yes
9. Nima RA/ New T.	31.1	33.1	2.1	11.8	16.5	3.8	3.5	2.1	nil	stop	yes	Yes
10. Kanda / N. Ridge	53.3	56.0	2.2	12.8	13.5	3.8	3.0	3.2	X-junct	stop	no	Yes
11. M'wyII /Achimota	45.5	52.1	5.6	12.6	14.2	4.0	3.6	2.2	X-junct	stop	no	No

Table 5IIJ

Junction- type and name	Vehicle approach speed on major road (km/h)			Average entry Width at neck of Junction (m)		Average width of approach lanes (m)		Major road width of median	Traffic signs on approach to junction		Designated Pedestrian Cross.ing?	Street lighting?
X-3	mean	85%ile	STDEV	Major	Minor	Major	minor	(m)	major	minor	YES/NO	YES/NO
1. Spintex / Lashibi	50.1	56.0	5.9	13.8	17.5	4.5	3.0	1.8	X-junct	stop	no	no
2. Secretariat / Dodoo	23.2	24.1	1.3	15.2	20.9	3.7	5.0	2.3	X-junct	stop	no	no
3. Oblogo / Sabon Zongo	43.8	46.1	5.0	13.6	16.8	3.8	3.5	2.1	X-junct	stop	no	no
4. Foreign Aff. / Secretariat	31.2	36.1	4.2	20.3	15.5	3.0	3.5	1.6	X-junct	stop	yes	yes
5. Zion Street / Hansen	50.0	56.0	7.0	13.8	19.6	4.0	3.5	2.5	X-junct	stop	yes	no
6. Top High / Bomso	55.3	63.6	10.1	11.5	18.7	3.8	3.5	3.9	X-junct	stop	yes	yes
7. KN Avenue / Graphic	45.8	49.1	2.9	13.5	18.6	3.8	3.5	3.9	X-junct	stop	no	yes
8. Giffard / 2nd Circular	44.3	49.2	6.9	11.8	13.2	3.5	3.2	2.3	X-junct	stop	yes	yes
9. Awoshie / Motorway III	44.9	49.2	5.3	16.4	18.2	4.0	3.6	2.2	X-junct	stop	no	no

APPENDIX 5III

Sample Output From GLIM Modelling

(A) Null Model for all (Total) Accidents for T-junctions

```
[i] ? $yvar tacc $link l $terms 1 $number theta=0 $use negbin theta $d e$
[w] -- model changed
[o] scaled deviance =  68.003 (change =   -244.3) at cycle 2
[o]    residual df =  56    (change =      0  )
[o]
[o]     ML Estimate of THETA =     1.218
[o]             Std Error = (  0.2979)
[o]
[o]  NOTE: standard errors of fixed effects do not
[o]      take account of the estimation of THETA
[o]
[o]  2 x Log-likelihood       =    739.2 on 56 df
[o]  2 x Full Log-likelihood  =   -330.3
[o]
[o]         estimate      s.e.    parameter
[o]    1     1.826     0.1312      1
[o] scale parameter 1.000
[o]
```

(B) Flow-based Model for all Accidents at T-junctions

```
[i] ? $terms lmajf+lminf $number theta=0 $use negbin theta $d e$
[w] -- model changed
[w] -- model changed
[o] scaled deviance =  70.262 (change =   -148.0) at cycle 2
[o]    residual df =  54    (change =      0  )
[o]
[o]     ML Estimate of THETA =     2.159
[o]             Std Error = (  0.6327)
[o]
[o]  NOTE: standard errors of fixed effects do not
[o]      take account of the estimation of THETA
[o]
[o]  2 x Log-likelihood       =    760.1 on 54 df
[o]  2 x Full Log-likelihood  =   -309.3
[o]
[o]         estimate      s.e.    parameter
[o]    1    -7.358      1.957      1
[o]    2     0.5010     0.1842     LMAJF
[o]    3     0.5825     0.1405     LMINF
[o] scale parameter 1.000
[o]
```

(C) Full Model for all Accidents at T-junctions

```
[i] ? $terms lmajf+lminf+ssd+tcon+medw $number theta=0 $use negbin theta $d e$
 [w] -- model changed
 [w] -- model changed
 [o] scaled deviance = 71.000 (change =  -110.6) at cycle 2
 [o]    residual df = 50    (change =     0  )
 [o]
 [o]     ML Estimate of THETA =     3.008
 [o]              Std Error = (  0.9723)
 [o]
 [o]  NOTE: standard errors of fixed effects do not
 [o]       take account of the estimation of THETA
 [o]
 [o]  2 x Log-likelihood       =   771.0 on 50 df
 [o]  2 x Full Log-likelihood  =  -298.5
 [o]
 [o]          estimate      s.e.   parameter
 [o]    1     -7.158      1.881     1
 [o]    2      0.5729     0.1981    LMAJF
 [o]    3      0.4801     0.1319    LMINF
 [o]    4     0.06908    0.03603     SSD
 [o]    5     -0.4795     0.2244    TCON(2)
 [o]    6     -0.9526     0.3377    TCON(3)
 [o]    7     -0.1657    0.08204     MEDW
 [o] scale parameter 1.000
 [o]
```