UNIVERSITY OF SOUTHAMPTON

JOURNEY TIME FORECASTING IN URBAN NETWORKS

by

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A thesis submitted for the degree of
DOCTOR OF PHILOSOPHY

Department of Civil and Environmental Engineering

June 1995

to my Parents

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF ENGINEERING AND APPLIED SCIENCES
DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING

Doctor of Philosophy

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Journey time forecasts are required in many new dynamic traffic control and route guidance systems. This study has concentrated on the development of journey time forecasting models in urban networks. Two different traffic conditions (Normal and Incident) were categorised and hence two different modelling approaches were considered.

For normal traffic conditions, requirements are typically for a forecast of journey time on a link-by-link basis for periods of up to about one hour ahead depending on the application. The development of short term forecasting models required initial analysis of the underlying time dependent variability in the parameter to be forecast. This was achieved by collecting and statistically analysing traffic data. The data was collected from Southampton using SCOOT Urban Traffic Control system over a period of six months. Time series methods (Box-Jenkins and Horizontal-Seasonal) were then used to develop journey time forecasting models, on a link-by-link basis. The developed forecasting models were tested by applying them on real data sets. The models are considered to be very useful for on-line application under normal traffic conditions particularly for Drivers Information Systems.

The performance of time-series forecasting models deteriorates in situations of traffic accidents or other unexpected incidents and therefore a different modelling approach is required for incident cases. Traffic incidents in urban networks are the source of higher journey times and may cause serious congestion. In these situations journey times may be increased not only on the incident link, but also on the links which are the upstream links of incident location.

A new modelling approach was considered in which an 'incident database' was compiled using the CONTRAMI simulation tool applied to a range of network, traffic and incident scenarios. A set of parameters were defined and effects of these parameters on traffic conditions were studied. Generalised statistical models were then developed to predict the number of links which would be affected by an incident. To find the location of affected links in the network, an algorithm was developed which constructs a backward tree from the incident link. Finally models were developed, which when supplied with incident severity and location in the network, forecast journey time on incident link and on the affected links. Models were validated by applying them on a bigger network. The application of developed models can be found in incident management strategies and in dynamic route guidance systems.

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ACKNOWLEDGEMENTS

I would like to take this opportunity to thank Dr. Nick Hounsell for his superb guidance and advice in the supervision of this thesis. His continuous support and encouragement kept me enthusiastic throughout the course of my study. I am also very grateful to Prof. Mike McDonald for his valued advice and guidance. My sincere thanks to all the staff at 'Transportation Research Group' (TRG) for their friendliness and good working environment.

The first half of this study was completed while I was working on a project sponsored by the 'Science and Engineering Research Council' (SERC) of UK (grant no. GR/F89992); and the second half of the study was completed while I was working on 'European Commissions' DRIVE2/MARGOT project (No. V2033). My thanks to both the organisations for their financial support and the opportunities they provided me to meet and discuss the subject with many experts in the field of transportation. I also wish to thank Traffic Control Unit of Southampton city for giving me access to their computer for the collection of SCOOT data.

I take this opportunity to mention the contributions of my late father towards my academic career. His love, guidance and enlightenment has been a constant source of inspiration. May Allah keep his soul in peace. I would also like to thank my Mother, Brother and Sisters for their love, confidence and continuous support despite being so far away. I would also like to express my sincere thanks to all my friends for sharing with me the wonderful moments of their friendship.

LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
ARIMA	Auto-Regressive Integrated Moving Average
ASTRID	Automatic SCOOT TRaffic Information Database
ATT	Advanced Transport Telemetics
BJ	Box-Jenkins
CONTRAM	CONtinuous TRaffic Assignment Model (a traffic assignment model developed by TRL)
CONTRAMI	Enhanced version of CONTRAM to model traffic in Incidents
CT	Cruise Time
CV	Coefficient of Variation
D.F	Degree of Freedom
DRG	Dynamic Route Guidance
DRIVE	Dedicated Road Infrastructure for Vehicle safety in Europe
HS	Horizontal-Seasonal
IVHS	Intelligent Vehicle Highway Systems
JT	Journey Time
LISB	Leit-und Information System Berlin
LPU	Link Profile Units
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ME	Mean Error
MPE	Mean Percentage Error
MSE	Mean Square Error
O-D	Origin-Destination
PROMETHEUS	PROgram for European Traffic with Highest Efficiency and Unprecedent Safety

RTI	Road Traffic Informatics
SATURN	Simulation and Assignment of Traffic of Urban Road Networks
SCOOT	Split Cycle Offset Optimization Technique
	(a traffic responsive method of coordinating signals)
SD	Standard Deviation
S.O.V	Source of Variation
STATGRAPHICS	Statistical computing software package
UTC	Urban Traffic Control
VMS	Variable Message Signs
TRANSYT	TRAffic Network StudY Tool
TRG	Transportation Research Group
TRL	Transport Research Laboratory

CHAPTER 1

INTRODUCTION

The rapid rise in traffic growth in almost every city of the world is leading to increased traffic congestion and its related problems air pollution, over utilization of scarce petroleum resources, time consuming delay to people and goods movement, other economic and environmental effects. A range of increasingly sophisticated traffic management measures have been introduced in recent years which have improved traffic efficiency and generally 'kept traffic moving', albeit at low level of service. The SCOOT on-line Urban Traffic Control system (Hunt et al, 1981) is an example of such measures, improving efficiency by optimally co-ordinating networks of traffic signals in order to make the efficient use of the available road space. Such systems are designed to cope with existing traffic patterns and use only current values of traffic parameters upon which to base their actions and therefore by themselves do not try to avoid the unfavourable conditions that can occur (one exception is the new 'gating' facility in SCOOT where congestion in one part of a network can be used as a criterion to control traffic entering upstream).

However in urban areas where the scope for road improvements is limited, it becomes more difficult to achieve efficient signal co-ordination. There is a growing need of the derivation and design of intelligent measures to combat urban traffic problems by making maximum use of available road space. Dynamic methods are therefore required for the effective management and control of urban traffic. While many of the existing dynamic methods are **responsive** to the existing patterns of traffic, new techniques involving signal control and/or vehicle routing require a **predictive** element involving short term forecasting of traffic conditions.

Requirements for short term traffic forecasting can be identified in many new dynamic traffic management and control systems, such as :

* Traffic control systems, in which a forecast of critical traffic parameters could trigger a 'remedial' control strategy.

* Dynamic Route Guidance systems, where the calculation of optimum routes requires a forecast of traffic conditions on links for the time at which vehicles will arrive on those links.

* Drivers Information Systems, where forecast of travel time for a given journey will be required.

* Parking guidance systems, where a forecast of car park occupancy is required for efficient guidance.

In its 'simplest' form, requirements are for a forecast of traffic conditions on a link-by-link basis for periods of up to about 1 hour ahead depending on the application. For traffic control, a much shorter range forecast will typically be most appropriate, while for routing systems, the required forecast horizon depends on the journey time from the point of routing advice to the destination. The parameter to be forecast also depends on the application, for example, traffic control system may require forecast of traffic demand and queue length, while route guidance systems require link journey time/cost forecasts.

Another situation when forecast of traffic parameters would be required is during incidents. Traffic incidents occur in a variety of forms. The net affect of an incident is a reduction in road capacity which leads to higher than normal journey time, not only on the link of incident link but also on the approaching links and other links in the network. This could lead to serious congestion, rise in energy consumption, environmental nuisance. The prediction of the effects of traffic incidents is therefore an important issue for better efficiency for on line Dynamic Route Guidance (DRG) systems and other traffic control systems.

1.1 Objectives

The objectives of this study were :

1 To develop models for short term forecasting of journey time on link-by-link basis for non-incident cases.

2 To develop model for short term forecasting of journey time under incident conditions, on link of incident and on affected links, in urban networks.

3 Test the effectiveness of methods developed in (1) and (2), on a range of data.

1.2 Method of Approach

Improvements in understanding of urban traffic congestion and its related problems were achieved by combining a full literature review followed by collection of traffic data (flow, journey time etc) over a 6 month period (January-July 1991). This provided data from 134 peak periods from congested parts of the Southampton network (Figure 3.1). Data was obtained from the SCOOT Urban Traffic Control system (Hunt et al, 1981) with automatic recording undertaken at the University via a dedicated telephone line installed between the SCOOT computer in Southampton Traffic Control Unit offices and Transportation Research Group (TRG) offices.

An initial screening of areas for detailed data collection was first carried out following a "blanket" collection of sample data at all locations. This revealed that "normal" congestion levels in Southampton were generally low and confined to a limited number of links. (The widespread use of SCOOT and the introduction of new road schemes in some congested areas were probably contributory factors to the low levels of congestion). After selection of the most congested links/regions, data was collected for three hour morning (07:00-10:00) and three hour evening (16:00-19:00) peaks at 10 links, 10 regions and at 1 route over the 6 months period. Data was also obtained from a London SCOOT region where, during the peak hours, congestion was much higher than in the Southampton SCOOT network. Data was processed using the ASTRID (Hounsell and Mcleod, 1990) database software.

The development of short term forecasting models required initial analysis of the underlying time dependent variability in the parameter to be forecast. This was achieved by statistically analysing the available traffic data from Southampton SCOOT network. Two Time-series methods, Box-Jenkins ARIMA modelling (Box et al, 1976) and Horizontal-Seasonal modelling (Thomopoulos, 1980), were then used to develop journey time forecasting models, on a link-by-link basis. These journey time forecasts are based on historical journey time information on the particular link and updated to reflect the current conditions.

Though, the time series models which were developed as above, capture small day-to-day variations and adjust the journey time forecasts according to the present day conditions, these models can not be used successfully in situations of traffic accidents or other unexpected events. To study the effects of incidents, an 'incident database' was compiled using the CONTRAMI (University of Southampton, 1992) simulation tool applied to a range of network/traffic/incident scenarios. Regression techniques were then used to develop generalised statistical models for predicting the number of links which would be affected by an incident. To find the location of affected links in the network, a procedure was developed which constructs a backward tree from the incident link.

The increase in journey time on incident link and on affected links is a function of many parameters, such as incident severity, duration and importance of the link in the network. A set of parameters were defined and effects of these parameters on journey time after an incident were studied. Models were then developed, which when supplied with incident severity and location in the network, predict the increase in journey time on incident link and on affected links following the on-set of an incident.

Models were evaluated by comparing the simulated and predicted results and by statistically analysing the forecasting errors. A type of validation of the developed models was also achieved by applying them on a bigger network (London network).

1.3 Outline of This Thesis

This thesis is divided into 7 chapters. Following this chapter, Chapter 2 is the review of earlier work on traffic forecasting. Forecasting methods are discussed which can be used to forecast traffic parameters, some of these methods have been used earlier by different organisations, their performance is discussed relative to the earlier applications. 2nd part of chapter 2 gives a review of traffic parameters, which can be predicted and used in order to achieve the effective management and control of urban traffic. In third part of this chapter, idea of an incident is presented, it's affects on journey times are discussed. Methods of incident detection are reviewed and need for new modelling approach is discussed.

In Chapter 3, details of data collection are given. Data was collected from SCOOT system. Details of SCOOT messages are presented and description is given how different traffic parameters are defined and calculated in SCOOT.

In Chapter 4, a comprehensive analysis of the data is made. Sources of variability in the data are discussed. The principles of the statistical analysis are introduced and the general expressions used in the analysis of journey time are specified. A possible pattern for the variability of journey time between time of day, between days of week and between months is investigated.

Chapter 5, presents the development and application of journey time forecasting models, which have the ability to accommodate random variability in journey times and update the forecasts when the new data is available. Box-Jenkins and Horizontal-Seasonal methods are used to develop these models. The results of the application of the developed models are presented. The models are tested on real data sets collected from two different links and a route in Southampton SCOOT network. The performance of the models are evaluated in terms of forecast errors analysis.

In Chapter 6, different incident scenarios are studied using traffic simulation model CONTRAMI. A database was compiled and from this database models are developed which predict, number and location of links which are affected by an incident, journey time on incident link and on incident affected links.

Finally, Chapter 7 summarises the conclusions obtained in this research and presents suggestions to continue the investigation of the subjects discussed in this thesis.

1.4 Research Time Table

Table 1.1 Research Time Table

Activities	Time (Months)											
	3	6	9	12	15	18	21	24	27	30	33	36
Review of literature/ associated activities	———	———	— —	— —	— —	— —	— —	— —	— —	— —		
Data Collection		———	———	———								
Data Analysis			— —	———	———							
Development of journey time forecasting models - Normal conditions.				— —	———	———						
Application/Testing					———	———	— —					
Development of journey time forecasting models - Incident conditions.						— —	———	———				
Application/Validation								— —	———			
Recommendations and Reporting										— —	———	———

CHAPTER 2

BACKGROUND

This chapter is divided into three parts. In first part forecasting techniques are reviewed which can be used to forecast traffic parameters in normal traffic conditions. In the second part traffic parameters are discussed in the view to find such parameters which can be forecasted and used in solution of traffic related problems.

The third part is a review of the characteristics of traffic incidents in urban networks, based on previous research studies. Types of incidents are discussed which occur most frequently in urban networks. The review also deals with information on traffic incidents, from data gathering to incident detection methods. The aim is to study the characteristics of various types of incidents and the effects they make on network performance and then to develop the predictive models to forecast the effects of incidents in urban networks.

Traffic speeds have been generally maintained in urban areas despite the continuing growth of traffic, mainly due to the introduction of a range of traffic management measures. Of particular significance has been the introduction of Urban Traffic Control (UTC) systems which have helped in running traffic by efficient linking of traffic signals within the urban network despite the continuous growth in traffic. However, most UTC systems are fixed time systems (i.e, they have signals linked by off-line derived coordinated timings based on historical traffic data. A number of fixed time UTC systems are in operation in many of cities throughout the world (McShane et al, 1990), e.g. TRANSYT (Robertson, 1969). Such systems can control known patterns of traffic, rather than respond to demand.

This limitation led to the development of traffic responsive control systems, which continually monitor traffic conditions in a network by some form of detection and react to the information received by implementing appropriate signal settings. They thus adapt themselves to traffic patterns and respond to traffic demand as they occur. An example of such a system is SCOOT (Split Cycle Offset Optimisation Technique) (Hunt et al, 1981), which is designed to optimize network performance usually by minimizing overall delay on the basis of on-line traffic demand. SCOOT employs a number of inductive vehicle detectors located on approaches to all controlled junctions. The data collected from these detectors is processed by a central coordinating computer, which can then alter the green split, cycle time, or offset at any junction. SCOOT is a fully adaptive control system. It is operational in many cities around the world. Field trials with the SCOOT system showed (Hunt et al, 1981) that it reduces the average delay at traffic signals by about 12 per cent. This saving is in comparison with up-to-date fixed time signal plans which were derived mainly from the TRANSYT method.

Several other real-time traffic control systems have been developed in recent years. These include OPAC (Optimisation Policies for Adaptive Control) (Gartner, 1983) developed in USA; UTOPIA (Urban Traffic Optimisation by Integrated Automation) (Mauro et al, 1989), implemented in Turin (Italy); PRODYN (Henry et al, 1983) developed by CERT in France; SCATS (Sydney Coordinated Adaptive Traffic System) (Sims and Finlay, 1984) in Australia.

Although UTC systems have been able to provide some degree of success in alleviating congestion in urban areas, perhaps more efficient use of road space could be achieved if the traffic conditions can be forecasted and control actions are taken beforehand to avoid the unfavourable conditions that can occur.

Developments in information technology and telecommunications together with advances in computing and operations research provide several opportunities for alternative approaches to traffic management and control. In recent years a great deal of effort has been invested in what is becoming known as Advanced Transport Telemetics (ATT).

ATT systems in Europe are collectively known as Road Transport Informatics (RTI) systems, in America as Intelligent Vehicle Highway Systems (IVHS), and in Japan as Super Smart Vehicle Systems (SSVS). All the systems have the common objective of using advanced computer, information and communications technologies to improve the performance of transportation systems, and at the same time reduce the impact of transport on the environment.

European DRIVE and PROMETHEUS (Keen et al, 1991) initiatives involve the development and implementation of a wide range of Advanced Transport Telematics (ATT) systems, of which Dynamic Route Guidance (DRG) and Driver Information Systems constitute a major part. A DRG system is based on providing guidance to drivers to their optimum route via in-car equipments, taking into account current and forecasted traffic conditions.

IVHS program in America has the main goal to develop the state-of-the-art vehicle/highway management, information and control systems which will effectively combat congestion, and succeed in providing an increased level of safety, mobility, driver convenience and environmental quality in both rural and urban areas.

The main aim of Japan's Super Smart Vehicle System (SSVS) is to develop advanced vehicle control systems, traffic management and driver information systems. The concept of SSVS is based on info-mobility, which corresponds to RTI and IVHS concept.

These technological developments also offer new opportunities for road information provision. Of particular interest are Driver Information Systems (DIS). When making travel choices, drivers constantly combine various sources of information to form perceptions and expectations of traffic conditions.

The techniques for providing drivers with improved information include (i) traffic information broadcasting systems; (ii) pretrip electronic route planning; (iii) on board navigation systems; and (iv) electronic route guidance systems. Information available to drivers may conceptually fall into one of three categories (Ben-Akiva et al, 1991).

Historical information - information which describes the state of the transportation system during previous time periods.

Current information - the most up-to-date information about current traffic conditions.

Forecasted information - information concerning expected traffic conditions during subsequent time periods when travel can occur.

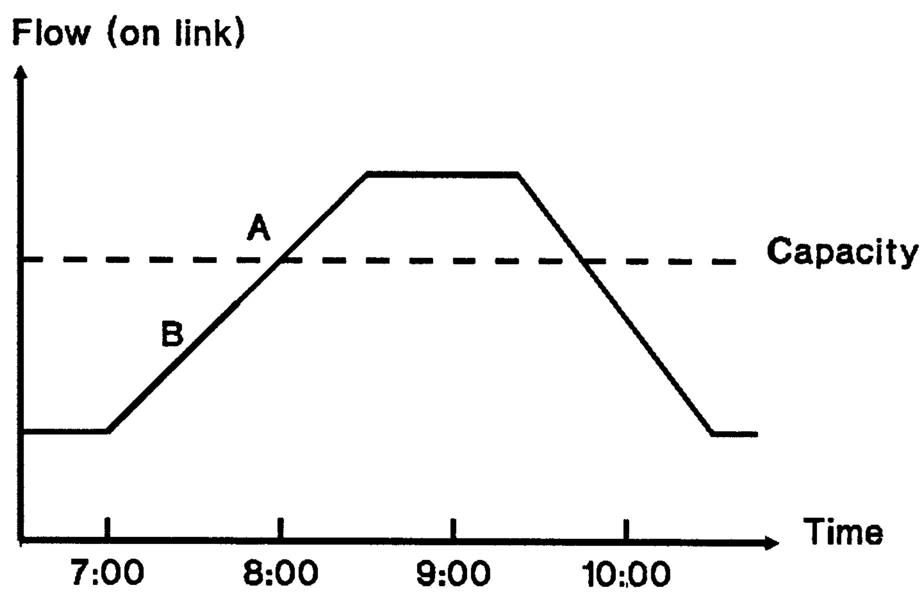
Since drivers decisions are affected by expected network conditions, the most useful type of information to a driver faced with travel choices would be reliable forecasted information.

The success of the emerging traffic control and driver information systems will largely depend on the quality of the forecasting procedures. Considering the variety of issues regarding forecasting, the basis of this thesis is to develop appropriate traffic forecasting models which can be incorporated into the driver information and traffic control systems in order to achieve better efficiency and to combat growing congestion particularly in urban areas.

2.1 Control Actions Based On Forecasts

Traffic forecasts have been recognised as a core issue in the area of Urban Traffic Management, such forecasts need to be produced in real-time, be accurate, and have a sufficiently large time horizon. With such information, measures can be taken not only to inform and warn drivers about existing congestion, but also to reduce expected near-future congestion or even avoid it altogether. In most urban networks traffic demand is dependent upon time. There are typically two occasions during the "normal" working day when traffic is higher than other periods. When demand exceeds capacity, the result is a formation of a queue of stopped (or crawling) vehicles at bottleneck locations. Therefore, the volume of traffic momentarily drops to zero, leaving only congestion on the facility until a clearout can be effected.

Figure 2.1 Control actions based on forecasts



In figure 2.1, "A" represents the point where congestion is identified from the data and necessary control action can be taken. Ideally, however one would like to be able to predict congestion at time "B" so that control actions can be introduced before congestion occurs.

Some form of network control can be imposed which limits traffic growth in a network and overrides growth that might otherwise occur. Possible control actions which are based on prediction of traffic parameters are :

2.1.1 Dynamic Route Guidance

As traffic flows and delays increase in a network, new routes are often sought by drivers to minimise their journey time. A number of route guidance systems have been developed in the past decade. They include self-contained navigation units, radio broadcasting systems and fully automatic route guidance systems in which units within vehicles interact with roadside equipment to give automatic guidance. The aim is to provide guidance to drivers to their optimum route via in-car equipments, taking into account current and forecasted traffic conditions. The recommendations are frequently updated, e.g. every five minutes.

Dynamic route guidance systems need the prediction of journey times for the links of their networks in order to give optimum route recommendations, so that the driver can be routed round transient congestion or blockages caused by accidents or other incidents. In this case it is not possible to provide all the necessary information autonomously within the database held in the vehicle's system (usually on CD-ROM), but a central system is required to calculate continuously-varying best routes based on current and predicted traffic situations. Some elaborate and versatile systems are being developed to demonstration stage in Europe's DRIVE program: ALI-SCOUT (V. Tomkewitsch, 1986) in Germany and similar system in Britain AUTOGUIDE (West et al, 1991) have already been demonstrated, while the SOCRATES, CARMINAT and TRAVEL Pilot systems are still under development.

Japan, and the US IVHS programme are also developing these systems.

2.1.3 Variable Message Signs (VMS)

Road signs are at present the main method of obtaining route information while travelling. Electronically controlled 'Variable Message' signs (VMS) are being increasingly used particularly on motorways and on major urban corridors to provide dynamic route information to travellers. In the UK, such systems have mainly been associated with warnings of hazards, speed restrictions and lane closures. However, a number of other systems also incorporate traffic detection devices (usually via buried loops), so that messages can be directly related to levels of traffic flow, estimated journey time and so on.

2.1.3 Gating

It is usual for a small proportion of links in a network to become full during mid-peak periods, thereby reducing the capacity of feeding links upstream. Where this propagates beyond junctions adjacent to the critical junction, more widespread congestion occurs and this has been defined as the start of system oversaturation (McShane et al, 1978). To prevent this, the Transport Authorities may include the implementation of "gating" where traffic is stored on the outskirts of the network. Traffic flows entering the network are then regulated in an attempt to avoid congestion.

Activity in these areas are increasing; these systems require predictions to be made of appropriate traffic parameters (e.g. link journey time, flows). It is estimated (Jeffery, 1987) that, on average journey times would be reduced by about 10% for vehicles benefiting from in-vehicle route guidance systems, with smaller benefits for non-equipped vehicles due to a general reduction in congestion.

Forecasting can also play an important role to improve the public transport systems and hence encouraging people to make more use of it. Computerised trip planning systems are becoming available, though only at major terminals, and dynamic journey time predictions, taking account of current road conditions, will become possible via similar systems to those needed for dynamic route guidance. This also make possible to predict the time of arrival of the next bus at a stop. Time-to-next-bus indicators are being tested in London (COUNTDOWN project) and Southampton (McDonald M, 1994; ROMANSE project). Since waiting time and uncertainty are greatly disliked aspects of public transport, the prediction of time-to-next-bus could considerably improve the perception of the services. On the whole, forecasting of traffic parameters will play an important role in the emerging Advanced Transport Telematics systems.

2.2 Review of Forecasting Techniques

The dynamic behaviour of traffic parameters has been the subject of interest for many years. Different approaches for forecasting traffic parameters has been used. Lam and Rothery (1970) used discrete time series from uniformly sampled or aggregated values analysing vehicle speeds, while Wright (1972) proposed a time series model for flow and concentration. Nicholson and Swann (1974) studied a spectral technique for predicting traffic volumes. Hillegas et al (1974) postulated stationary first-order autoregressive models for predicting 'occupancies'. Ahmed and Cook (1977) used Box-Jenkins ARIMA technique to forecast freeway traffic volume and occupancy data. Nihan et al (1980) and Wang (1981) also used ARIMA models to empirically estimate travel demand. Davis et al (1990) used adaptive forecasting method to predict the freeway congestion. More recently several projects within DRIVE I and DRIVE II programme were involved in development and application of journey time prediction models; of these projects is the CAR-GOES project (DRIVE I, 1990) where journey time forecasting is discussed by relating flow and occupancy to journey time; however, models relating journey time to flow are needed only if they result in better estimations and predictions of journey time than are available from direct journey time prediction methods. Another technique which is being used for traffic forecasting is Kalman Filtering; Whittaker (1991) used this technique for network travel time prediction.

While the previous studies mentioned above present reasonably accurate models for forecasting traffic parameters, relatively few studies have attempted to develop models which can be implemented for real time application and make the best use of large amount of traffic data which is available in real time from Urban Traffic Control systems.

Recently, for the LISB field trial of the dynamic route guidance system ALI-SCOUT (Von-Tomkewitsch, 1986) a special method for journey time prediction has been developed for real time application. It is based on control strategies in traffic engineering and uses multiple exponential smoothing with variable weighting parameters. However, this method is also constrained by its special data collection procedure.

Advances in computing technology provides the opportunity to develop traffic forecasting models which can be used for real time application. From traffic engineer point of view a wide range of forecasting methods are available which can be used to develop traffic forecasting models. Such methods can be classified and are discussed below.

2.2.1 Time-Series Methods

In the field of Statistics and Operation Research a number of methods for time series analysis and forecasting have been developed which in traffic engineering can be used for the prediction of traffic parameters. In time series models, forecasts are based on historical (past) data, this historical data is analyzed in order to identify a pattern that can be used to describe it, then this pattern is extrapolated or extended into the future in order to prepare a forecast. All the models in this field have the same general mathematical background and the same objective function, the minimizing of the squared differences between predicted and observed values. Many of these techniques have been used by different organisations to generate traffic forecasts. Possible time series forecasting techniques are discussed in the following sections and their relevance to typical traffic data described.

2.2.1.1 Exponential Smoothing

In its basic form exponential smoothing is used for non-seasonal time series showing no trend. Given a stationary, non-seasonal time series, z_1 , z_2 , - - -, z_N , it is natural to take as an estimate of z_{N+1}, a weighted sum of the past observations.

$$z_{(N+1)} = c_0 z_N + c_1 z_{N-1} + c_2 z_{N-2} + - - - \qquad (2.1)$$

where the $\{c_i\}$ are weights.

In order that the weights sum to one, we take

$$c_i = \alpha(1-\alpha)^i \qquad (i=0,1,- -) \qquad (2.2)$$

where

$$0 < \alpha < 1$$

The prediction equation can be written as

$$z_{(N,1)} = \alpha z_N + (1-\alpha) z_{(N-1,1)} \qquad (2.3)$$

If we set $z_{(1,1)} = z_1$, then equation (2.3) can be used recursively to compute forecasts.

Choice of Smoothing Constant

The smoothing constant α determines the extent to which past observations influence the forecast. A small α results in a slow response to changes in the level; a large α results in a rapid response, which, however will also make the forecast respond to irregular movements in the time series. The smoothing constant is frequently determined by simulation. Forecasts are generated for various α's (usually over the range 0.05 to 0.30) and are then compared to the actual observations z_1 , z_2 , - - -, z_N. For each α, one-step ahead forecast errors:

$$e_{t-1}(1) = z_t - z_{t-1}(1) \qquad (2.4)$$

and the sum of the squared one-step ahead forecast errors:

$$SSE(\alpha) = \Sigma e^2_{t-1}(1) \qquad (2.5)$$

are calculated. The smoothing constant, which minimises the sum of the squared forecast errors, is then used as smoothing constant in the derivation of future forecasts.

The notation $e_{t-1}(1)$ expresses the fact that it is the one-step ahead forecast error of the forecast that is calculated from the past data up to and including time t-1. In general $e_t(l) = z_{t+l} - z_t(l)$ is the l-step ahead forecast error corresponding to the l-step ahead forecast made at time t. The main reason for the widespread use of simple exponential smoothing comes from the updating equation :

$$z_n(1) = \alpha z_n + (1-\alpha)z_{n-1}(1) \qquad (2.6)$$

Since this make the calculation of new forecasts computationally very convenient, only the previous forecast and the most recent observation have to be stored when updating the forecast. Another reason exponential smoothing techniques have received broad attention is that they are fully automatic. Once a computer program has been written and a smoothing constant α has been chosen, forecasts for any time series can be derived without manual intervention of the forecaster.

University of Southampton (1987) in " Traffic incidents and Route Guidance in a SCOOT network" considered this method and conclude that the method is only useful in off-peak traffic forecasting when traffic demand is stationary. A stationary demand situation is one in which, although demand fluctuates from one time period to the next, the average value remains steady over a reasonably long period of time.

2.2.1.2 Holt-Winters Forecasting Method

Exponential smoothing may easily be generalized to deal with time series containing trend and seasonal variation. The resulting procedure is usually referred to as the Holt-Winters procedure. Trend and seasonal terms are introduced which are also updated by exponential smoothing. Suppose the observations are monthly. Let m_t denote the estimated current mean in month t, r_t denote the estimated trend term in month t (i.e. the expected increase or decrease per month in the current mean), and s_t denote the estimated seasonal factor appropriate to month t. Then as each new observation becomes available, all three terms are updated. If the seasonal variation is multiplicative, the updating equations are:

$$m_t = \alpha\, z_t/s_{t-12} + (1-\alpha)\,(m_{t-1} + r_{t-1}) \qquad (2.7)$$

$$s_t = \beta\, z_t/m_t + (1-\beta)s_{t-12} \qquad (2.8)$$

$$r_t = \gamma\,(m_t-m_{t-1}) + (1-\gamma)r_{t-1} \qquad (2.9)$$

where z_t is the latest observation and α, β, γ are constants such that:

$$0 < \alpha, \beta, \gamma < 1$$

The forecasts from time t are then generated by the equation

$$z_{(t,h)} = (m_t + hr_t)s_{t-12+h} \qquad (2.10)$$

$$(h=1,2,\text{---},12)$$

If the seasonal variation is additive, the updating equations are:

$$m_t = \alpha\,(z_t\text{-}s_{t-12}) + (1\text{-}\alpha)\,(m_{t-1} + r_{t-1}) \qquad (2.11)$$

$$s_t = \beta\,(z_t\text{-}m_t) + (1\text{-}\beta)s_{t-12} \qquad (2.12)$$

$$r_t = \gamma\,(m_t\text{-}m_{t-1}) + (1\text{-}\gamma)r_{t-1} \qquad (2.13)$$

A graph of the data should be examined to see if an additive or multiplicative seasonal effect is the more appropriate. Starting values for m_t, r_t, and s_t may be estimated in a fairly crude way from the first two years data, by taking:

$$m_1 = \Sigma z_t/12 \qquad (2.14)$$

$$r_1 = (\text{mean of 2nd year - mean of 1st year})/12 \qquad (2.15)$$

s_1, s_2, - - -, s_{12} to be the average seasonal effects in the first two years when the different months are compared with the yearly means.

This method has been used by many researchers to forecast traffic parameters. Richards A J (1991) used the method to forecast delay on link-by-link basis using Southampton SCOOT data. The method has also been used in (DRIVE CARGOES Project, 1990) where it was used for journey time prediction. The results from both the studies show that method is good when the historic data has relatively less noise, however when historic data has higher level of noise or when the current days data is very different from historic data, the model can give very inaccurate forecasts. Another disadvantage associated with Holt-Winter method is the selection of suitable values for parameters α, β and γ, often these are calculated from historic data.

2.2.2 Adaptive Forecasting

Statistical techniques for modelling time-series data are of course well established; however another forecasting technique which gained popularity in engineering applications particularly in control is adaptive forecasting, in this technique the parameters of time-series model are continually being modified to correct for past errors in prediction. One such technique is Kalman filtering, which has been used in traffic forecasting, e.g. (Okutani and Stephanides, 1984), (Willsky, 1980) and (Whittaker, 1991).

2.2.2.1 Kalman Filtering

The Kalman-Filter technique has been developed as an instrument in control engineering. It deals with two distributions. The knowledge of observed values is used in a recursive process to predict a distribution of expected values, individual factors control the (long term) updating and the short term prediction.

In this technique, the problem of short term traffic forecasting can be considered with the help of the following basic assumptions.

* Traffic parameters in an urban network have similar profiles in following days of the same class (week days, weekend).
* Changes in daily profiles may be of three types:
    - Changes due to specific events in a particular day. In this case,

normally, modifications are of short duration (eg incident on a link).

- Trends in the profile, such to modify continuously the profile, on a day-by-day basis.
- Casual and totally unpredictable changes of small amplitudes.

* Parameter values, to be significant, have to be averaged on suitable time intervals, of the order of few minutes.

From these basic assumptions, a suitable dynamic stochastic model for the parameter can be outlined, as follows:

$$T_{i,k} = T_{i,k-1} + w_{i,k} \tag{2.16}$$

$$(t-T)_{i,k} = a(t-T)_{i-1,k} + v_{i,k} \tag{2.17}$$

where

$t_{i,k}$ is the parameter value on interval i of day k.

$T_{i,k}$ is the "ideal profile" at the same time.

a is a suitable coefficient.

v,w are white noises.

Equation (2.16) states that the "ideal profile" behaves, on a day-by-day basis. Equation (2.17) states that, during day k, short time variation may arise. Moreover these variations (t-T) behave, within day k, as a linear, first order, stable process. Equations (2.16) and (2.17) are the simplest mathematical formulation of the previous assumptions. Equations (2.16) and (2.17) are very useful in the prediction problem. Indeed they allow for the separation of "short time, non repetitive" events (as described by (t-T) from the trend in the daily profile represented by T). The best estimates for t and T are to be used for the prediction within day k, while only T will then be used as the starting point for day k+1. This method is also called adaptive-forecasting, because it relies on a continuous comparison of past predictions and realisations in order to adapt its forecasts to observed forecasting errors. In this way forecasting errors will be damped out, instead of being amplified by subsequent applications of the model.

The Kalman Filtering, defined above, has been used to predict journey time on link-by-link basis (DRIVE CARGOES Project, 1990). Also in Whittaker (1991) an outline is given of a dynamic state space model with its associated Kalman filter for very short-term prediction of traffic on a highway network. However, literature on the successful use of the Kalman filter for traffic forecasting is rather sparse, furthermore due to its strong data requirements, the technique is not easy to implement.

2.2.3 Neural Networks

Neural networks is a large, growing subject (Clark et al, 1993). They differ from the statistical methods conventionally used to analyze data, since relationships between inputs and outputs are not pre-defined. In essence, such system deduce the strength to be attached to different relationships. The networks 'learn' by exposing to examples. The main features of neural networks are 'input data' entering at various nodes along the bottom layer and is converted into 'output data' along the top layer via a weighting and thresh holding function at other nodes in an intermediate or hidden layer. There are many different ways of defining and training a neural network (Beale and Jackson, 1990). One problem with neural networks is that they can be trained to exhibit many interesting behavioural properties, it can often be very difficult to interpret why the training was successful. The fact that convergence has occurred means that pattern exist, but it may be impossible to isolate them. This means neural networks are often treated as a 'black box' and incorporated into software accordingly. Although this can be very successful, it complicates the question of system verification and validation and can also cause difficulties in providing sufficient explanation to the end user.

(Kirby et al 1993), used neural networks to predict traffic flows and compared the results with three other methods, these were : linear regression, time series ARIMA and Transfer functions. They concluded that regression techniques were not very good; that ARIMA methods provided results equivalent to those obtained using neural networks; and that the use of transfer functions could show an additional improvement, but at a cost of greater complexity in fitting method.

2.2.4 LISB Method : (the method used in the Berlin LISB field trial)

For the LISB (Von-Tomkewitsch, 1987) field trial in Berlin vehicles collect the actual travel times from the links in the road network and send these data first to the beacons and then to the central computer, the travel time prediction consists of three stages:

- development of travel time standard profiles for each link in the network.
- continuation of standard profiles after a day of operation by incorporating the gathered travel time data of that day.
- prediction of travel times on the basis of the travel time standard profiles and current day travel time by using multiple exponential smoothing with variable weighting parameters.

Considering the problems associated with above forecasting techniques, and the less than good forecasting results for on-line application, there is a need to consider new modelling approach where better results could be obtained.

2.3 Review Of Traffic Parameters

The choice of a traffic parameter to be forecast depends on the application for which this forecast is going to be used. The initial stage of this study involved a literature review of the characteristics of the traffic parameters. A description of these parameters is given in the following section.

2.3.1 Flow

The average number of vehicles passing a given point on the road in the same direction per unit of time is called flow. Volume and rate of flow are two measures that quantify the amount of traffic passing a point on a lane or roadway during a designated time interval. These terms are defined as follows:

i. Volume : The total number of vehicles that pass over a given point or section of a lane or roadway during a given time interval; volume may be expressed in terms of annual, daily, hourly or subhourly periods.

ii. Rate Of Flow : The equivalent hourly rate at which vehicles pass over a given point or section of a lane or roadway during a given time interval less than one hour, usually 5 minutes or 15 minutes.

The values of traffic flow required in traffic engineering are a key point in many control and planning strategies. The usage of the average, or mean, value is generally accepted as a standard. It is possible to estimate average hourly flow in a specific weekday, in a particular month of the year by the application of factors available in the Traffic Appraisal Manual (DTp, 1981a, p 591). Nevertheless, the existence of variability in traffic flow throughout each hour, day, week and month is widely recognised. Therefore, forecasting of traffic flows on 5-minute or 15-minute basis can be of great interest in many traffic control applications.

2.3.2 Capacity

Capacity is the maximum number of vehicles that can pass a point on a lane or roadway during a given period of time under prevailing roadway and traffic conditions. So capacity is a particular rate of flow "the maximum rate".

2.3.3 Delay

The difference between the actual and desired travel times is delay. Two widely used measure of delay are :

i. Aggregate Delay

The total delay to all vehicles on an intersection approach during some time period. This is usually measured in vehicle hours/hour. Aggregate delay is an indicator of the magnitude of oversaturation and is generally useful as a control parameter.

ii. Average Delay

The average delay is delay per vehicle on an intersection approach during some time period, this is usually measured in seconds/vehicle. Average delay is a good indicator of the magnitude of saturation. It is well correlated to other characteristics of intersections such as volume, queue length and characteristics of signal operations.

Delay can be used as an indication of the existence of congestion or a measure of the degree of congestion in a system. It is seen that when flow reaches about 90% of the ultimate capacity, the delay rises steeply. Theoretically the delay increases to infinity as the flow tends to the ultimate capacity; but in practise the level of flow rarely remains at a high value for a long period. Delay however is a complex variable that is affected by many variables.

The forecasting of delay can be useful in signal control applications, however for information systems delay may not be the best parameter to forecast as for general public it is not always easy to understand the exact meaning of delay.

2.3.4 Journey Time

Journey time is defined as the time taken to travel from one point to another in free flow conditions plus any delay (e.g. due to traffic signals, by other vehicles on the road etc) incurred during the journey.

2.3.4.1 Distribution of Journey Time

A number of studies have been carried out to examine the distribution of journey time and identify those factors affecting it's variability. Smeed and Jeffcoate (1971) and May, Bonsall and Marler (1989) showed that the distribution of journey time is 'normal'. However, other studies such as those carried out by Mogridge and Fry (1984) have reported a positively skewed distribution of travel time. Mogridge and Fry (1984) concluded that the distribution of journey time is 'log normal'.

The previous studies (Smeed and Jeffcoate, 1971) also showed a positive relationship between the mean and standard deviation of journey times. May et al (1989) also reported a significant relationship between the mean and standard deviation of journey time, with standard deviation increasing with increasing mean journey time.

Although Smeed and Jeffcoate (1971) reported that journeys were significantly longer on Mondays, May et al (1989) found no general trend in the day to day values of standard deviation or any relationship with weather condition.

2.3.5 Queue Length

Queue length is the number of vehicles in, or the length in metres of, a given queue. This is an intersection measure of utility in both characterizing conditions and on line control. It is indicative of the magnitude of saturation. Queue length is well correlated with other intersection measures, such as delay and input. It is the most frequently used control parameter with delay.

Queue length may be the intersection measure that most directly affects drivers behaviour under saturated conditions because it is most readily observable. Various detection systems and techniques for estimating queue length have been developed in recent years. In some systems, queue length is used as a congestion indicator. Several control schemes with the queue as a control parameter have been developed and some of them are applied.

Delay is currently the most widely used parameter in existing control schemes because minimum delay relates to minimum operating cost. However once saturation occurs, optimization of flow, based on a delay parameter may be less valid because delay may not be a primary problem. The primary task of the control scheme may then be prevention of contamination of other intersections. Queue parameters are also more easily observed and measured than delay parameters. Thus, a measure expressed in terms of queue appears to be the most promising.

2.3.6 Degree Of Saturation

" The ratio of the average flow to the maximum flow which can be passed through the intersection from the particular approach is called degree of saturation ".

Serious congestion is likely to occur as the degree of saturation approaches 100% and it is desirable that stop lines be no more than 90% saturated. The degree of saturation is affected by the choice of signal cycle time and the percent of the cycle time that signals are effectively green on any one approach. It is given by:

$$x = qc/gs \tag{2.18}$$

where

x = degree of saturation

q = flow ; average number of vehicles/sec

g = green time

s = saturation flow

c = cycle time

McShane et al (1978), in their review of traffic control in oversaturated street networks adopt the following definitions:

i. Congested Operations

"The entire range of operations which may be experienced when traffic demand approaches or exceeds, or both, the capacity of the signal."

ii. Saturated Operations

"The range of congestion wherein queues form but their adverse affects on the traffic in terms of delay and/or stops are local. Local affects in this context means that traffic performance is only affected at the intersection at which the queue occurs and that no other intersections performance is affected by this queue. Saturated operations have been sub-categorized further into:

a: Stable Saturation

When a queue formed but not growing and delay effects are local.

b: Unstable Saturation

When a queue exists and is growing and delay effects are still local. Unstable saturation is a transient state whose duration may be quite short depending on such factors as rate of queue formation and distance to next upstream intersection.

iii. Oversaturated Operations

A situation where a queue exists and that have grown to the point where the upstream intersections performance is adversely affected.

2.3.7 Density

Density is the number of vehicles per unit length of roadway or lane. Density is not sufficient in itself, because the presence of high density does not necessarily guarantee the presence of queues sufficiently long as to cause oversaturation.

This measure may be useful in conjunction with queues or velocity measures. Such combined measures must be calibrated for individual links to permit their use as descriptors and predictors. If possible a more general type of measure is desirable. Direct measurement of density in the field is difficult, it can be computed, however, from the average travel speed and rate of flow, which are more easily measured.

$$\text{density} = \text{flow/space mean speed} \tag{2.19}$$

2.3.8 Congestion

Congestion is a qualitative term, used by the general public as well as traffic engineers, which refers to what can quantitatively be defined as vehicular density. The results of an oversupply of vehicles is the formation of a queue of stopped (or crawling) vehicles at bottleneck locations (a breakdown of the operation) such that volumes momentarily drop to zero, leaving only congestion on the facility until a clearout can be effected. Basically, congestion will be a direct result of the nature of the "supply and demand" on a facility. If it is possible on a given system, for more vehicles to enter than the facility can handle, congestion will result whenever the demand exceeds capacity.

2.4 Traffic Incidents

The time-series forecasting methods discussed in section 2.2 can be applied to individual links under normal traffic conditions where day-to-day patterns of journey time do not change dramatically. However, a different modelling approach is required to predict the journey time after an incident occurs on an urban road. Traffic incidents occur in a variety of forms and contribute to increase congestion and hence journey time by reducing the capacity of road networks for various periods of time and at various levels of severity. The disruptions which they create depend on the type of incident (University of Southampton, 1987).

2.4.1 Types of Incidents

A commonly adopted definition of a traffic incident is 'an unusual occurrence which reduces the capacity of the road on which it occurs' (Collings J F, 1981). Incidents occur in a variety of forms and can be classified into two main categories:

2.4.1.1 Predictable Incidents

Incidents due to planned events are predictable incidents, such as roadworks, traffic signal maintenance, special events. Authorities may advise drivers of their occurrence, or of diversions. Also, where such 'incidents' are prolonged, drivers will learn of their effects and adjust their travel habits accordingly.

2.4.1.2 Unpredictable Incidents

The second main category of incidents which may be termed 'unpredictable' are those due to accidents, traffic signal failures, vehicle breakdowns, illegal parking/stopping, abnormal weather conditions, other emergencies. As may be expected, it is these events which cause most difficulties to traffic authorities and road users due to the uncertain nature of the incident and its effects.

2.4.1.3 Other Classification

A recent review of incidents in London area (Holmes and Leonard, 1992) was based on a traffic database maintained by the London Metropolitan police for a 6-month period in 1991. The database, covering the London area bordered by the M25 peripheral motorway, recorded approximately 4000 incidents causing traffic congestion. The incidents are classified into the three following causes:

- Network effects:

  Traffic signal failure, roadworks, burst water mains, other works.

- Vehicle effects:

  Traffic accidents, heavy vehicle breakdowns, light vehicle breakdowns, diesel fuel spillage.

- Other causes:

  Special events, weather, hazards, security, unclassified.

The results of the database analysis on the type of incident shows that most numerous of the specific incidents are traffic accidents (28%), roadworks (22%), vehicle breakdowns (11%), traffic signal faults (8%), security alerts (6%), hazards (6%) and unclassified categories. It was anticipated that the severity of congestion caused by an incident increases according to the level of the network traffic, with the greatest impact during the morning and evening peak periods. The duration of incidents were also analyzed. For the incidents of known duration and as a percentage of all incidents, 25% lasted less than one hour, 31% between one to four hours, 11% between four to twelve hours, with 6% of incidents lasting over 12 hours. The database indicated that for incidents causing congestion lasting up to four hours, traffic accidents are the main cause. The longer term incidents, that is over four hours, are dominated by roadworks. The review provided useful information on the various degrees of traffic congestion and typical duration for an urban network and will be directly applicable to the computer simulation work.

2.4.2 Effects of Incidents

For both the categories of incident defined above, the net effect is a reduction in road capacity, which lasts for varying lengths of time. The result is an excess of traffic demand over reduced capacity which leads to higher than normal journey time, not only on the link of incident but also on the approaching links and other links in the network.

2.4.3 Incident Detection Methods

Incident detection is an essential element of adaptive network control in Advanced Transportation Management Systems (Stephanedes et al,1992). Successful detection and dynamic prediction are necessary for assessing on-line traffic data at the highest level of intelligence and guiding the network control strategies to an optimal solution. Traffic management, control and guidance can be facilitated by detecting incidents and predicting traffic behaviour in the network.

2.4.3.1 Information Gathering

Incident information can be obtained by several means including Police department, motoring organisations, meteorological offices, emergency services, Urban Traffic Control Systems (UTC). The general public can also be a useful source of information, particularly in the case of unpredictable incidents which the public is often the first one to be aware of, this initial information from general public can then be pass on to the local police division via the telephone network. Predictable events are usually passed on by those responsible either to the local police or to a designated department at police headquarters. There has also been an increase in the use of CCTV monitors in police control centres covering key areas, such as Urban Traffic Control networks.

2.4.3.2 Control systems and road sensors in urban areas

Information from UTC systems and road sensors is a major source of traffic data. Incidents can be detected from this information. On-line incident detection methods are also being developed within UTC systems. A number of such techniques have been developed in UK (Collings J F, 1983 and Hall M D et al, 1984) and overseas (Levin et al, 1979 and Shibata et al, 1984) based on the processing of detector information on vehicle occupancy and speed (e.g. high occupancy and low speed would be indicative of congestion which could be caused by a traffic incident if such conditions were not expected.

2.4.3.3 Automatic Incident Detection

The use of vehicle detectors allows incidents to be detected automatically provided a suitable detection algorithm can be devised. Automatic Incident Detection (AID) techniques allow a faster knowledge of incident occurrences on the network for vehicles equipped with an information transmission system such as radio or a route guidance system and for traffic responsive control system.

At present most Automatic Incident Detection algorithms are designed to operate with limited traffic data, typically traffic volume and occupancy, simple functions are used to compare raw volume and occupancy measurements against preselected thresholds. Within the most widely known algorithms those following the California logic (Payne et al, 1976) rely on the principle that an incident is likely to significantly increase occupancy upstream while reducing the occupancy downstream. A typical algorithm includes a test to ensure that exceeding a threshold is not due to random fluctuations in the data.

Algorithms employing statistical forecasting of traffic behaviour consider a time series model to provide short term forecasts of traffic behaviour. The simplest models consider the occupancy mean and standard deviation over the most recent few minutes (Dudek C L, 1974) or are based on double exponential smoothing (Cook et al, 1974). Significant deviation between observations and values forecast by the algorithms are attributed to incidents.

The McMaster algorithm (Persaud et al, 1990) is based on a two-dimensional analysis of the traffic data and proposes separating the flow-occupancy diagram into four areas corresponding to different states of traffic conditions. Incidents are detected after observing specific changes of the traffic state in a short time period. The HIOCC algorithm (Collings et al, 1981) is based on one-second occupancy data. the algorithm looks for several consecutive seconds of high detector occupancy in order to identify the presence of stationary or slow moving vehicles over individual detectors.

One of the shortcomings of incident detection algorithm is that, as a consequence of point based, rather than spatial measurements of the data detection algorithms sometimes lack efficiency. Indeed, traffic flow dynamics rely on two dimensions (time and space), only one of which (time) is taken into account in the measurements, Consequently, a large number of false alarms and missed detection has been reported in operational use. Nevertheless, when the traffic data collection is to be combined with an Automatic Incident Detection algorithm some other systems can be used. At the same time as new, more efficient Automatic Incident Detection algorithms are developed, some new Automatic Incident Detection systems have appeared, such as **video image processing**. The technique of video image processing for the detection of queues and incidents in urban networks gains by the extensive level of coverage which the cameras provide within their field of view. The research which has been carried out recently on video image processing includes the DRIVE project INVAID (INtegration of computer vision techniques for Automatic Incident Detection), and a project to design 'AUTOSCOPE' video image processing system (Michalopoulos, Jacobson et al., 1993).

2.4.4 Incident Management Strategies

Following an incident and its detection by a suitable method, there is a need to predict the effects of an incident in the network and to bring some incident management strategies which provides the appropriate response to minimize the adverse effects of the incident. The current automated management strategies coping with traffic incidents are based on traffic data collection and processing. They aim at adapting traffic signal timings to the new congested traffic conditions in the streets comprising or bordering the incident location and in some cases to make use of variable message signing. Today these techniques are still being improved so as to decrease the number of false alarms and missed detection being made. As for man-operated techniques for the detection of incidents (e.g. using video cameras), they are demanding and, although they minimise the risk of false alarms, some incidents are still missed or detected long after they have appeared. Moreover, the latter techniques are against the current trend to develop an automatic Integrated Traffic Management.

The Automatic Incident Detection (AID) techniques described earlier can be used effectively within management strategies to decrease the detection process duration. Then, vehicle-drivers whose vehicles are equipped with an information transmission system such as a radio or route guidance system have a faster knowledge of incident occurrences on the network.

2.4.4.1 Radio Information System

Vehicles which are equipped with a radio working in certain frequencies can receive current traffic information about the area of the network where they are located. Some **radio information systems** are developed so as to minimise the time gap between the actual detection of an incident and its radio transmission to road users. Radio Data Systems (RDS) as well as common FM radio stations can be used for this purpose. These systems are coupled with automatic traffic control systems which analyze the data for traffic incidents. Then, the German ARIAM Car-Driver-Radio-Information system (Giesa, 1987) for instance, automatically elaborates a text describing an incident and transmits it to the broadcasting station. Moreover radio information systems are one possible basis for the development of route guidance systems.

2.4.4.2 On-line Route Guidance Systems

Because of their ability to divert vehicles on to routes which avoid an incident, route guidance systems are assumed to achieve greater time savings in urban areas than simple traffic information systems. Dynamic Route Guidance (DRG) systems 'aim at guiding drivers on their optimum route to their destination, taking account of existing/forecast traffic conditions, with guidance being provided by in-vehicle units (Hounsell et al, 1992b). The principle of these systems consists of transmitting traffic information both ways between an in-vehicle unit and a central computer via road-side beacons or directly, for instance using cellular radio communications (e.g. APPLE project in London).

2.4.4.3 EURO-SCOUT System

When the information is not transmitted directly between the in-vehicle unit and the central computer, it can be transmitted by infra-red between road-side beacons located at key intersections and vehicles, and by telephone lines between the beacons and the central computer. An incident management system (IMS) was developed (Janko, 1989) for the Berlin field trial of the EURO-SCOUT route guidance system. The IMS has been designed to be operated by police officers in the traffic control centre. To start the incident management procedure information is required on the type of incident, the location and the (estimated) severity. Incidents are allocated to links; three degrees of severity are possible from minor restraints to the total blocking of a link. For travel time modifications in connection with predictable incidents the ratio between the predicted link travel time under normal conditions and the optimum link travel time is used. Travel time modification for unpredictable incidents depends on six parameters, the saturation flow of the considered link, saturation flow of the incident link, the severity of the incident, the maximum travel time to the management border, the travel time between the considered link and the incident link, the duration since the incident became known. The central computer operates route calculations repeatedly on the basis of 'static' network information and real-time data provided mainly by equipped vehicles. The interaction between vehicles and the central computer provides knowledge of the current traffic conditions on the network, particularly concerning incidents and congestion.

Other forms of DRG (eg. cellular radio) involve in-vehicle systems able to calculate the optimum route in each single vehicle, on the basis of real-time 'broadcast' information (eg. link journey times). Some studies have shown the benefits of route guidance systems (JMP Consultants Ltd, 1989) and potential benefits in some other cities provided with a traffic control system such as SCOOT (University of Southampton, 1987) when traffic incidents were taken into account. The detection of an incident by the central computer is made from the analysis of data indicating very long journey times on a link, or no information received from a certain beacon. In the latter case, when the possibility of a beacon breakdown has been dismissed, it can be assumed that no equipped vehicle is travelling on the relevant link, which is a plausible sign that an incident has occurred, and which can be checked out easily. The future calculated routes then avoid the 'disrupted' link. At this stage it should be mentioned that DRG systems face a problem in the event of an incident, with all vehicles diverted from the incident location link, and no more feedback on the incident evolution and the end of the disruption. A solution to get the missing information would be to direct a small number of equipped cars on to routes including the incident regularly.

2.4.5 Need for Statistical Modelling

One way of predicting incident effects is by running an assignment model on line, however there are two problems involved in this, firstly road traffic assignment and simulation models are very demanding in computing (processing) time and computer main memory particularly with very large networks. This is mainly due to the variety of traffic parameters and scenarios that have to be represented in sufficient detail to enable rational deductions to be made from results of simulations. The detailed representation of network traffic by most of the existing models requires high computing time on commonly available and affordable computer hardware (i.e, desktop PCs). Running a model like CONTRAM on a 1600 link network with average demand matrix on a top of the range 486 PC takes several hours. These models are currently being undertaken off-line, which is appropriate for traffic management schemes and traffic appraisal. However to predict the effects of an incident, for dynamic route guidance systems and for other on-line control systems requires real-time processing, this would further substantially increase the computing requirements. The performance of widely available and affordable single processor hardware would be struggling to keep pace with these requirements. Secondly even when sufficiently powerful computers will be available in the future to run an assignment model on-line, it will require detailed representations of the network before an on-line simulation can be run, which can be very costly and will not be available for most of the networks. For such reasons there is a need for simple statistical models which can be used on-line to predict the affects of an incident in a network.

2.5 Discussion

The review of forecasting techniques in section 2.2 indicate that a number of forecasting methods have been tested before. However, there is a need to apply new forecasting techniques which have not been used either due to the complexity of the technique or due to the unavailability of much needed computing power. But with the availability of powerful computers and new developments in forecasting techniques lead to consider the application of these methods for traffic forecasting.

Time-Series type of forecasting methods may be equally successful in 'stable' conditions where current data has relatively little variability and is close to historically-based expectations. However, where current data differs markedly (i.e. when forecasts are most needed) the form of prediction algorithm is important, this lead to the consideration of another type of forecasting where the effects of incidents can be incorporated successfully into the forecasting model.

For both the categories of incident defined above, the net effect is a reduction in road capacity, which lasts for varying lengths of time. The result is often an excess of traffic demand over reduced capacity which leads to higher than normal journey time, not only on the link of incident but also on the approaching links and other links in the network. This could lead to serious congestion, rise in energy consumption, environmental nuisance. The prediction of the effects of traffic incidents is therefore an important issue for better efficiency and for on line Dynamic Route Guidance (DRG) systems and other traffic control and information systems which may be used as possible incident management strategy.

CHAPTER 3

DATA COLLECTION

A number of methods are available for traffic data collection. They cover a range of different techniques; such as number plate matching techniques, vehicle detectors at traffic signals and on-street surveys.

For this study, it was decided to collect data from Southampton SCOOT network system (Figure 3.1). Southampton is considered suitable for monitoring of the traffic conditions since there is a relatively large proportion of the city network within the SCOOT area and also data is readily available as Transportation Research Group has close links with traffic authorities who are responsible of SCOOT operation in Southampton.

3.1 SCOOT Data

The primary purpose of SCOOT (Hunt et al, 1981) system is to calculate and implement signal settings in urban networks which optimise overall traffic performance (see figure 3.2). However in the process of optimisation, the traffic model within SCOOT provides a large quantity of on-line traffic data such as flow, delay and congestion, which is potential source of useful information (see figure 3.3).

Figure 3.1 Area of Southampton controlled by SCOOT

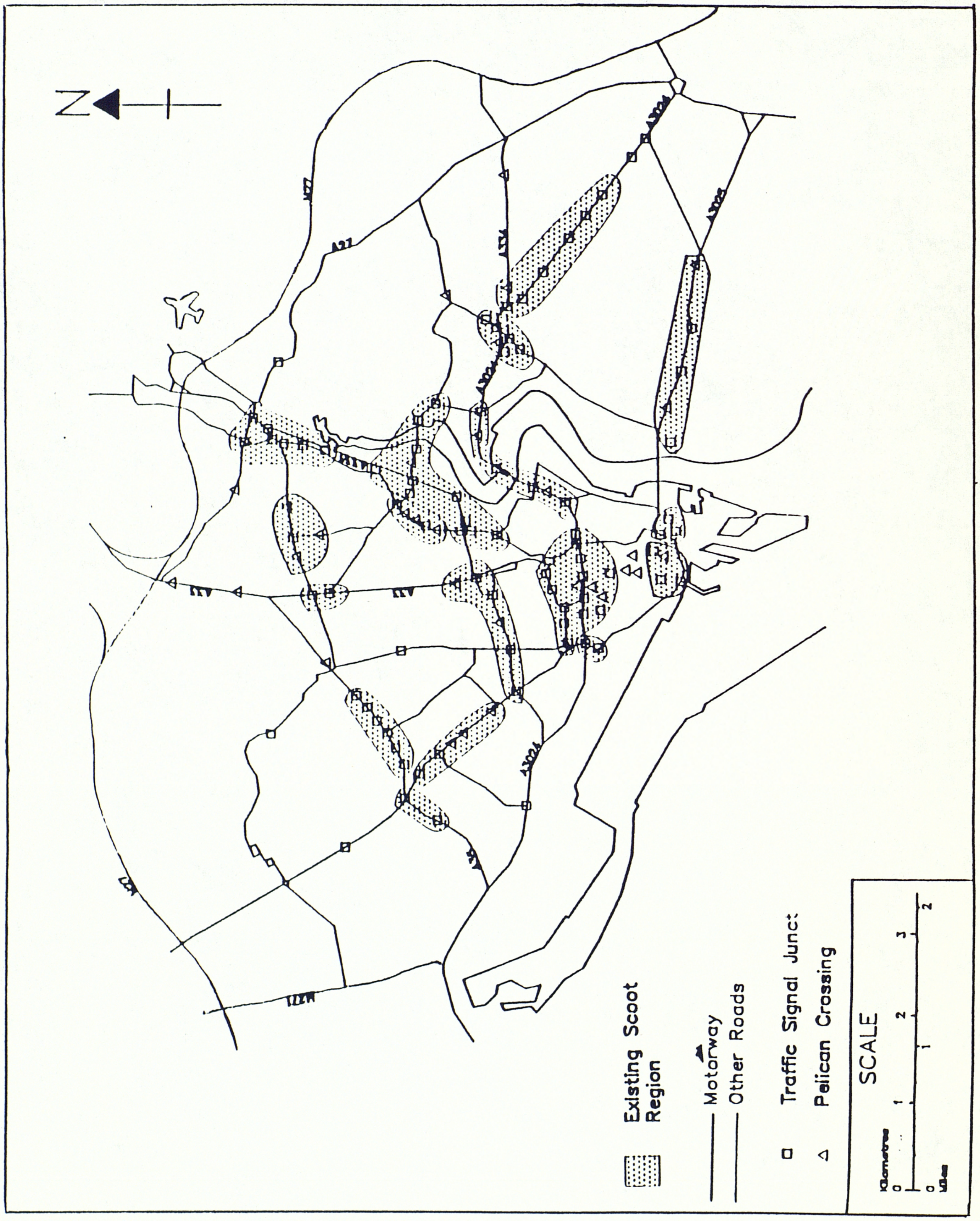
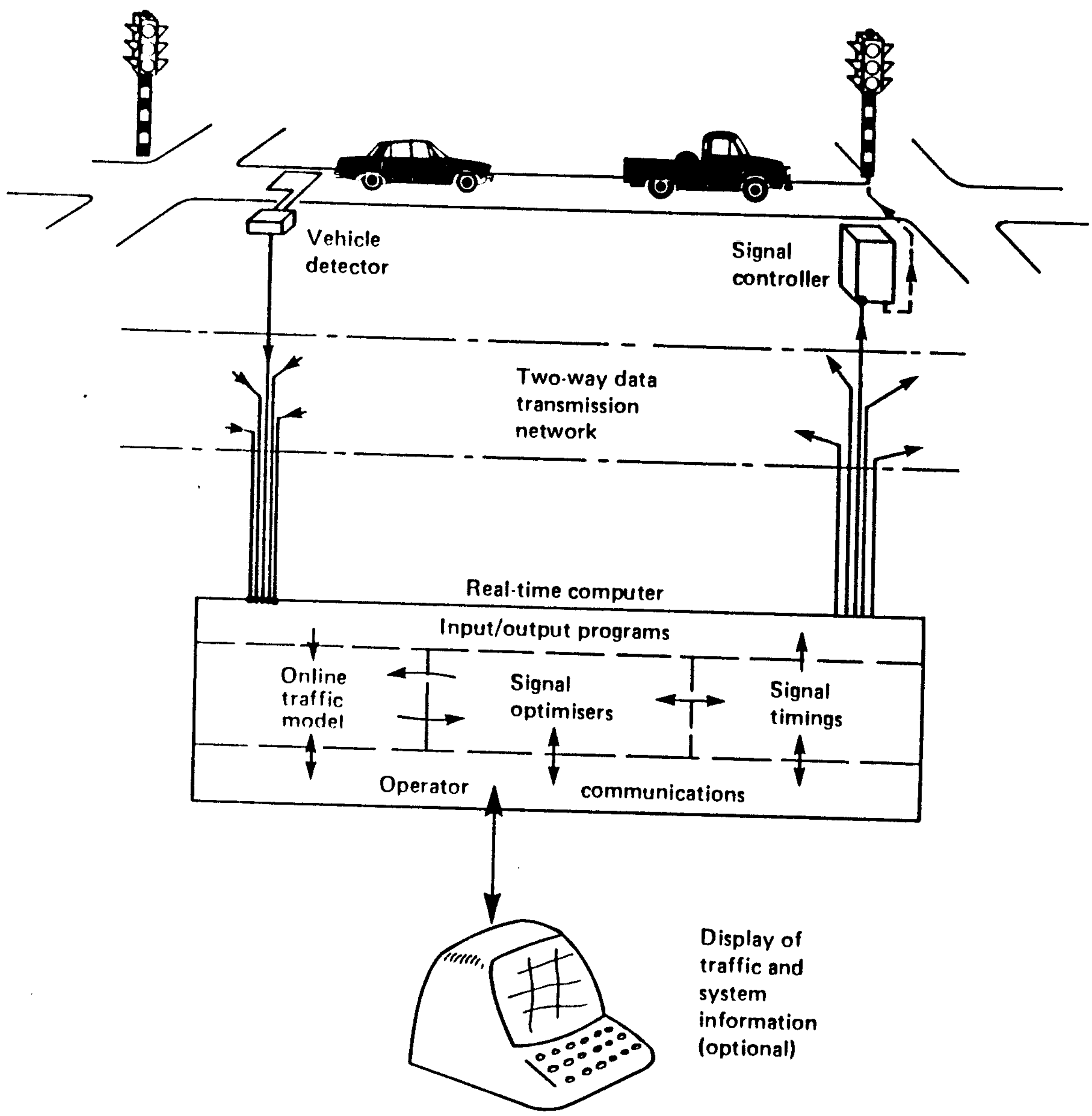
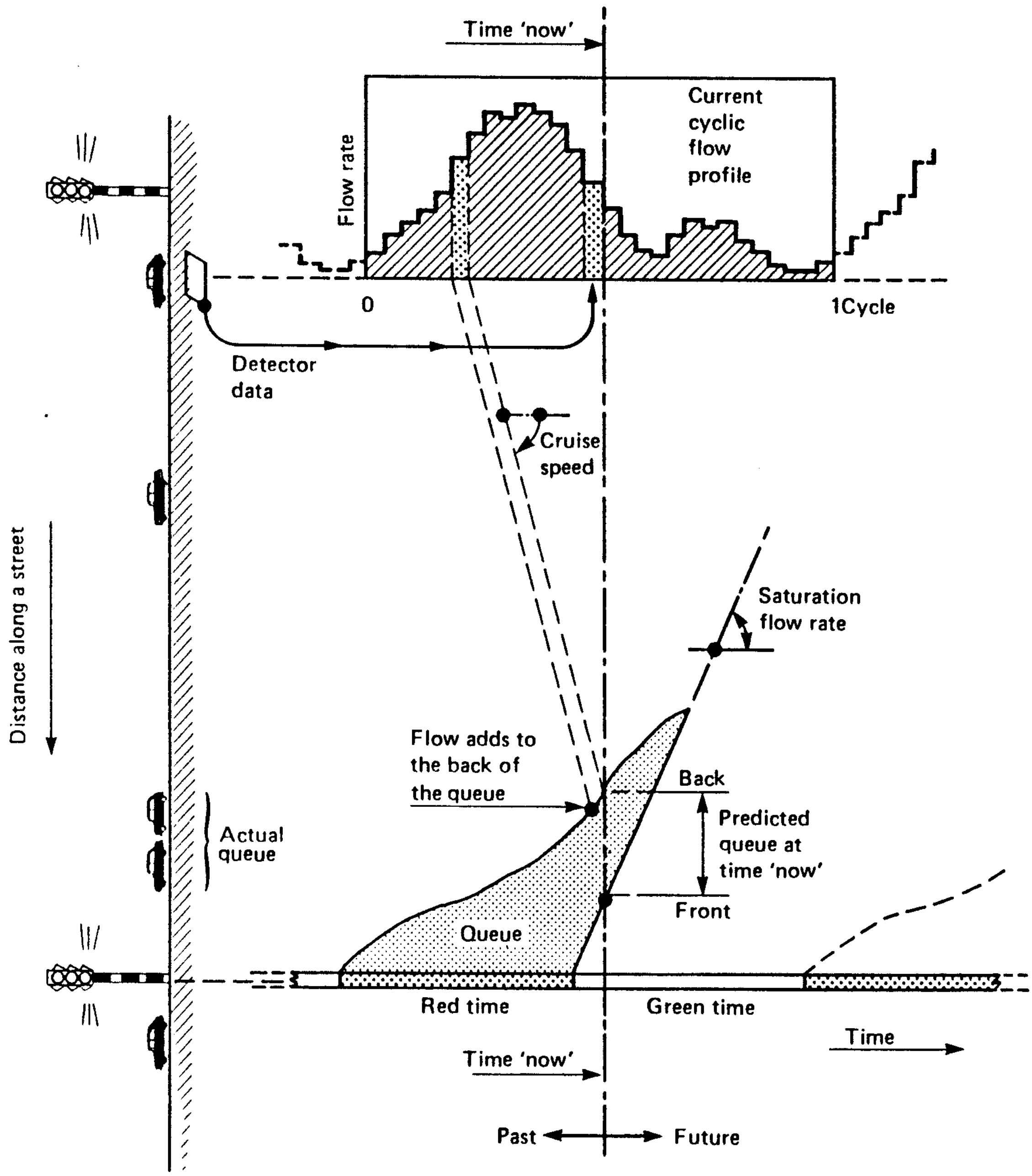


Figure 3.2 The flow of information in a SCOOT urban traffic control system



Source : T.R.L Report LR 1014

Figure 3.3 Principles of the SCOOT traffic model



Source : T.R.L Report LR 1014

3.2 SCOOT in Southampton

The SCOOT system is operating in Southampton since 1983. The model initially comprised four distinct regions of Southampton, but has since been expanded to contain smaller sub areas. There are now 15 regions in the SCOOT network which contain most of the signal controlled junctions in the city. These junctions control traffic on a total of over 200 SCOOT links. The regions and junctions within the SCOOT system are illustrated in figure 3.1. Since SCOOT data was used for this study, a critical review is presented to see how these traffic parameters are described and calculated in SCOOT.

3.3 Traffic Parameters in SCOOT

The SCOOT traffic model predicts the effects of changes in traffic signal settings. The current signal settings and measurements from vehicle detectors are used to produce the estimates of traffic queues, delay and vehicle stops. The output from SCOOT also includes traffic flow from the vehicle detectors and the estimated queue length.

3.3.1 Traffic Flow In SCOOT

SCOOT records information on vehicle presence (i,e occupancy) at each detector and produces estimates of traffic arrivals on each link in terms of link profile units (LPU). Each detector is interrogated at the roadside 4 times every second to see whether it is occupied or not, and this information is transmitted to the central SCOOT computer every second for processing. LPUs are a hybrid of flow and occupancy, although it is possible to obtain flow estimates from SCOOT LPUs.

SCOOT outputs traffic flow estimates in its M02, M03 and M04 messages in vehicles per hour, having divided its LPU count by 17. The factor 17 is a global average found from measurement, but there are considerable between-link variations depending on detector location, the number of traffic lanes and so on. An average conversion factor over all links surveyed in Southampton (Carden et al, 1987) was found to be 16.6 LPUs per vehicle. This does not adversely affect SCOOT's performance, as these fluctuations are catered for by validation. It is also probably not significant if the traffic flow/delay data is only to be used to indicate trends. However, if the flow data is used directly as an absolute value, a link specific lpu/vehicle conversion factor -obtained by measurement- would be required to ensure accuracy.

3.3.2 Traffic Delay in SCOOT

SCOOT's estimate of delay on a link is based on its queue model. Aggregate delay per cycle is equal to the area between the arrival and discharge profiles, while delay per vehicle (which is not output by SCOOT) can be calculated from the time between arrival and discharge.

3.3.3 Link Journey Time from SCOOT

Estimates of delay per vehicle can be obtained by dividing aggregate delay by flow, average journey time (in secs) is then calculated by adding a 'cruise time' for vehicle movements between the SCOOT detector(s) at the upstream end of the link and the stop line.

$$\text{Delay (secs/veh)} = (\text{Delay (veh. hr/hr)} \,/\, \text{Flow (vehs/hr)}) * 3600 \quad (3.1)$$

$$\text{Journey Time (secs)} = \text{Delay (secs/veh)} + \text{Cruise Time (secs)} \quad (3.2)$$

Such estimates of journey time from SCOOT data have been shown (Carden et al, 1989) to accurately reflect on-street journey times over a wide range of conditions.

3.4 Data Availability

The data collected for this study is traffic flow, delay, congestion and degree of saturation at link level and flow, delay and congestion at region level. Data is also collected for a route. The information on these traffic parameters were obtained from SCOOT by M02, C30 and M04 messages. The message M02 as come from the SCOOT computer contains following information:

TIME M02 LINK NO PERIOD STP DLY*10 FLO CONG RAW FLTS

where

PERIOD	is the time in seconds over which the figures were collected.
STP	is the approximate number of vehicle stops per hour.
DLY	is the approximate delay in vehicle hours per hour.
FLO	is the approximate flow in vehicles per hour.
CONG	is SCOOT congestion in intervals per hour
RAW	is the number of 4-seconds intervals per hour where detector was continuously occupied. (maximum = 900)
FLTS	indicate the detector status of the link. (FLTS=0 for OK ; FLTS=1 for FAULTY or SUSPECT)

Region data given by M04 message is equal to the sum of the data from all links within the region. The format of the message which comes from the SCOOT computer is:

TIME M04 REGION NO PERIOD STP/10 DLY FLO/10 RAW/10 FLTS

where

PERIOD	is the time in seconds over which the figures were collected.
DLY	is the approximate delay in vehicle hours per hour and is the sum of DLY values from all the links within the region.
FLO	is the approximate flow in vehicle hours per hour and is the sum

	of FLO values from all the links within the region.
RAW	is the sum of RAW parameters from all the links within the region.
FLTS	number of faulty links within the region.

3.5 Data Correction

3.5.1 Faulty Detectors

In SCOOT model each detector has status OK , SUSPECT or FAULTY. The FLTS parameter in the M02 message indicates the number of FAULTY and SUSPECT detectors within the link.

(FLT = 0 "OK" ; FLTS = 1 "SUSPECT OR FAULTY")

If FLTS = 1, then M02 is still output but data items are zero, this data was not used.

Within the regions where there may be a large number of links, it is possible that some of the detectors are Faulty or Suspect. Whenever the FLTS parameter in M04 message has value greater than zero, the M04 data is factored up by the ratio of the links in the region to the number of OK links.

3.5.2 Missing Data

During data collection some messages were lost for a variety of reasons, such as transmission faults, corruption of the data, power failure, or whenever the SCOOT computer is down. This data was discarded and was not included in the database.

3.6 Pilot Survey

An initial screening of areas for detailed data collection was first carried out following a "blanket" collection of sample data at all locations. This revealed that "normal" congestion levels in Southampton were generally low and confined to a limited number of links. (The widespread use of SCOOT and the introduction of new road schemes in some congested areas were probably contributory factors to the low levels of congestion. On the basis of this survey, 10 links, 10 regions and 1 route were selected for regular monitoring.

3.7 Regular Monitoring

After selection of the most congested links/regions, SCOOT data was collected for three-hour morning and three-hour evening peaks at 10 links, 10 regions and at 1 route over the 6 months (21-01-91 to 07-07-91) data collection period. Recording of data from SCOOT was undertaken at the University via a dedicated telephone line installed between the SCOOT computer in Southampton civic centre offices and Transportation Research Group (TRG) offices. This communications facility, together with associated terminal equipment (such as modems and visual display units), allowed requests for information to be sent to the central computer as needed. The information was then recorded on the PC at the TRG offices. The ASTRID database system (Hounsell et al, 1989) was used for data collection, processing and initial analysis.

3.7.1 Data Collection Sites

Information on traffic flow, delay, congestion and degree of saturation at link level were collected from the following links:

N020A N019D N018E N017C N016D N073A N072C N010E N071D N071A

and on flows, delays and congestion at region level from the following regions

A B C E L P R S T U

3.7.2 Data Collection Time Table

Data was collected on working week days during three hours morning peak (0700-1000) and three hours evening peak (1600-1900) periods at five minute aggregation level. Tables 3.1 and 3.2 show the data collection time tables.

3.8 Discussion

Journey time data used in this study are derived from the output of SCOOT UTC system in Southampton. The primary purpose of the SCOOT system is to calculate and implement signal settings in urban networks which optimise overall traffic performance. However in the process of optimisation, the traffic model within SCOOT provides a large quantity of on-line traffic data such as flow and delay, from which link journey time can be calculated. Flow is measured in 'link profile units' (lpu) per hour. The lpu is a combined measure of vehicle flow and occupancy of the detector. For absolute measure of flow estimates, link specific lpu conversion factor may be required. However this is not necessary for the purpose of journey time calculations as in journey time calculation (see equation 3.1) the units of lpu's cancel out to give delay in seconds. Such estimates of journey time from SCOOT data have been shown (Carden et al, 1989) to accurately reflect on-street journey times over a wide range of conditions.

It was decided to take advantage of this rich data source for this study, following selection of appropriate links exhibiting relatively high congestion characteristics which would be most suitable for developing and testing journey time forecasting models, data was collected for three hour morning (7:00-10:00) and three hour evening peak (16:00-19:00) at 10 links, 10 regions and at 1 route over the six months period. This provided data from 138 peak periods from congested parts of the Southampton network (Figure 3.1). This data set is subsequently used as a historic database for the development of journey time forecasting models.

Table 3.1 Data Collection Time Table - Morning Peak (07:00-10:00)

Week No.	Date 1991	Mon	Tue	Wed	Thr	Fri
1	21/01 - 25/01	*	*	*	*	*
2	28/01 - 01/02	*	*	*	*	*
3	04/02 - 08/02	*	*	*	*	*
4	11/02 - 15/02	*	*	*	*	*
5	18/02 - 22/02	*	*	*	*	-
6	25/02 - 01/03	-	-	-	*	*
7	04/03 - 08/03	*	*	-	-	-
8	11/03 - 15/03	-	-	-	-	-
9	18/03 - 22/03	*	-	-	-	-
10	25/03 - 29/03	-	-	-	-	-
11	01/04 - 05/04	-	-	-	-	-
12	08/04 - 12/04	-	-	-	-	*
13	15/04 - 19/04	*	*	-	*	*
14	22/04 - 26/04	-	-	-	*	-
15	29/04 - 03/05	-	-	-	-	-
16	06/05 - 10/05	-	-	-	-	*
17	13/05 - 17/05	*	*	*	*	*
18	20/05 - 24/05	*	*	*	*	*
19	27/05 - 31/05	*	*	*	*	*
20	03/06 - 07/06	-	-	*	*	*
21	10/06 - 14/06	-	*	*	*	*
22	17/06 - 21/06	*	*	-	*	*
23	24/06 - 28/06	*	-	-	-	-
24	01/07 - 05/07	-	-	*	*	*
25	08/07 - 12/07	*	-	*	-	-

* Data Available - Data Not Available

Table 3.2 Data Collection Time Table - Evening Peak (16:00-19:00)

Week No.	Date 1991	Mon	Tue	Wed	Thr	Fri
1	21/01 - 25/01	*	*	*	*	*
2	28/01 - 01/02	*	*	*	*	*
3	04/02 - 08/02	*	*	*	*	*
4	11/02 - 15/02	*	*	*	*	*
5	18/02 - 22/02	*	*	*	*	-
6	25/02 - 01/03	-	-	-	*	*
7	04/03 - 08/03	*	-	-	-	-
8	11/03 - 15/03	-	-	-	-	*
9	18/03 - 22/03	-	-	-	-	-
10	25/03 - 29/03	-	-	-	-	-
11	01/04 - 05/04	-	-	-	-	-
12	08/04 - 12/04	-	-	-	*	*
13	15/04 - 19/04	*	-	-	*	*
14	22/04 - 26/04	-	-	*	-	-
15	29/04 - 03/05	-	*	*	*	*
16	06/05 - 10/05	-	-	-	*	-
17	13/05 - 17/05	*	*	*	*	*
18	20/05 - 24/05	*	*	*	*	*
19	27/05 - 31/05	*	*	*	*	*
20	03/06 - 07/06	-	*	*	*	*
21	10/06 - 14/06	*	*	*	*	-
22	17/06 - 21/06	-	-	*	*	*
23	24/06 - 28/06	-	*	-	-	-
24	01/07 - 05/07	-	*	*	*	*
25	08/07 - 12/07	-	*	-	-	-

* Data Available   - Data Not Available

CHAPTER 4

ANALYSIS OF DATA

In this chapter, after checking the distributional form of the empirical data set, the variability through time in traffic parameters is studied and statistically analyzed. The parameters which were analyzed are Journey Time (secs) and Flow (vehs/hr) at link and route level and Delay (secs/veh) and Flow (vehs/hr) at region level. This analysis is intended to test the data sets available, trying to discover different sources of variability which can be incorporated into forecasting models.

4.1 The Normality of the Data

Before any further data analysis is carried out, it is required to determine the characteristics of traffic pattern in terms of the statistical distribution. Several previous studies (e.g Smeed and Jeffcoate, 1971; May et al, 1989; Mogridge and Fry, 1984) have attempted to explore the distributional forms of traffic parameters. However, here our aim is not try to fit any distribution on the data but rather to show that the data set used in this study is normally distributed (or approximately normally distributed) and hence classical statistical methods can be employed for further data analysis.

For this purpose, Link N019D is used here as an example to check the distribution form of journey times. Figure 4.1 shows the frequency histogram of journey time on link N019D, the graph shows that the distribution has long right tail, however the frequency of journey time of more than 45 secs is very small. The data set contain some outlier, which may be distorting the distribution curve.

Figure 4.1 Frequency distribution of journey times on link N019D

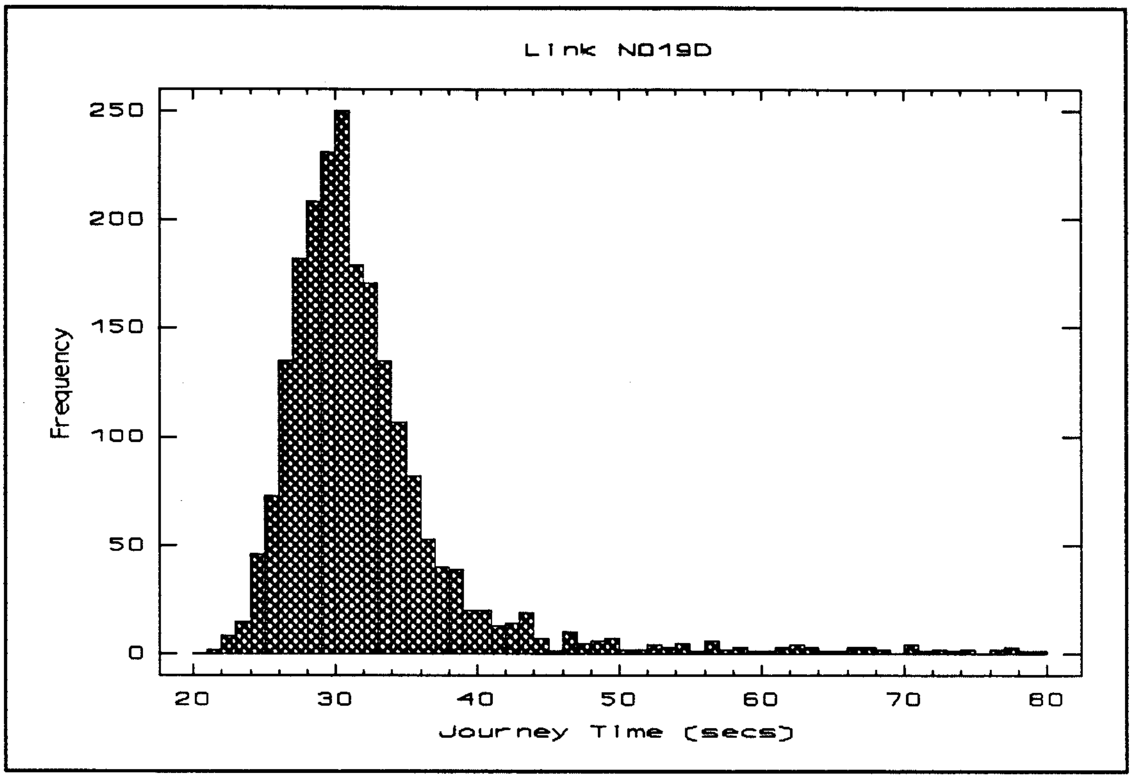


Figure 4.2 Frequency distribution of journey times (truncated data) on link N019D

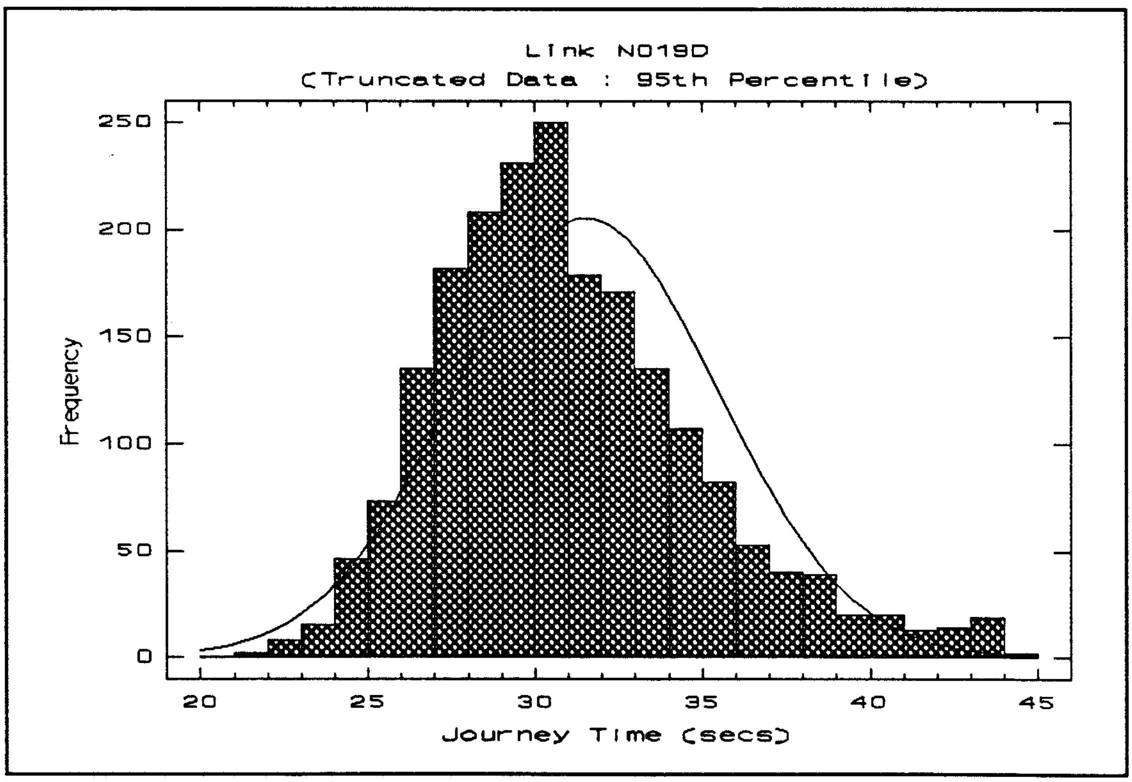


Figure 4.2 shows the frequency histogram of the data which contains all the journey times upto 95th percentile. With this relaxed condition, the distribution of journey time appeared to be normal. Similar approach was used to test the distributional form of journey times on other sites. Overall it is concluded that journey time on links are approximately normally distributed.

4.2 Time Dependent Variability

The development of appropriate short-term forecasting models required an initial analysis of the underlying time dependent variability in the parameter to be forecast. The accuracy of such forecasts depend on the variability of traffic conditions through time; identification of different sources of variability in traffic will clearly allow much more accurate forecasts to be made than situations where different sources of variability are not separated. Clearly, if the parameter values are relatively stable within and between days, the forecasting process is greatly simplified. It is widely recognised (Montgomery et al, 1987) that several sources of variability are present in traffic data (e.g: peak and off peak, between-days, within-days). These sources of variability can affect the forecasts. In order to have good forecasts, data should be grouped in such a way that it has minimum possible variability.

The detailed statistical analysis of the collected data revealed the following sources of time dependent variability in the data :

4.2.1 Cyclic Variability

The cyclic nature of traffic signal operations in urban areas gives rise to a cyclic pattern of flows and journey times. Thus one driver may clear a set of signals at the end of green time undelayed, while another following driver may be delayed by the red signal and preceding queuing traffic. The extent to which this pattern is repeatable depends largely on junction capacity, which determines whether or not vehicles are delayed for more than one cycle.

Accounting for cyclic patterns in very short term forecasting may be necessary; e.g. for signal control application. However, it becomes less relevant for longer forecast horizons typically required for information systems etc. To do so would require a forecast of the location of each vehicle in relation to the likely signal aspect at that time; this would involve too many uncertainties except perhaps for very short term forecasting. In reality, cyclic variability would either be 'swamped' by other sources of variability, or where routes involve negotiation of a number of signal controlled junctions, underestimates of a traffic parameter on some links (due to cyclic variation) are likely to be balanced by overestimates on others. Therefore this very short term variability is usually not of interest in traffic forecasting, except for particular signal control applications.

4.2.2 Variability By Time Of Day

In an urban network the level of traffic varies during different times of the day, such as peak (morning and evening) and off peak hours. Furthermore, the level of traffic may also vary between morning and evening peak. Since for this study the data was collected for three hours morning (07:00-10:00) and three hours evening (16:00-19:00) peak, it was possible to test whether the data differed significantly between morning and evening peak. The statistical procedure that was used is : 'Hypothesis test for the equality of the means for two populations'. This test generally known as standard Z test is described in detail.

4.2.2.1 Hypothesis test for the equality of the means for two populations

This test is applied to establish whether an observed difference between two sample means can be attributed to chance, or whether it is statistically significant. If $\bar{x}_1$ and $\bar{x}_2$ are means of two independent samples of sizes n_1 and n_2, then to test the hypothesis that there is no difference in population means we adopt the following procedure.

(i) The null hypothesis is $H_0 : \mu_1 = \mu_2$

the alternative hypothesis is $H_1 : \mu_1 \neq \mu_2$

(ii) The level of significance is α

(iii) The test statistic to be used is

$$Z=\frac{\bar{x}_1-\bar{x}_2}{\sqrt{\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2}}}$$

where

$\bar{x}_1$ and $\bar{x}_2$ are the means to be tested and

s_1^2 and s_2^2 are unbiased estimates of population variances σ_1^2 and σ_2^2

(iv) The critical region is

$$Z_{-\alpha/2} \leq Z \leq Z_{\alpha/2}$$

(v) Compute the value of Z from the sample data.

(vi) Reject H_0 if $Z < Z_{-\alpha/2}$ or $Z > Z_{\alpha/2}$

The standard Z test (described above) was applied to the data of all sites to test the variability in traffic parameters between morning and evening peak. The results of the application of this test on all sites are summarised in tables 4.1 and 4.2. This revealed that there is significant difference in mean level of parameters during morning and evening peak. The variability between morning and evening peak at link and route level is much higher than the regional level (which are an aggregation of results for all links in each region). At link level the mean flow and journey time is much higher during the morning peak, this is due to the tidal nature of traffic flow (all the links monitored for this study have the same direction of traffic flow, i,e towards the city centre). At region level the evening peak is more busy than the morning peak though the variability is not as high as at link level.

In the following tables, the following notations are used.

1 Flow is Flow in vehicles per hour
JT is Journey Time in seconds
Delay is average delay in seconds per vehicle

2 Mean is the average of the parameter over given number of days
SD standard deviation
SS sample size (number of days)
CV coefficient of variation (SD/Mean) in %

Table 4.1 Variability between Morning and Evening peak (Link level)

Site	Parameter	Morning Peak (07:00-10:00)				Evening peak (16:00-19:00)			
		Mean	SD	SS	CV	Mean	SD	SS	CV
N071A	Flow	* 584	49	57	8	290	30	61	10
	JT	* 16	2	57	13	12	1	61	8
N018E	Flow	* 977	48	54	5	638	38	55	6
	JT	* 45	14	54	31	28	1	55	4
N073A	Flow	* 933	55	57	6	511	30	61	6
	JT	* 43	1	57	2	41	1	61	2
N071D	Flow	* 320	18	58	6	348	18	61	5
	JT	21	6	58	29	21	3	61	14
N072C	Flow	* 836	30	48	4	489	34	52	7
	JT	* 23	3	48	13	32	2	52	6
N019D	Flow	* 1069	84	55	8	771	41	60	5
	JT	* 34	4	55	12	27	1	60	4
N020A	Flow	* 568	83	54	15	251	21	61	8
	JT	* 17	3	54	18	20	3	61	15
N017C	Flow	* 810	60	58	7	580	36	60	6
	JT	* 19	1	58	5	16	1	60	6
N016D	Flow	* 754	58	58	8	544	31	57	6
	JT	* 28	3	58	11	19	3	57	16
N010E	Flow	* 539	30	52	6	328	19	57	6
	JT	* 20	2	52	10	16	3	57	19
Route 1	Flow	* 6651	333	58	5	4275	234	60	5
	JT	* 244	18	58	7	217	9	60	4

* Differ significantly from evening peak at 5% level of significance.

Table 4.2 Variability between Morning and Evening peak (Region level)

Site	Parameter	Morning Peak (07:00-10:00)				Evening Peak (16:00-19:00)			
		Mean	SD	SS	CV	Mean	SD	SS	CV
Region A	Flow	* 8140	602	59	7	9852	597	62	6
	Delay	* 34	3	59	9	46	5	62	11
Region B	Flow	11977	871	58	7	11798	859	60	7
	Delay	* 27	4	58	15	14	2	60	14
Region C	Flow	* 17584	599	59	3	19158	976	62	5
	Delay	* 24	1	59	4	26	3	62	11
Region E	Flow	* 11219	400	52	4	13673	418	59	3
	Delay	* 27	5	52	19	21	3	59	14
Region L	Flow	* 5506	329	57	6	6599	470	59	7
	Delay	* 19	2	57	10	22	3	59	14
Region P	Flow	* 20004	786	59	4	22670	700	62	3
	Delay	* 16	2	59	12	14	1	62	7
Region R	Flow	* 3896	180	61	5	5501	303	63	6
	Delay	* 22	3	61	14	20	2	63	10
Region S	Flow	* 4556	388	55	9	5739	399	61	7
	Delay	* 13	4	55	31	11	2	61	18
Region T	Flow	* 8203	304	61	4	9400	356	63	4
	Delay	* 16	2	61	13	17	1	63	6
Region U	Flow	* 4097	139	58	3	4489	222	62	5
	Delay	* 57	10	58	18	76	18	62	24

* Differ significantly from evening peak at 5% level of significance.

4.2.3 Variability By Day of Week

Variability here is largely due to the variations in activities which occur on different days; such as working and non-working days. The level of between-day variability in traffic parameters is important in determining the requirements for forecasting. It is already well documented (Montgomery, 1987) that traffic flows and journey times differ substantially at weekends and on public holidays than on normal working days, and separate measurements and forecasts for these days would be required. However, variability between working days may also be sufficient to warrant separate measurements and predictions for each day of the week. Table 4.3 shows the mean (Mean), standard deviation (SD) and coefficient of variation (CV) of flows and journey times on different days of the week for three sites of Southampton.

Table 4.3 Variability by day of week

Site	Day	SS [1]	Flow (vehs/hr)			Journey Time (secs)		
			Mean	SD	CV	Mean	SD	CV
	Mon	9	977.41	50.15	5.1	39.41	9.84	25.0
	Tue	9	985.89	43.72	4.4	44.62	13.51	30.3
N018E	Wed	9	971.42	58.14	6.0	43.56	14.05	32.2
	Thr	15	982.52	57.93	5.9	41.93	11.82	28.2
	Fri	15	969.32	34.91	3.6	45.78	10.14	22.2
	Mon	10	1082.91	84.73	7.8	31.74	1.04	3.3
	Tue	9	1100.19	97.31	8.8	33.45	3.54	10.6
N019D	Wed	8	1087.60	74.77	6.9	32.68	3.23	9.9
	Thr	16	1063.74	82.90	7.8	32.97	2.81	8.5
	Fri	15	1043.69	76.03	7.3	33.19	3.25	9.8
	Mon	10	6632.66	293.00	4.4	231.92	12.41	5.35
	Tue	10	6746.73	387.88	5.7	239.16	20.45	8.55
Route1	Wed	10	6657.91	331.71	5.0	238.92	19.35	8.10
	Thr	16	6663.50	359.75	5.4	236.90	19.81	8.36
	Fri	15	6609.62	300.84	4.6	244.23	16.52	6.76

1 SS sample size (number of days)

Level of between-day variability can be assessed statistically by applying Analysis of Variance (ANOVA) test. The following section describes the ANOVA test in detail.

4.2.3.1 Analysis of Variance Test

This technique is used to decide whether observed differences among more than two sample means can be attributed to chance, or whether there are real differences among the means of the populations sampled. The analysis of variance has been shown the most powerful and useful technique whenever the statistical data can be categorised in groups and the aim is to test for homogeneity. The classification according to a single criterion is called a one-way classification, while the classification according to two criteria is known as a two-way classification.

Here we want to test whether the mean level of traffic parameters (flow, journey time etc) on different days of week (Mon-Fri) are significantly different from each other; the criterion used for this purpose is One-Way classification, which is described below.

4.2.3.2 One-Way Classification

Suppose we have k random samples of sizes m from k populations.

	Sample-1	Sample-2	Sample-k
	x_{11}	x_{21}	x_{k1}
	x_{12}	x_{22}	x_{k2}
	. . . . . .	. . . . . .	. . . . . .
	x_{1m}	x_{2m}	x_{km}
Mean	$\bar{x}_1$	$\bar{x}_2$	$\bar{x}_k$

Assuming that the populations are independently and normally distributed (see section 4.1) with means $\mu_1, \mu_2, ---, \mu_k$ and common variance σ^2, we wish to test the hypothesis that all the means are equal, i.e. $H_0 : \mu_1 = \mu_2 = --- = \mu_k$

against the alternative hypothesis

H_1 : At least two of the means are not equal.

In practical terms the ANOVA test is performed based on the following formulae:

SST (Total Sum of Squares) $= \Sigma\Sigma\, x_{ij}^2$ - C.F

SSB (Between Sum of Squares) $= \Sigma\, T_{i.}^2/k$ - C.F

SSE (Error Sum of Squares) = TSS - SSB

where

x_{ij} is the observation in ijth cell.

T_i is the sum of the observations of ith sample.

C.F is correction factor given by T^2/n

T being the grand total of all the observations.

and n is total number of observations

The summary of calculations is shown in table 4.4, generally referred as ANOVA table.

Table 4.4 Summary of ANOVA

Source of Variation	Degrees of freedom	Sum of Squares	Mean Squares	F-ratio
Between Samples	k-1	SSB = Q_1	$s_b^2 = Q_1/k-1$	$F=s_b^2/s_w^2$
Error	n-k	SSE = Q_2	$s_w^2 = Q_2/n-k$	
Total	n-1	SST = Q	s_t^2 = Q/n-1	

The ratio ($F=s_b^2/s_w^2$) has the F-distribution with k-1 and n-k degrees of freedom, the calculated value of F is compared with the table value of F and if ($F > F_{\alpha;\, k-1,\, n-1}$) then the null hypothesis is rejected otherwise accepted.

4.2.3.3 Samples of Unequal Size

The above procedure of One Way Classification deals with the case of equal sample sizes, the above procedure can also be applied for samples of unequal sizes with the slight modifications described below.

Let the k random samples of sizes $m_1, m_2, \ldots, m_k$ respectively with $n = \Sigma\, m_i$. The formulas for computing the Total SS and Between SS are given as below :

$$\text{SST (Total SS)} = \Sigma\Sigma\, x_{ij}^2 - C.F$$

$$\text{SSB (Between SS)} = \Sigma\, T_{i.}^2/m_i - C.F$$

$$\text{SSE (Error SS)} = \text{Total SS} - \text{Between SS}$$

where

x_{ij} is the observation in ijth cell.

T_i is the sum of the observations of ith sample.

C.F is correction factor given by T^2/n

T being the grand total of all the observations.

The variance ratio $F = s_b^2 \,/\, s_w^2$, will still be valid. For d.f we replace mk by n, therefore the respective d.f are (n-1)(n-k) and k-1. The rest of the analysis is same as described for equal sample sizes case. Between-day variability was assessed by applying the ANOVA test to flows, journey time and delays between 07:00-10:00. Table 4.5 shows the average daily flows on different days of week and table 4.6 summarise the calculations of ANOVA test.

Table 4.5 Link N018E - Average daily Flow (07:00-10:00) by day of week

Mon	Tue	Wed	Thr	Fri
970.00	1016.00	975.31	1018.64	960.56
984.28	1032.67	1001.61	1032.50	1017.61
976.81	980.25	1028.44	979.44	1032.39
904.06	912.31	908.97	867.11	990.39
1049.56	1005.78	1028.36	1035.33	968.36
1008.36	980.08	1046.89	994.97	975.56
1041.81	1035.56	916.86	1012.33	988.56
932.56	923.83	891.89	1016.09	954.94
929.28	986.53	944.42	1015.00	984.53
			1071.97	983.69
			898.67	888.14
			926.11	930.61
			915.47	940.31
			953.93	953.75
			1000.19	970.44

Table 4.6 Link N018E Flows - Analysis of variance (ANOVA)

Source of Variation	Degrees of freedom	Sum of Squares	Mean Squares	F-ratio
Between Days	4	2333.99	583.50	0.24
Error	52	126501.86	2432.73	
Total	56	128835.85		

Analysis of variance test applied on the above table at 5% level of significance show that the difference in mean level of flows between different days of the week is not significant.

Table 4.7 Link N018E - Average daily Journey Time (07:00-10:00) by day of week

Mon	Tue	Wed	Thr	Fri
38.52	46.46	31.04	31.03	46.34
42.34	41.76	37.64	31.88	36.51
32.11	31.13	31.10	31.25	62.72
34.20	40.22	30.72	33.16	38.13
32.24	31.30	32.70	32.30	31.07
30.70	30.70	68.65	43.15	31.12
33.47	66.08	55.17	54.53	46.04
55.45	49.57	49.09	47.35	50.15
55.67	64.39	55.95	63.24	60.34
			34.04	32.08
			32.21	46.39
			49.84	52.03
			53.77	51.17
			60.12	55.06
			31.04	47.56

Table 4.7 shows the average journey time at link N018E on different days of week and the result of ANOVA test are summarised in table 4.8.

Table 4.8 Link N018E Journey Times - Analysis of Variance (ANOVA)

Source of Variation	Degrees of freedom	Sum of Squares	Mean Squares	F-ratio
Between Days	4	272.76	68.19	0.49
Error	52	7208.14	138.62	
Total	56	7480.90		

Analysis of variance test applied on the above table at 5% level of significance show that the difference in mean level of journey time between different days of the week is not significant.

The same test procedure was applied to flows and journey time and delays at other sites to assess the variability between different days of weeks. The results are summarised in table 4.9.

Table 4.9 Link Flows (07:00-10:0) - Analysis of variance (ANOVA) results

Site	Source of Variation	F-calculated	F-tabulated	Significantly Different
N020A	Days of Week	0.50	2.55	NO
N019D	Days of Week	0.85	2.55	NO
N018E	Days of Week	0.24	2.55	NO
N017C	Days of Week	0.50	2.54	NO
N016D	Days of Week	0.55	2.54	NO
N073A	Days of Week	0.39	2.54	NO
N071A	Days of Week	1.63	2.54	NO
N072C	Days of Week	0.12	2.54	NO
N010E	Days of Week	0.80	2.55	NO
N071D	Days of Week	0.91	2.54	NO
Route1	Days of Week	0.27	2.54	NO

Table 4.10 Region Flows (07:00-10:00) - Analysis of variance (ANOVA) results

Site	Source of Variation	F-calculated	F-tabulated	Significantly Different
Region A	Days of Week	0.39	2.53	NO
Region B	Days of Week	0.64	2.53	NO
Region C	Days of Week	0.79	2.53	NO
Region E	Days of Week	0.24	2.53	NO
Region L	Days of Week	1.16	2.53	NO
Region P	Days of Week	0.60	2.53	NO
Region R	Days of Week	1.01	2.54	NO
Region S	Days of Week	1.56	2.54	NO
Region T	Days of Week	0.08	2.54	NO
Region U	Days of Week	1.46	2.53	NO

Table 4.11 Link Journey Times (07:00-10:00) - Analysis of variance (ANOVA) results

Site	Source of Variation	F-calculated	F-tabulated	Significantly Different
N020A	Days of Week	0.84	2.55	NO
N019D	Days of Week	0.53	2.55	NO
N018E	Days of Week	0.49	2.55	NO
N017C	Days of Week	1.44	2.54	NO
N016D	Days of Week	0.99	2.54	NO
N073A	Days of Week	0.54	2.54	NO
N071A	Days of Week	1.38	2.54	NO
N072C	Days of Week	0.27	2.54	NO
N010E	Days of Week	0.06	2.55	NO
N071D	Days of Week	0.71	2.54	NO
Route1	Days of Week	0.75	2.54	NO

Table 4.12 Region Delays (07:00-10:00) - Analysis of variance (ANOVA) results)

Site	Source of Variation	F-calculated	F-tabulated	Significantly Different
Region A	Days of Week	1.22	2.53	NO
Region B	Days of Week	0.20	2.53	NO
Region C	Days of Week	0.38	2.53	NO
Region E	Days of Week	0.87	2.53	NO
Region L	Days of Week	1.65	2.53	NO
Region P	Days of Week	1.27	2.53	NO
Region R	Days of Week	0.27	2.54	NO
Region S	Days of Week	0.35	2.54	NO
Region T	Days of Week	1.34	2.54	NO
Region U	Days of Week	0.75	2.53	NO

The results showed that between-day differences in mean flows, journey time and delays were never significant. These results are clearly site dependent and affected by the sampled data available, thus if between-day variability is significant, separate measurements and predictions may be required for each day of week. However, from the results shown in tables above, it is clear that for this particular data set, data would be grouped together for all working days of the week and there is no need of profiles for separate day of the week, this also has the advantage that journey time profiles from which the predictions may be made, have less uncertainty (i.e tighter confidence limits) with increasing sample size.

4.2.4 Variability By Month

This 'seasonal' variability may be related to environmental changes, changes in work practices (e.g. vacation periods) and so on. Individual monthly profiles from Jan-July in the following table.

Table 4.13 Variability by Month

Site	Month	SS	Flow Mean	Flow SD	Flow CV	Journey Time Mean	Journey Time SD	Journey Time CV
N018E	Jan	7	993.92	28.06	2.8	39.64	6.49	16.4
	Feb	14	976.23	56.05	5.7	35.93	8.29	23.1
	Mar	4	1008.02	33.18	3.3	31.33	0.66	2.1
	Apr	6	998.89	24.67	2.5	39.83	9.65	24.2
	May	11	993.08	58.92	5.9	48.47	14.40	29.7
	Jun	12	933.43	23.73	2.5	54.28	4.52	8.3
	Jul	3	971.68	27.90	2.9	44.85	12.67	28.3
N019D	Jan	9	1120.44	69.82	6.2	31.49	1.41	4.5
	Feb	14	1043.77	102.44	9.8	32.74	1.98	6.0
	Mar	4	1111.73	58.21	5.2	32.62	0.39	1.2
	Apr	6	1098.71	27.90	2.5	32.44	2.14	6.6
	May	11	1056.82	111.03	10.5	36.08	4.26	11.8
	Jun	11	1054.59	48.38	4.6	31.10	1.43	4.6
	Jul	3	1048.52	14.06	1.3	33.16	2.05	6.2
Route1	Jan	9	6622.37	212.98	3.2	234.25	9.56	4.08
	Feb	16	6521.26	341.87	5.2	228.25	11.66	5.11
	Mar	4	6742.50	196.13	2.9	221.54	3.70	1.67
	Apr	6	6849.08	173.16	2.5	230.25	21.28	9.24
	May	11	6823.96	538.21	7.9	253.21	22.16	8.75
	Jun	12	6596.08	147.45	2.2	251.20	9.41	3.74
	Jul	3	6636.92	100.95	1.5	242.12	15.52	6.41

Monthly variability was assessed by applying the ANOVA (One-Way Classification, described in section 4.3.1) to flows and journey time between 07:00-10:00.

Table 4.14 Link N018E - Average daily flows (07:00-10:00) by month

Jan	Feb	Mar	Apr	May	Jun	Jul
970.00	976.81	1049.56	1041.81	1035.56	932.56	944.42
984.28	904.06	1008.36	980.08	1028.36	929.28	1000.19
1016.00	980.25	1005.78	994.97	1046.89	923.83	970.44
1032.67	912.31	968.36	1012.33	1016.09	986.53	
975.31	1001.61		975.56	1015.00	916.86	
1018.64	1028.44		988.56	1071.97	891.89	
960.56	908.97			898.67	926.11	
	1032.50			954.94	915.47	
	979.44			984.53	953.93	
	867.11			983.69	930.61	
	1035.33			888.14	940.31	
	1017.61				953.75	
	1032.39					
	990.39					

Table 4.15 Link N018E Monthly Flows - Analysis of variance (ANOVA)

Source of Variation	Degrees of freedom	Sum of Squares	Mean Squares	F-ratio
Between Months	6	34444.90	5740.82	3.04
Error	50	94390.95	1887.82	
Total	56	128835.85		

Analysis of variance test applied on the above table at 5% level of significance show that the difference in mean level of flows at link N018E between different months is significant.

Table 4.16 Link N018E - Average daily Journey Time (07:00-10:00) by month

Jan	Feb	Mar	Apr	May	Jun	Jul
38.52	32.11	32.24	33.47	66.08	55.45	55.95
42.34	34.20	30.70	30.70	32.70	55.67	31.04
46.46	31.13	31.30	43.15	68.65	49.57	47.56
41.76	40.22	31.07	54.53	47.35	64.39	
31.04	37.64		31.12	63.24	55.17	
31.03	31.10		46.04	34.04	49.09	
46.34	30.72			32.21	49.84	
	31.88			50.15	53.77	
	31.25			60.34	60.12	
	33.16			32.08	52.03	
	32.30			46.39	51.17	
	36.51				55.06	
	62.72					
	38.13					

Table 4.17 Link N018E Monthly Journey Times- Analysis of Variance (ANOVA)

Source of Variation	Degrees of freedom	Sum of Squares	Mean Squares	F-ratio
Between Months	6	3246.41	541.07	6.39
Error	50	4234.49	84.69	
Total	56	7480.90		

Analysis of variance test applied on the above table at 5% level of significance showed that the mean level of journey time at link N018E between different months was significantly different. The same test procedure was applied to flows and journey time at other sites to assess the variability between different months. The results are summarised in the following table.

Pages 74-76 were not included in the bound thesis.

4.3 Discussion

Among the parameters measured by SCOOT were traffic flow (veh/hr) and delay (veh hrs/hr). From flow (veh/hr) and delay (veh hr/hr); journey time (sec/veh) were calculated. The data set includes links with different characteristics and different patterns of variability of flow, delay and journey time.

Analysis of the data suggests that the variability in traffic parameters caused by traffic signal cycles will not be possible to account for. The aggregation periods for forecasting should include several complete cycles (for example five minutes). Analysis also show that there is significant difference in mean level of parameters between morning and evening peak. So data from both peaks should be grouped separately.

To determine whether the day of the week made any difference to the traffic flow and journey time, analysis of variance test applied to the data of all sites. In the majority of the cases, it was found that when any two of the five days were compared, the difference was not significant. In such cases the data for different days of the week are grouped together to form a single time series.

Monthly variability is site dependent. Where it is significant, it should be reflected in the journey time patterns from which predictions are to be made. This will require updating of the forecasting model's parameters, however if decrease/increase in the journey time between different months is gradual then there may not be the need of separate monthly profiles as the change will be covered by updating the historical profiles.

CHAPTER 5

DEVELOPMENT AND APPLICATION OF JOURNEY TIME FORECASTING MODELS - (Normal Conditions)

The objective of this chapter is the development and application of journey time forecasting models on link-by-link basis. A number of forecasting methods were discussed in chapter 2. Some of these methods particularly Holt-Winter and Kalman Filtering have been applied earlier by different organisations (University of Southampton (1987), Richards A (1991), Whittaker J (1991), Drive Project deliverable 10; 1990) for the prediction of traffic parameters. In this chapter, two time-series methods were used to develop journey time forecasting models. The developed models were tested on two links (N018E, N019D) and a route (Route1) in Southampton network. Links N018E and N019D, both are signalised links with relatively more congestion than other links in the network. Route1 consists of 9 links with the traffic flow towards the city centre and usually a busy route particularly during the peak period.

5.1 Selection of Forecasting Methods

The journey time data in this study is available as a series of observations collected at regular time intervals (5-minutes). A suitable approach for analysis of this type of data is the use of time series methods. These methods rely upon an underlying period-to-period relationship in the data. Thus the observation at the current time period is related to a previous observation. Another advantage of time-series methods is their ability to forecast the parameter of interest directly. Journey Time data analyzed in chapter 4, revealed periodic behaviour in it, during the three hour period

(0700-1000). Journey Times steadily increase to a peak and then steadily decrease back to normal. This periodic behaviour in the data suggests the use of seasonal forecasting methods. With these findings as a background, two standard time series forecasting methods, Box-Jenkins ARIMA modelling (Box and Jenkins, 1976) and Horizontal-Seasonal modelling (Thomopoulos, 1980) were selected to develop journey time forecasting models on link-by-link basis.

5.2 Box-Jenkins ARIMA Modelling

5.2.1 Basic assumptions and model

In this section, journey time forecasting models are developed using the Box-Jenkins technique, with the following basic assumptions.

- Journey times on links in an urban network have similar profiles in following days of the same class (week days, Saturdays ...).

- Daily historical journey time are assumed available for previous days for each of the 5-minute time period.

Box and Jenkins (Box G et al, 1976) proposed a family of Algebraic models called ARIMA models (Auto Regressive Integrated Moving Average) from which one is selected that seems appropriate for forecasting a given data series.

The term AutoRegressive means that JT_t, the current value of the journey time, is "regressed" or expressed as a function of JT_{t-1}, JT_{t-2}, - - -, JT_{t-p} ,which are the previous values of the journey times, and to an unknown noise a_t ,in a linear manner by the relation:

$$JT_t = \phi_1 JT_{t-1} + \phi_2 JT_{t-2} + - - - + \phi_p JT_{t-p} + a_t \qquad (5.1)$$

The term Moving Average means that the current value of the journey time can be expressed as a finite linear aggregate of previous a_t's (random shocks) by the relation:

$$JT_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \; - - - \; - \theta_q a_{t-q} \qquad (5.2)$$

The parameters of Autoregressive Integrated Moving Average models are:

$$\text{ARIMA } (p,d,q)\ (P,D,Q)_s \qquad (5.3)$$

where

p = Order of Non-Seasonal Autoregressive operator
d = Order of Non-Seasonal Differencing
q = Order of Non-Seasonal Moving-Average operator

P = Order of Seasonal Autoregressive operator
D = Order of Seasonal Differencing
Q = Order of Seasonal Moving-Average operator
s = Length of Seasonality

The values of d and D in ARIMA $(p,d,q)(P,D,Q)_s$ determines the degree of non-seasonal and seasonal differencing. Differencing is required when a series is non-stationary, i,e: a series which has a mean changing over time. The values of p,q and P,Q in ARIMA $(p,d,q)\ (P,Q,D)_s$ determines that how far into the past is necessary to go to establish a relation between different values of the time series.

Season here refers to a period after which the pattern of the series repeats itself, e.g. journey time is expected to be higher during peak hours on every day, where day here is one season and on different days the patterns of journey time are more or less the same.

Consider an example where journey time on different days at different time periods are denoted by :

	Day_1	Day_2	Day_3	Day_4
t_1	JT_{11}	JT_{12}	JT_{13}	JT_{14}
t_2	JT_{21}	JT_{22}	JT_{23}	JT_{24}
t_3	JT_{31}	JT_{32}	JT_{33}	JT_{34}
- - - -	- - - -	- - - -	- - - -	
- - - -	- - - -	- - - -	- - - -	
t_n	JT_{n1}	JT_{n2}	JT_{n3}	JT_{n4}

Here, JT_{34} is a function of JT_{24}, JT_{14} and JT_{33}, JT_{32}, JT_{31}

The Box-Jenkins technique uses the previous days journey time for the estimates of the model's parameters. The starting point is the following stochastic dynamic model.

$$\phi_p(B)\ \Phi_P(B^s)\ \nabla^d\ \nabla_s^D\ JT = \theta_q(B)\ \Theta_Q(B^s)\ a_t \tag{5.4}$$

where

$\phi_p(B) = (1-\phi_1 B-\phi_2 B^2-\ \text{- - - -}\ -\phi_p B^p)$

is the Non-Seasonal Autoregressive operator of order p.

$\Phi_P(B^s) = (1-\Phi_s B^s-\Phi_{2s} B^{2s}-\ \text{- - - -}\ -\Phi_{Ps} B^P)$

is the Seasonal Autoregressive operator of order P.

$\theta_q(B) = (1-\theta_1 B-\theta_2 B^2-\ \text{- - - -}\ -\theta_q B^q)$

is the Non-Seasonal Moving Average operator of order q.

$$\Theta_Q(B^s) = (1-\Theta_s B^s-\Theta_{2s}B^{2s}- \text{ - - - - } -\Theta_{Qs}B^{Qs})$$

is the Seasonal Moving Average operator of order Q.

$$\nabla^d = (1-B)^d$$

is the non-seasonal differencing operator of order d

$$\nabla_s^D = (1-B^s)^D$$

is the seasonal differencing operator of order D

s = Length of Seasonality.

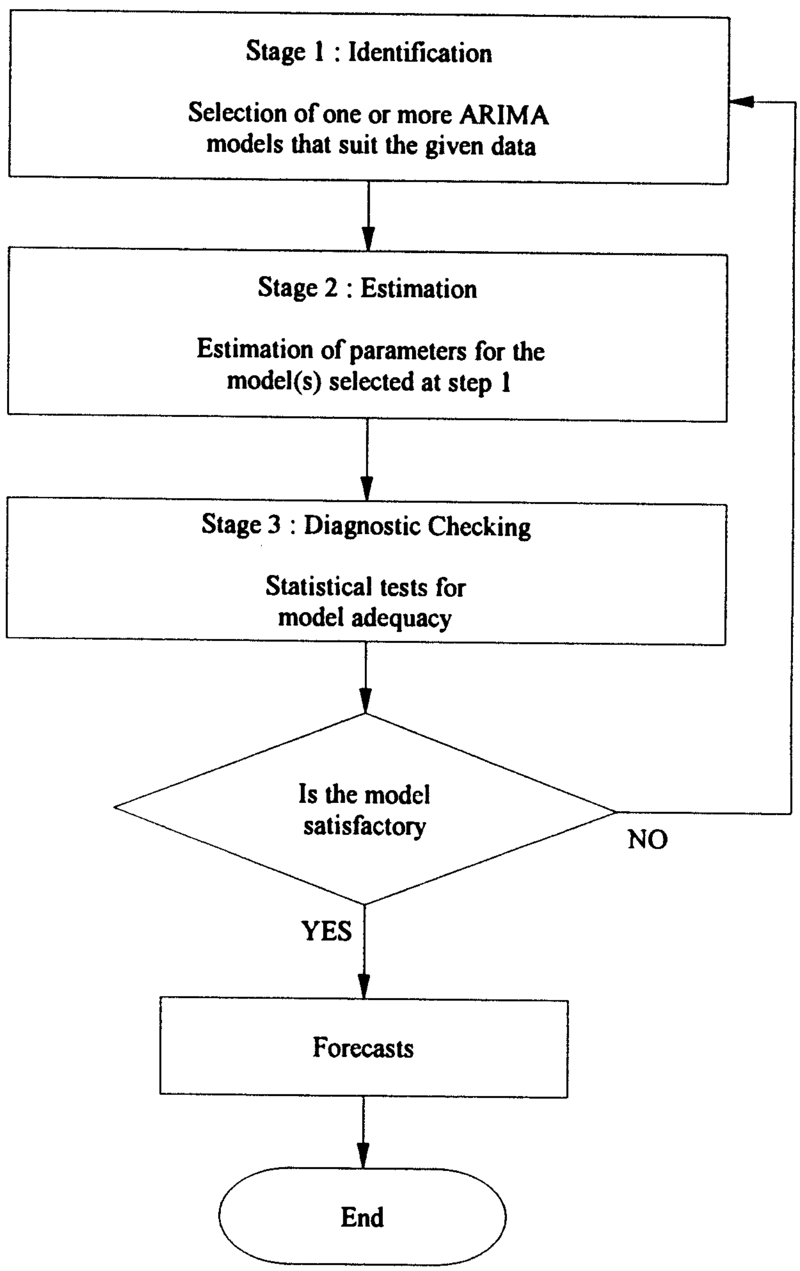
B = Backshift operator so that $B^n JT_t = JT_{t-n}$

a_t = the random error

ARIMA models are fitted to a particular data set by a three stage iterative procedure; Identification, Estimation and Diagnostic checking. The schematic representation of these three stages is shown in figure 5.1.

The model's building starts with the analysis of the historical data. Suppose journey time data for every 5-minute time interval between 0700-1000 for six days is available. The first step is to plot the data, if the data is non-stationary (i.e. the mean changing over time) then the non-stationarity of the data is removed by taking seasonal and/or non-seasonal differences, the order of non-seasonal difference is denoted by 'd' and of seasonal difference is denoted by 'D'. Once the stationarity is achieved by taking differences, the next step is identify a parsimonious (with the smallest number of estimated parameters needed to fit adequately the patterns in the available data). This can be done by looking at two graphs derived from the available data. These graphs are called an estimated autocorrelation function (ACF) and an estimated partial autocorrelation function (PACF).

Figure 5.0 Flow chart of ARIMA modelling process



An estimated autocorrelation function (ACF) shows the correlation between ordered pairs (JT_t , JT_{t+k}) separated by various time spans (k = 1,2,3, - - -). Each estimated autocorrelation coefficient r_k is an estimate of the corresponding parameter ρ_k. An estimated partial autocorrelation function (pacf) shows the correlation between ordered pairs (JT_t, JT_{t+k}) separated by various time spans (k = 1,2,3, - - -) with the effects of intervening observations (JT_{t+1} , JT_{t+2} , - - - , JT_{t+k-1}) accounted for. The ordered pairs are drawn from a single time series. We choose a model whose associated theoretical ACF and PACF look like the estimated ACF and PACF calculated from the data.

At the estimation stage, estimates of the parameters for the ARIMA model tentatively chosen at the identification stage. This is usually done by using a computer program, for this study, STATGRAPHICS software package was used to obtain the estimates of the model's parameters. The estimates of the model parameters should satisfy the stationarity and invertibility conditions. The stationarity condition for autoregressive models is checked by ensuring:

$$|\phi_1| < 1 \qquad \text{(for first order autoregressive AR(1) models)}$$

and for second order autoregressive AR(2) models it should be:

$$|\phi_2| < 1, \quad |\phi_2 + \phi_1| < 1 , \quad |\phi_2 - \phi_1| < 1$$

Similarly the invertibility condition for moving average models requires that

$$|\theta_1| < 1 \qquad \text{(for first order moving average MA(1) models)}$$

and for second order moving average models it should be:

$$|\theta_2| < 1 , \quad |\theta_2 + \theta_1| < 1 , \quad |\theta_2 - \theta_1| < 1$$

At diagnostic-checking stage, tests are performed to see if the estimated model is statistically adequate. If it is not satisfactory we return to the identification stage to tentatively select another model. In particular, we test the random shocks (forecasting residuals, that can not be predicted within the ARIMA model). Analysis of autocorrelations of the estimated residuals is an appropriate means of doing this.

Recognizable patterns in the ACF of the a_t's could point to appropriate modifications in the model.

Box-Jenkins also describe a lack of fit test which examines a group of autocorrelations (say the first 20) as a whole, as opposed to considering the individual autocorrelations. If the fitted model is appropriate, then the first k autocorrelations, yielding a value Q is approximately distributed as $\chi^2_{(k-p-q)}$, where Q is computed as:

$$Q = (n-d)\Sigma r^2_t$$

n is number of observations in the original series

d is the degree of differencing

r_t is the sample autocorrelation of residuals separated by lag t

If the value of Q is large relative to χ^2 then the model is inappropriate. If this assumption is not satisfied there is an autocorrelation pattern in the original series that has not been explained by the ARIMA model. Our goal however is to build a model that fully explains any autocorrelation in the original series.

Once an appropriate ARIMA model is selected, point forecasts can be calculated by writing the model in algebraic equation form.

5.2.2 Examples of Algebraic Forms of ARIMA Models

Two examples are given, how to develop the algebraic form of the ARIMA (p,q,d) (P,Q,D) models.

5.2.2.1 ARIMA (0,1,1)(0,1,1)

The general form of the model is

$$\phi_p(B)\ \Phi_P(B^s)\ \nabla^d\ \nabla_s^D\ JT = \theta_q(B)\ \Theta_Q(B^s)\ a_t$$

Substituting p=0, d=1, q=1 and P=0, D=1, Q=1 in the above equation, we get

$$\nabla^1\ \nabla_s^1\ JT = \theta_1(B)\ \Theta_1(B^s)\ a_t$$

$$(1\text{-}B)\ (1\text{-}B^s)\ JT_t = (1\text{-}\theta B)\ (1\text{-}\Theta_s B^s)\ a_t$$

$$(JT_t - JT_{t-1})\ (1\text{-}B^s) = (a_t - \theta a_{t-1})\ (1\text{-}\Theta_s B^s)$$

$$JT_t - JT_{t-1} - JT_{t-s} + JT_{t-s-1} = a_t - \theta a_{t-1} - \Theta_s a_{t-s} + \theta\Theta_s a_{t-s-1}$$

$$\hat{JT}_t = JT_{t-1} + JT_{t-s} - JT_{t-s-1} - \theta a_{t-1} - \Theta_s a_{t-s} + \theta\Theta_s a_{t-s-1} \qquad (5.5)$$

where

$\hat{JT}_t$	=	Predicted journey time for time interval t.
JT_{t-1}	=	Observed (or predicted) journey time at time interval t-1.
JT_{t-s}	=	Observed journey time at time interval t on previous day.

and so on.

5.2.2.2 ARIMA (1,0,0)(2,1,0)

The general form of the model is

$$\phi_p(B)\ \Phi_P(B^s)\ \nabla^d\ \nabla_s^D\ JT_t = \theta_q(B)\ \Theta_Q(B^s)\ a_t$$

Substituting p=1, d=0, q=0 and P=2, D=1, Q=0 in the above equation, we get

$$(1\text{-}\phi_1 B)\ (1\text{-}\Phi_s B^s\text{-}\Phi_{2s} B^{2s})\ (1\text{-}B^s)\ JT_t = a_t$$

$$(1-\Phi_s B^s-\Phi_{2s}B^{2s})\,(1-B^s)\,(JT_t - \phi_1 JT_{t-1}) = a_t$$

$$(1-\Phi_s B^s-\Phi_{2s}B^{2s})\,(JT_t - B^s JT_t - \phi_1 JT_{t-1} + \phi_1 B^s JT_{t-1}) = a_t$$

$$(1-\Phi_s B^s-\Phi_{2s}B^{2s})\,(JT_t - JT_{t-s} - \phi_1 JT_{t-1} + \phi_1 JT_{t-s-1}) = a_t$$

$$JT_t - \Phi_s B^s JT_t - \Phi_{2s}B^{2s}JT_t - JT_{t-s} + \Phi_s B^s JT_{t-s} + \Phi_{2s}B^{2s}JT_{t-s} - \phi_1 JT_{t-1} + \phi_1 \Phi_s B^s JT_{t-1}$$
$$+ \phi_1 \Phi_{2s} B^{2s} JT_{t-1} + \phi_1 JT_{t-s-1} - \phi_1 \Phi_s B^s JT_{t-s-1} - \phi_1 \Phi_{2s} B^{2s} JT_{t-s-1} = a_t$$

$$\hat{JT}_t = \Phi_s JT_{t-s} + \Phi_{2s} JT_{t-2s} + JT_{t-s} - \Phi_s JT_{t-2s} - \Phi_{2s} JT_{t-3s} + \phi_1 JT_{t-1} - \phi_1 \Phi_s JT_{t-s-1} -$$
$$\phi_1 \Phi_{2s} JT_{t-2s-1} - \phi_1 JT_{t-s-1} + \phi_1 \Phi_s JT_{t-2s-1} + \phi_1 \Phi_{2s} JT_{t-3s-1}$$

$$\hat{JT}_t = \phi_1 JT_{t-1} + (1+ \Phi_s) JT_{t-s} + (\Phi_{2s} - \Phi_s) JT_{t-2s} - \Phi_{2s} JT_{t-3s} - \phi_1(\Phi_s + 1) JT_{t-s-1} -$$
$$\phi_1(\Phi_{2s} - \Phi_s) JT_{t-2s-1} + \phi_1 \Phi_{2s}\, JT_{t-3s-1} \tag{5.6}$$

where

$\hat{JT}_t$ = Predicted journey time for time interval t.

JT_{t-1} = Observed (or predicted) journey time at time interval t-1.

JT_{t-s} = Observed journey time at time interval t on previous day.

and so on.

5.2.3 Implementation on Computer For Real Time Application

The Box-Jenkins modelling procedure starts by analysing the historical data. This analysis is carried out off-line in order to find a suitable model. Several statistical software packages are available which provides procedures for Box-Jenkins modelling process. For this study, the STATGRAPHICS (Statistical Graphics Corporation, 1991) software package was used which provides functions for model identification and estimation of the model's parameters (this uses a basic Marquardt nonlinear least squares algorithm). Once a model was selected and its parameters estimated, forecasts were generated by using the algebraic form of the selected model (examples of algebraic forms of models are given in section 5.2.2). Box-Jenkins modelling does not provide any procedure which automatically update the estimates of the model parameters, however for forecasts of more than one-period ahead, one can use the last available observation instead of its forecast. For example in equation (5.4) JT_{t-1} is not available when making several steps ahead forecasts, but on a current day at any time interval t, the value of observed journey time at time (t-1) would be available, this observed value can be substituted in place of forecasted value to update the forecasts. To achieve this purpose a FORTRAN program (Appendix C.1) was written which updates the forecasts as soon as new journey time value is observed. The program also analyze forecast-errors by calculating forecast-error statistics (i,e ME, MAE, MAPE as described in section 5.4.3).

5.3 Horizontal-Seasonal Modelling

Most of the traffic parameters (flow, journey time etc) show periodic behaviour within a day, i,e there are higher flows and journey time during the peak period, this periodic behaviour of the parameters can be explained by so called seasonal models, here season refers to the period after which the pattern of the data repeats itself.

In these models smoothing of the past demand entries is used and higher weights are assigned to the more current entries. The feature allows the forecasts to react quicker to more current shifts in the level or seasonal influences of the demands. The model applies when the expected journey time at time t is

$$JT_t = \mu\rho_t \tag{5.7}$$

where

μ represents the average journey time per day and

ρ_t represents the seasonal ratio at time t.

The seasonal ratio for time period t is found from the relation between JT_t and μ. The seasonal ratios are always greater or equal to zero and over a day their average value is 1. When $\rho_t=1$, the expected journey time at time period t is the same as the average daily journey time; when $\rho_t < 1$, then JT_t is less than μ and when $\rho_t > 1$, then JT_t is greater than μ.

Two phases are necessary in order to implement the model. The first is concerned with initializing the system and the second is with updating the forecasts.

In the initializing phase the past journey time entries (JT_1, JT_2, - - -, JT_T) are used to find estimates of μ and ρ_t. The estimate of μ as of time T is $\hat{a}_T$ and estimates of the seasonal ratios ρ_{T+i} are r_{T+i} for i=1,2,3, - - -.

With these estimates available, the initializing phase is complete. From this time period on, the estimates above are updated as each new journey time entry becomes available, the forecast for ith future time period made at time T is

$$\hat{JT}(i) = \hat{a}_T I_{T+i}$$

For journey time forecasts, the initializing phase of the modelling process is carried out by the following steps.

1: Find the average daily journey time for each of the m days data

$$\bar{JT}_{(1)} = (JT_{11}+JT_{12}+ \text{ - - - } +JT_{1n})/n$$
$$\bar{JT}_{(2)} = (JT_{21}+JT_{22}+ \text{ - - - } +JT_{2n})/n$$
- - - - - - - - - - - - - - - - -

- - - - - - - - - - - - - - - - -
$$\bar{JT}_{(m)} = (JT_{m1}+JT_{m2}+ \text{ - - - } +JT_{mn})/n$$

Where

m = Number of days.

n = Number of time periods per day.

2: Calculate the seasonal ratios for each day on time period t by the relation

$$\tilde{r}_t = \begin{cases} JT_t/\bar{JT}_{(1)} & \text{for } t = 11,12, \text{ - - -},1n \\ JT_t/\bar{JT}_{(2)} & \text{for } t = 21,22, \text{ - - -},2n \\ \text{- - - - - - - - - - - -} & \\ \text{- - - - - - - - - - - -} & \\ JT_t/\bar{JT}_{(3)} & \text{for } t = m1,m2, \text{ - - -},mn \end{cases}$$

where

$m = 1 \ldots$ Number of days.

$n = 1 \ldots$ Number of time periods.

3: Calculate the average seasonal ratio for each of the n time periods

$\hat{r}_1 = (\tilde{r}_{11}+\tilde{r}_{21}+ \text{- - -} +\tilde{r}_{m1})/m$

$\hat{r}_2 = (\tilde{r}_{12}+\tilde{r}_{22}+ \text{- - -} +\tilde{r}_{m2})/m$

- - - - - - - - - - - - - -

- - - - - - - - - - - - - -

$\hat{r}_n = (\tilde{r}_{1n}+\tilde{r}_{2n}+ \text{- - -} +\tilde{r}_{mn})/m$

4: Let $\hat{a}_0 = \overline{JT}_{(1)}$

Now, starting with t=1 and estimating until t=mn, apply the following recursive relations.

$$\hat{a}_t = \alpha(JT_t/\hat{r}_t)+(1-\alpha)\hat{a}_{t-1} \tag{5.8}$$

$$\hat{r}_{t+n} = \gamma(JT_t/\hat{a}_t)+(1-\gamma)\hat{r}_t \tag{5.9}$$

Here at time t, the ratio $(JT_t/\hat{r}_t)$ represents the current seasonally adjusted journey time. This is smoothed with the corresponding prior average $\hat{a}_{t-1}$ to yield an updated average $\hat{a}_t$. The ratio $(JT_t/\hat{a}_t)$ gives the seasonal ratio for time period t. This is smoothed with $\hat{r}_t$ to generate the new seasonal ratio $\hat{r}_{t+n}$. The jump of n time periods is necessary because there are n time periods per day. For example when t corresponds to a 1st time period of day one, t+n is associated with the 1st time period of following day.

α and γ are smoothing constants, their values should be between 0 and 1, higher values of α and γ gives more weight to the current data.

5: The most current n seasonal ratios

$$\hat{r}_{T+1},\ \hat{r}_{T+2},\ ---,\ \hat{r}_{T+n}$$

are normalized so that their average is 1. This is performed by first finding the average

$$\bar{r} = (\hat{r}_{T+1} + \hat{r}_{T+2} + \hat{r}_{T+n})/n$$

and then adjusting the ratios by

$$r_{T+i} = \hat{r}_{T+i} / \bar{r} \qquad \text{for } i=1,2,---,n$$

Having carried out these five steps, the initialization phase is complete. At this time the first set of forecasts can be generated. The forecast for the ith future time period is

$$\bar{JT}_T(i) = \hat{a}_T r_{T+i} \tag{5.10}$$

5.3.1 Updating

As each new demand entry becomes available, an updating scheme is carried forward to obtain the current estimates of the mean journey time level and the seasonal ratios. Calling the current time period T, the new observation is JT_T and the updating relations are the following:

$$\hat{a}_T = \alpha(JT_T/r_T)+(1-\alpha)\hat{a}_{T-1}$$
$$r_{T+n} = \gamma(JT_T/\hat{a}_T)+(1-\gamma)r_T$$

As before,the seasonal ratios are normalized so that their average is 1. Three steps are required for this purpose.

1: $\bar{r} = (r_{T+1}+r_{T+2}+ - - -+r_{T+n})/n$

2: $r_{T+i} = r_{T+i} / \bar{r}$ for $i=1,2,- - -,n$

3: $r_{T+i} = \hat{r}_{T+i}$ for $i=1,2, . . .,n$

With updating of the estimates completed, the forecasts for the ith future time period is generated by

$$\bar{JT}_T(i) = \hat{a}_T r_{T+i}$$

5.3.2 Implementation on the Computer for Real Time Application

Horizontal-Seasonal model (described above) is implemented on a computer by writing a FORTRAN program (Appendix C.2). The input for this program are:

1 Number of days historical data.

2 Number of time periods per day.

3 File which contains historical data.

The program calculates all the steps of Horizontal-Seasonal model (as described in section 5.3), forecasts are generated by using equation (5.10) and then updated by using the current day's observations. The program also analyze forecast-errors by calculating forecast-error statistics (i,e ME, MAE, MAPE as described in section 5.4.3).

5.4 Journey Time Forecasting

Journey Time parameter was selected as it is a suitable descriptor of congestion on a link basis and is relatively easily interpreted. Also it is a key parameter (or component) in control systems such as traffic signals and dynamic route guidance (DRG). The development of journey time forecasting models required some pre-modelling decisions, e.g. forecast aggregation level, forecast horizon, these requirements are discussed here and are incorporated in the modelling process.

5.4.1 Aggregation Level of Forecast

Different application of journey time forecasts would need different aggregation level. For signal control settings, the forecast aggregation level can be any fraction of a second to the signal cycle length. For route guidance and traffic information broadcasting, the forecast aggregation level could be from 1-minute to 15-minute. In reality for any application there can be many level of aggregation. For this study 5-minute aggregation level is used.

5.4.2 Forecast Horizon

This is the length of time into future for which forecasts are required and depends upon the purpose for which the forecast is needed, e.g. for route guidance systems, the forecast horizon would be length of journey time between the points of advice to the destination. For traffic information broadcasting system the forecasts may be required for the whole of the peak period which may last from 0700-1000. For this study, the forecast horizon was as much as three hours ahead at 5-min aggregation level.

5.4.3 Forecasts Accuracy

The accuracy of forecasts is determined through forecast errors. The forecast error for lead time k at time t is defined as:

$$e_t = JT_t - \hat{JT}_{t-1}(k) \qquad (5.11)$$

where

JT_t is the observed journey time at time t

$\hat{JT}_{t-1}(k)$ is the k-period ahead forecast generated at time t-1.

Various checks based on these errors are then performed. These comparison are based on the following statistics.

<u>1 : Mean Error</u>

$$ME = \Sigma e_t/n \qquad (t= 1 ..n) \qquad (5.12)$$

<u>2: Mean Percent Error</u>

$$MPE = (100/n)*\Sigma(e_t/JT_t) \qquad (t = 1 .. n) \qquad (5.13)$$

<u>3: Mean Square Error</u>

$$MSE = \Sigma e_t^2/n \qquad (t = 1 .. n) \qquad (5.14)$$

<u>4: Mean Absolute Error</u>

$$MAE = \Sigma|e_t|/n \qquad (t = 1 .. n) \qquad (5.15)$$

<u>5: Mean Absolute percent Error</u>

$$MAPE = (100/n)*\Sigma|e_t/JT_t| \qquad (t = 1 .. n) \qquad (5.16)$$

The first two statistics measure forecast bias and should be close to zero. The other three measure forecast accuracy; methods that has small values for these statistics consider to be better than other.

5.4.4 Journey Time Data

The journey time data used in this study is derived from the output of SCOOT (Hunt et al, 1981), a fully-adaptive urban traffic control system. In the course of its signal optimisation SCOOT measures detector presence through time, which can be converted into traffic flow and calculates delay, from which link journey time can be calculated. Carden et al (1989) in their report "SCOOT model accuracy" have shown that journey time estimates from SCOOT are accurate. Mean journey time for a vehicle, during a five minute period was estimated as follows:

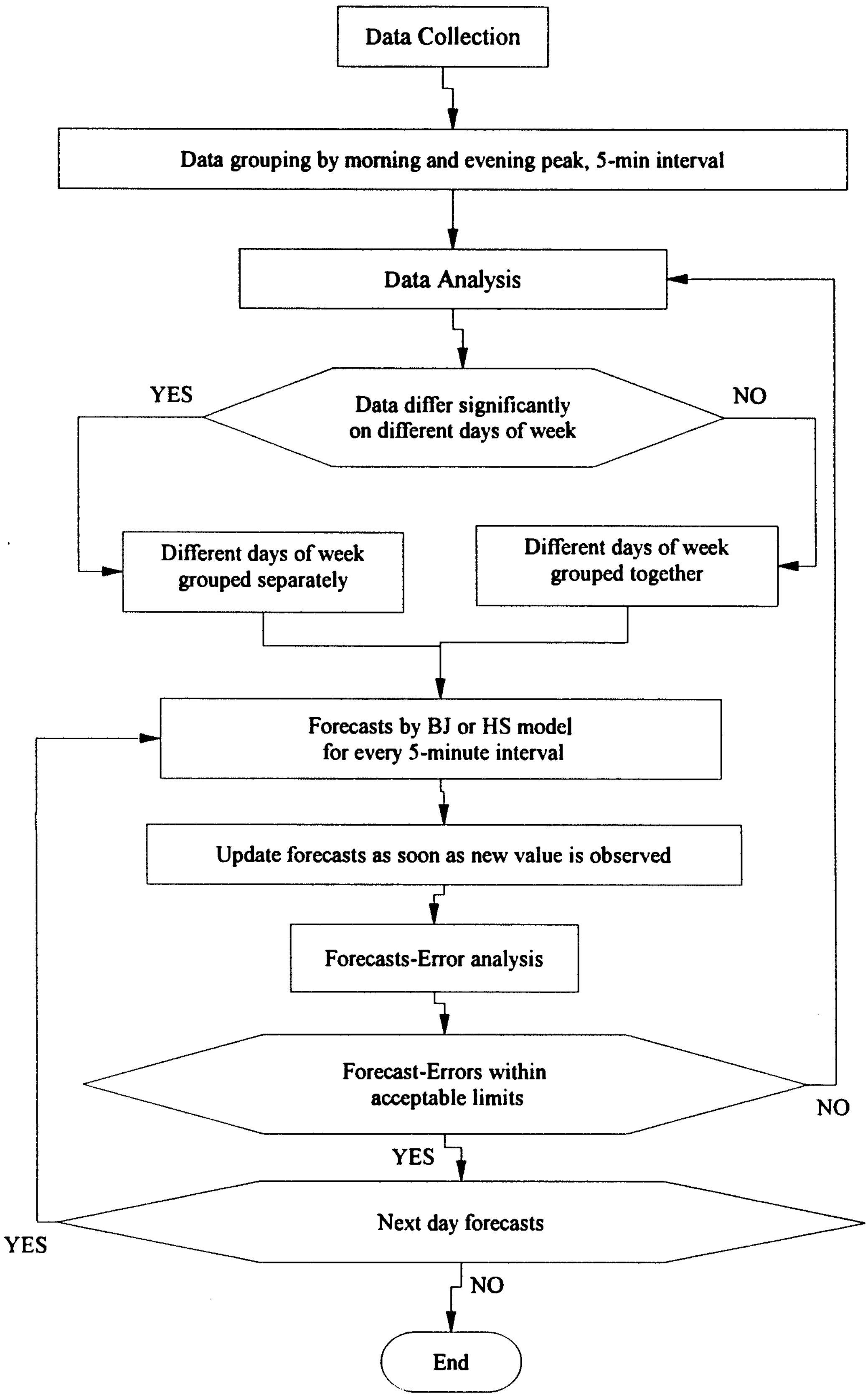
$$\text{Mean Delay per vehicle (sec)} = \text{Mean Total Delay (lpu)} * 3600/\text{Mean Flow(lpu/hour)}$$

$$\text{Journey Time (sec)} = \text{Cruise Time (sec)} + \text{Mean Delay per vehicle (sec)}$$

It should be noted that in the above formula for Mean Delay per vehicle, the units of lpu's cancel out to give Delay in seconds. The cruise time (i.e. undelayed journey time) used for each link were the constant values within the SCOOT model which were obtained by observations when the system was calibrated.

For each day during morning peak, the data was collected between 07:00 - 10:00 at 5-min aggregation level. To determine whether the day of the week made any difference to the links journey time, Analysis of Variance (ANOVA) test applied on the data of all the sites (section 4), it was found that links journey time do not differ significantly on different days of the week (Mon-Fri). So the data was grouped together (Mon-Fri). Journey time forecasting models are developed for three sites (Link N019D, Link N018E and Route1).

Figure 5.1 Flow-Chart of the Forecasting Process



5.5 Application of Box-Jenkins Modelling

5.5.1 Application of Box-Jenkins Modelling to Link N019D

Link N019D is a signalised link in Southampton SCOOT network (Appendix O.1) with cruise time of 21 secs. The analysis of journey time data (section 4.3) showed that the mean level of journey time between days of week is not significantly different on this link, so a single model for all working days was used to predict journey times on the link.

In the example given here, eight days of historical data between 07:00-10:00 at 5-min aggregation level was used to generate journey time forecasts for 9th day. The eight days observed journey times are plotted in figure 5.2.

The first step in ARIMA modelling is to check whether the data is stationary or not. From figure 5.2, it is clear that the data is non-stationary (i.e. the mean is not constant over time). To make the data stationary, first order non-seasonal (d=1) and first order seasonal differences (D=1) were obtained. The differenced data is plotted in figure 5.3, which shows the data is stationary after differencing.

The second step is to find the appropriate values of p,q and P,Q of ARIMA (p,d,q)(P,D,Q). For this, autocorrelation structure is used. The autocorrelations of differenced data is plotted in figure 5.4. The strong autocorrelation values at lag 1 and 2 suggest the inclusion of non-seasonal moving average operators of order 1 and 2 (q=2). Similarly the strong autocorrelation at lag 36 suggests the inclusion of seasonal moving average operator of order 1 (Q=1). The selected model is ARIMA (0,1,2)(0,1,1), the algebraic form of the model is:

$$J\hat{T}_t = JT_{t-1} + JT_{t-s} - JT_{t-s-1} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \Theta_s a_{t-s} + \theta_1 \Theta_s a_{t-s-1} + \theta_2 \Theta_s a_{t-s-2} \qquad (5.17)$$

The estimates of the parameters θ_1, θ_2 and Θ_s were obtained from eight days of historical data using STATGRAPHICS software package. These estimates of the parameters with their estimated standard error and χ^2-test on the first 36 residual autocorrelations are given in table 5.1. An adequate model satisfies the assumption that random shocks are independent. This can be checked by analysing the residual autocorrelations. The residual autocorrelation shown in figure 5.5, exhibit no systematic pattern and are quite small, which shows that the selected model is adequate. The adequacy of the model is also confirmed by the χ^2-test which has value 24.46, which is less than the table value of χ^2 at 5% level of significance.

The forecasting equation can be written by substituting the estimates of the parameters in equation (5.17), which is:

$$\begin{aligned} \hat{JT}_t = {} & JT_{t-1} + JT_{t-s} - JT_{t-s-1} + a_t - 0.6391\ a_{t-1} - 0.3069\ a_{t-2} - 0.6849\ a_{t-s} \\ & +0.4377\ a_{t-s-1} + 0.2102\ a_{t-s-2} \end{aligned} \tag{5.18}$$

where

$\hat{JT}_t$ = Predicted journey time for time interval t.

JT_{t-1} = Observed (or predicted)journey time at time interval t-1.

JT_{t-s} = Observed journey time at time interval t on previous day.

and so on.

Using equation (5.18), forecasts at link N019D were generated for all 5-minute time intervals between 07:00-10:00 on 9th day (20-2-91). The observed and forecasted journey times are plotted in figure 5.6. These forecasts are generated at 7:00 for all the 5-minute time periods until 10:00 and are referred to as 36-steps ahead (not-updated) forecasts. However, for real time application, on-street information may well be available for every 5-minute time interval, this latest information could be used to update the forecasts.

Box-Jenkins modelling does not provide any procedure which automatically updates the estimates of the model parameters. However for forecasts of more than one-period ahead, one can use the last available observation instead of its forecast. For example in equation (5.18) JT_{t-1} was not available when making 36-steps ahead forecasts, but on a current day at any time interval t, the value of observed journey time at time (t-1) would be available and this observed value can be substituted in place of forecast value to update the forecasts.

To update the forecasts for every 5-minute time interval a FORTRAN program (Appendix C.1) was written which updates the forecasts as soon as a new journey time value is observed. One step ahead updated forecasts at link N019D which are obtained by using this program are plotted in figure 5.7.

Models were also developed based on 6, 7, 9, and 10 days of historical data. The estimates of parameters are given in table 5.1 with their estimated white noise standard deviation and χ^2-test values on the first 36 residuals. The adequacy of models is confirmed by the χ^2-test on first 36 residual autocorrelations, which is less than the table values for all the models.

Forecasting accuracy was evaluated through analysis of forecast-errors. For 9th day not-updated forecasts the mean absolute percentage error is 8.97, this is reduced to 8.89 for updated forecasts. Table 5.2 shows forecast-errors for all days when forecasts were generated. It can be seen from this table that in most cases updated forecasts are better than 36-step ahead forecasts.

Figure 5.2 Link N019D : Eight days observed journey times (7:00-10:00)

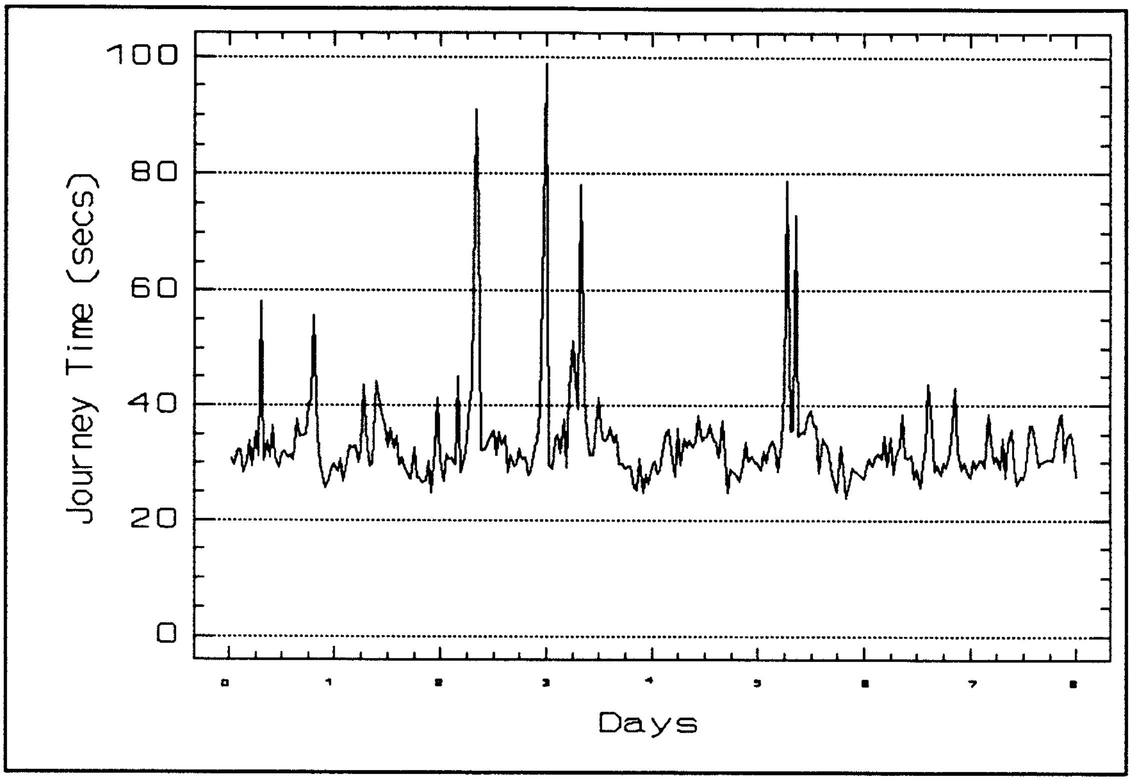


Figure 5.3 Link N019D : Differenced data

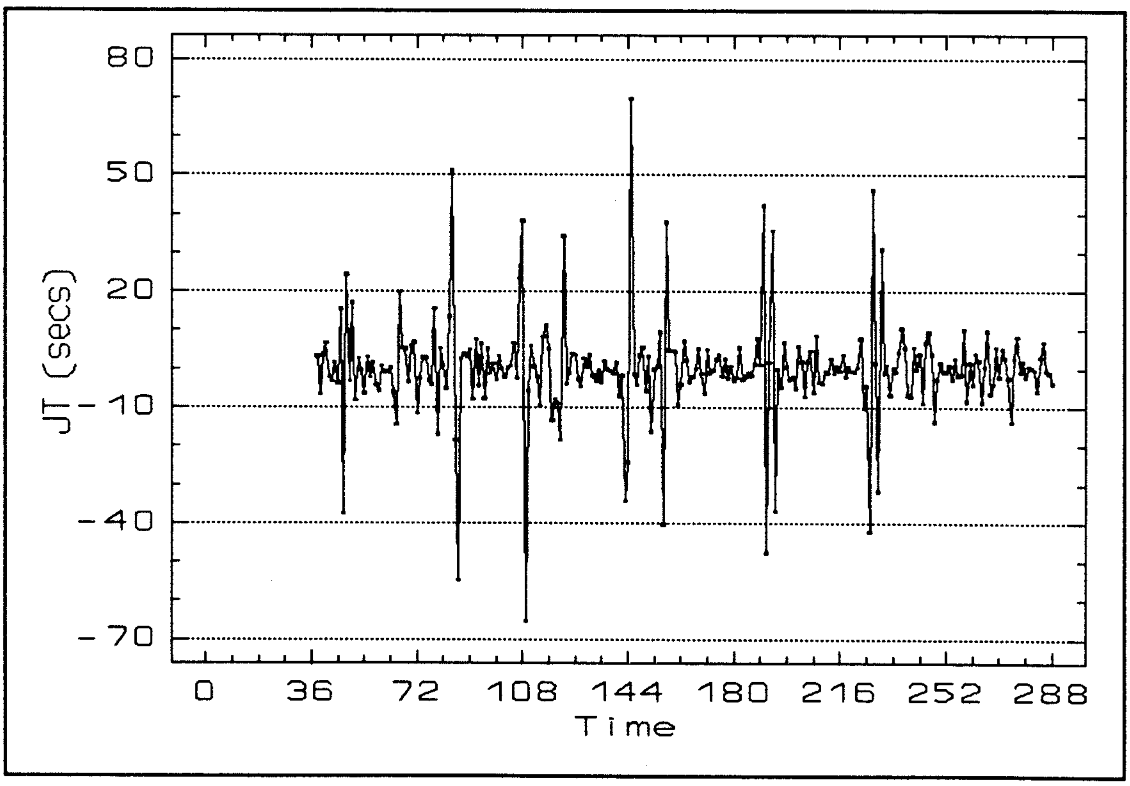


Figure 5.4   Link N019D : Estimated autocorrelations of differenced data

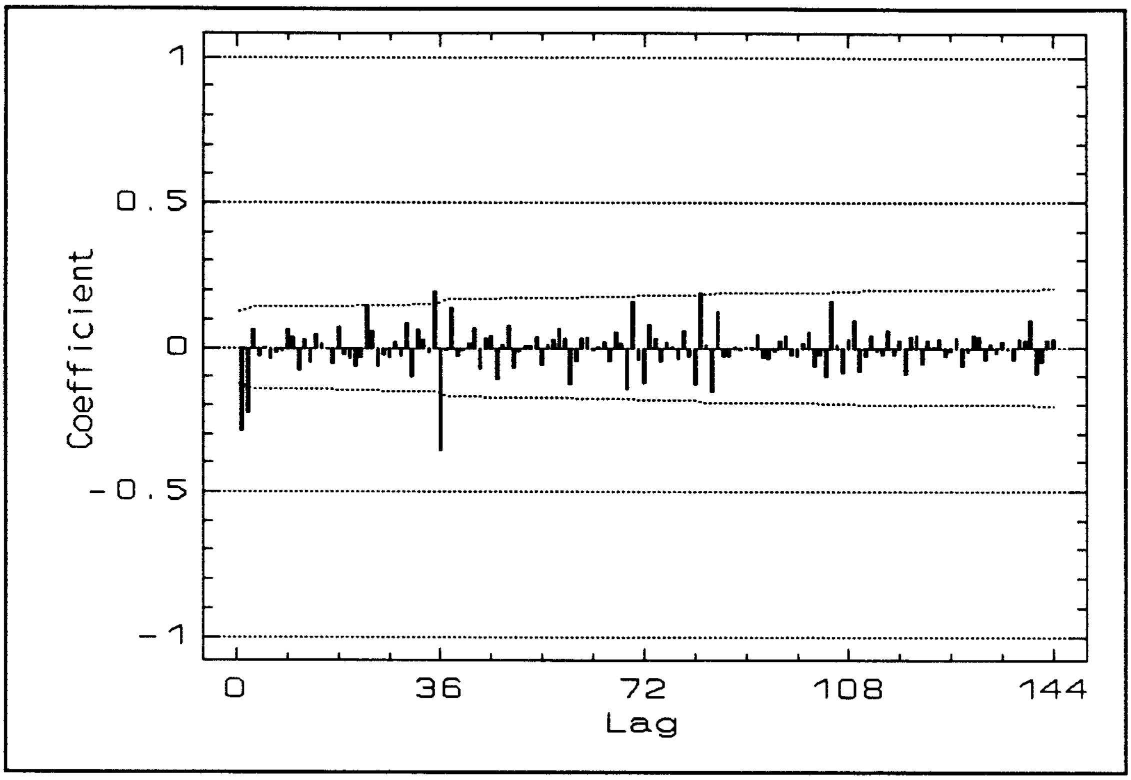


Figure 5.5   Link N019D : Estimated residual autocorrelations

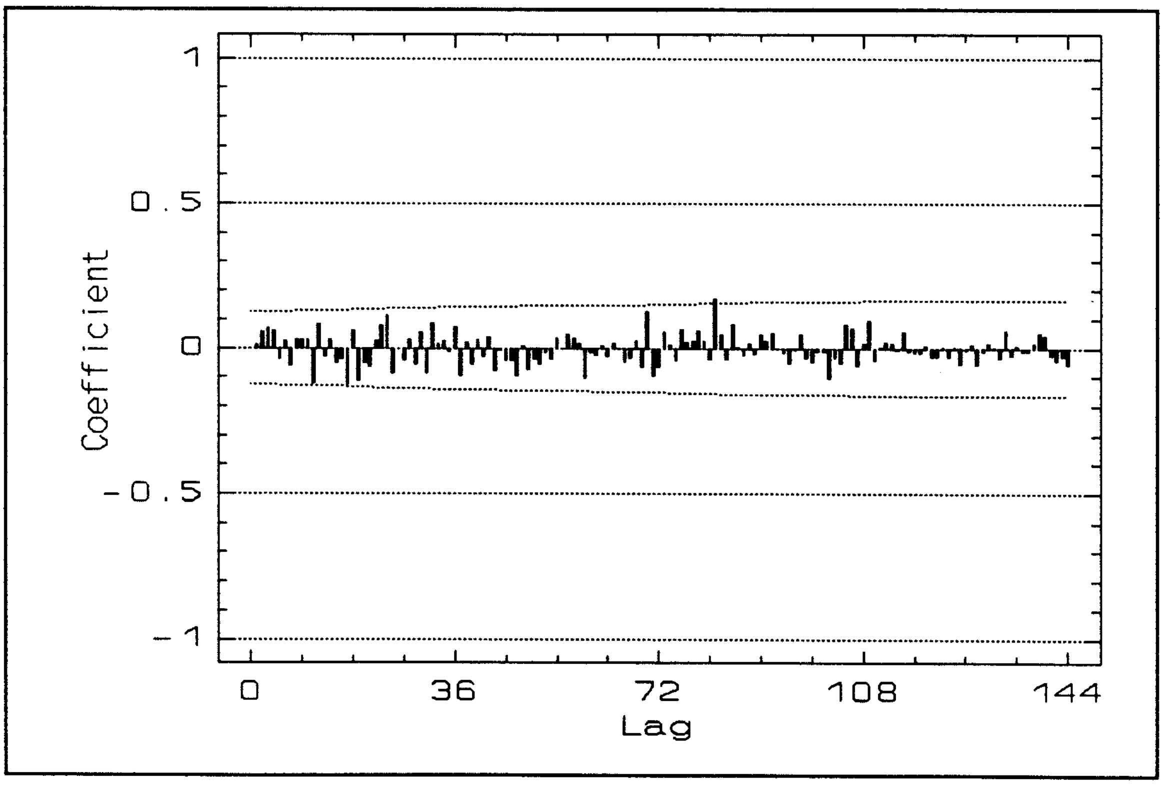


Figure 5.6 Link N019D : 36-steps ahead forecasts

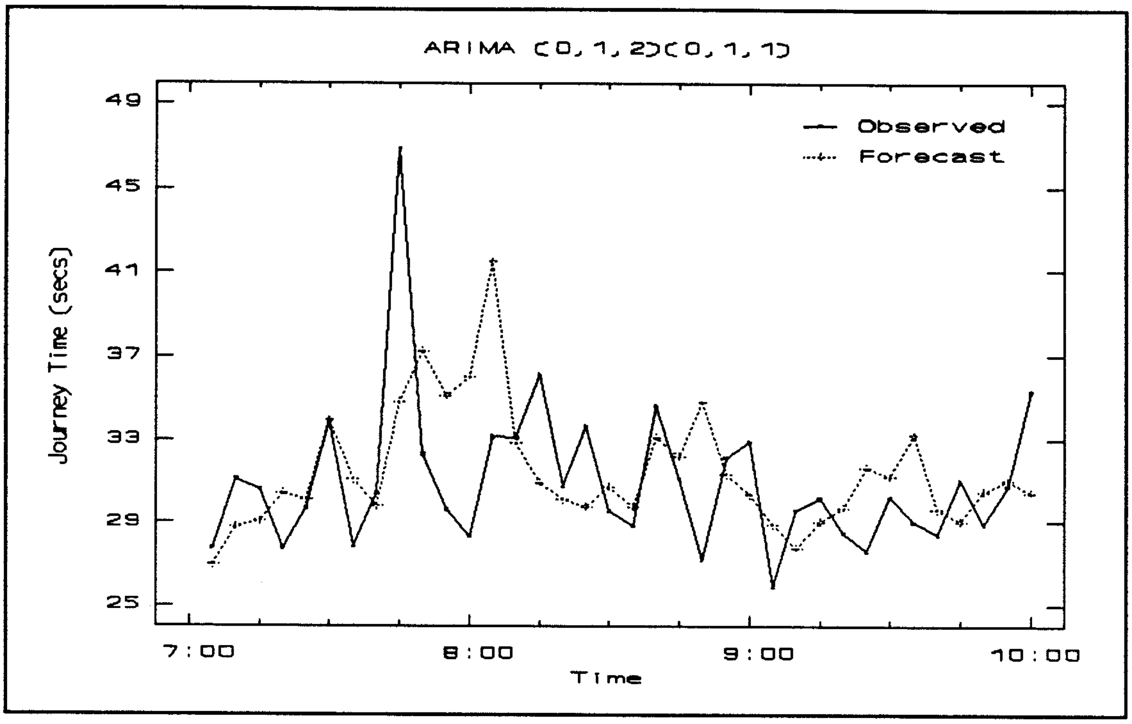


Figure 5.7 Link N019D : 1-step ahead updated forecasts

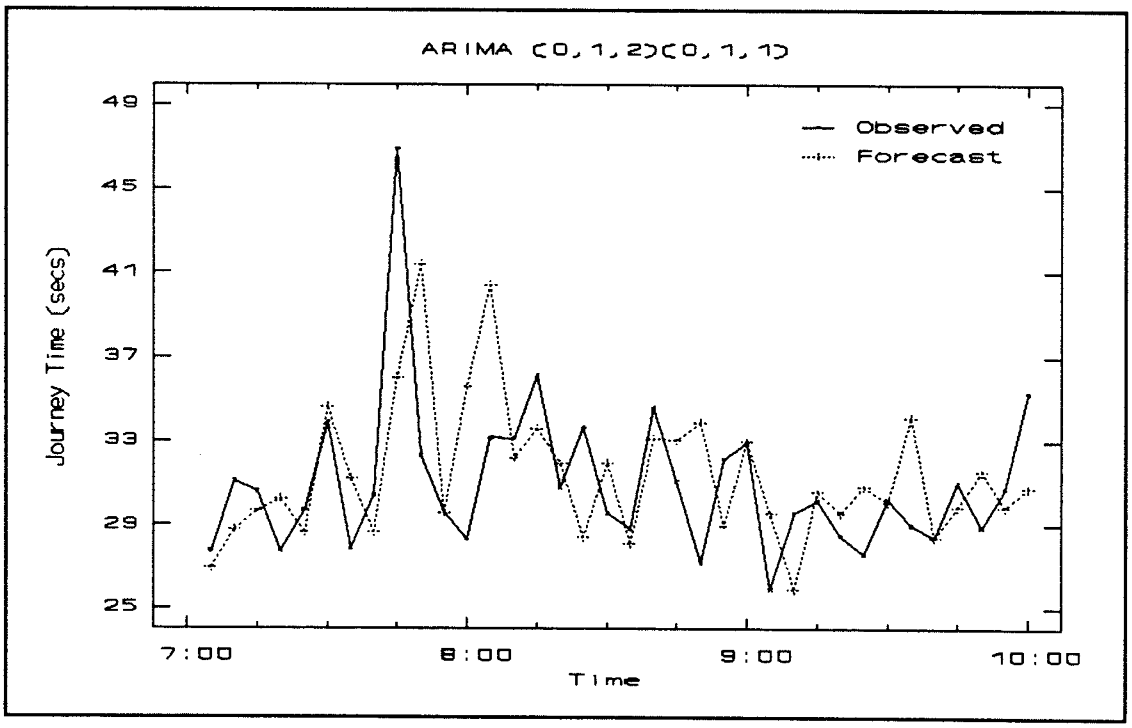


Table 5.1 Link N019D : ARIMA (0,1,2)(0,1,1) parameters estimates

No. of day's Historical data	Date of Fore--casts	Parameter's Estimates θ_1	θ_2	Θ_s	Estimated white noise SD σ_a	χ^2-test on 1st 36 residual
6	18-2-91	0.63878	0.30502	0.62787	10.98	26.46
7	19-2-91	0.64005	0.30016	0.67881	10.32	31.09
8	20-2-91	0.63909	0.30687	0.68488	9.72	35.52
9	21-2-91	0.64117	0.30931	0.68593	9.19	39.31
10	28-2-91	0.65329	0.29221	0.69010	8.92	40.63

Table 5.2 Link N019D : Box-Jenkins Forecast-Errors statistics

No. of day's Histori-cal data	Date of Fore--casts	Forecasts	Forecast-Error Statistics MAE	MSE	MAPE
6	18-2-91	Not-Updated	5.0	48.8	15.5
		Updated	4.7	44.1	14.7
7	19-2-91	Not-Updated	4.2	28.8	13.1
		Updated	3.8	26.0	12.1
8	20-2-91	Not-Updated	2.8	15.3	9.0
		Updated	2.8	14.8	8.9
9	21-2-91	Not-Updated	3.6	40.3	9.3
		Updated	3.9	44.9	10.6
10	28-2-91	Not-Updated	3.2	16.2	10.0
		Updated	3.2	16.5	10.2

5.5.2 Application of Box-Jenkins Modelling to Link N018E

Link N018E is also a signalised link with cruise time of 24 secs. The analysis of journey time data (section 4.3) showed that the mean level of journey time between days of week is not significantly different on this link, so a single model for all working days can be used to predict journey times on the link.

In the example given here, Journey time data for six consecutive days between 07:00-10:00 at 5-min aggregation level is plotted in figure 5.8. This figure shows that journey times are within a day have peaks and troughs; the peak is usually during the middle, with the pattern of journey times more or less same between days. The modelling procedure started with finding the appropriate values of p,d,q and P,D,Q in ARIMA (p,d,q)(P,D,Q). From figure 5.8, it is clear that data is non stationary and has strong seasonality. To remove this seasonality and to make the data stationary, first order non-seasonal (d=1) and first order seasonal differences (D=1) were obtained. The differenced data is plotted in figure 5.9, which shows that the data is stationary after differencing.

The autocorrelation of differenced data is plotted in figure 5.10. The strong autocorrelation values at lag 1 and 2 suggest the inclusion of non-seasonal moving average operators of order 1 and 2. Similarly the strong autocorrelations at lags 36 suggests the inclusion of seasonal moving average operator of order 1. The selected model is ARIMA (0,1,2)(0,1,1), the algebraic form of the model is:

$$\hat{JT}_t = JT_{t-1} + JT_{t-s} - JT_{t-s-1} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \Theta_s a_{t-s} + \theta_1 \Theta_s a_{t-s-1} + \theta_2 \Theta_s a_{t-s-2} \tag{5.19}$$

The estimates of the parameters θ_1, θ_2 and Θ_s were obtained from six days historical data using STATGRAPHICS software package. These estimates with their estimated standard error and χ^2-test on first 36 residual autocorrelations are given in table 5.3.

By substituting the estimates of these parameters in equation (5.19), the prediction equation can be written as:

$$\hat{JT}_t = JT_{t-1} + JT_{t-s} - JT_{t-s-1} + a_t - 0.5934\ a_{t-1} - 0.3868\ a_{t-2} - 0.5110\ a_{t-s} + 0.3032\ a_{t-s-1} + 0.1976\ a_{t-s-2} \tag{5.20}$$

where

$\hat{JT}_t$	=	Predicted journey time for time interval t.
JT_{t-1}	=	Observed (or predicted)journey time at time interval t-1.
JT_{t-s}	=	Observed journey time at time interval t on previous day.

and so on.

Using equation (5.20) forecasts at link N018E were generated for all 5-minute time intervals between 07:00-10:00 on 7th day (14-6-91). The observed and forecasted journey times are plotted in figure 5.12. These forecasts were generated at 7:00 for all time intervals and are referred to as not-updated forecasts. Forecasts were updated (as at link N019D) using UPDATE program. One step ahead updated forecasts are plotted in figure 5.13. From the plots of observed vs predicted journey times that forecasts follow the pattern of present day data. Forecasts accuracy is evaluated by making analysis of forecast-errors. For 7th day not-updated forecasts the mean absolute percentage error is 12.66, this is reduced to 12.16 for updated forecasts.

Models were also developed based on 7, 8, 9 and 10 days of historical data, the estimates of parameters are given in table 5.3. Forecast-errors for these days are shown in table 5.4 which shows that on this link forecasts are quite good and further improvement in forecasts are achieved in all cases by updating the forecasts.

Figure 5.8 Link N018E : Six days observed journey times (7:00-10:00)

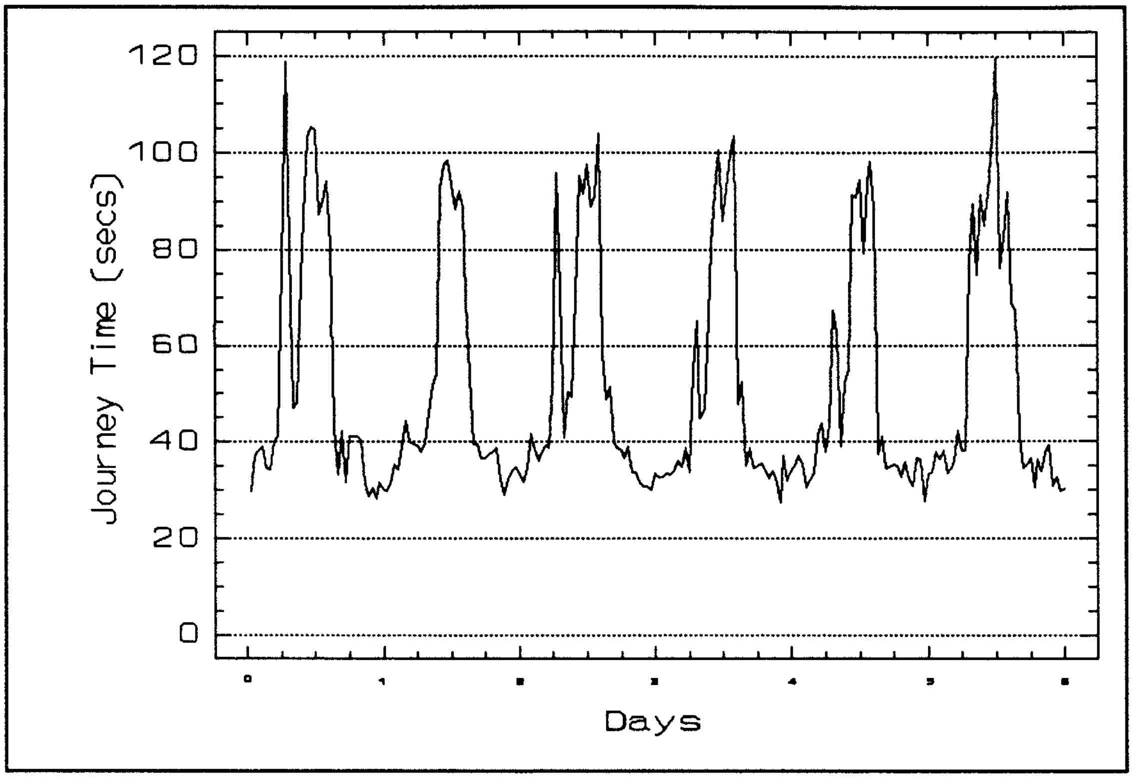


Figure 5.9 Link N018E : Differenced data

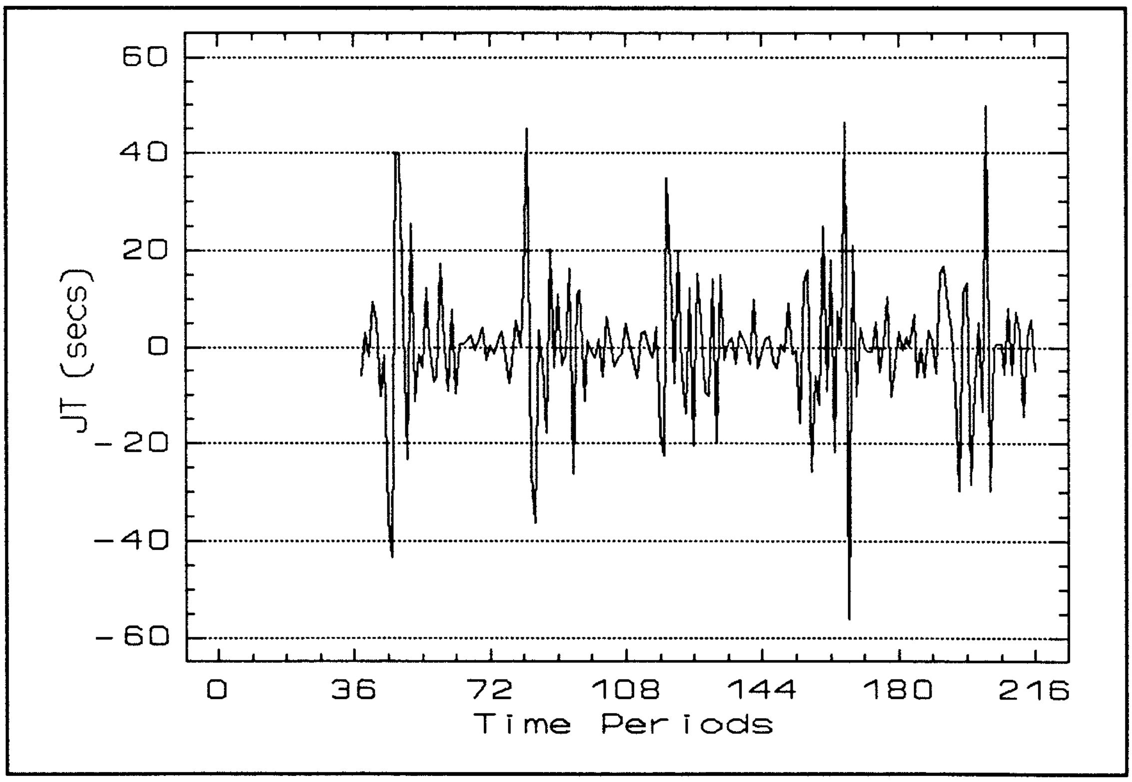


Figure 5.10 Link N018E : Estimated Autocorrelations of differenced data

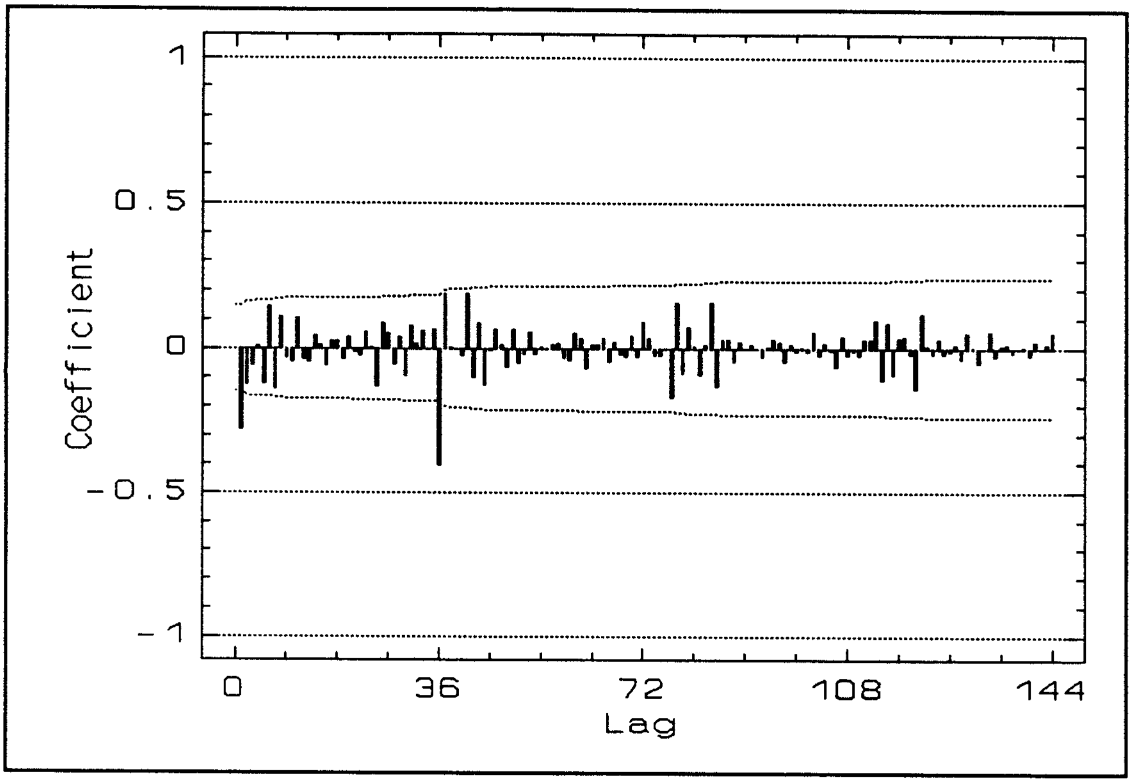


Figure 5.11 Link N018E : Estimated Residual Autocorrelations

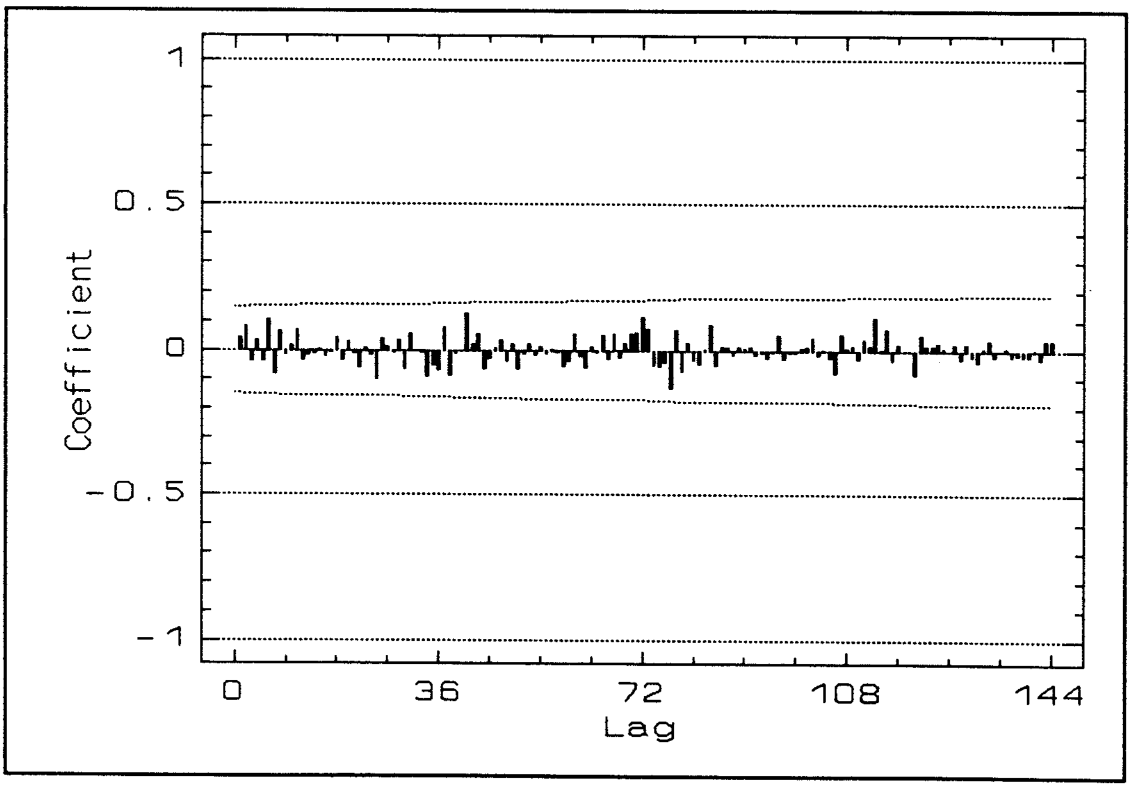


Table 5.3 Link N018E : ARIMA (0,1,2)(0,1,1) parameters estimates

No. of day's Historical data	Date of Fore--casts	Parameter's Estimates θ_1	θ_2	Θ_s	Estimated white noise SD σ_a	χ^2-test on 1st 36 residual
6	14-6-91	0.59336	0.38679	0.51096	10.93	14.64
7	17-6-91	0.60167	0.38914	0.58169	10.47	18.35
8	18-6-91	0.57447	0.40411	0.59952	10.49	17.01
9	21-6-91	0.55087	0.39011	0.56479	11.22	25.10
10	24-6-91	0.49637	0.36205	0.57830	11.13	29.83

Table 5.4 Link N018E : Box-Jenkins Forecast-Errors statistics

No. of day's Historical data	Date of Fore--casts	Forecasts	Forecast-Error Statistics MAE	MSE	MAPE
6	14-6-91	Not-Updated	6.3	72.0	12.7
		Updated	6.2	68.3	12.2
7	17-6-91	Not-Updated	8.1	146.6	12.4
		Updated	7.8	123.3	12.6
8	18-6-91	Not-Updated	12.2	384.8	15.7
		Updated	12.7	376.2	17.1
9	21-6-91	Not-Updated	12.9	268.2	28.1
		Updated	12.1	236.2	26.1
10	24-6-91	Not-Updated	9.9	278.5	17.2
		Updated	9.0	208.5	16.6

Figure 5.12 Link N018E : BJ 36-step ahead forecasts

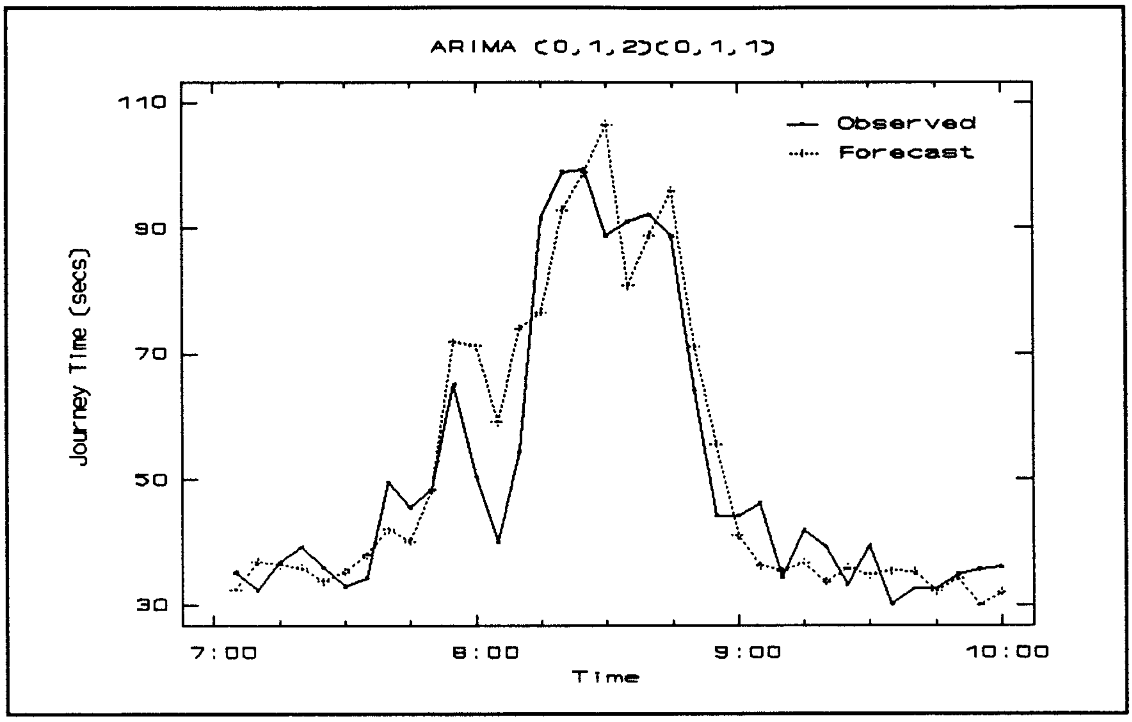
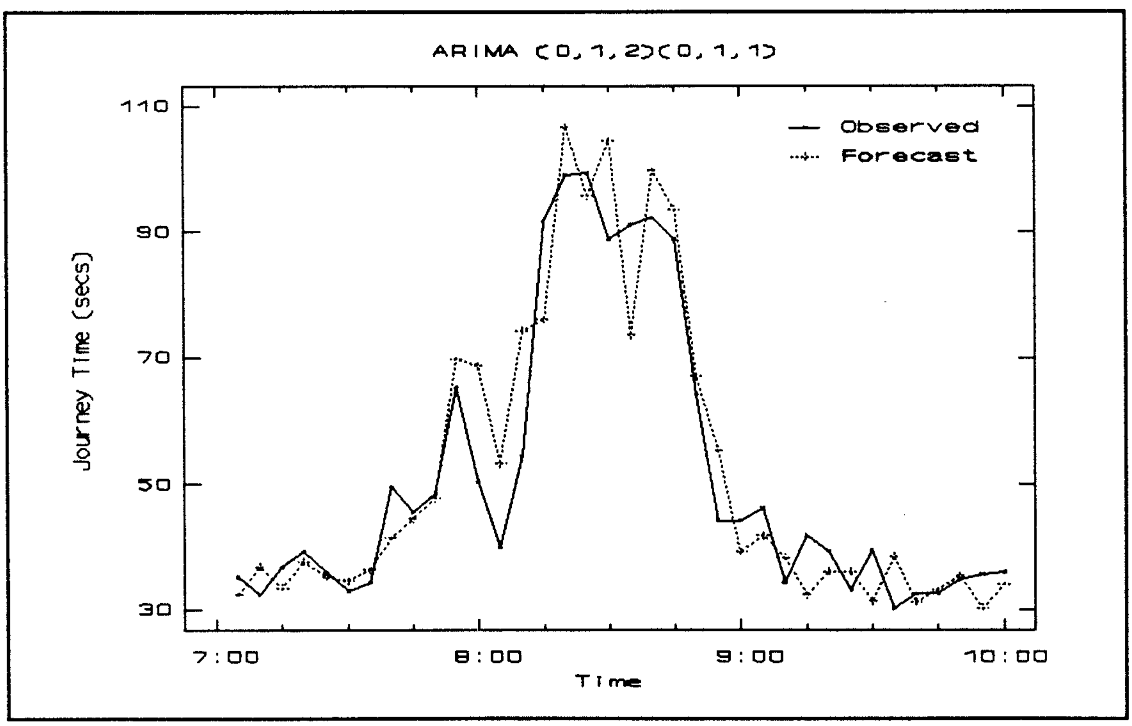


Figure 5.13 Link N018E : BJ 1-step ahead updated forecasts



5.5.3 Application of Box-Jenkins Modelling to Route1

Route1 consist of 9 links (Appendix O.1) with the total cruise time of 136 secs, journey time on these links are summed to obtain the journey time for whole route. The analysis of journey time data at Route1 (section 4.3) showed that the mean level of journey time between days of week is not significant, so a single model for all working days can be used to predict journey times on Route1.

Journey time data for six consecutive days between 07:00-10:00 at 5-min aggregation level is plotted in figure 5.14, which shows that data has strong seasonality. To remove this seasonality and to make the data stationary, first order seasonal differences (D=1) and first order non-seasonal differences (d=1) were obtained. The autocorrelation of differenced data is plotted in figure 5.16. The strong autocorrelation values at lag 1 and at lag 2 suggest the inclusion of non-seasonal moving average operator of order 1 and 2 (q=2), also the strong autocorrelation at lags 36 suggest the inclusion of seasonal moving average operator of order 1 (Q=1). The selected model is ARIMA (0,1,2)(0,1,1), the algebraic form of the model is:

$$J\hat{T}_t = JT_{t-1} + JT_{t-s} - JT_{t-s-1} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \Theta_s a_{t-s} + \theta_1 \Theta_s a_{t-s-1} + \theta_2 \Theta_s a_{t-s-2} \tag{5.21}$$

The estimates of the parameters θ_1, θ_2 and Θ_s were obtained from 6 days historical data. By substituting the estimates of these parameters in equation (5.21), the prediction equation can be written as:

$$J\hat{T}_t = JT_{t-1} + JT_{t-s} - JT_{t-s-1} + a_t - 0.4451\ a_{t-1} - 0.2499\ a_{t-2} - 0.5340\ a_{t-s} + 0.2380\ a_{t-s-1} + 0.1335\ a_{t-s-2} \tag{5.22}$$

where

$\hat{JT}_t$ = Predicted journey time for time interval t.

JT_{t-1} = Observed (or predicted)journey time at time interval t-1.

JT_{t-s} = Observed journey time at time interval t on previous day.

and so on.

Using equation (5.22) forecasts at Route1 were generated for all 5-minute time intervals between 07:00-10:00 on 7th day (14-6-91), the observed and forecasted journey times are plotted in figure 5.18. Forecasts were also updated using UPDATE program. One step ahead updated forecasts are plotted in figure 5.19. Forecasts successfully follow the pattern of current days data. Forecasts accuracy were evaluated by making analysis of forecast-errors. For 7th day not-updated forecasts the mean absolute percentage error is 7.48, this is reduced to 5.89 for updated forecasts.

Models were also developed based on 7, 8, 9 and 10 days of historical data. The estimates of parameters are given in table 5.5. Forecast-errors for these days are shown in table 6.6. In all cases forecasts are improved when updated.

Figure 5.14 Route1 : Six days observed journey times (7:00-10:00)

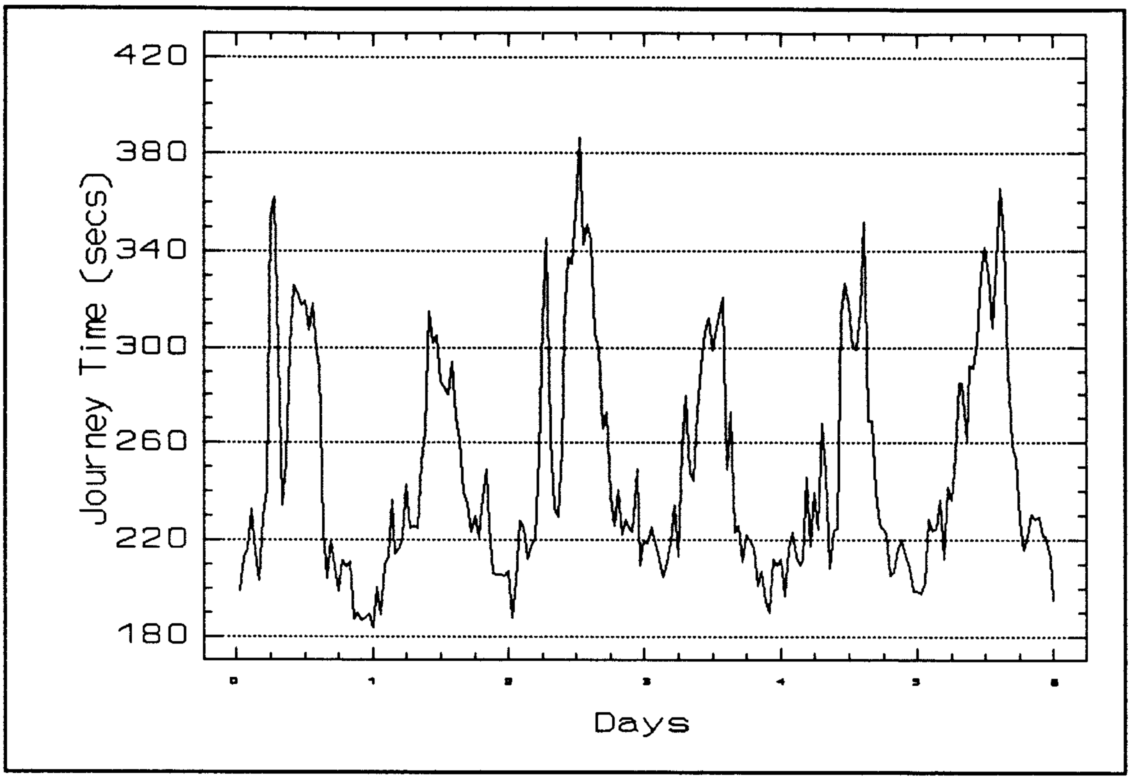


Figure 5.15 Route1 : Differenced data

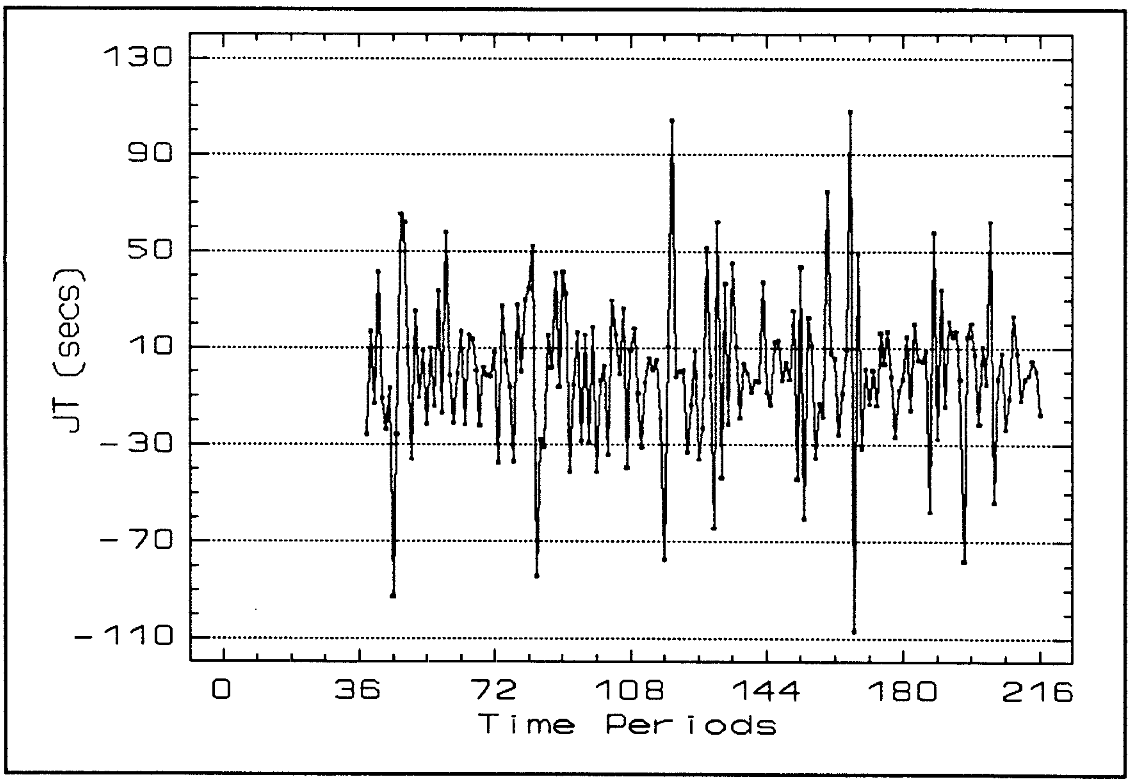


Figure 5.16 Route1 : Estimated autocorrelations of differenced data

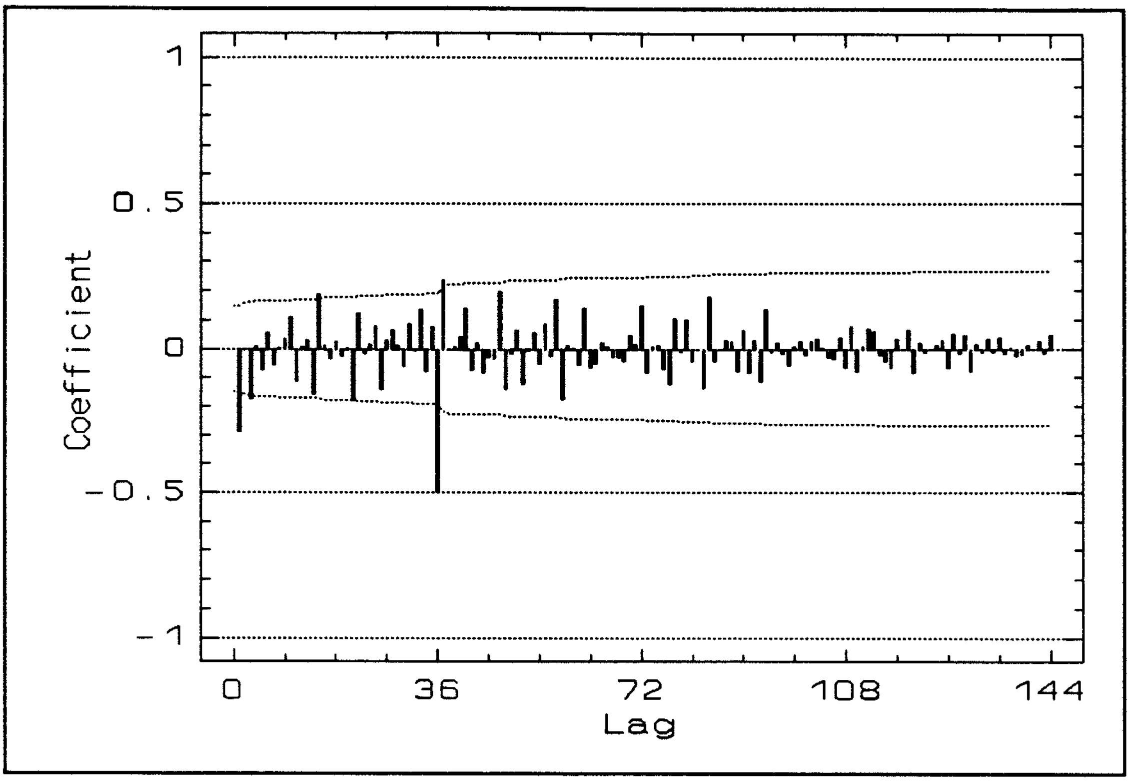


Figure 5.17 Route1 : Estimated Residual Autocorrelations

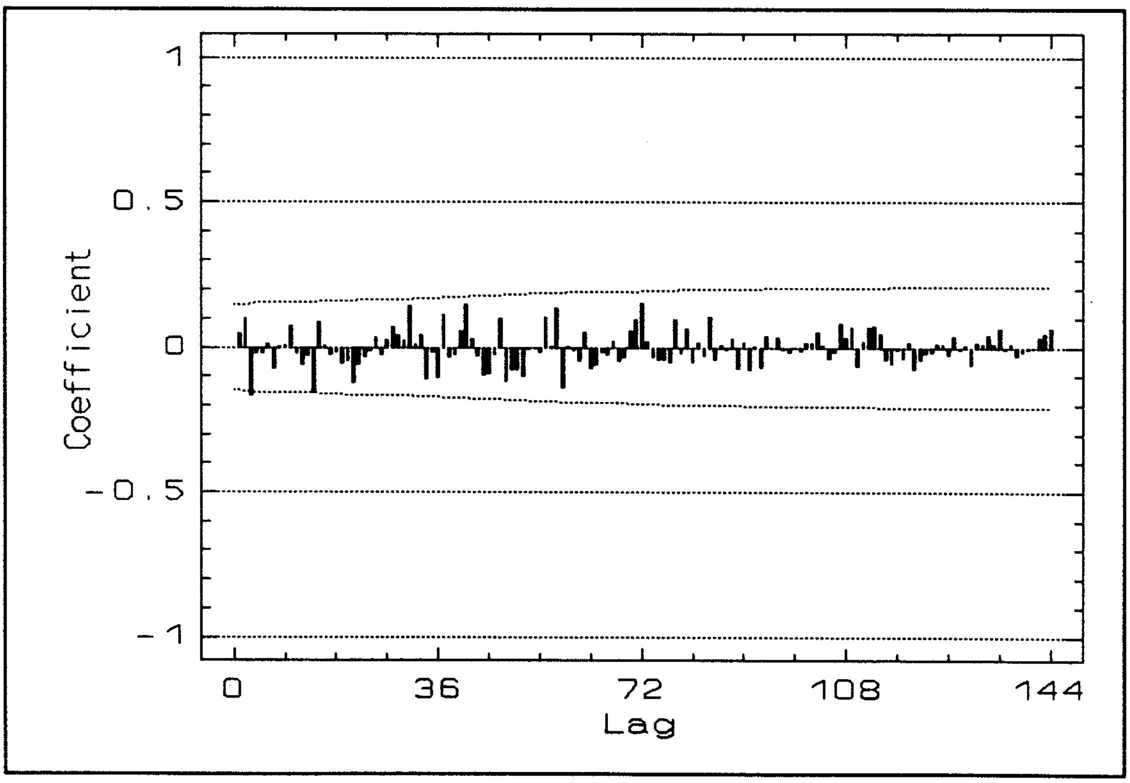


Table 5.5 Route1 : ARIMA (0,1,2)(0,1,1) parameters estimates

No. of day's Historical data	Date of Fore- -casts	Parameter's Estimates θ_1	θ_2	Θ_s	Estimated white noise SD σ_a	χ^2-test on 1st 36 residual
6	14-6-91	0.44510	0.24995	0.53403	24.93	29.99
7	17-6-91	0.42941	0.26533	0.57771	23.86	33.27
8	18-6-91	0.44365	0.27666	0.58649	22.96	37.62
9	21-6-91	0.43858	0.27431	0.60691	22.97	37.08
10	24-6-91	0.43007	0.28181	0.62076	22.64	35.09

Table 5.6 Route1 : Box-Jenkins Forecast-Errors statistics

No. of day's Historical data	Date of Fore- -casts	Forecasts	Forecast-Error Statistics MAE	MSE	MAPE
6	14-6-91	Not-Updated	18.3	544.7	7.5
		Updated	14.6	339.7	5.9
7	17-6-91	Not-Updated	13.8	309.9	5.9
		Updated	13.9	282.7	5.8
8	18-6-91	Not-Updated	21.7	1015.9	7.3
		Updated	18.8	714.9	6.4
9	21-6-91	Not-Updated	17.2	540.4	7.1
		Updated	14.3	423.0	5.9
10	24-6-91	Not-Updated	19.1	659.1	7.4
		Updated	17.0	564.5	6.6

Figure 5.18 Route1 : 36-steps ahead forecasts

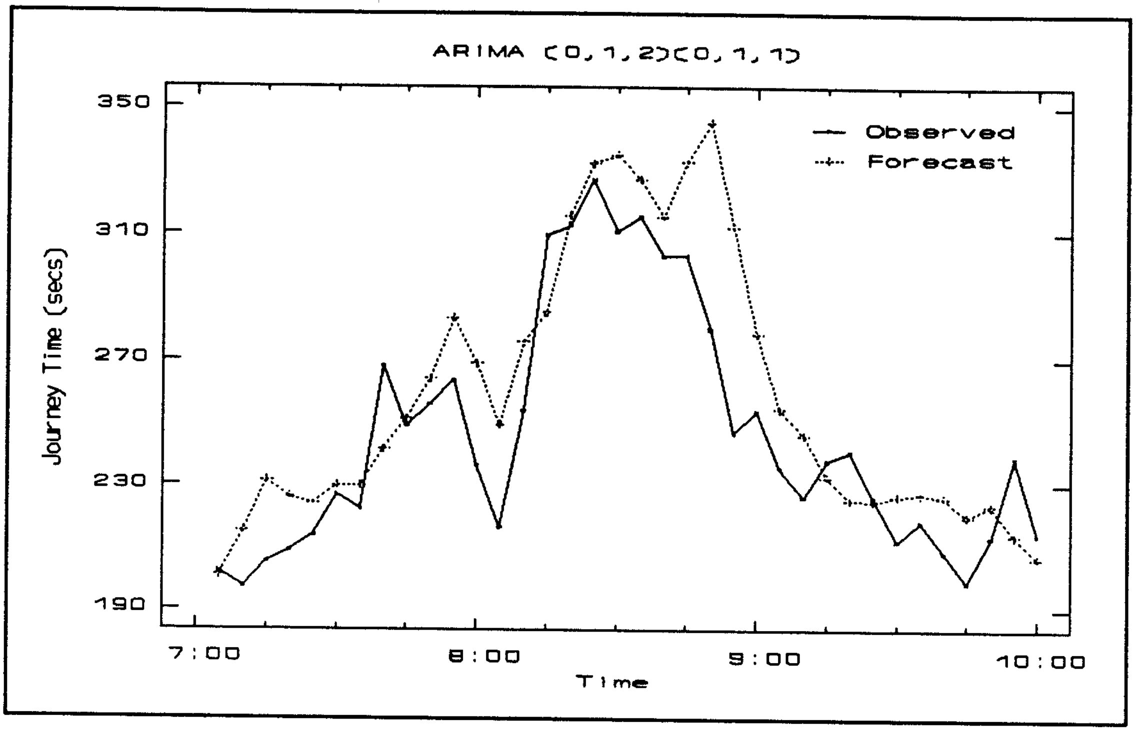
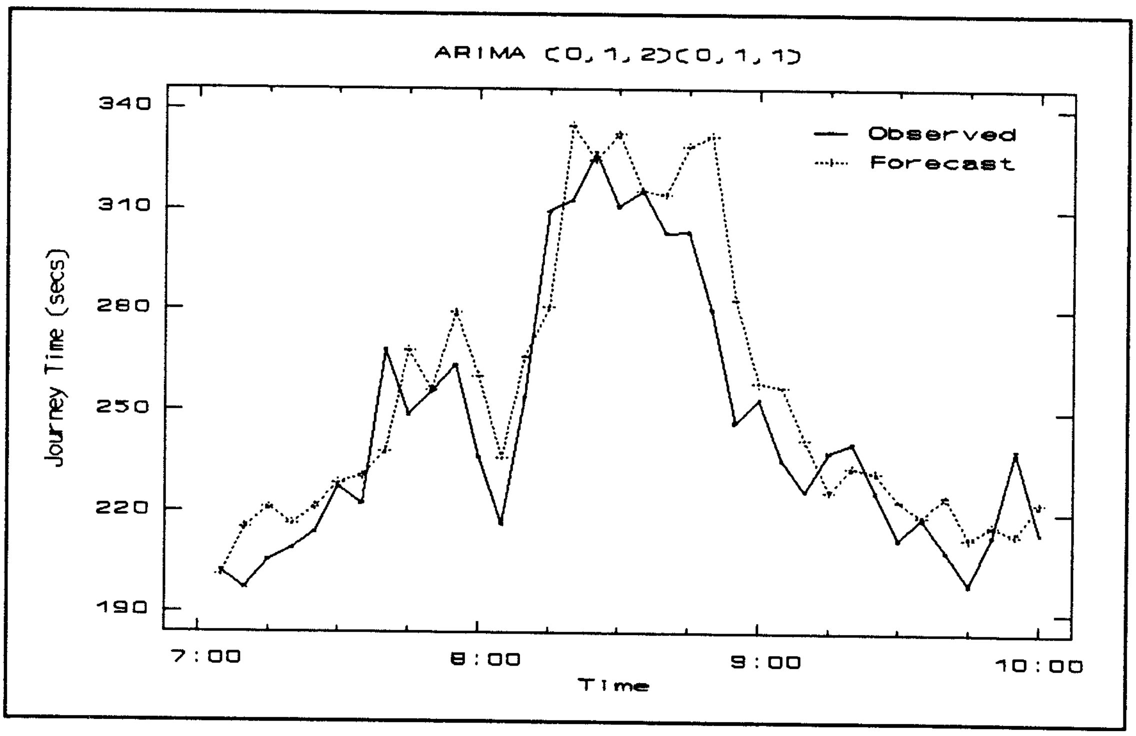


Figure 5.19 Route1 : 1-step ahead updated forecasts



5.6 Application of Horizontal-Seasonal Modelling

Horizontal-Seasonal model (discussed in section 5.2) is applied in this section to generate journey time forecasts on link N019D, N018E and on Route1. A FORTRAN program (Appendix C.2) is written to implement the model. The smoothing constants $\alpha=0.3$ and $\gamma=0.2$ were used. The prediction equation is:

$$JT_T(i) = \hat{a}_T r_{T+i} \tag{5.23}$$

where

$\hat{a}_T$ is estimate of μ (mean journey time per day)

r_{T+i} estimates of seasonal ratios, which are estimated from the historical data of the link or Route concerned.

5.6.1 Application of Horizontal-Seasonal Modelling to Link N019D

The initial estimate of μ which is calculated from eight days of historical data (plotted in figure 5.2) is 32.91. The seasonal ratios from eight days historical data are given in Appendix A.1. Substituting the estimate of μ and seasonal ratios in equation (5.23), forecasts were generated for all 5-minute time periods between 07:00-10:00. Forecasts were updated for all time periods as new values of journey time were observed. These forecasts are given in Appendix B.1 and are plotted in figure 5.20 and figure 5.21.

Figures 5.20 and 5.21 show that the current days journey time are not consistent and changing from one time period to another. However, forecasts still close enough to the observed values apart from few time periods when forecasts are high as compared to observed journey times. overall forecasts accuracy is quite good and mean absolute percentage error is 9.95%.

Forecasts were also generated for four other days based on previous 7, 8, 9 and 10 days historical data. The forecast errors given in table 5.7 show that overall forecasts accuracy is quite good.

Table 5.7 Link N019D : Horizontal-Seasonal Forecast-Errors statistics

No. of day's Historical data	Date of Fore--casts	Forecasts	Forecast-Error Statistics		
			MAE	MSE	MAPE
6	18-2-91	Not-Updated Updated	4.8 4.3	40.0 32.8	14.4 13.4
7	19-2-91	Not-Updated Updated	4.1 3.7	27.5 24.1	12.8 11.6
8	20-2-91	Not-Updated Updated	3.2 3.2	19.2 17.6	10.3 10.0
9	21-2-91	Not-Updated Updated	3.4 4.0	33.6 42.2	9.5 11.4
10	28-2-91	Not-Updated Updated	3.0 2.8	13.7 11.5	9.8 9.2

Figure 5.20 Link N019D : 36-steps ahead forecasts HS-Model

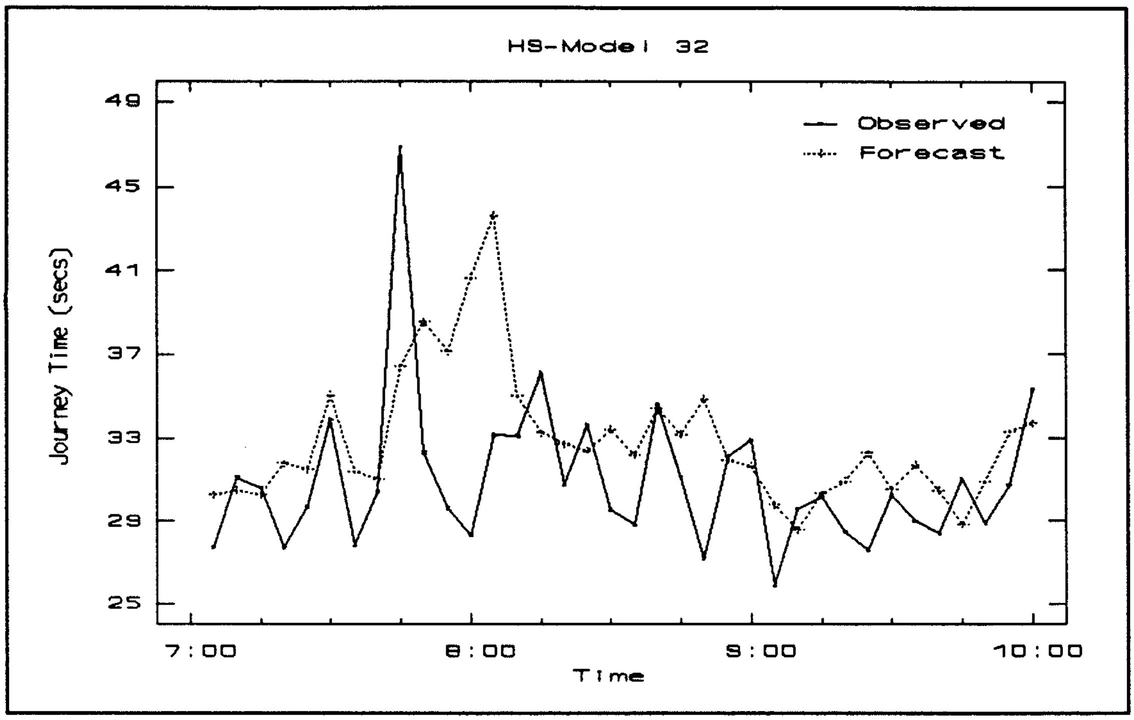
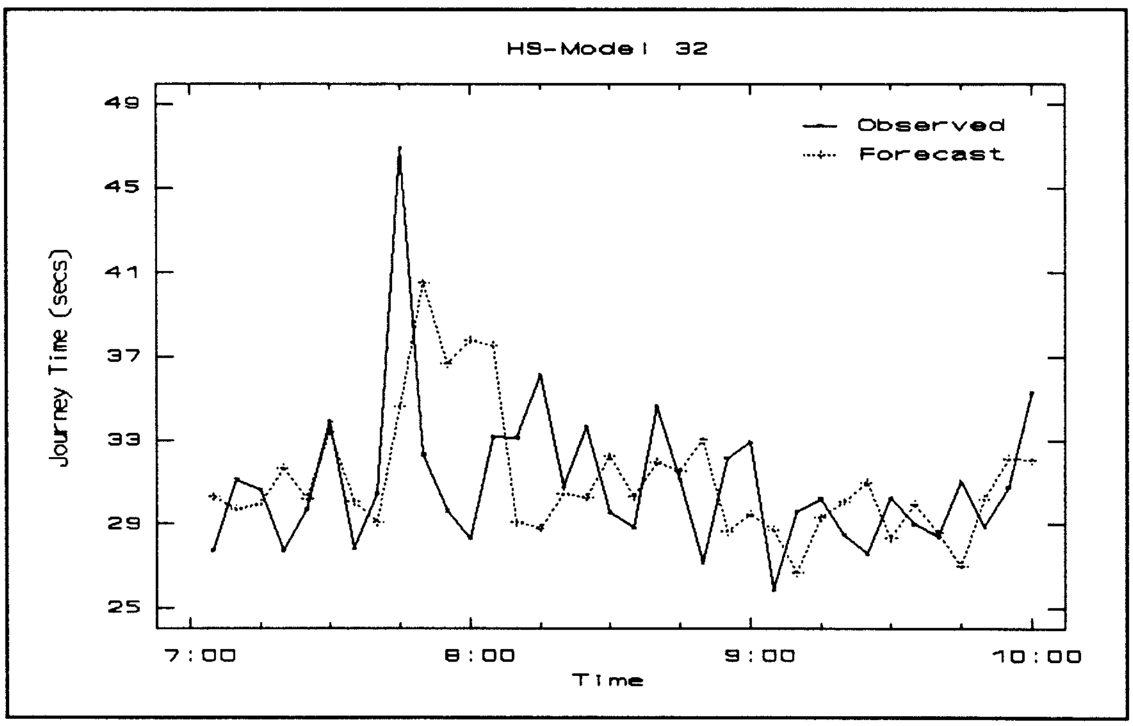


Figure 5.21 Link N019D : 1-step ahead updated forecasts HS-Model



5.6.2 Application of Horizontal-Seasonal Modelling to Link N018E

The initial estimate of μ which is calculated from six days of historical data (plotted in figure 5.8) is 50.64. The seasonal ratios from 6 days historical data are given in Appendix A.2. Substituting the estimate of μ and seasonal ratios in equation (5.23), forecasts were generated for all 5-minute time periods between 07:00-10:00. Forecasts were updated for all time periods as new values of journey time were observed. These forecasts are given in Appendix B.2 and plotted in figure 5.22 and figure 5.23. It can be seen from these figures that forecasts are quite good and follow the pattern of observed data. Forecasts were also generated 8th, 9th, 10th and 11th days based on previous days historical data. Table 5.8 shows forecast errors for all the days for which forecasts were generated.

Table 5.8 Link N018E : HS Model Forecast-Errors statistics

No. of day's Historical data	Date of Fore--casts	Forecasts	Forecast-Error Statistics		
			MAE	MSE	MAPE
6	14-6-91	Not-Updated Updated	4.9 4.9	35.8 46.3	10.0 9.7
7	17-6-91	Not-Updated Updated	7.9 8.1	122.2 133.3	12.4 13.2
8	18-6-91	Not-Updated Updated	14.0 13.1	506.1 324.1	17.5 20.5
9	21-6-91	Not-Updated Updated	9.5 8.8	183.4 138.4	17.0 17.0
10	24-6-91	Not-Updated Updated	8.0 8.7	192.0 158.4	12.1 14.2

Figure 5.22 Link N018E : 36-steps ahead forecasts HS-Model

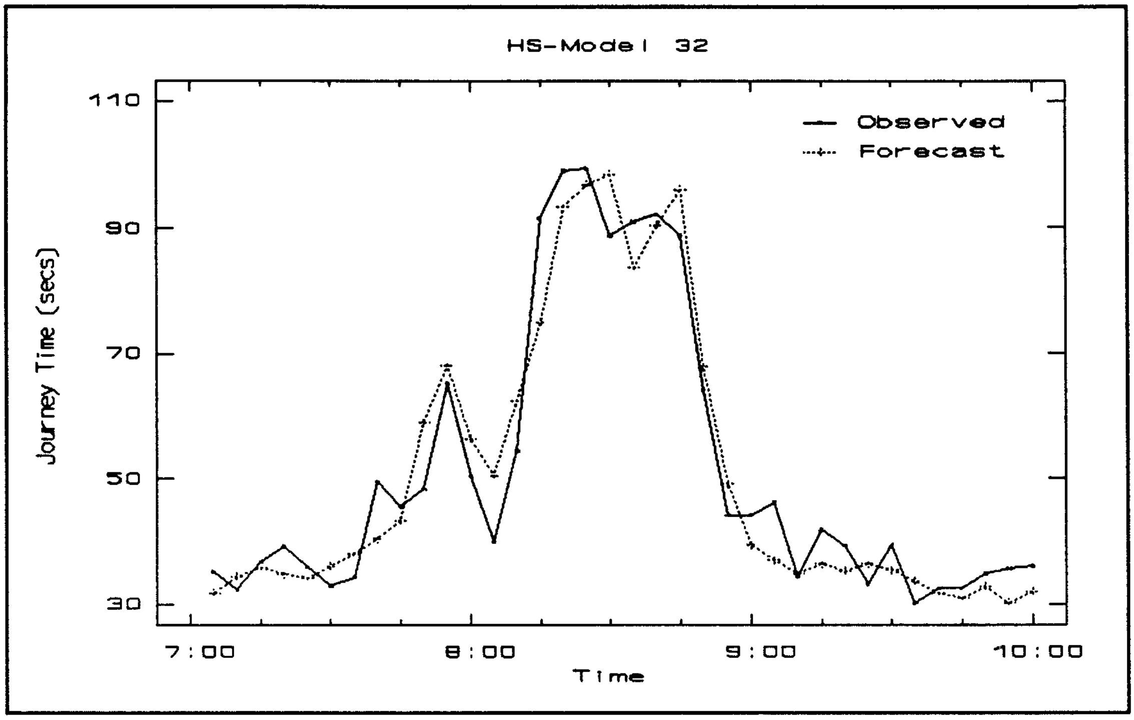
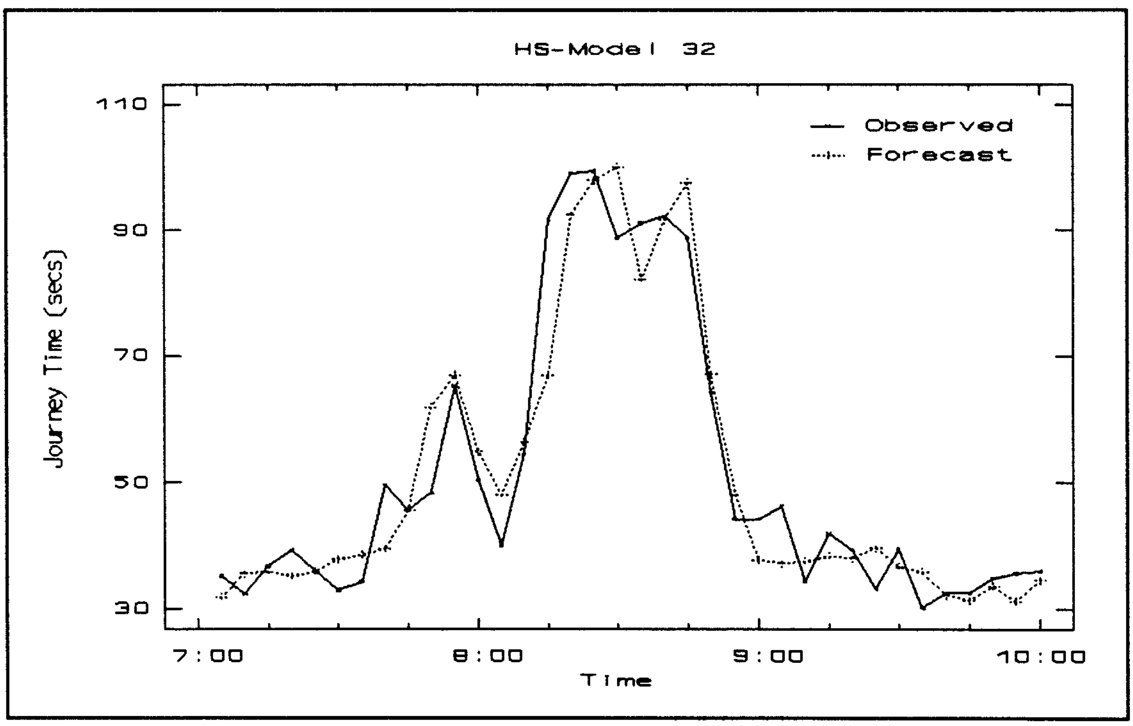


Figure 5.23 Link N018E : 1-step ahead updated forecasts HS-Model



5.6.3 Application of Horizontal-Seasonal Modelling to Route1

The initial estimate of μ which is calculated from 6 days of historical data (plotted in figure 5.14) is 254.14. The seasonal ratios from 6 days historical data are given in Appendix A.3. Substituting the estimate of μ and seasonal ratios in equation (5.23), forecasts were generated for all 5-minute time periods between 07:00-10:00. Forecasts are updated for all time periods as new values of journey time were observed, these forecasts are given in Appendix B.3 and plotted in figure 5.24 and figure 5.25. It can be seen from these figures that forecasts are quite good and follow the pattern of observed data. Forecasts were also generated 8th, 9th, 10th and 11th days based on previous days historical data. Table 5.9 shows forecast errors for all the days for which forecasts were generated.

Table 5.9 Route1 : HS Model Forecast-Errors statistics

No. of day's Historical data	Date of Fore--casts	Forecasts	Forecast-Error Statistics		
			MAE	MSE	MAPE
6	14-6-91	Not-Updated Updated	14.6 11.9	307.5 247.4	6.0 4.8
7	17-6-91	Not-Updated Updated	16.1 13.9	422.7 290.5	6.9 5.8
8	18-6-91	Not-Updated Updated	21.3 19.8	921.0 589.1	7.3 7.1
9	21-6-91	Not-Updated Updated	17.4 16.3	560.3 467.4	7.0 6.4
10	24-6-91	Not-Updated Updated	16.1 14.9	439.6 334.1	6.2 5.9

Figure 5.24 Route1 : 36-steps ahead forecasts HS-Model

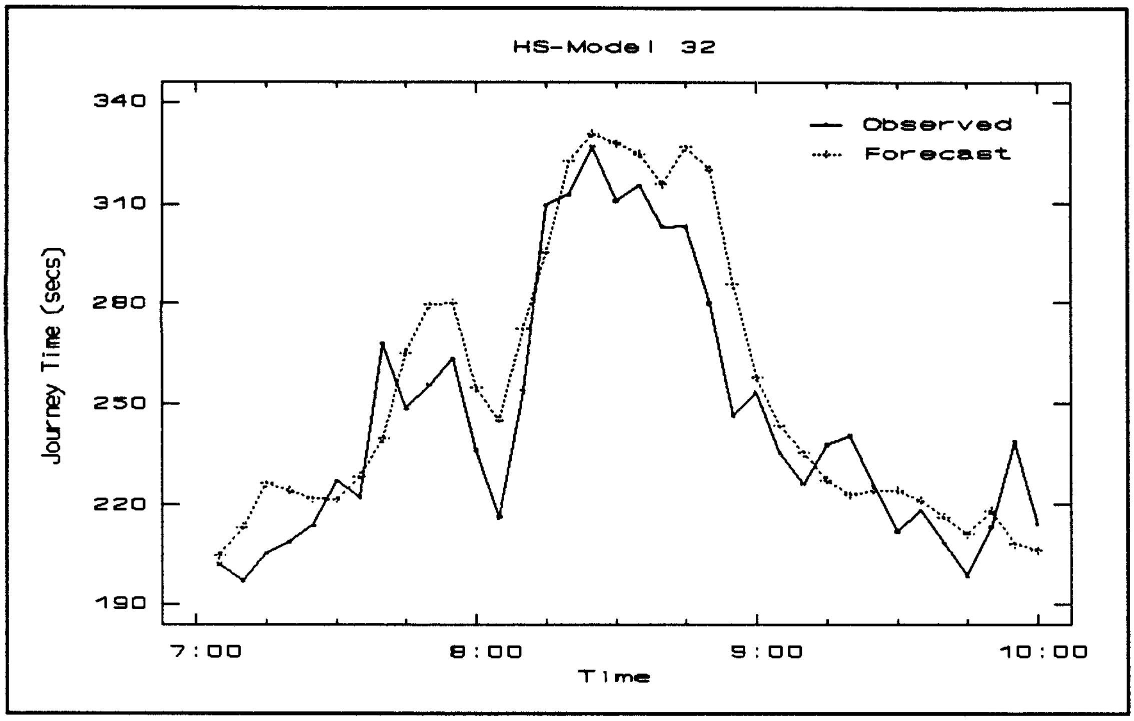
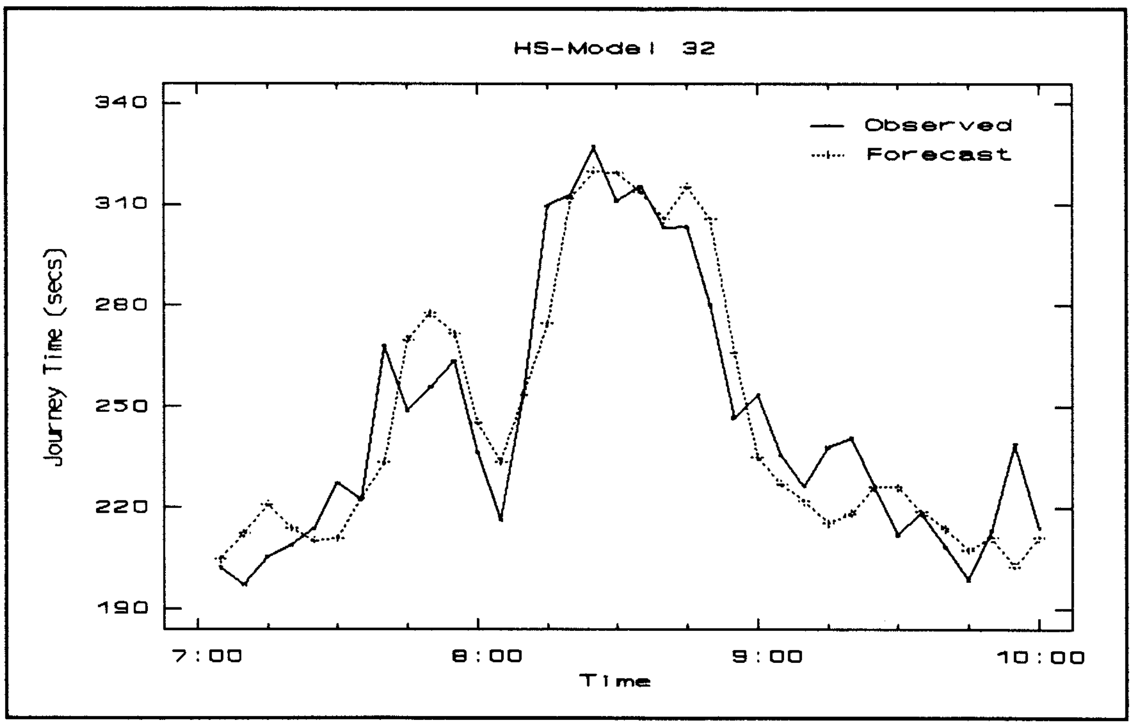


Figure 5.25 Route1 : 1-step ahead updated forecasts HS-Model



5.7 Comparison of BJ and HS modelling results

Two forecasting methods "Box-Jenkins" (BJ) and "Horizontal-Seasonal" (HS) were used to generate journey time forecasts on link-by-link basis. Both techniques proved appropriate for forecasting on an individual link basis in conditions of low/moderate congestion.

Table 5.10 gives overall comparison of both the forecasting methods. The comparison is based on Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE). MSE detects the presence of frequent large forecasting errors, while MAPE gives forecasting errors in terms of percentage. The method which has less MSE and MAPE values is considered to perform better. The comparison of MSE in Table 5.10 shows that on average HS method performed slightly better than BJ method. Forecasts accuracy by both the methods was further improved by updating the forecasts. This can be seen in Table 5.10 where updated forecasts have less MSE in all cases. For Box-Jenkins method the MAPE values ranged from 6.13% to 17.22% and for HS method MAPE ranged from 6.01% to 14.93%.

Table 5.10 Comparison of BJ and HS forecasting-errors statistics

Site	No. of Days Forecast	Model	MSE (Average) Journey Time (secs)		MAPE (Average) Journey Time (secs)	
			Not Updated	Updated	Not Updated	Updated
N019D	6 6	BJ HS	29.9 26.8	29.3 25.6	11.4 11.4	11.3 11.1
N018E	5 5	BJ HS	230.0 207.9	202.5 160.1	17.2 13.8	16.9 14.9
Route 1	5 5	BJ HS	614.0 530.2	465.0 385.7	7.0 6.7	6.1 6.0

5.8 Discussion

In this chapter two time-series methods were used to develop journey time forecasting models. The first method is Box-Jenkins ARIMA modelling. This dynamic modelling technique which accounts for interdependence of data is applied successfully to forecast journey times. An ARIMA (0,1,2)(0,1,1) model was found to represent journey time data from three different sites of varying congestion level. In ARIMA (0,1,2)(0,1,1) model, the first order non-seasonal differencing of the data was necessary to account for the trends and level shifts which occur within a day and first order seasonal differencing was required to account for level shifts which occur between days. The autocorrelation structure of the data sets of all sites showed that first order non-seasonal moving average term was always significant, so does the first order seasonal moving average term. The second order non-seasonal moving average term was also significant in most of the cases and therefore kept in the model for the sake of universality. The advantages of the ARIMA type of time series model include explicit structural relationships that can be clearly understood. Once a model is developed, it can be used on-line for journey time forecasting for real time applications.

The second technique which was used for journey time forecasting is Horizontal-Seasonal modelling. The HS method is simpler than Box-Jenkins technique and required less computing time. The method uses the historical journey time data to calculate seasonal ratios which are smoothed over time by using suitable smoothing parameters. For the application of HS model on three sites in this study, the smoothing constants $\alpha=0.3$ and $\gamma=0.2$ were used. The application of the method produced good forecasting results.

Overall it has been shown that both the methods leads to a feasible application for journey time forecasting. Moreover, the methods has been tested on real data sets for two links and a route in Southampton. Result of the application have been fairly good. The forecasts by both methods for any site was never more than 17.22% in error (see Table 5.10), which shows that overall both the methods performed satisfactorily. The developed models can be used in real-time to provide short-term journey time forecasts and may be used in Dynamic Route Guidance systems and other information and control systems where link journey time forecasts would be required.

CHAPTER 6

DEVELOPMENT AND APPLICATION OF JOURNEY TIME FORECASTING MODELS - (Incident Conditions)

Time-Series forecasting models (developed in chapter 5), are appropriate for the situations where historical journey time patterns are reasonably recurrent. However, for high and variable congestion situations particularly those related to traffic incidents, historic patterns become unstable and time-series forecasting is more difficult.

Also the time-series models (developed in chapter 5) apply to individual links and do not encompass link interactions, the build up/decay of congestion 'trees' or other network influences. The link-based analysis remains relevant as it reflects the operation of many systems such as traffic control and dynamic route guidance and a specific forecast can be made of the parameter of interest (e.g. journey time). However, in cases of traffic incidents, queues in urban networks spread to affect a number of upstream links. Journey time on adjacent links are then interrelated both in time and space, and 'isolated' link-based forecasting becomes less relevant. A network-based, rather than link-based interpretation is then required.

The extent of the additional journey time caused by an incident is difficult to assess (Holmes and Leonard, 1993) as it needs to be separated from the existing background congestion and needs to take account of its effect over the network as a whole. The quantitative assessments for incident effects must therefore be inferred from modelling studies. A useful approach for studying the time varying network affects of an incident is through the dynamic assignment modelling. From this point, this study has concentrated on modelling a number of incident/network/traffic scenarios and compiling a database from which to develop generalised statistical models for predicting the spread of congestion effects following an incident and the required journey time modifications on the incident and affected links.

Four stages were involved in the modelling process. At stage one, a database was compiled for different incident, traffic and network scenarios. At stage two, statistical models were developed to predict the number of links affected by an incident. Stage three involved the development of an algorithm to find the location of links which would be affected by an incident. At stage four, statistical models were developed to predict the increase in journey times on the incident and affected links. The aim would be to use such models in real time systems as an aid to predict optimum routes for route guidance purposes, and in traffic control systems to implement better control strategies based on these predictions.

6.1 Selection of Method to Compile Incident Database

The uncertain and wide-range nature of traffic incidents requires a flexible and reliable method of study. The objective is to study the time varying congestion phenomenon in a variety of network, traffic and control scenarios to try and then develop short term forecasting models for networks. It may be possible, for example, to relate statistically the rate of increase of journey time with its key controlling parameters, such as the incident characteristics (severity, location, duration), the underlying level of flow and capacity and so on.

To compile an incident database the method which is to be chosen among the two most obvious ones, namely: trials on streets and simulation.

6.1.1 Trials on Streets

Trials on streets are laborious, sometimes require a long time to be carried out, and can be expensive. Moreover they are not practical with unpredictable incidents. For these reasons their scope is limited.

6.1.2 Simulation

Simulation is easier to realise than trials on streets and can be repeated with least extra-cost, also the same traffic conditions can be identically repeated, which is not always possible with trials on streets. Therefore given an appropriate simulation with realistic driver behaviour assumptions, the reliability of simulation can be compared to the one of on-street trials and at the same time it is less time consuming and less expensive.

Therefore, simulation appears to be the method for the study of incident effects.

6.2 Selection of a Simulation Model

The task described above can be performed by simulation modelling incorporating dynamic traffic assignment. The simulation models are commonly grouped into three levels of aggregation, namely macroscopic, mesoscopic and microscopic, respectively from the least detailed representation of traffic to the most detailed one.

Macroscopic models are flow-based and involve speed/flow relationships based on fluid analogy and 'continuously' divisible of flows of vehicles. **Microscopic** models are based on individual vehicles and the modelling implies fundamental rules such as the 'safe headway theory' and distribution laws (statistical distribution, gap acceptance). **Mesoscopic** models lie between the two previous ones and involve an intermediate level of aggregation either in time (allowing within-cycle variations in flow, which is not possible with macroscopic models) or in space by considering the movement of small, discrete and indivisible groups of vehicles following the same route.

At present the traffic assignment models which might be suited for incident simulation are SATURN (Van Vliet, 1980 and 1982), INTEGRATION (Van Aerde and Yagar, 1988) and CONTRAM (Leonard et al., 1978; Leonard et al., 1989; also in CONTRAMI: University of Southampton, 1992).

6.2.1 SATURN

SATURN (Simulation and Assignment of Traffic to Urban Road Networks) is a macroscopic model incorporating a simulation and an assignment sub-models. The assignment sub-model predicts route choices and the simulation sub-model moves traffic through the network and calculates the corresponding delays. The program performs an iterative loop between the assignment and simulation phases until a specified number of iterations has been achieved or until convergence has been reached. SATURN is largely based on a signalised intersection approach (using cyclic flow profiles, very much like TRANSYT). But the macroscopic and equilibrium nature of SATURN make it less than ideal for incident modelling.

6.2.2 INTEGRATION

INTEGRATION is a microscopic simulation model which considers the behaviour of individual vehicles having self-assignment capabilities. The program assigns vehicles to a loaded network applying the minimum-path theory at each node in the network every 6 seconds. Although this program has been specifically developed to perform traffic assignment in typical integrated controlled/uncontrolled roads, it lacks application to a larger number of networks, particularly large ones.

6.2.3 CONTRAM

CONTRAM (Leonard et al., 1989) is a mesoscopic dynamic traffic assignment model which predicts vehicle routes, as well as flows and queues on road network links. The program uses an 'incremental' form of vehicle loading which assign packets of vehicles to their minimum journey time routes in the network through a number of iterations, for each time interval. It is a capacity restrained model taking account of the interactive effects of traffic between intersections and the variations in traffic conditions through time. Particularly, it models the build up and decay of congestion such as occurs during peak periods. As a result it appears that CONTRAM structure is overall more flexible than the one of SATURN and INTEGRATION.

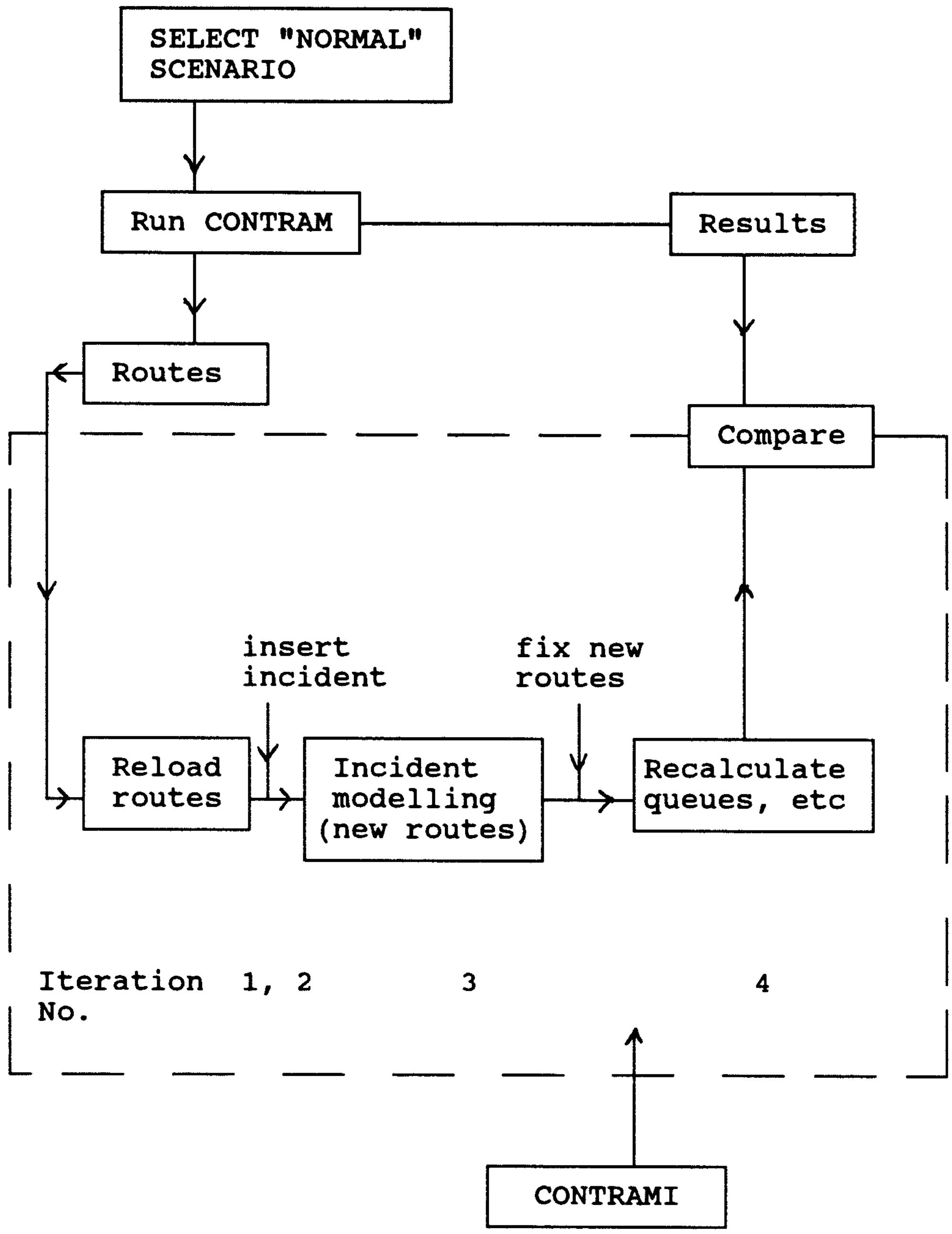
However, the simulation of incidents by dynamic traffic assignment involves different assignment procedures from the 'optimum' ones (here 'optimum' implies a cost minimising assignment). When visual effects of an incident occur, drivers may either change lane (and look for a gap in the traffic of a non-blocked lane) or modify their routes. In the latter case the 'diversion' is generally not a re-optimised route because drivers do not have sufficient knowledge of the current traffic conditions (unless they use a dynamic guidance/information system). Therefore, when selecting an incident simulation model the permitted driver responses will have to be considered. It appears that only CONTRAM offers a version which simulates incidents and includes driver behavioural options towards diversions.Indeed, **CONTRAMI** (Incident Module for CONTRAM, University of Southampton, 1992) has been developed on the basis of CONTRAM for taking account of the effects of traffic incidents in urban

networks, and particularly of their unpredictability. Unpredictable incidents create complex effects in terms of uncertain driver responses and of traffic interactions over the whole network. Although CONTRAM models traffic interactions over the network, it assumes that drivers are aware of the current traffic conditions and they choose their routes accordingly. This assumption is consistent with 'normal' traffic conditions, but becomes unrealistic with unpredictable incidents because drivers then do not know how traffic conditions are going to change all over the network.
CONTRAMI has been developed to model drivers responses to changes in traffic conditions (flows, queues etc), i.e. decisions to remain on their usual routes (e.g. if not familiar with alternative routes) or to divert. CONTRAMI therefore allows incident modelling with various types of strategies and simultaneously benefits from CONTRAM basic attributes.

Consequently it is CONTRAMI (version of CONTRAM for incidents) which has been selected to study the effects of traffic incidents.

The flow chart in figure 6.1 summarises the CONTRAMI modelling process which starts by a normal CONTRAM run to obtain the usual routes taken by vehicles. Only one normal run is required for a particular set of 'normal' network conditions. After the normal run, the assignment procedure has 3 distinct phases. (i) Loading the network, the 'usual' routes are read in from the file and used to load the network. A number of iterations are performed, keeping these routes fixed, to model the interaction of vehicles properly and to calculate the queues and delays in the network. (ii) Introduction of an incident, this assignment may be performed for one or more (user specified) iterations (it is considered that one iteration is sufficient). (iii) Fixed routeing, after the diversions has been made, a number of iterations are performed, keeping the new routes fixed in order to calculate the new queues and delays in the network.

Figure 6.1 Flow Chart of CONTRAMI Modelling Process



6.2.4 Information Required And Provided By CONTRAMI

Because CONTRAMI consists of a module added to CONTRAM, a large amount of input data is the same for both packages. In particular, CONTRAMI input data comprise the three major input components which are:

- The network and time data, which define the network geometry properties and the period to be simulated.
- The demand data, which specify the flow rates for each Origin-Destination (O-D) movement for each time interval.
- The control data, with two major functions. The first one describes the running of the program and defines the number of iterations to be carried out and the types of output required. The second function is to provide the additional data required for signalised intersections.

In addition CONTRAMI requires supplementary information on the incident specification (in terms of location, severity and duration) to be added into the network data file (using the new card type 100), and on the methodology logic (the specification of the number of iterations for network loading, permitted diversions and fixed routing). A 'diversion logic' is also included in the control data file (using card types 101 and 93) respectively. The diversion logic information reflects the drivers strategy towards diversions and is input into the programme as: the maximum number of diversions allowed for a driver, the coefficient of diversion, the percentage of packets which will not divert and the percentage of occupancy which will trigger diversions. In summary, drivers who are eligible for diversion can divert at any junction along their route if they encounter an unexpected queue ahead, and if the journey time on the normal 'next best' route is acceptable (ie. within a specified multiple of that of the normal route, as controlled by the coefficient of diversion).

The output information provided by CONTRAMI is basically of the same type as the CONTRAM one. The information contained in the result file consists of link-by-link and overall data for each time interval such as:

- Journey time
- Overall distance travelled
- Average speed on the network
- Point-to-Point O-D speed
- Fuel consumption
- Queues
- Total link counts (flows)
- Congestion Index: ratio of the travel time to the cruise time on a link.

A "route" file is also output from CONTRAM/CONTRAMI runs. It provides vehicle route data for further analysis of journey patterns over the network. Moreover CONTRAMI provides a "diversions" and an "occupancy" output files. The first one is a record of all diversions taken by packets of vehicles and the corresponding cruise times. The second file is a record of the percentage occupancy values for every link in the network and each time slice.

6.2.5 Implications

The incident version (CONTRAMI) of the CONTRAM traffic dynamic assignment model has been selected for study the effects of various unpredictable incidents, which equilibrium assignment models cannot achieve. These effects are characterised by increases in journey times, delays, decreases in mean speeds and new or longer queues, which can be calculated from CONTRAMI output data.

6.3 Modelling Scenarios

6.3.1 The Study Networks

The simulation of incidents was carried out on two urban road networks located in the U.K. Networks were developed and calibrated by the local authorities concerned. The networks are:

- Kingston (in London)
- Boscombe (in Bournemouth)

This has allowed network dependence to be assessed as well as the other traffic and incident related parameters.

6.3.1.1 Kingston Network

The first road network where incidents have been simulated is located in Kingston (Appendix O.1). The network data comprise 150 coded links and 55 junctions of all types (including 14 signal junctions) and 28 pairs of origins and destinations. Links are defined as a section of road between two intersections and are allocated a number. The study network is made of:

- 43 signal-controlled links (28.7%);
- 67 uncontrolled links (44.7%);
- 40 give-way links (26.7%).

The demand data was available for the morning peak period. The data is known for each O-D movement and has been disaggregated into twelve five-minute time slices between 0800 and 0900 hours. This detailed data also allows queue growth and decay to be monitored in five-minute intervals.

6.3.1.2 Boscombe Network

The second road network which has been used for incident simulations is located in Boscombe (Appendix O.2). The network data comprise 190 coded links and 71 junctions of all types (including 7 signal junctions) and a set of 28 origins and 29 destinations. Moreover the study network is made of:

- 22 signal-controlled links (11.5%);
- 117 uncontrolled links (61.5%);
- 51 give-way links (27%).

This network is made of smaller and more numerous roads than Kingston network, and is characterised by a higher proportion of uncontrolled links and a much lower proportion of signalised links. The demand data was again in twelve five-minute intervals.

6.3.2 The Incidents

6.3.2.1 Incident Type

As the effects of unpredictable incidents are the least well known, it has been decided to simulate unpredictable short-term incidents whose duration does not exceed 45 minutes. This type of incident is most suited to CONTRAMI applications rather than predictable incidents (eg. longer term roadworks) where drivers would gradually re-optimise their routes.

6.3.2.2 Incident Locations

In each of the two networks three incident locations were chosen. In Kingston, links 714, 725 and 730 were selected (Appendix O.1); in Boscombe network, links 1163, 1494 and 1692 (Appendix O.2). Five of the six selected links are signalised only link 1163 in Boscombe network is uncontrolled. The selected links are of average or major importance and their lengths vary between 65 and 410 metres. They have been chosen to the proximity of an exit to the network, and with a sufficient number of upstream links to show the evolution of the affected links over time. In order to give a representation of the relative importance of the links their characteristics are shown in table 6.1 below:

Table 6.1 Links characteristics

Link	Length (meters)	Cruise Time (secs)	Saturation Flow (pcu/h)
Kingston 714	120	10	2650
Kingston 730	150	17	1960
Kingston 725	170	17	1850
Boscombe 1494	410	31	1950
Boscombe 1692	65	5	1900
Boscombe 1163	130	10	1825

6.3.2.3 Severity and Duration of Incidents

On each location 12 types of incidents have been created with different combinations of durations and severities:

- Three durations were simulated: 15 minutes, 30 minutes, 45 minutes.

- Four levels of severity were simulated: 0.20, 0.50, 0.70, 0.99, which correspond to reductions in saturation flow to 80%, 50%, 30% and 1% respectively. (for programming reasons 0% is not achievable).

All incidents have been simulated from the first time slice, which makes their duration last for 3, 6, 9 time slices.

6.3.3 Permitted Diversions

It was decided to simulate 'fixed route' strategy which allows no diversion to drivers who are then 'forced' into the incident link, whichever the incident severity. The results of such a scenario are expected to produce somewhat worse traffic conditions than might occur in practice, but considered reasonable for this study. As the main uncertainty with another approach concern the proportion of drivers who will divert and the diversion criteria adopted (knowledge on both of these issues is scarce). There are also likely to be other behavioural issues involved. Therefore at this stage 'fixed route' strategy is considered to form a good basis for the development of predictive models and is suitable for further enhancements as more information on behavioural issues becomes available.

6.3.4 Simulation Runs

The process of CONTRAMI has been explained in section 6.2.3. CONTRAM is first run on each network in non-incident conditions, in order to:

- keep a record of the data in normal conditions for future calculations;
- initialise the following CONTRAMI runs in incident conditions.

The details of the information relevant to the incident cases are given in (Appendix D). Basically the extra information needed by CONTRAMI deals with the location and modified saturation flow of the incident link as well as the drivers 'diversion strategy'.

6.4 Development of Predictive Models

Four stages are involved for the development of predictive models for incident management procedure. At stage-A, an incident is detected, its location and severity is fed in; this information may come from the traffic operator in the traffic control centre which confirms the location of the incident through CCTV and can also estimate the severity of the incident from number of lanes closed. The model output is not used for incident detection, although the task of incident detection can also be achieved with the development of suitable software.

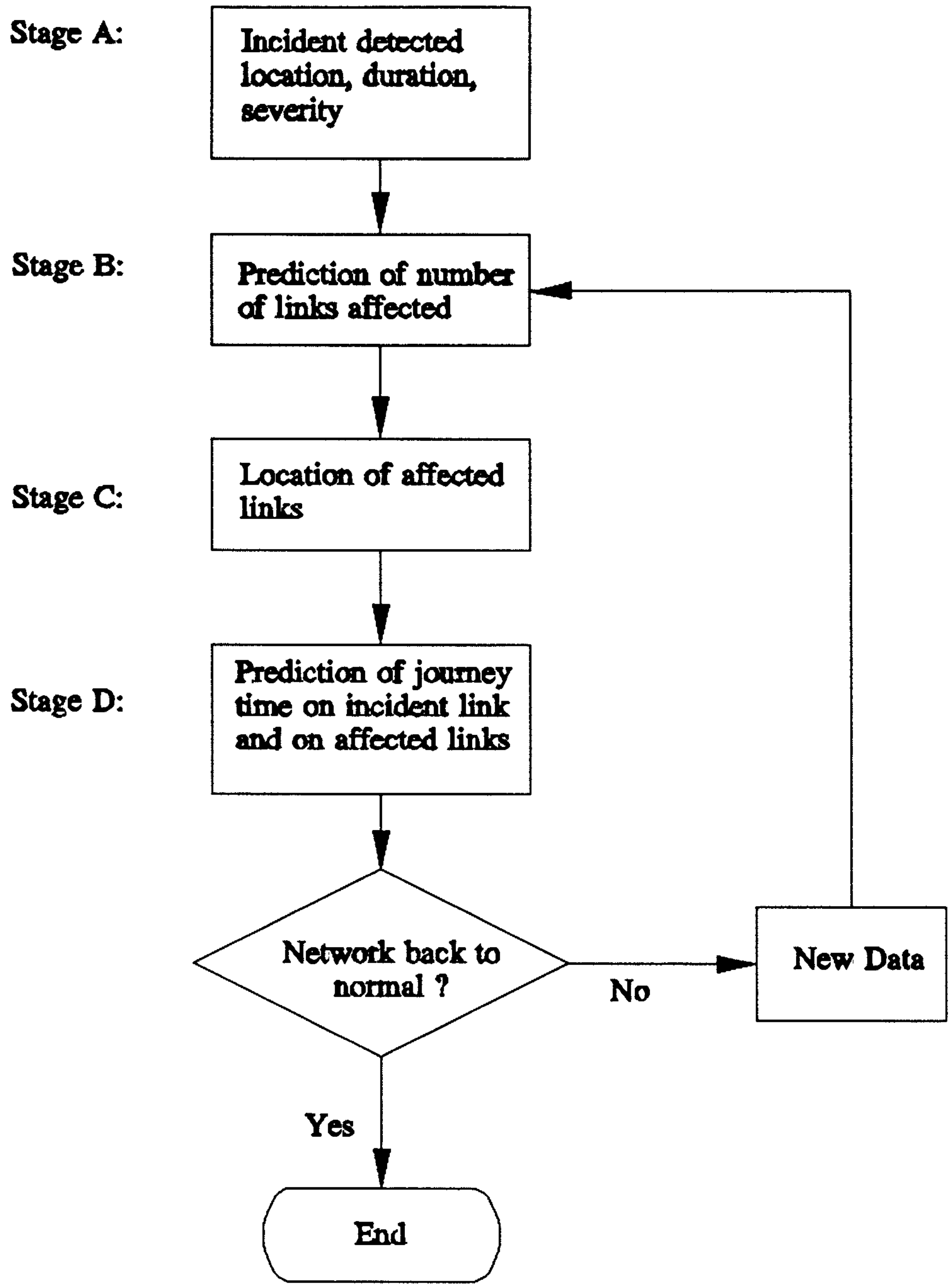
At stage-B, the number of links which would be affected by an incident are predicted; the prediction of 'Number of links affected' is important here as this information is subsequently used as a threshold for the extent of backward route search required for predicting the location of incident affected links in the network (here we are not modelling queue build up explicitly with this procedure, if we were, we would not need to predict how many links are affected).

Stage-C involves finding the location of affected links in the network.

At stage-D, journey times on incident link and on affected links are predicted. Then as the new data becomes available, it is analyzed and if the data is normal (close to historic profiles) then the procedure ends otherwise stages B to D are repeated and the predictions are updated using the new data.

The flow chart of the modelling procedure is shown in figure 6.2.

Figure 6.2 Flow chart of the modelling procedure



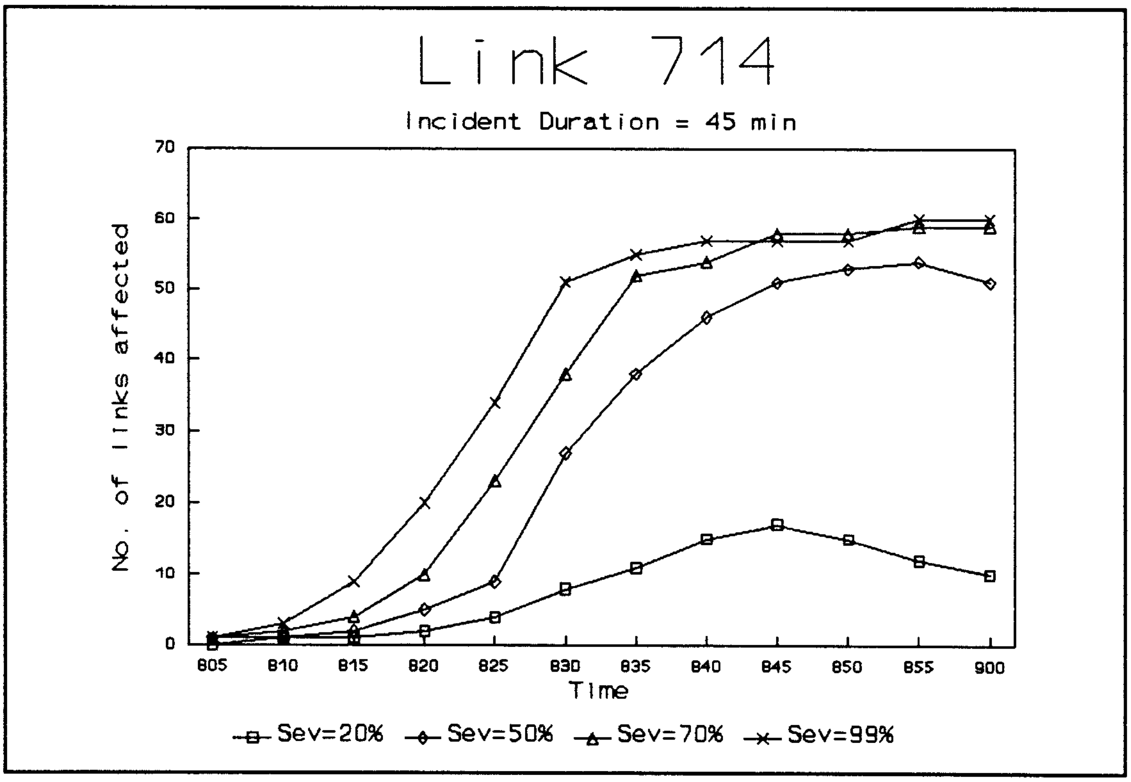
6.4.1 Identification of the Key Parameters

The effects (increase in journey time, number of links affected) of an incident is attributed to many parameters, it can be seen from the simulation results that the incident characteristics which are defined as duration and severity are two of the many key parameters. Moreover the effect of an incident from one link to another is different, this can be attributed to link characteristics (geometric, traffic characteristics) as well as of each network. The geometric properties are assumed not to vary strongly from one link to another according to the available information provided by the original data-files. However the importance of a link in a network and its 'traffic performance' seem to have an important role to play in the effects that an incident could have on other links. A range of parameters can reflect these situations, for example Congestion Index (link journey time/link cruise time), Degree of saturation (number of arrivals/link capacity), or Delay (link journey time - cruise time). However, it was decided that the variables which will be used in modelling are restricted to those which would be available in a DRG system. This therefore excluded traffic flow and flow-related parameters, such as degree of saturation, even though these parameters may have produced a superior model. Furthermore, because the key goal of the study is to build predictive models, the independent parameters in the models will have to refer to non-incident conditions. More precisely, in a future application the parameters should be practically available for all links of any network, which is only possible for 'normal' traffic conditions (although subject to updating with real time incident data as it becomes available). Some appropriate parameters would be Congestion Index, Delay (secs/veh).

6.4.2 Prediction of Number of Links Affected

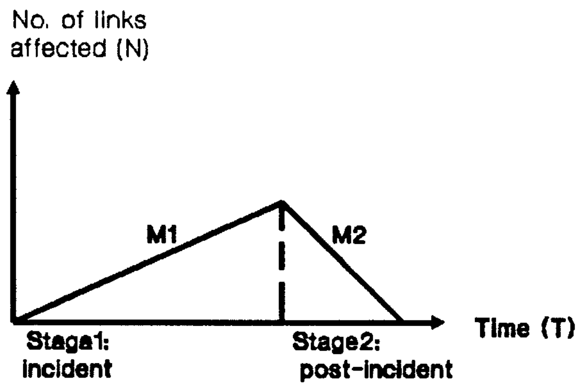
For DRG systems, the important quantification is the identification of those links whose journey times are affected by the incident. However CONTRAMI output files do not provide the numbers of affected links directly. For this purpose a FORTRAN program was written (Appendix J) which compares the journey times in non-incident and in incident conditions for all links and all time slices. The criterion for a link to be named 'affected' during at least one time slice is to have a total journey time in incident conditions exceeding by at least 20% the total journey time in non-incident conditions and then if for any time slice the journey time for incident case is 20% higher than the journey time for non-incident case, then the link is considered as affected during that time slice. By using this criteria the number of affected links were evaluated for different incident scenarios (severity, duration, location), the results are shown in Appendix E.1 - E.4. An example of number of links affected by an incident is shown in figure 6.3 below:

Figure 6.3 Example of Number of Links Affected (simulation)



A quantification of the number of links affected was then related to the key incident characteristics for the full database. As expected, incident severity proved to be a dominant parameter. Plots such as those in figure 6.3, were used to develop a method for predicting the number of links affected by the incident. Methods tested initially for predicting the curve forms included the use of (i) curve fitting and (ii) probability distribution fitting to the data. However, these methods proved relatively complex and a simpler approach was finally calibrated which also gave a better statistical fit. This preferred approach consisted of producing a linear two stage profile, with stage 1 describing congestion build-up during the incident and stage 2 describing post-incident "recovery". This is illustrated in figure 6.4 below:

Figure 6.4 Envisaged Model for Number of Links Affected



The requirement here is to predict the two slopes of the profile termed M1 and M2 here. Analysis centred on predicting M1 from key incident, network and traffic characteristics and M2, based on similar parameters excluding those describing the incident. Predictions of these slopes and incident duration would then provide predictions of the numbers of links affected at any time following the onset of the incident. Constant slopes are illustrated here for simplicity, although in practice, slopes would be recalculated (and may vary) for every time interval (e.g. 5 minutes).

6.4.2.1 Database for Slope M1

The slope M1 represents the increase in number of links affected from the beginning until the actual end of the incident, this situation is clearly defined by a 'build up' slope.

From the simulated results (Appendix E), the rate of increase in number of links affected per minute were calculated by the relation :

$$M1 = (\text{No. of links affected at time t - No. of links affected at time t-1}) / 5 \qquad (6.1)$$

In this way a database (see Appendix G.1) for slopes M1 was created for different incident scenarios.

6.4.2.2 Model for M1

From the database of slopes M1 (Appendix G.1), it can be seen that a greater severity produce a steeper slope, moreover if the incident link is particularly likely to get congested rapidly (this is represented by Congestion Index in the database), then the number of affected links in the network will grow faster, several models were produced from this database and are given in (Appendix H.1) with their statistics. A simple and robust model produced from incident database (which will be used for all future application) is of the form:

$$M1_t = 0.37 * Sev_t * LCI_t \qquad (R^2 = 0.51) \qquad (6.2)$$

where

$M1_t$ = rate of increase of number of links affected with time (number/minute)

Sev_t = incident severity at time interval t (range 0 to 1 (blocked link))

LCI_t = link congestion index for the incident link during the time interval t, from the historic profile.

In this model, the congestion index reflects the normal state of congestion on the incident affected link during the analyzed time interval. The higher the CI, the greater the incident effects, as expected. Similarly, the higher the incident severity, the greater are the incident affects. This product model proved to have equally as good a fit as other additive and power function models tested and hence selected for future applications.

Time interval specific forecasts of $M1_t$ would then allow predictions to be made of the number of links affected, for any forecast horizon. For example, slopes $M1_1$, $M1_2$ and $M1_3$ may apply to consecutive 5 minute time intervals t_1, t_2 and t_3. The prediction of the number of links affected by the incident after 15 minutes would then be:

$$\text{Number of links affected} = 5 * (M1_1 + M1_2 + M1_3) \qquad (6.3)$$

6.4.2.3 Database for Slope M2

Slope M2 represents the function to calculate the number of links affected for 'post incident' case. M2 values were calculated from the numbers of links affected during the time slices following the incident ends, by the relation :

$$M2 = (\text{No. of links affected at time } t - \text{No. of links affected at time } t\text{-}1) \;/\; 5 \qquad (6.4)$$

The database for slope M2 is given in (Appendix G.2).

6.4.2.4 Model for M2

For "post incident" slope, it seems that the decay of the number of affected links sometimes starts only after a transition period has been achieved. This transition period would reflect a situation where the network was still partly congested at the time of the incident end, and where drivers would be re-optimising their routes according to the latest traffic conditions; for this reason the number of affected links would either rise or remain almost constant for a short time. Hence the link 'traffic performance' parameter is expected to be involved in the number of affected links of the 'after incident' situation. Several regression models were developed (Appendix H.2) by using 'post-incident' database (Appendix G.2), but because of negative and positive values of M2 slopes, few models are suitable for a good fit. A preferred model which is developed from post-incident database is:

$$M2_t = 0.44 - 1.75/LCI_t \qquad (R^2 = 0.20) \qquad (6.5)$$

where

$M2_t$ = rate of decrease of number of links affected with time (number/minute)

LCI_t = congestion index for the incident link during the time interval t, from the historic profile.

With this model M2 value is positive when the ratio (1.75/LCI) is less than 0.44, it will be negative if the ratio (1.75/LCI) is greater than 0.44 and for the ratio (1.75/LCI) is 0.44 the value of M2 is zero.

6.4.3 Prediction of Location of Affected Links

Given a time-dependent prediction of the number of links affected, it is then necessary to locate these links in the network. It is usual that the first affected links are the nearest upstream links to the incident link, and that the propagation will continue in the direction of the nearest upstream links connected to affected links until the maximum number of affected links has been reached. Then, after the incident has ended, the number of affected links will decrease following the reverse process. To find out the location of affected links in the network, a reverse route search has to be made from the upstream node of incident link, in this way a backward tree is constructed considering (i) all feasible upstream links, (ii) upstream links prioritised according to the proportion of traffic on the link which also (normally) proceeds through the incident affected link. (It is expected that the spread of congestion will predominate on routes/trees which contribute most traffic to the incident affected link.).

For example, if a network connection is constructed as:

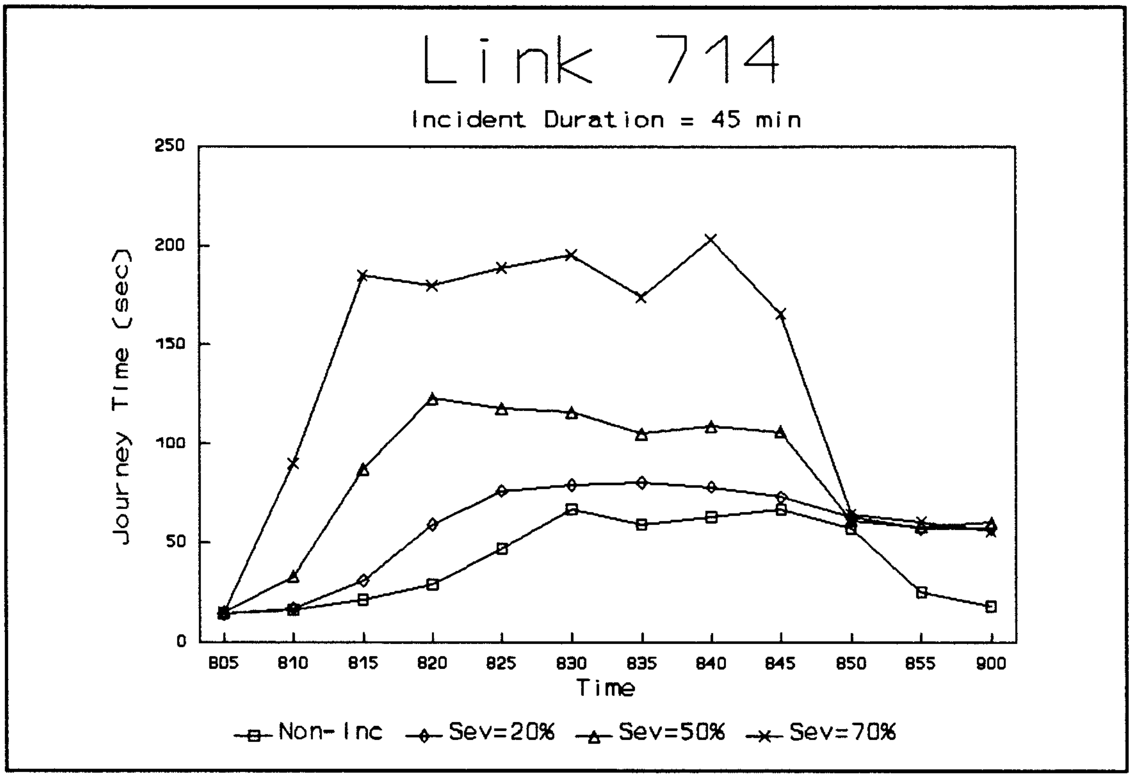
Link No.	Upstream Links		
730	518	603	604
518	517		
603	515	108	
604	523		
517	703	117	
- - -	- - -	- - -	- - -
- - -	- - -	- - -	- - -

and if there is an incident on link 730 then link 518 is expected to be affected before links 603 and 604, link 603 is expected to be affected after link 518 but before link 604 and so on.

6.4.4 Prediction of Journey Time on Incident Link

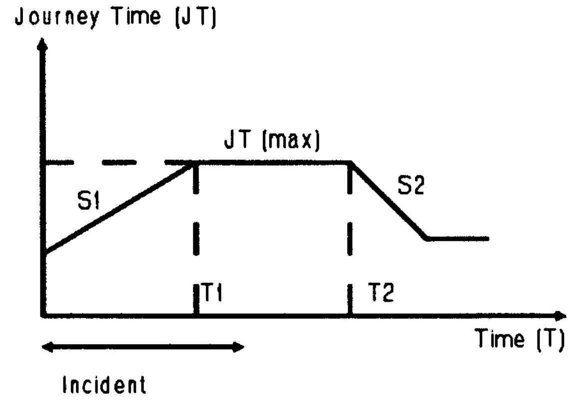
Journey time prediction on incident links was analyzed using techniques compatible with those described in (Section 6.4.2), looking initially at the incident link itself. The incident modelling using CONTRAMI produced a number of journey time profiles (see Appendix F), one example being given in Figure 6.5 below:

Figure 6.5 Example of increased journey time (simulation)



This example illustrates the increase in journey time following the onset of an incident, and how the journey time stabilises to a relatively constant value if/when the link becomes full. It also illustrates how the maximum journey time on the link (when it is full) varies according to the incident severity, as would be expected, as severity is directly related to reduction in capacity. A three stage model is therefore suggested for the incident-affected link. This is illustrated in figure 6.6 below:

Figure 6.6 Envisaged model for increased journey time



With this model, S1 represents the rate of increase of journey time with time, following the onset of the incident, (again a linear slope is illustrated here for simplicity). At time T1 the link becomes full (and queues extend upstream) so that a maximum journey time (JT max) is maintained for a period (T2-T1). Some time after the end of the incident, the link journey time will start to decline at a rate S2. Analysis was concentrated to develop predictive models for S1, MaxJT and S2.

6.4.4.1 Database for Slope S1

The slope S1 represents the increase in Journey Time on incident link from the beginning of the incident until the journey times reach its maximum, this situation is defined by an 'upward' slope. From the simulated journey times (Appendix F), the rate of increase in journey time per minute for different incident scenarios were calculated by the relation :

$$S1_t = (JTI_t - JTI_{t-1})/5 \qquad (6.6)$$

where

$S1_t$ = rate of increase of journey time on incident link with time, (secs/minute).

JTl_t = Journey time at time t, following the onset of an incident

JTI_{t-1} = Journey time at time t-1, following the onset of an incident

In this way a database for slopes S1 was created for different incident scenarios. This database is given in (Appendix G.3).

6.4.4.2 Model for S1

From the simulation results, it can be seen that the incident characteristics which are defined as duration and severity, are the key parameters of increase in journey time, moreover the effect of an incident from one link to another is different, this can be attributed to link characteristics (geometric, traffic characteristics). Two parameters (Congestion Index and Delay) were selected to represent link characteristics. Regression techniques were then used to develop several forms of additive and multiplicative models (Appendix H.3), the preferred model for S1 is:

$$S1_t = 1.25 * Sev_t * Delay_t \qquad (R^2 = 0.69) \quad (6.7)$$

where

$S1_t$ = rate of increase of journey time on incident link with time, (secs/minute).

Sev_t = incident severity at time t (range 0 to 1).

$Delay_t$ = Delay (secs/veh) on the incident link during the time interval t, (for non-incident case).

Time interval specific forecasts of $S1_t$ would then allow predictions to be made of increased journey time on incident link, for any forecast horizon. The forecasting equation would be:

$$JTI_t = JTI_{t-1} + 5*S1_t \qquad (6.8)$$

where

JTI_t = Increased Journey time on the link at time interval t.

JTI_{t-1} = Increased Journey time on the link at time interval t-1.

$S1_t$ = Rate of increase of journey time (as calculated by equation 6.7) on incident link.

6.4.4.3 Maximum Journey Time on Incident Link

With the model given in equation (6.8), the journey time after an incident will keep increasing with the time, however in reality there is an upper limit of journey time faced by vehicles on a link, this upper limit is defined here as MaxJt and is a function of incident severity and link characteristics.

6.4.4.4 Database for MaxJt

MaxJt represents the maximum journey time faced by vehicles on a link after an incident. From the simulation results a database (Appendix G.4) of maximum journey time was compiled. In this database MaxJtNon is the maximum journey time on the link at any time slice during normal traffic conditions and MaxJt is the maximum journey time on the link at any time slice for a given incident scenario.

6.4.4.5 Model for MaxJt

Regression analysis were carried out on the MaxJT database (Appendix G.4) to develop the models for maximum journey time on a link; the developed models are given in Appendix H.5, the selected model for MaxJt is:

$$\text{MaxJt} = \text{MaxJtNon} + (27.34 * \text{Sev} * \text{CT}) \quad (R^2 = 0.73) \qquad (6.9)$$

where

MaxJt	=	Maximum journey time (secs) on the link after an incident.
MaxJtNon	=	Maximum journey time (secs) on the link in non-incident case at any time interval.
Sev	=	Severity of the incident (range 0 to 1).
CT	=	Cruise time (secs) on the link.

With this model when severity equal to zero, the maximum journey time after an incident would be the same as the maximum journey time in non-incident conditions and as severity is higher so does the MaxJt. MaxJt is also related to the cruise time on link which represents the link characteristics. For longer links the increase in MaxJt would be higher for a given incident scenario.

6.4.4.6 Database for Slope S2

Slope S2 represents the function to calculate rate of decrease in journey time for 'post incident' case. The database for slope S2 compiled from simulated results is given in Appendix G.5. In the database, S2 values were calculated by the following relationship:

$$S2_t = (JTI_t - JTI_{t-1})/5 \qquad (6.10)$$

The negative values of S2 shows the rate of decrease in journey time for post incident time periods; whereas positive values of S2 shows that for some cases journey times may not start decreasing soon after the end of an incident.

6.4.4.7 Model for S2

For "post incident" slope, it seems that the decrease in journey time starts only after a transition period has been achieved. This transition period would reflect a situation where the network was still partly congested at the time of the incident end; for this reason the journey times would remain almost constant (at MaxJt) for a short time. Regression models were developed by using 'post-incident' database (Appendix G.5), but because of negative and positive values of S2 slopes, few models are suitable for a good fit. The developed models for S2 are given in Appendix H.4; the preferred model for S2 is :

$$S2_t = -1.46 * (MaxJT/Delay_t) + 2.25 \quad (R^2 = 0.52) \tag{6.11}$$

where

$S2_t$	=	rate of decrease of journey time on incident link with time, (secs/minute).
MaxJt	=	Maximum journey time (secs) on the link after an incident.
$Delay_t$	=	Delay (secs/veh) on the incident link during the time interval t, (for non-incident case).

With this model, slope S2 is inversely proportional to delay, lower the delay (representing link importance in the network) value, steeper the slope S2 and journey time quickly back to normal, whereas links with higher delay values take longer time to come back to normal.

Time interval specific forecasts of slope $S2_t$ would allow predictions to be made of decrease in journey time on incident link, for any forecast horizon. The forecasting equation would be :

$$JTI_t = JTI_{t-1} + 5*S2_t \tag{6.12}$$

where

JTI_t = Increased Journey time on the link at time interval t.

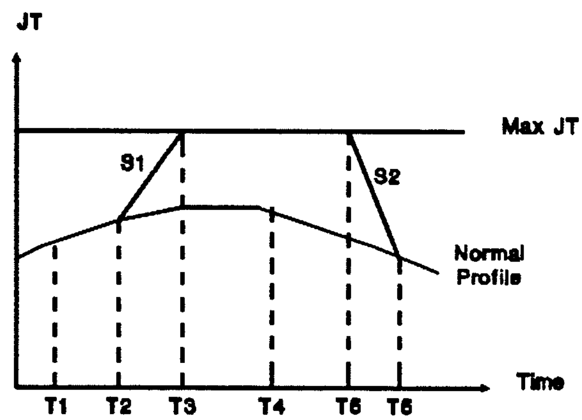
JTI_{t-1} = Increased Journey time on the link at time interval t-1.

$S2_t$ = Rate of decrease of journey time (as calculated by equation 6.11) on incident link.

6.4.5 Prediction of Journey Time on Affected Links

Finally, it is necessary to predict journey times on all upstream links affected by the incident, as identified in (Section 6.4.3). Similar procedures are envisaged to those described above, with some factoring of S1 and S2 slopes according to the remoteness of the link concerned from the incident link. In the figure 6.7 below:

Figure 6.7 Envisaged model for increase in journey time on affected links



T1 is the start time of the incident, T2 is the time when a link is affected by the incident, this time is predicted from section 6.4.2 and 6.4.3. Once the link is affected, the increase in JT on affected link is predicted by slope S1, the JT on affected links keep increasing until it reaches to the maximum at time T3. The maximum JT on affected link can be predicted by the MaxJT model given in equation (6.9). T4 is the End time of the incident, however the JT on affected link stays at maximum until time T5, after which JT start decreasing. At time T6 the link is no more affected (this time is predicted in section 6.4.3) and at time T6 the journey time back to normal profile.

6.5 Application, Evaluation And Validation of the Models

The predictive models which were developed in section 6.4 are based on simulated database for different incident scenarios. The goodness of fit of these models on this database is illustrated by comparing the results with that of CONTRAMI simulated results and by analysing forecasting errors statistically. Secondly, a type of validation of these predictive models is also achieved by applying them to an alternative larger network (London Network). It should be noted that the choice of a larger network such as London would be particularly relevant, considering the large number of links expected to be affected in the event of an incident.

6.5.1 Application of M1 and M2 Models

Models for M1 and M2 slopes can be used to predict the number of links affected after an incident occur. These models were applied to predict the 'number of links affected' with incident on links, K-714 (Kingston network), B-1494 (Boscombe network) and L-3232 (London network) for different incident scenarios by using the models given in equations (6.3) and (6.5), the detailed results of the application of these models are given in Appendix M. Examples of simulated and predicted 'Number of links affected' are shown in figures 6.8, 6.10 and 6.12. The predicted results were compared with the simulated results of CONTRAMI, the accuracy of the forecasts can be seen in figures 6.9, 6.11 and 6.13 which shows the corresponding plots of simulated and predicted 'Number of links affected'. These figures show how the models perform following the onset of the incident. The forecasting errors statistics for 'Number of links affected' for different incident scenarios were calculated and are given in table 6.2.

Figure 6.8 Number of links affected with incident link 714 (Sim vs Pre)

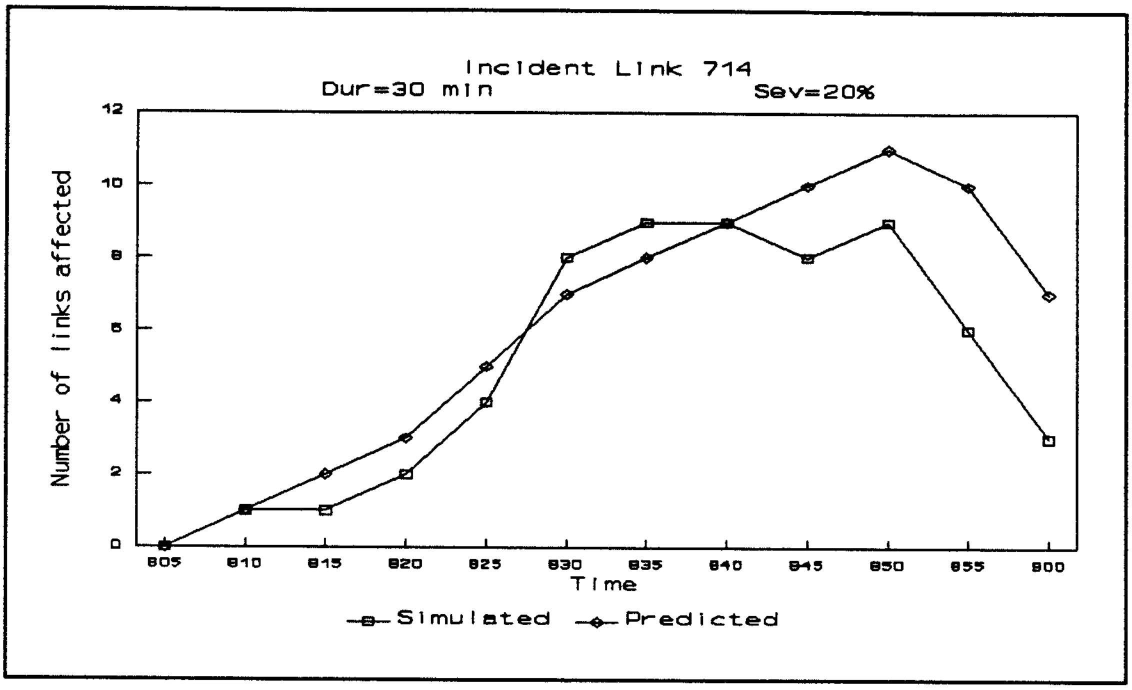


Figure 6.9 Simulated vs Predicted 'Number of links affected' incident link 714

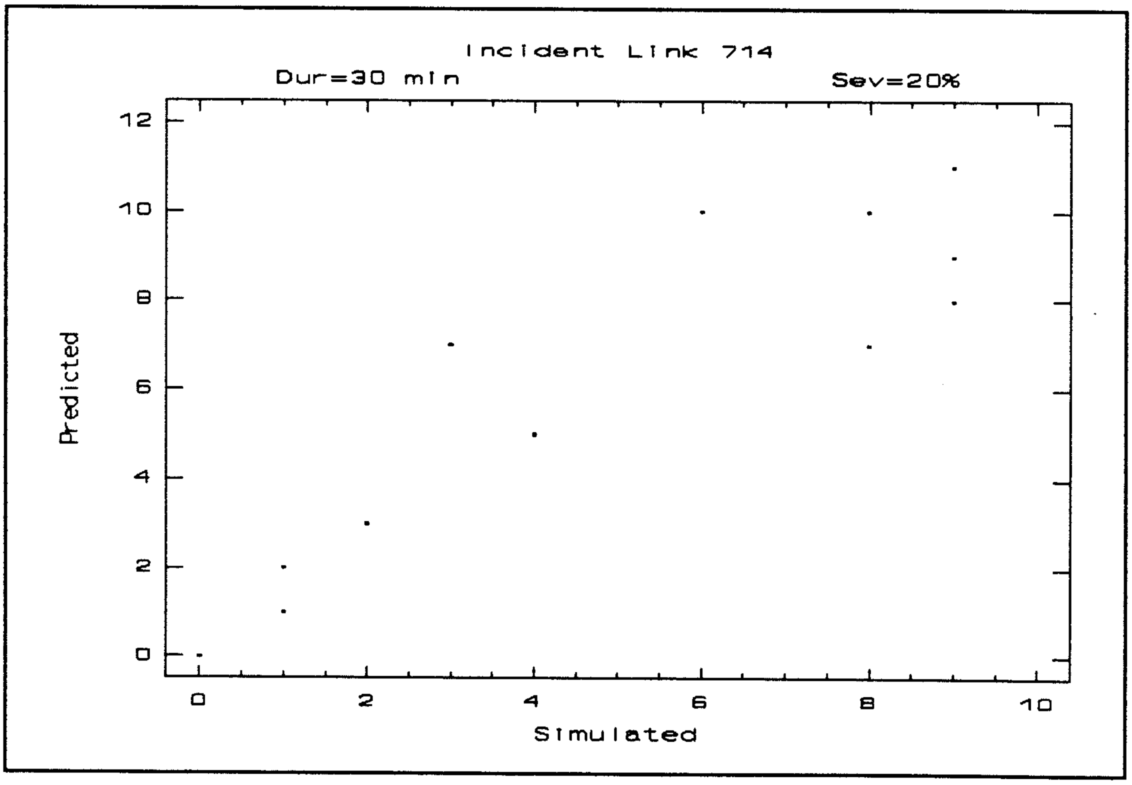


Figure 6.10 Number of links affected with incident link 1494 (Sim vs Pre)

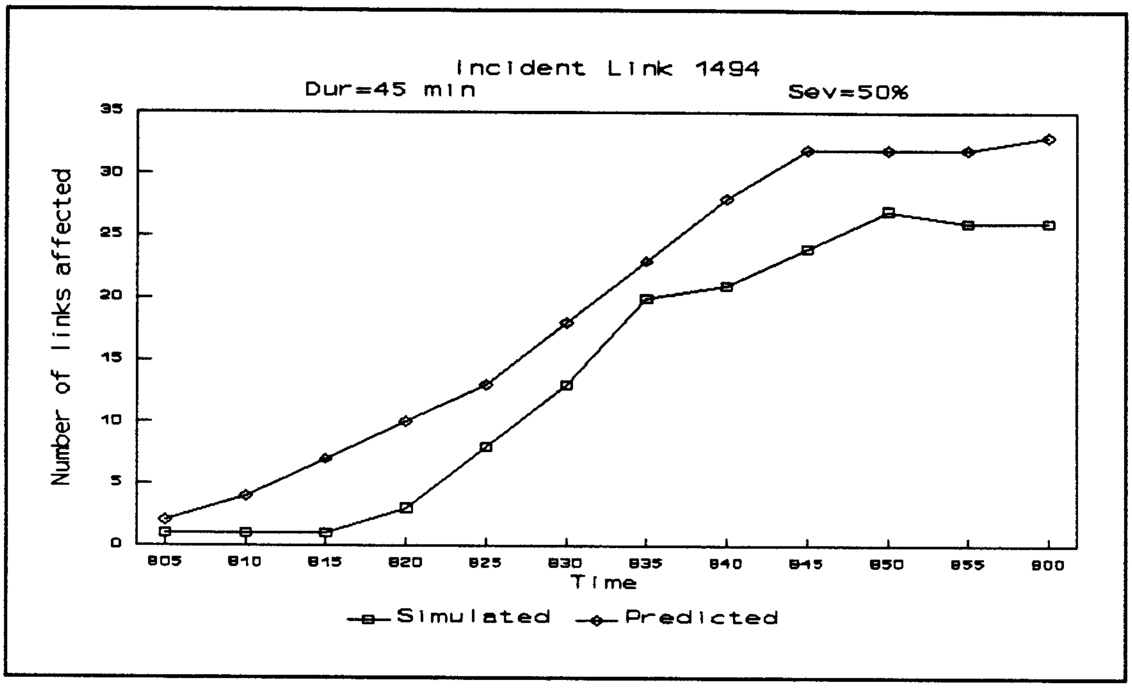


Figure 6.11 Simulated vs Predicted 'Number of links affected' incident link 1494

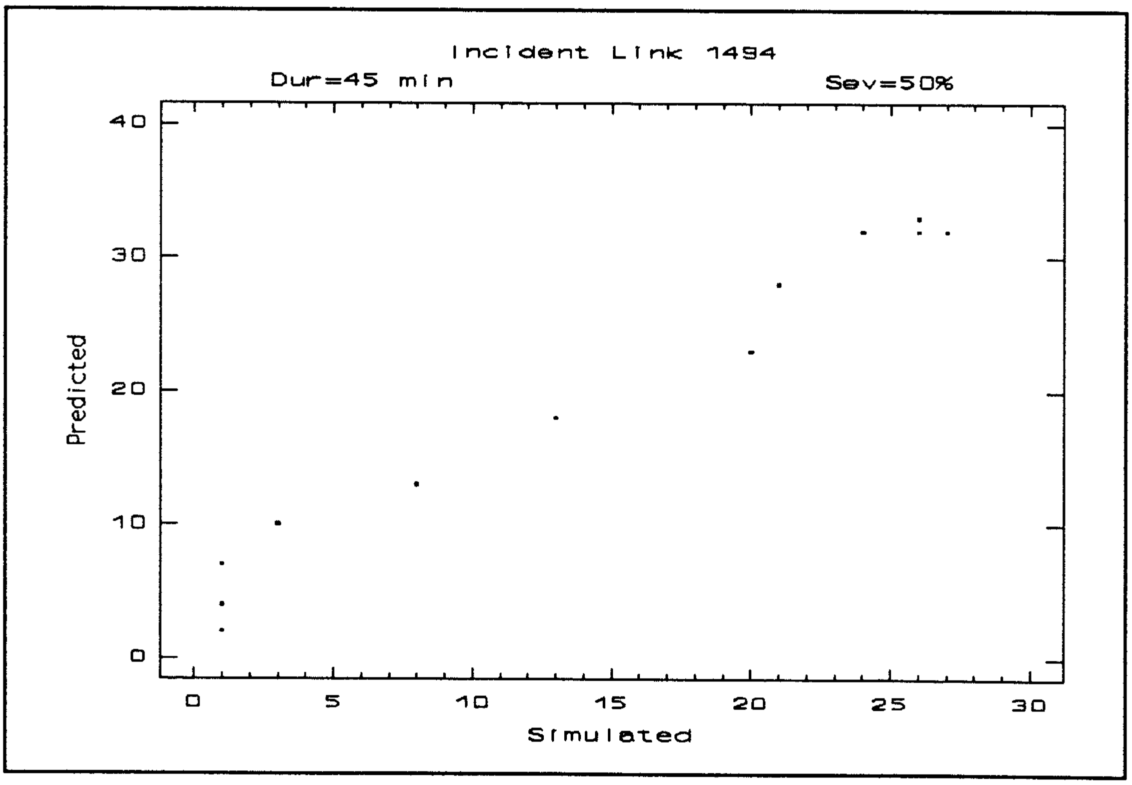


Figure 6.12 Number of links affected with incident link 3232 (Sim vs Pre)

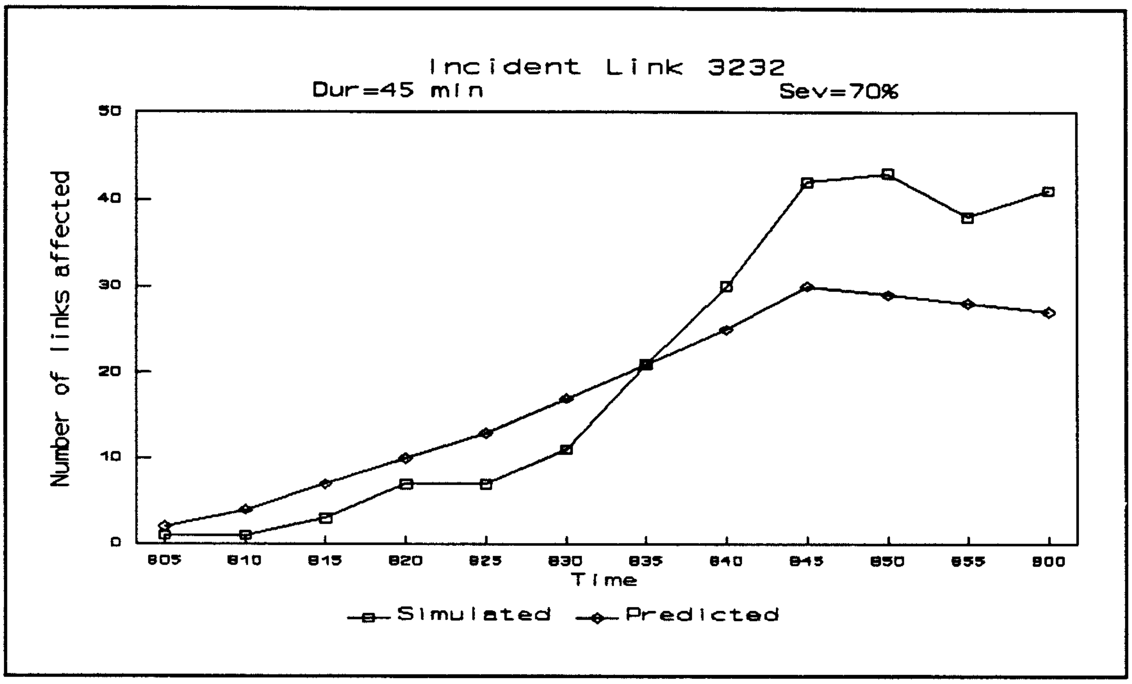
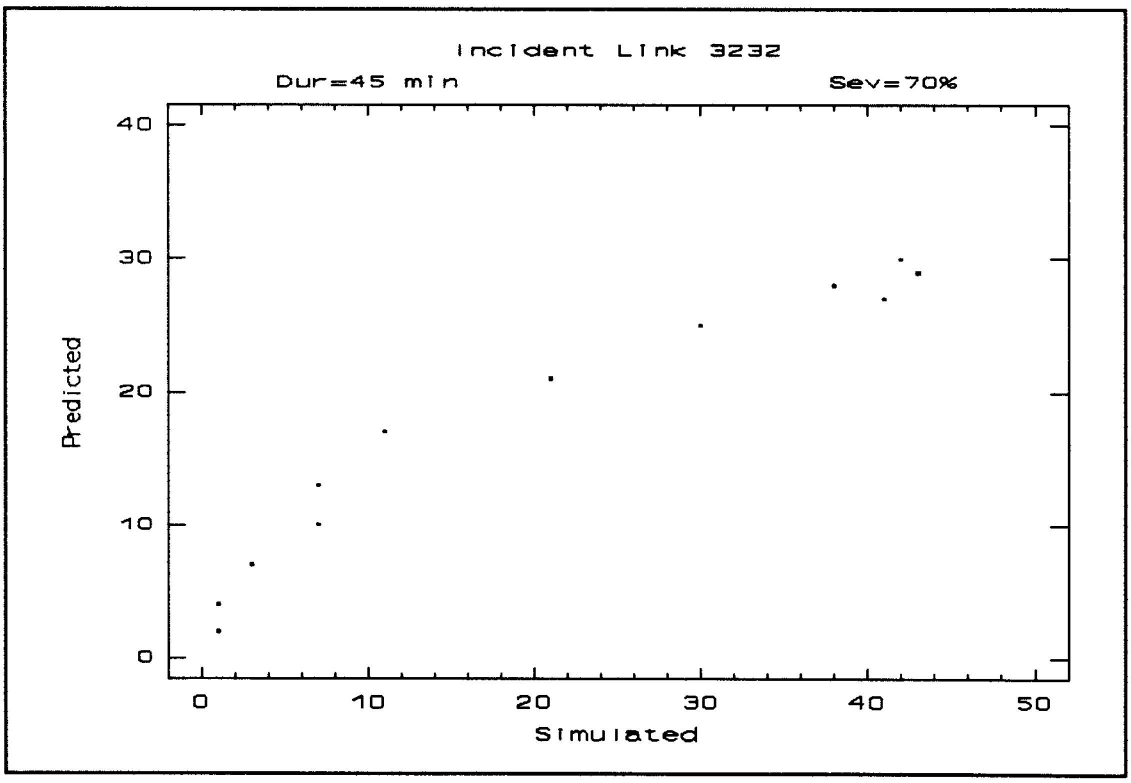


Figure 6.13 Simulated vs Predicted 'Number of links affected' incident link 3232



The forecasting results show that the models are capable of predicting 'Number of links affected' in the network with reasonable quality, however further improvements in the models can be achieved by careful calibration of the model's parameters and with updating of forecasts.

Table 6.2 Forecast-Errors statistics for 'Number of links affected'

Site[1]	Incident[2] Type	ME[3]	MAE	MAPE
K-714	I3	0	1	31
	I6	9	10	55
	I9	7	8	37
L-3232	I3	14	14	58
	I6	9	10	62
	I9	3	6	71

1 K-714 = Kingston link 714 L-3232 = London link 3232

2 I3 = Incident Severity = 20% I6 = Incident Severity = 50%
I9 = Incident Severity = 70%

3 ME = Mean Error MAE = Mean Absolute Error
MAPE = Mean Absolute Percentage Error

6.5.2 Application of Procedure to find Location of Affected Links

The procedure for finding the location of affected links in the network is implemented on computer for real time applications by writing two FORTRAN programs (see Appendix L). The first program (NETTREE), when supplied with number of links affected by an incident, finds the location of affected links by using the network connection files and the second program (GRAPH) plots them graphically on the computer screen.

Network Connection File

In this file all the links in the network are defined with their upstream links, upstream links are prioritised according to the proportion of traffic on the link which also (normally) proceeds through the incident link. The proportion of traffic was determined by using card 54 during CONTRAMI run. Network connection files for Kingston and Boscombe networks are given in (Appendix K).

NETTREE Program

Input :	Network Connections File
	Number of links affected
Output :	Location of affected links in the network

GRAPH Program

Input :	Nodes file
	Links file
	Location of affected links (obtained from NETTREE program)
Output	Shows the affected links graphically

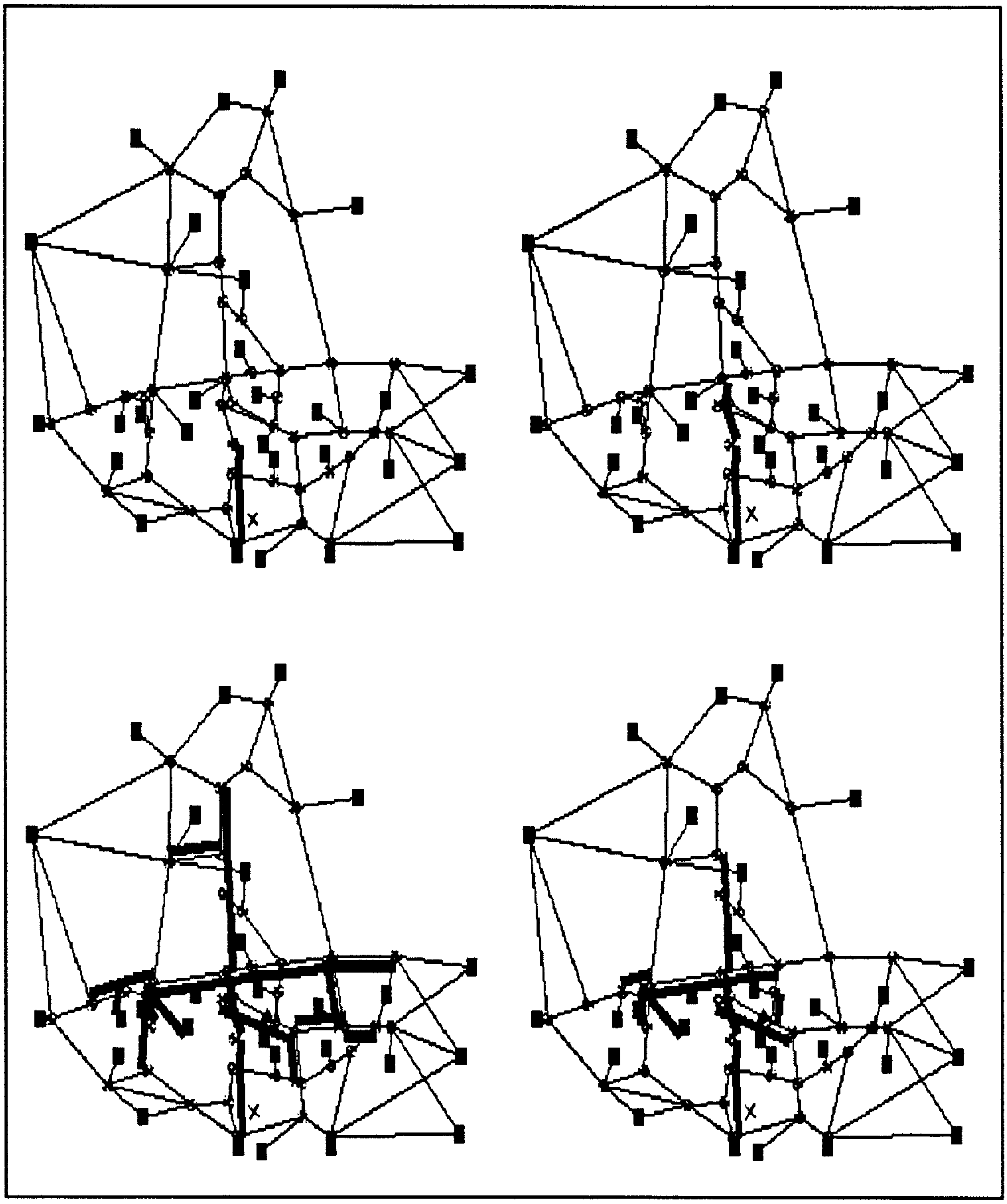
Nodes file was obtained by digitising the network and Links file contains the link numbers of two joining nodes.

The application of this procedure has produced promising results, as illustrated in figures 6.14 and 6.15. These figures show (in thicker lines) those links predicted to be affected after an incident at different times, using this route search process, and can be compared with simulated results for a quality of prediction.

Figure 6.14 Location of affected links (Kingston Network)

After 15 minute (Simulated) After 15 minute (Predicted)

(i) (ii)



(iii) (iv)

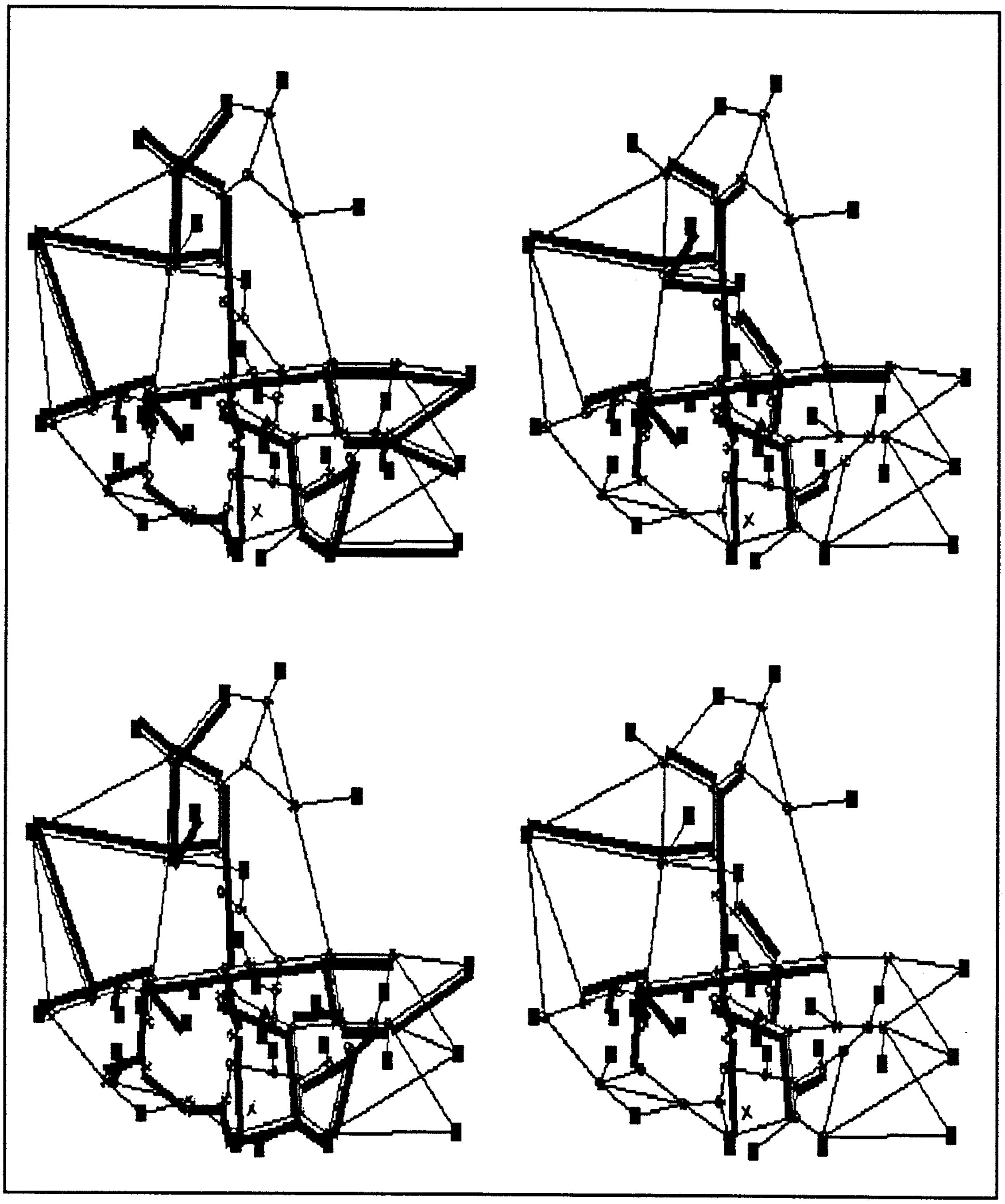
After 30 minute (Simulated) After 30 minute (Predicted)

After 45-min (Simulated)

(v)

After 45-min (Predicted)

(vi)



(vii)

After 60-min (Simulated)

(viii)

After 60-min (Predicted)

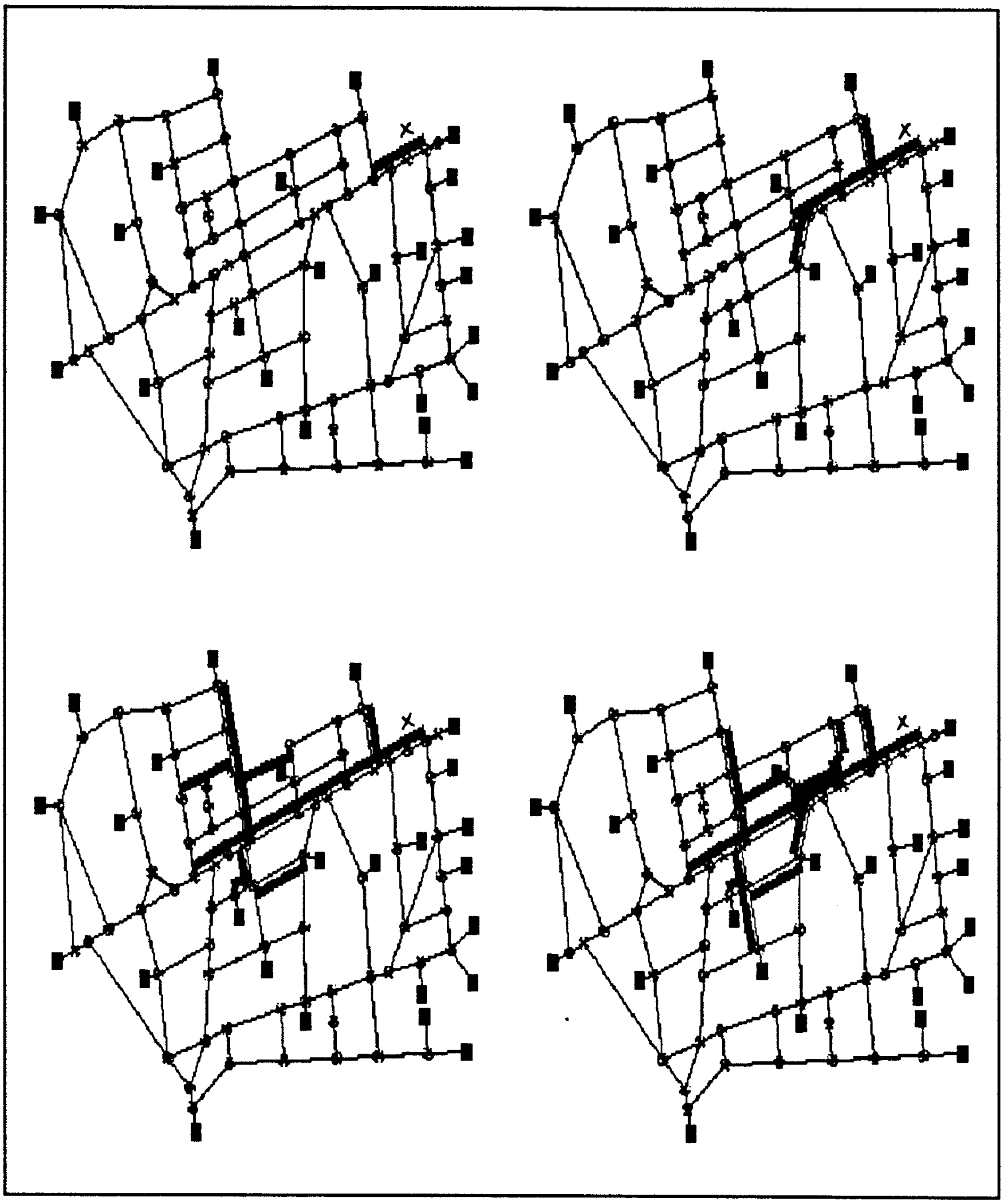
x : Incident link

Incident Severity = 50%

Figure 6.15 Location of affected links (Boscombe Network)

After 15-min (Simulated) — (i)

After 15-min (Predicted) — (ii)



(iii) After 30-min (Simulated)

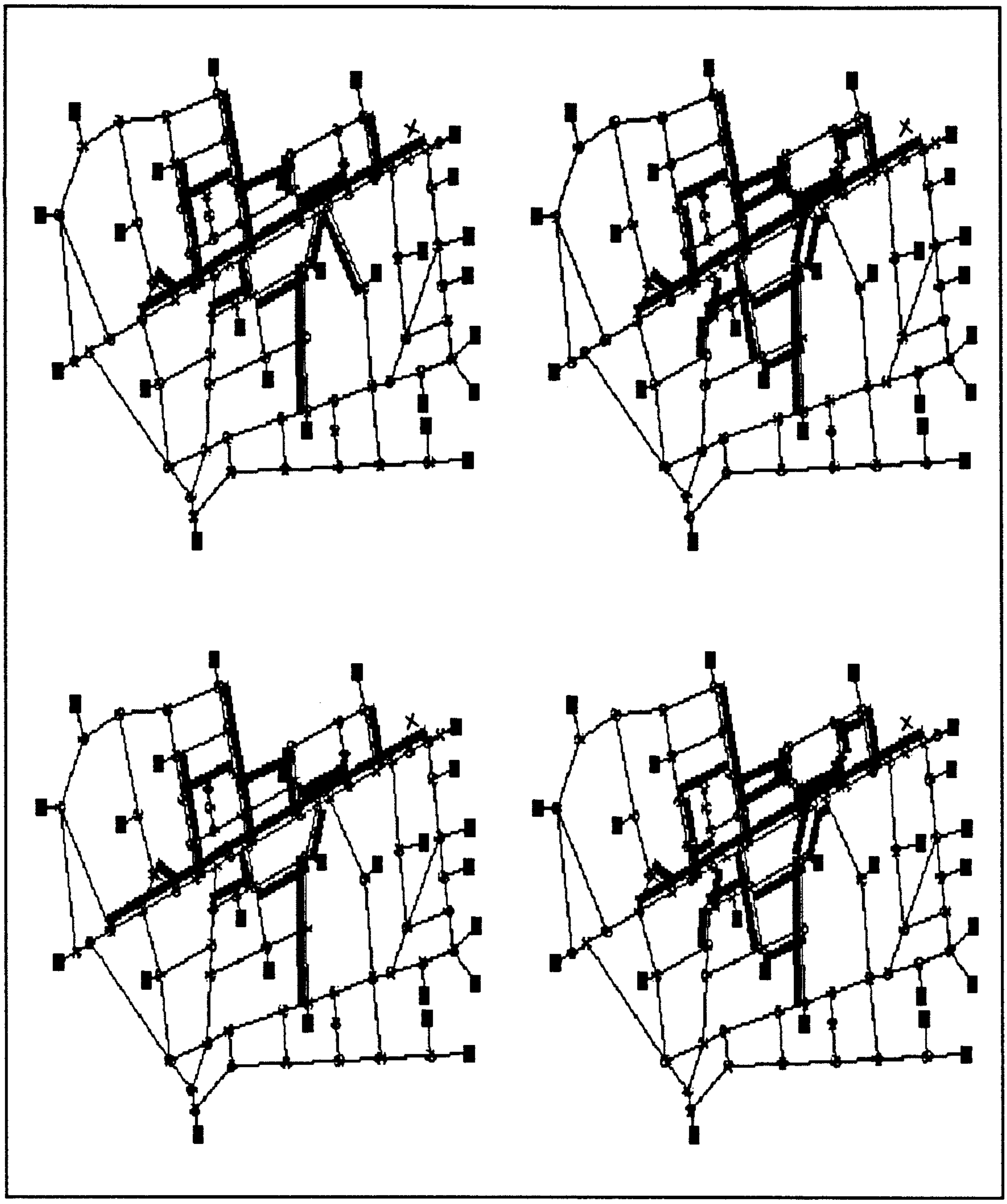
(iv) After 30-min (Predicted)

After 45-min (Simulated)

(v)

After 45-min (Predicted)

(vi)



(vii)

After 60-min (Simulated)

(viii)

After 60-min (Predicted)

x : Incident link

Incident Severity = 70%

6.5.3 Application of S1, MaxJt and S2 Models

Models S1, MaxJt and S2 can be used to predict increase in journey time on incident link. Increase in journey time on incident link is predicted for different incident scenarios by using the S1 model given in equation (6.7), MaxJt model given in equation (6.9) was used as a cut off for maximum journey time on incident link and S2 model given in equation (6.11) was used to obtain the post incident slopes, examples of simulated and predicted journey time on three links (Kingston-714, Boscombe-1494, London-3232) are given in figures 6.16, 6.18 and 6.20, and figures 6.17, 6.19 and 6.21 show the corresponding comparison of predicted vs simulated journey times.

Figure 6.16 Increased Journey Time on incident link 714 (Simulated vs Predicted)

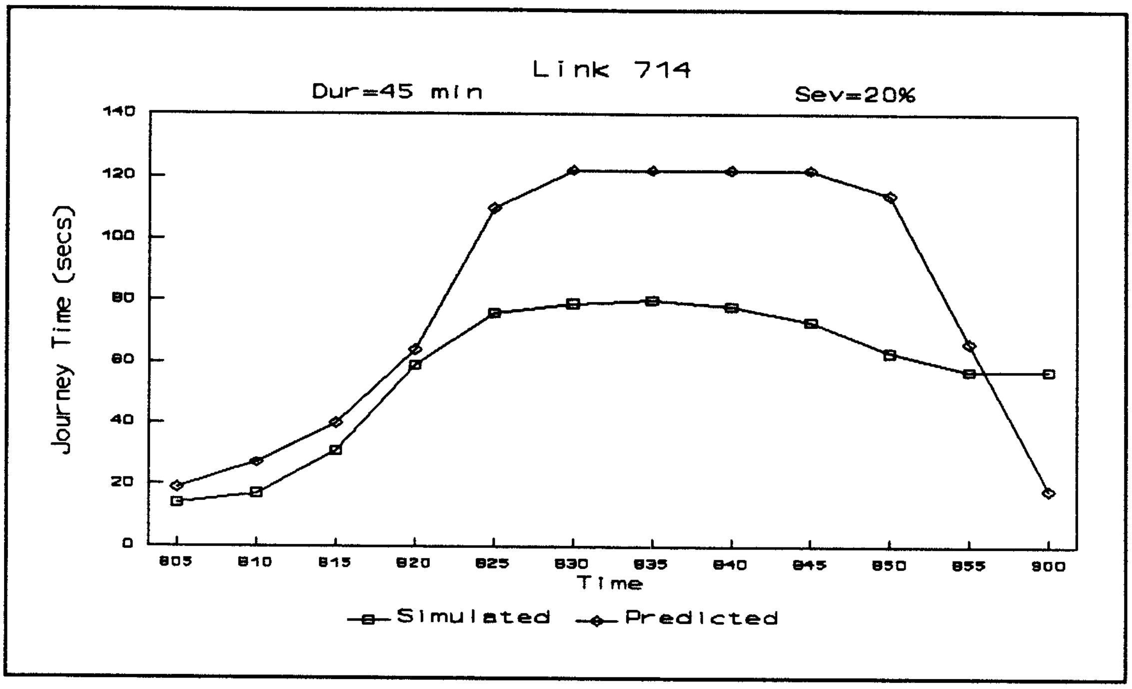


Figure 6.17 Simulated vs Predicted journey times - Link 714

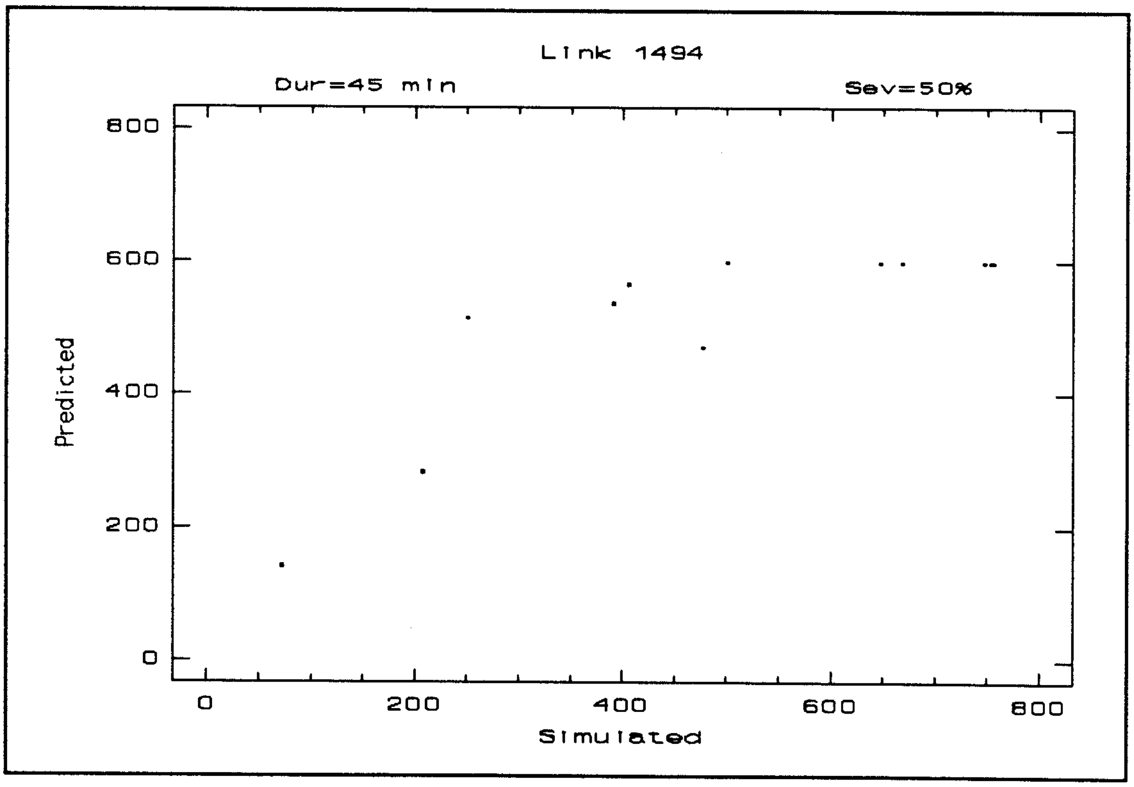


Figure 6.18 Increased Journey Time on incident link 1494 (Simulated vs Predicted)

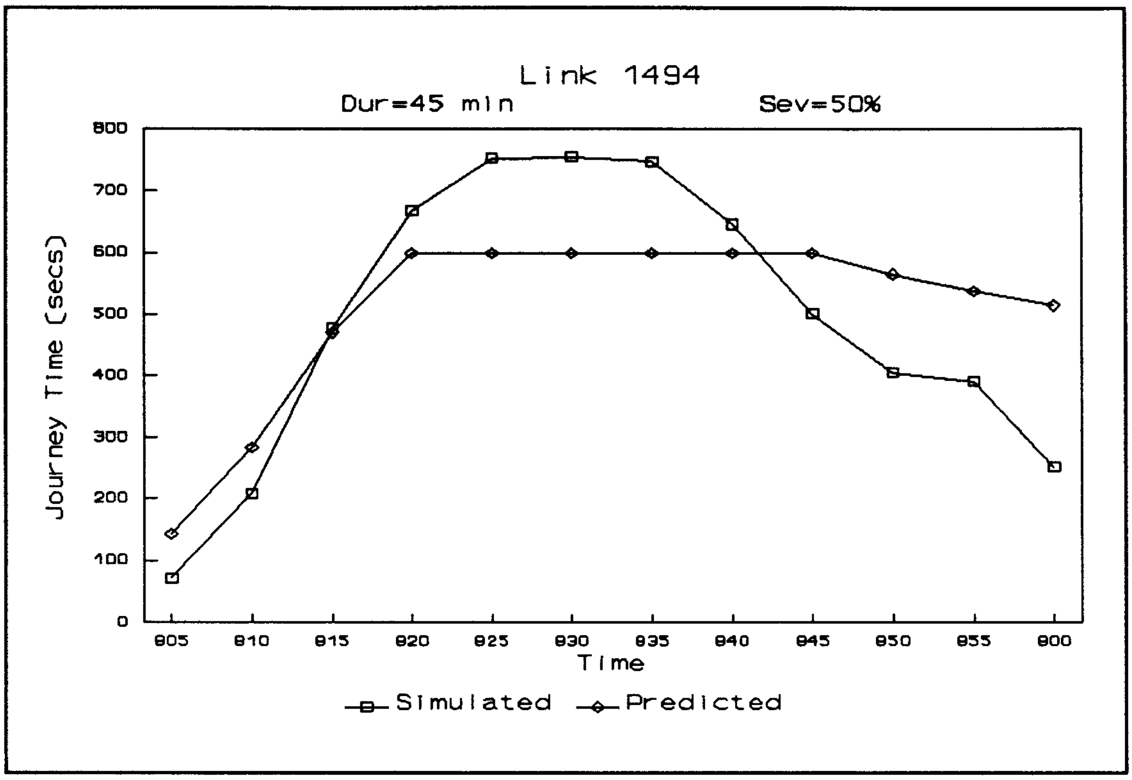


Figure 6.19 Simulated vs Predicted journey times - Link 1494

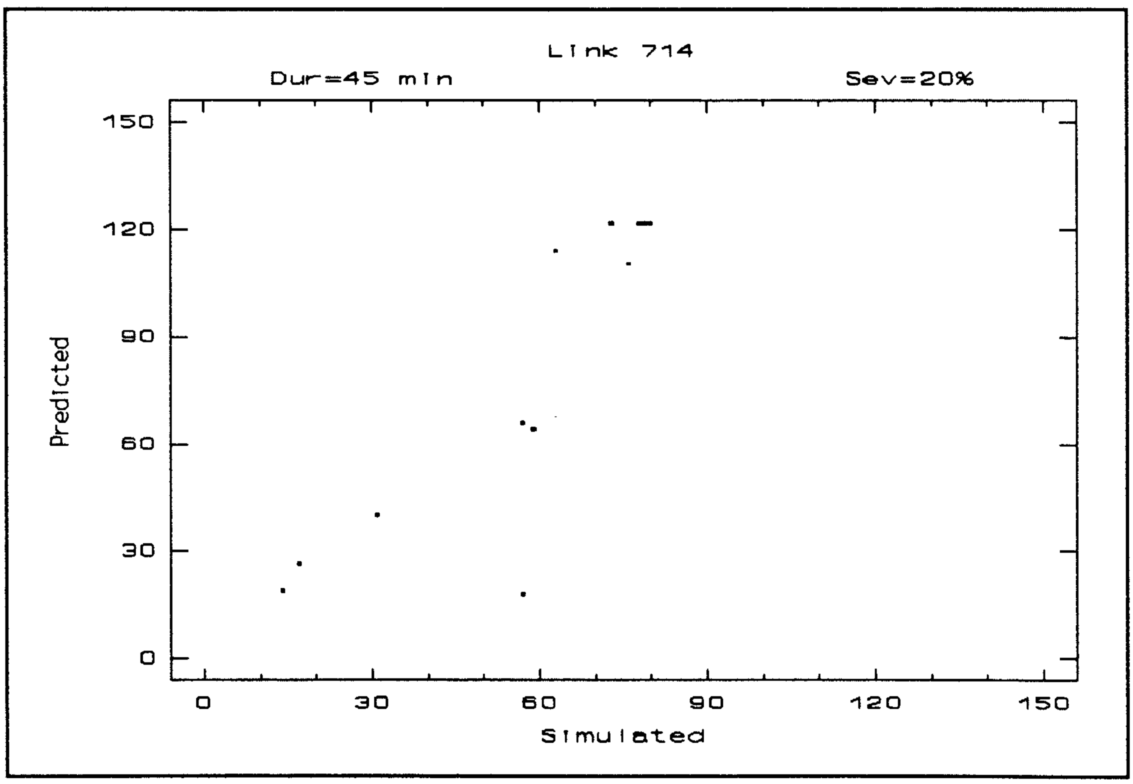


Figure 6.20 Increased Journey Time on incident link 3232 (Simulated vs Predicted)

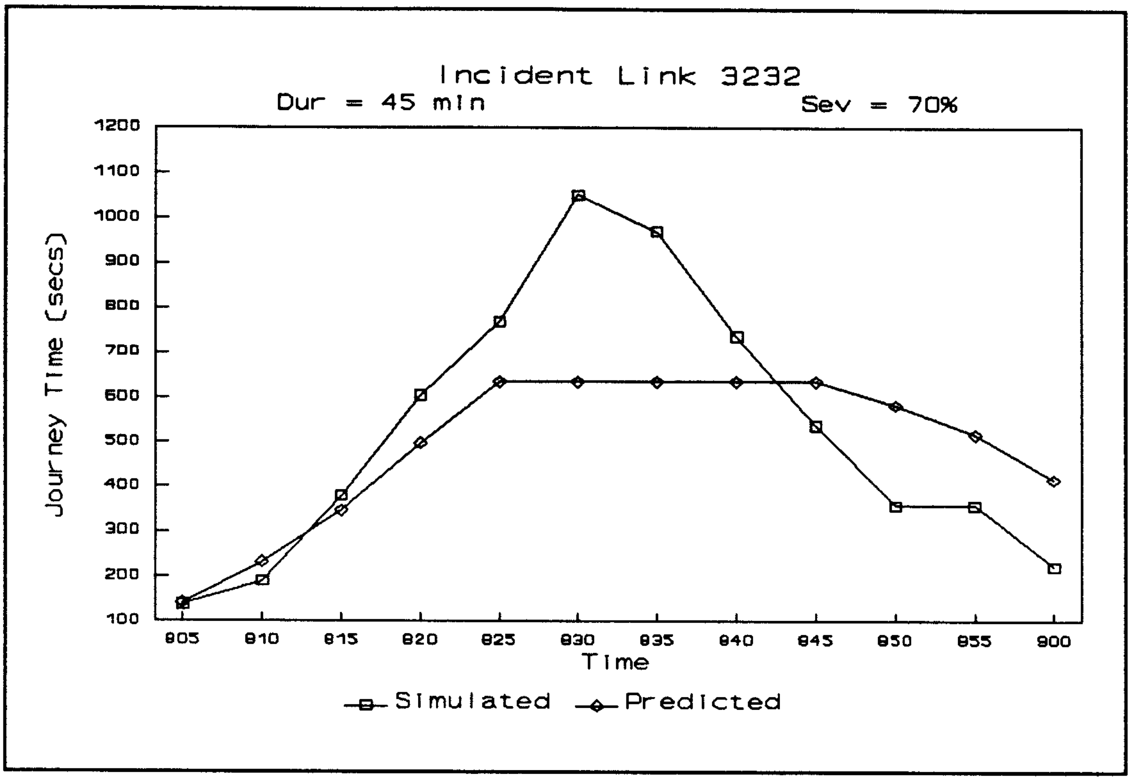
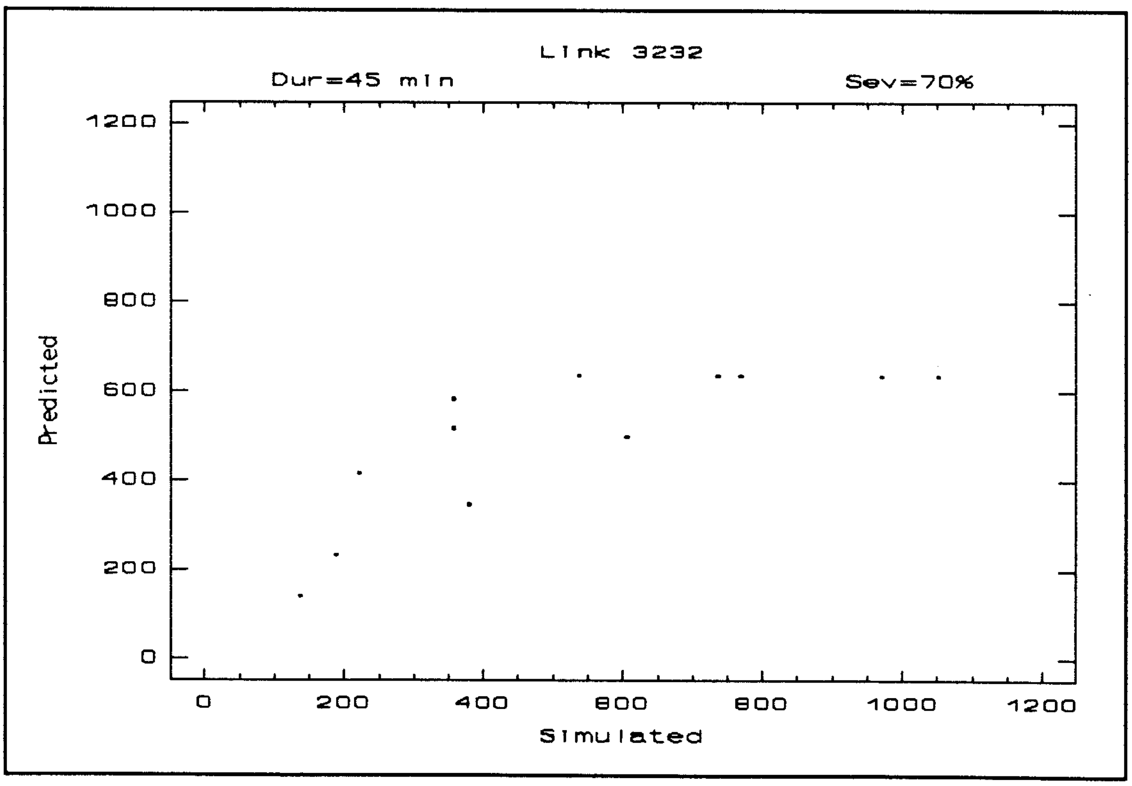


Figure 6.21 Simulated vs Predicted journey times - Link 3232



Forecasting quality of S1, MaxJt and S2 models were checked analysing forecasting errors statistically. Summary statistics of forecasting errors based on ME, MAE and MAPE is given in table 6.3. The MAPE error range from 27% to 74%, which are rather high. However, given the big variations in networks and traffic characteristics, the forecasting results are considered encouraging. Further improvements in forecasts can be achieved by updating the forecast using latest on-street information and by careful calibration of the models for the particular network.

Table 6.3 Forecast-Errors statistics for 'Journey Times'

Site[1]	Incident[2] Type	ME[3]	MAE	MAPE
K-714	I3	-22	28	47
	I6	-51	59	74
	I9	-38	63	68
B-1494	I3	23	71	27
	I6	19	116	34
	I9	54	272	48
L-3232	I3	-60	60	60
	I6	-71	78	46
	I9	33	153	30

1 K-714 = Kingston link 714 B-1494 = Boscombe link 1494
L-3232 = London link 3232

2 I3 = Incident Severity = 20% I6 = Incident Severity = 50%
I9 = Incident Severity = 70%

3 ME = Mean Error MAE = Mean Absolute Error
MAPE = Mean Absolute Percentage Error

6.5.4 Application of Models to Predict Journey Times on Affected Links

Models developed in section 6.4.2 can be used to predict the number of links that will be affected at a given time after an incident and then the location of affected links in the network can be found by using the procedure developed in section 6.4.3. These models also predict the time when a link is affected, once a link is affected it is treated as incident link for the increase in journey time, models for S1, MaxJt and S2 are used to predict the journey time on the affected links (for simplicity, no factoring of S1, MaxJt and S2 was considered here, however for more accurate forecasts, factoring may be required). Table 6.4 shows the results of application of the above procedure. In this table, following the on-set of an incident, 'Number of links affected' were predicted for each time slice using M1 model, then the location of affected links were predicted using the procedure developed in section 6.4.3. Journey times on affected links were predicted using S1, MaxJt and S2 models developed in section 6.4.4. The predicted results are compared with simulated results, it can seen from table 6.4 that the prediction of 'Number of links affected' and the prediction of 'Location of affected links' is quite good. Also, prediction of 'Journey times' on incident affected links is reasonably good, apart from the incident link itself, where in most cases, the model is over predicting journey times. Again it is expected that updating of forecasts (say every 5-minutes) will help in reduction of forecasting errors.

Table 6.4   Increase in Journey Time on affected links (Simulated vs Predicted)

Incident Link = 714   Severity=20%   Duration=30-min

Time	Number of links affected (Simulated)	Number of links affected (Predicted)	Location [1] of affected links (Simulated)	Location of affected links (Predicted)	Journey Time (Simulated)	Journey Time (Predicted)
8:05	0	0	-	-		
8:10	1	1	714	714	17	24
8:15	1	2	714	714 535	31	37 9
8:20	2	3	714 535	714 535 711	59 10	61 9 24
8:25	5	5	714 535 711 708 724	714 535 711 710 712	76 22 35 46 25	107 13 30 19 28
8:30	8	7	714 535 711 710 712 708 707 520	714 535 711 710 712 708 724	78 41 80 31 30 52 59 27	122 19 39 25 32 77 48

1   See map on page 270 for location of affected links in the network.

6.6 Implementation of the Models in Real Time

The models which are developed above, predict the effects of an incident at the start of incident for the rest of the time periods. However for real time applications, on-street information would be available at regular time intervals (e.g. 5-minutes). Forecasts can then be compared with this information and be updated accordingly. Consider an example where the 'Number of links affected' were predicted by using M1 (equation 6.2) and M2 (equation 6.5) slopes.

$$\text{Number of links affected} = 5 * (M1_1 + M1_2 + M1_3 + --- + M2_{t-1} + M2_t) \quad (6.13)$$

Here at any time interval the predicted 'Number of links affected' is the sum of previous predicted slopes plus the current slope, to update the forecasts, sum of predicted slopes can be replaced by the observed 'number of links affected' at time t-1. So the forecasts can be updated by using the following equation:

$$\text{Number of links affected } (t) = 5 * (\text{observed number of links affected } (t\text{-}1) + M1_t) \quad (6.14)$$

The above equation was used to obtain updated forecasts for ' Number of links affected', these forecasts are given in Appendix N. Results were compared with not-updated forecasts; an example of updated forecasts is shown in figure 6.22 below with the forecasts error-statistics given in Table 6.5.

Once the forecast for 'Number of links affected' is updated, then the prediction of 'location of affected links' can also be updated by re-running the NETTREE and GRAPH programs (section 6.5.2) which predict the location of affected links in the network.

Figure 6.22 Updated forecasts for 'number of links affected' : Incident link K-714

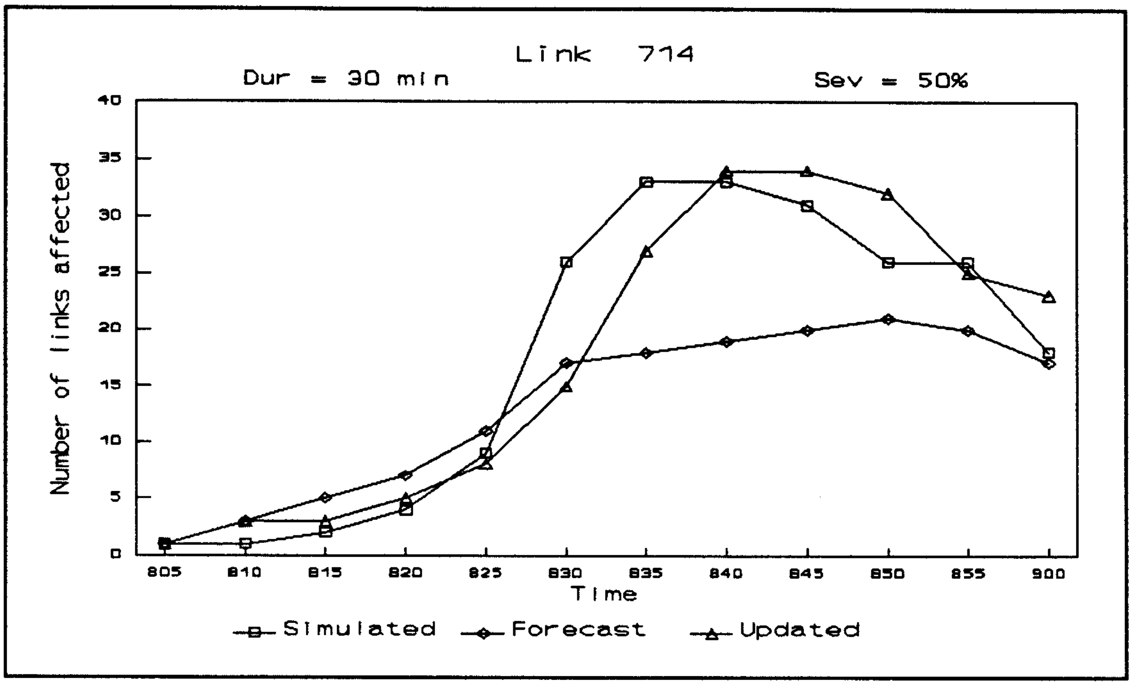


Table 6.5 Comparison of not-updated and updated forecasts for 'Number of links affected' with incident link K-714

Site	Incident Type	Forecasts	Error-Statistics		
			ME	MAE	MAPE
K-714	I5	Not-Updated	4	6	54
		Updated	-0.2	3	35

It can be seen from the above table that updated forecasts are more close to the observed values and therefore has smaller forecast errors. The MAPE is reduced to 35% for updated forecasts as compared to 54% for not-updated forecasts.

Similarly, journey time forecasts which were obtained by using the equation (6.8) as:

$$JTI_t = JTI_{t-1} + 5*S1_t$$

where

JTI_t	=	Predicted Journey time on the link at time interval t.
JTI_{t-1}	=	Predicted Journey time on the link at time interval t-1.
$S1_t$	=	Rate of increase of journey time (as calculated by equation 6.7) on incident link.

can be updated by replacing predicted journey times at time t-1 with observed journey time t-1, the prediction equation would then be :

$$JTI_t = JTO_{t-1} + 5*S1_t \qquad (6.15)$$

where

JTI_t	=	Predicted Increased Journey time on the link at time interval t.
JTO_{t-1}	=	Observed Journey time on the link at time interval t-1.
$S1_t$	=	Rate of increase of journey time (as calculated by equation 6.7) on incident link.

The above equation was used to obtain updated forecasts for ' Journey times' and compared with not-updated forecasts, these forecasts are given in Appendix N. An example of updated forecasts is shown in Figure 6.23 below with the forecasts error-statistics are given in Table 6.6.

Figure 6.23 Updated forecasts for 'Journey Time' with incident link B-1494 I6

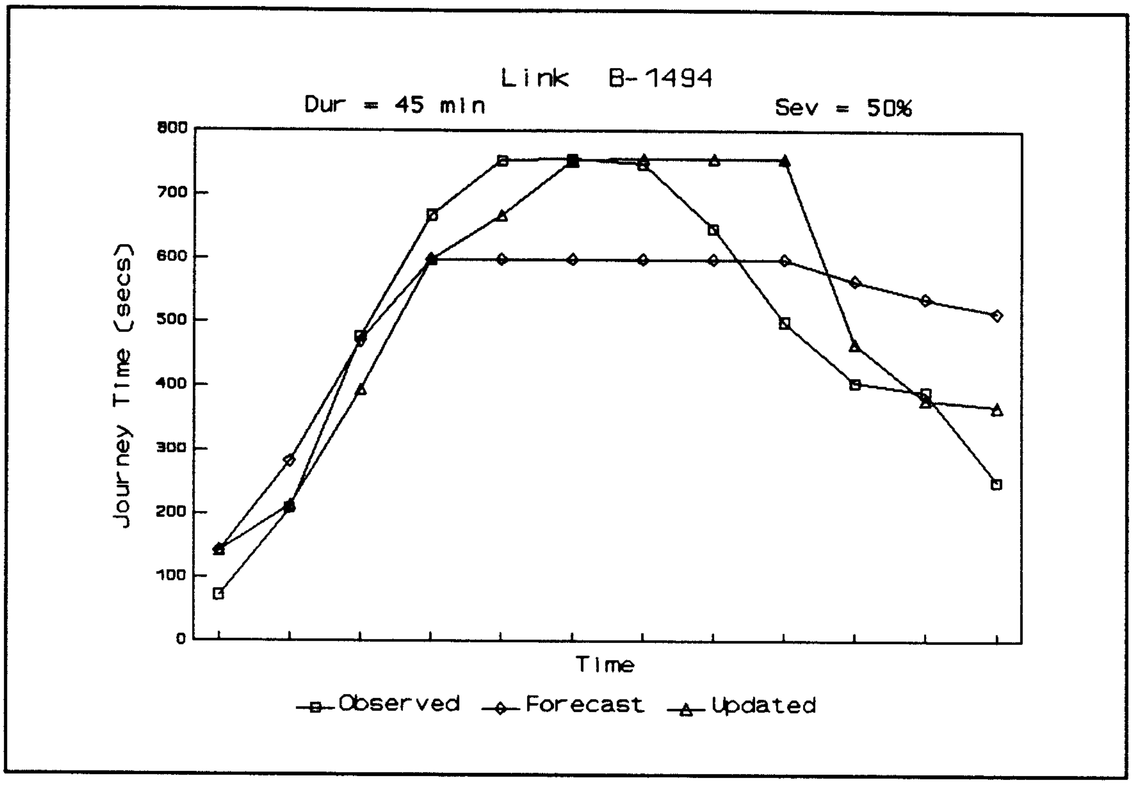


Table 6.6 Comparison of not-updated and updated forecasts for 'Journey times' with incident link B1494

Site	Incident Type	Forecasts	Error-Statistics		
			ME	MAE	MAPE
B-1494	I6	Not-Updated	-19	116	35
		Updated	-31	73	23

Again forecasts have been improved by updating and MAPE reduced from 35% to 23%.

6.7 Discussion

This chapter has been based on simulation modelling of a variety of traffic/network incident scenarios, producing a database from which generalised statistical models have been developed for predicting the spread of congestion effects following an incident and the required journey time modifications on incident link and on affected links. The 'goodness' of fit of the models were evaluated by comparing the results of developed models with that of CONTRAMI (simulation) results. A type of validation was also achieved by applying the developed models on a larger network (London network).

These models have demonstrated a reasonable predictive quality, given the highly variable effects of unexpected incidents and could readily be implemented on-line. However, before these models can be used, some improvements are envisaged. The incident simulations were based on 'no diversion' strategy for drivers, therefore, although the results were considered reasonable for this study, they are expected to produce somewhat worse traffic conditions than those which could occur in practice. As a consequence the predicted values of 'M1' and 'S1' slopes are expected to be slightly greater than practical ones. There is evidence (Sparmann, 1991) from on-street observations that a certain number of drivers do divert from their original route when an incident happens although no quantification of this effect has been achieved. This could be simulated by CONTRAMI by describing the maximum number of diversions allowed per driver, the coefficient of diversion and the percentage of vehicles diverting. Several strategies could therefore be experienced by CONTRAMI simulation, and it can be imagined that the strategies could be adjusted to each network and type of road users.

The developed procedure is therefore recommended as a valuable real-time tool to help journey time prediction within DRG incident management strategies and for other traffic control and information systems.

CHAPTER 7

CONCLUSIONS

This study was involved in the development and testing of short-term journey time forecasting models for normal traffic conditions and for incident conditions. The developed models have demonstrated the potential as a real time tool for link-based journey time forecasting in low/moderate congestion and for network-based DRG (Dynamic Route Guidance) incident management strategies particularly in low penetration level. The general conclusions which are drawn from the research are outlined below.

7.1 General Conclusions

- Among the parameters measured by SCOOT UTC system in Southampton were traffic Flow (veh/hr) and Delay (veh hrs/hr). From Flow (veh/hr) and Delay (veh hr/hr); average journey time (sec/veh) can be calculated. Such estimates of journey time accurately reflect on-street journey times over a wide range of conditions.

- Analysis of the SCOOT data suggested that journey time variability between morning and evening peak can be significant. Moreover variability between days of week (Mon-Fri) may also be sufficient to warrant separate measurements and predictions for each day of the week. However, for sites where between day variability is not significant, data should be grouped together for all working days of the week to form a single time series. This has the advantage that journey time profiles from which the predictions are made will have tighter confidence interval due to increased sample size.

- Monthly variability may also be significant, however if decrease/increase in journey time between different months is gradual then there may not be the need of separate monthly profiles as the change will be covered by updating of historical profiles (e.g. by using only last six days data as historical database).

- Another source of journey time variability which can be significant is caused by traffic signal cycles. Accounting for cyclic patterns may be necessary in very short term journey time forecasting such as for signal control application. However, it becomes less relevant for longer forecast horizons typically required for traffic information systems etc. Therefore this very short term variability is usually not of interest in journey time forecasting, except for particular signal control applications.

- Time-Series methods can be effectively used to develop journey time forecasting models. These methods had the merits of being relatively simple and of 'direct' forecasting of the parameter(s) of interest. These methods are appropriate for link-based forecasting in conditions of low/moderate congestion.

- Two time-series methods (Box-Jenkins ARIMA and Horizontal-Seasonal) were used to develop journey time forecasting models on a link-by-link and a route basis, models were tested on a variety of data sets.

- These forecasts are based on the historical data of previous days and at first forecasts were generated at the start of current day for all the 5-min time periods between 07:00-10:00 and then as soon as the new journey time value is observed, forecasts for all the next time periods can be updated by using the latest journey time information.

- Application of Box-Jenkins ARIMA and Horizontal-Seasonal forecasting methods on a variety of data sets show that overall both methods have performed satisfactorily with neither method proving consistently superior.

- The most important factor which influences the quality of forecasts is the variability in the historic data and how close is the current day's data to the historic data. Forecasts on a link, which has less variability in the historic data, are much better than the forecasts at a link where day to day variability was much higher.

- Improvement in forecasts was achieved when forecasts were updated for every 5-min interval and this is due to the fact that both the models used to generate forecasts are quite flexible and quickly adapt themselves to the current situations; e.g. if on the current day the level of journey time is higher than the historical journey time data, models react quickly and updated forecasts follow the pattern of the current day data.

- Forecasting errors decreased with increasing time aggregation. However, such aggregation could compromise the speed/usefulness of forecasting for traffic information and control.

- For Box-Jenkins ARIMA models, prediction is only a part of the method; it also includes the analysis of time series. It is therefore more general than the other method, where the user has to decide about the model's parameters. A family of (ARIMA) models is proposed and the analysis of historical data leads to the selection of an appropriate model.

- For real time application of the Box-Jenkins ARIMA method, the analysis of historical data, for the selection of an appropriate model, can be carried out off-line and once an appropriate model is selected the forecasts can be generated on-line in real time. The same selected model is used day after day unless the forecasting errors are out of specified limits, in this case analysis of historical data would be repeated off-line to select a new model and then forecasts would be generated by the new model.

- For the Horizontal-Seasonal method, the prediction equation contains a base value and a seasonal factor. The base value represents the mean value of the time series over one season and for every time period t of the season a seasonal factor is defined as the ratio between the travel time in period t and the base value. Base value and seasonal factors are being updated in every period using exponential smoothing with individual weighting parameters.

- The Horizontal-Seasonal method can be implemented on a computer for real-time application by writing a computer program in any high level language. The method is simple and forecasts can be generated on-line.

- Time-series forecasting methods were successfully used in 'normal' traffic conditions, where day-to-day pattern of journey time is not changed dramatically. This study has developed suitable models for such forecasting on a link-by-link basis and where congestion is reasonably recurrent. These models could be further refined and tested on-line by adopting methods for automatic validation within systems where such forecasts are used (e.g. for route guidance). An expert system approach could also be adopted in which the performance of a range of forecasting methods is automatically monitored and the method is chosen appropriate to the traffic situation.

- For high and variable congestion situations, including those related to traffic incidents, historic patterns become unstable and the performance of time-series forecasting methods deteriorates. Additional strategies are then necessary to handle such situations. Also a network-based, rather than link-based interpretation is then required.

- Traffic incidents occur in a variety of forms and contribute to increase congestion and hence journey time by reducing the capacity of road networks for various periods of time and at various levels of severity.

- A commonly adopted definition (Collings J F, 1983) of a traffic incident is 'an unusual occurrence which reduces the capacity of the road on which it occurs'. Incidents can be classified into two main categories (i) Predictable Incidents (such as roadworks etc) and (ii) Unpredictable Incidents (such as traffic accidents).

- For both the categories of incident defined, the net effect is a reduction in road capacity, which lasts for varying lengths of time. The result is an excess of traffic demand over reduced capacity which leads to higher than normal journey time, not only on the link of incident but also on the approaching links and other links in the network.

- Following an incident and its detection by a suitable method, there is a need to predict the incident effects in the network and to bring some incident management strategies which provides the appropriate response to minimize the adverse effects of the incident.

- One way of predicting incident effects is by running an assignment model on line, however there are two problems involved in this, firstly road traffic assignment and simulation models are very demanding in computing (processing) time particularly with very large networks. Secondly even when sufficiently powerful computers will be available in the future to run an assignment model on-line, it will require detailed representations of the network before an on-line simulation can be run, which can be very costly and will not be available for most of the networks.

- For such reasons there is a need for simple statistical models which can be used on-line to predict the affects of an incident in a network.

- In incident conditions under a variety of network traffic scenarios, models are required, to predict (i) Number of links that will be affected by an incident, (ii) Location of affected links in the network, (iii) Increase in Journey Time on incident link, (iv) Increase in Journey Time on incident affected links.

- The extent of the additional journey time caused by an incident is difficult to assess as it needs to be separated from the existing background congestion and needs to take account of its effect over the network as a whole. The quantitative assessments for incident effects must therefore be inferred from modelling studies.

- Two methods, (i) trial on street and (ii) simulation, were considered to compile a database for different incident/traffic/network scenario. However trials on streets are laborious and can be expensive, also they are not practical with unpredictable incidents, whereas simulation is easier to realise and can be identically repeated with less extra cost. Therefore simulation was considered to be the most appropriate method for the compilation of an incident data-base on which to build predictive models.

- CONTRAMI is a suitable simulation tool to study the affects of incidents, as it allows incident modelling with various type of strategies and simultaneously benefits from CONTRAM's fundamental attributes.

- The affects of unpredictable incidents are less well known. It was therefore, more need to simulate unpredictable short-term incidents.

- The simulation of incidents carried out on two urban road networks, allowed network dependence to be assessed as well as the other traffic and incident related parameters. These are real networks and the simulation results can be related to what would be effects of incidents on-street.

- The effects of an incident can be attributed to many parameters, it was seen from the simulation results that the incident characteristics which were defined as duration and severity are two of the many key parameters. Moreover the effect of an incident from one link to another was different, this can be attributed to link characteristics (geometric, traffic characteristics) as well as of each network. The geometric properties are assumed not to vary strongly from one link to another according to the available information provided by the original data-files. However the importance of a link in a network and its 'traffic performance' played an important role in the effects that an incident had on other links. A range of parameters can reflect these situations, for example Congestion Index (link journey time/link cruise time), Degree of saturation (number of arrivals/link capacity), or Delay (link journey time - cruise time).

- However, only those variables may be used in modelling which would be available in a DRG system. This therefore excluded traffic flow and flow-related parameters, such as degree of saturation, even though these parameters may have produced a superior model. Furthermore, because the key goal is to build predictive models, the independent parameters in the models referred to non-incident conditions so that they are practically available for all links of any network, which is only possible for 'normal' traffic conditions.

- For number of links that were affected by an incident, incident severity proved to be a dominant parameter. A linear two stage model can be used, with stage 1 describing congestion build-up during the incident and stage 2 describing post-incident recovery. For stage 1 slope, it was seen that a greater severity produce a steeper slope, moreover if the incident link was particularly likely to get congested rapidly, then the number of affected links in the network grew faster. For "post incident" slope, it was seen that the decay of the number of affected links sometimes started only after a transition period has been achieved. This transition period reflected a situation where the network was still partly congested at the time of the incident end, and where drivers would be re-optimising their routes according to the latest traffic conditions; for this reason the number of affected links would either rise or remain almost constant for a short time. Hence the link 'traffic performance' parameter was involved in the number of affected links of the 'after incident' situation.

- Following a time-dependent prediction of the number of links affected, it is then necessary to locate these links in the network. It is usual that the first affected links are the nearest upstream links to the incident link, and that the propagation will continue in the direction of the nearest upstream links connected to affected links until the maximum number of affected links has been reached. Then, after the incident has ended, the number of affected links decrease following the reverse process. To find out the location of affected links in the network, a reverse route search can be made from the upstream node of incident link, upstream links prioritised according to the proportion of traffic on the link which also (normally) proceeds through the incident affected link. Computer programs written to implement the above procedures produced promising results.

- Journey time prediction on incident link can be analyzed using techniques compatible with those as for the prediction of 'number of links affected'. The incident modelling using CONTRAMI produced a number of journey time profiles. These profiles showed that journey time gradually increase following the onset of the incident, and then stabilises to a relatively constant value if/when the link becomes full. It also illustrated that the maximum journey time on the link (when it is full) varies according to the incident severity, as would be expected, as severity is directly related to reduction in capacity. A three stage model was therefore developed for the prediction of journey time on incident link. As before (for the prediction of number of links affected), the incident characteristics which are defined as duration and severity, were the key parameters of increase in journey time, moreover the effect of an incident from one link to another is different, this can be attributed to link characteristics (geometric, traffic characteristics). Two parameters (Congestion Index and Delay) were selected to represent link characteristics.

- The developed models were applied to three different networks to predict the effects of an incident. The 'goodness' of fit of the models were evaluated by comparing the results of developed models with that of CONTRAMI (simulation) results and analysing the forecasting-errors. The models showed a reasonable predictive quality.

- The developed models have shown the potential for real-time applications.

7.2 Further Work

The time-series methods which were applied in normal-traffic conditions to generate journey time forecasts are univariate stochastic models, i.e. forecasts are based on historical journey time information on the particular link and updated to reflect the current conditions. These models have proved quite successful in forecasting day to day patterns of journey time.

Journey Time, however is a complex variable which is influenced by many other factors (e.g. flows, green-time), perhaps the accuracy of forecasts can be improved by extending the current models where genuine systematic effects which can be explained physically should be taken into account by the inclusion of a suitable deterministic component in the model. For example, if it is known that flow is being added to a network, then it would be better to explain the resulting increase in journey time by means of a suitable deterministic function, in addition to the stochastic component. This will require to construct deterministic models (multiple regression models and/or multiple time series models). Constructing a deterministic model that is likely to provide more accurate forecasts of a given time series requires both specifying an appropriate set of independent variables (say flow, queue length, green-time etc) and determining the functional form of the regression relationship between the dependent variable and a given set of independent variables.

Also, so far in normal-traffic conditions, the forecasting methods were applied to individual links and do not encompass link interactions, the build up/decay of queues or other network influences. In urban networks the traffic parameters journey time/congestion are often associated with one or more "pinchpoints" from which queues spread to affect a number of upstream links. Queues on adjacent links are then interrelated both in time and space, and the forecasting on an independent link-by-link basis becomes less relevant. A useful method for forecasting journey time in urban networks is the use of so called transfer function models. These models are the extension of univariate ARIMA models where journey time at a link can be related with its key controlling parameters, such as flow on upstream links. The methods could be further tested and refined on-line by adopting methods for automatic validation within systems where such forecasts are used (e.g. for route guidance). An expert system approach could also be adopted in which the performance of a range of forecasting methods is automatically monitored and the method chosen appropriate to the traffic situation.

For journey time forecasting in incident conditions, this study has been based on simulation modelling of a variety of traffic/network incident scenarios, producing a database from which generalised statistical models have been developed for predicting the spread of congestion effects following an incident and the required journey time modifications on incident link and on affected links. These models have demonstrated the potential in real time systems (such as in DRG). However, before these models can be used, some improvements are envisaged. The incident simulations were based on 'no diversion' strategy for drivers, therefore, although the results were considered reasonable for this study, they are expected to produce somewhat worse traffic conditions than those which could occur in practice. As a consequence the predicted values of 'M1' and 'S1' slopes are expected to be slightly greater than practical ones. There is evidence from on-street observations that a certain number of drivers do divert from their original route when an incident happens although no quantification of this effect has been achieved. This could be simulated by CONTRAMI by describing the maximum number of diversions allowed per driver, the coefficient of diversion and the percentage of vehicles diverting. Several strategies could therefore be experienced by CONTRAMI simulation, and it can be imagined that the strategies could be adjusted to each network and type of road users. Incident databases can then be compiled according to the individual network requirements and the developed models can then be re-calibrated by using the compiled database.

7.3 Concluding Comments

Journey time forecasting in urban areas is likely to become an increasingly important element in traffic information and control systems. This study has revealed suitable time-series methods for such forecasting on link-by-link basis and also illustrated the usefulness of a comprehensive historic database, such as can be obtained from SCOOT Urban Traffic Control system, in providing the basis for such short-term forecasting using time-series techniques. A key requirement is appropriate disaggregation of the database to represent all sources of "predictable" time variability. An appropriate forecasting update interval is also required to provide a dynamic forecast but one which is not dominated by "noise". A 5-minute interval has been used successfully in this study. Time series forecasting has the merits of relative simplicity and of "direct" forecasting of the parameter(s) of interest. It is appropriate for link-based forecasting in conditions of low/moderate congestion. These methods have been successfully used in this study to develop journey time forecasting models for real data sets where traffic was reasonably recurrent.

For incident conditions, historic patterns become unstable and time-series forecasting is more difficult. A different modelling strategy is then required. This study has demonstrated the usefulness of simulation tool such as CONTRAMI to compile an incident database for different incident/traffic/network scenarios to study the effects of an incident. From such simulated incident database, generalised statistical models can be developed for predicting the effects of an incident and required journey time forecasting on incident link and on affected links. Such models have been developed and applied for various incident scenarios in this study. Despite some limitations and required improvements mentioned earlier, it is considered that the developed models, would be very valuable for application within real time traffic control and information systems, such as in Dynamic Route Guidance Systems and in Drivers Information Systems.

APPENDICES

Appendix A

Estimates of Seasonal-Ratios For HS-Model

Table A.1 Seasonal Ratios for Link N019D on 20-2-91

Time	S-Ratio [1]	Time	S-Ratio	Time	S-Ratio
07:05	0.92	08:05	1.33	09:05	0.91
07:10	0.93	08:10	1.06	09:10	0.87
07:15	0.92	08:15	1.01	09:15	0.92
07:20	0.97	08:20	0.99	09:20	0.94
07:25	0.96	08:25	0.98	09:25	0.98
07:30	1.07	08:30	1.02	09:30	0.93
07:35	0.95	08:35	0.98	09:35	0.96
07:40	0.94	08:40	1.05	09:40	0.93
07:45	1.11	08:45	1.01	09:45	0.88
07:50	1.17	08:50	1.06	09:50	0.94
07:55	1.13	08:55	0.97	09:55	1.01
08:00	1.24	09:00	0.96	10:00	1.02

Table A.2 Seasonal Ratios for Link N018E on 14-6-91

Time	S-Ratio	Time	S-Ratio	Time	S-Ratio
07:05	0.63	08:05	1.00	09:05	0.73
07:10	0.68	08:10	1.23	09:10	0.69
07:15	0.71	08:15	1.48	09:15	0.72
07:20	0.69	08:20	1.84	09:20	0.70
07:25	0.67	08:25	1.91	09:25	0.72
07:30	0.71	08:30	1.94	09:30	0.70
07:35	0.75	08:35	1.65	09:35	0.67
07:40	0.80	08:40	1.79	09:40	0.63
07:45	0.86	08:45	1.90	09:45	0.61
07:50	1.16	08:50	1.34	09:50	0.65
07:55	1.35	08:55	0.97	09:55	0.60
08:00	1.11	09:00	0.78	10:00	0.63

1 Seasonal ratio : calculated by the relation $JT_t/\overline{JT}_{(1)}$

where

JT_t is journey time at time period t

$\overline{JT}_{(i)}$ is average journey time on day i

Table A.3 Seasonal Ratios for Route1 on 14-6-91

Time	S-Ratio	Time	S-Ratio	Time	S-Ratio
07:05	0.81	08:05	0.97	09:05	0.96
07:10	0.84	08:10	1.07	09:10	0.93
07:15	0.89	08:15	1.16	09:15	0.89
07:20	0.88	08:20	1.27	09:20	0.88
07:25	0.87	08:25	1.30	09:25	0.88
07:30	0.87	08:30	1.29	09:30	0.88
07:35	0.90	08:35	1.28	09:35	0.87
07:40	0.94	08:40	1.24	09:40	0.85
07:45	1.04	08:45	1.29	09:45	0.83
07:50	1.10	08:50	1.26	09:50	0.86
07:55	1.10	08:55	1.13	09:55	0.82
08:00	1.00	09:00	1.02	10:00	0.81

Appendix B

Journey Time Forecasts - Normal Conditions

Table B.1 Link N019D - Journey Time Forecasts on 20-2-91

Time	Observed	BJ-Model [1]		HS-Model [2]	
		Forecasts [3]	Updated [4]	Forecasts	Updated
07:05	27.75	26.95	26.95	30.27	30.27
07:10	31.10	28.79	28.79	30.46	29.70
07:15	30.59	29.08	29.66	30.28	29.94
07:20	27.75	30.42	30.26	31.80	31.65
07:25	29.69	30.10	28.67	31.51	30.20
07:30	33.91	33.95	34.62	35.05	33.43
07:35	27.84	31.09	31.20	31.40	30.07
07:40	30.41	29.80	28.64	31.04	29.07
07:45	46.90	34.80	36.02	36.44	34.59
07:50	32.31	37.23	41.41	38.58	40.53
07:55	29.64	35.08	29.59	37.20	36.71
08:00	28.32	36.01	35.57	40.65	37.80
08:05	33.15	41.53	40.42	43.66	37.55
08:10	33.10	32.86	32.20	35.05	29.08
08:15	36.14	30.93	33.59	33.30	28.77
08:20	30.78	30.11	31.92	32.72	30.44
08:25	33.67	29.78	28.42	32.38	30.23
08:30	29.58	30.74	31.94	33.41	32.25
08:35	28.81	29.74	28.12	32.16	30.28
08:40	34.61	33.10	33.12	34.45	31.96
08:45	31.08	32.20	33.03	33.14	31.51
08:50	27.19	34.78	33.92	34.88	33.03
08:55	32.15	31.34	28.94	31.93	28.63
09:00	32.91	30.37	32.99	31.65	29.43
09:05	25.92	28.90	29.57	29.81	28.70
09:10	29.59	27.76	25.90	28.58	26.72
09:15	30.18	29.03	30.61	30.36	29.30
09:20	28.50	29.71	29.56	30.89	30.08
09:25	27.60	31.64	30.85	32.32	30.98
09:30	30.24	31.19	30.10	30.56	28.33
09:35	29.03	33.23	34.13	31.68	29.96
09:40	28.39	29.64	28.41	30.49	28.57
09:45	31.04	29.02	29.85	28.86	26.99
09:50	28.91	30.47	31.58	30.88	30.18
09:55	30.74	31.03	29.85	33.27	32.11
10:00	35.28	30.40	30.77	33.68	32.08

1 BJ-Model is Box-Jenkins modelling : ARIMA (0,1,2)(0,1,1)
2 HS-Model is Horizontal-Seasonal modelling : $\alpha=0.3$ and $\gamma=0.2$
3 Forecasts are 36-steps ahead not-updated forecasts.
4 Updated are 1-step ahead updated forecasts.

Table B.2 Link N018E - Journey Time Forecasts on 14-6-91

Time	Observed	BJ-Model		HS-Model	
		Forecasts	Updated	Forecasts	Updated
07:05	35.29	32.52	32.52	31.78	31.78
07:10	32.34	36.96	36.96	34.49	35.63
07:15	36.82	36.48	33.53	35.81	35.97
07:20	39.41	35.87	37.79	34.78	35.19
07:25	36.00	33.92	35.23	34.18	35.83
07:30	33.05	35.26	34.74	36.08	37.87
07:35	34.34	38.10	36.40	38.20	38.56
07:40	49.64	42.17	41.50	40.59	39.63
07:45	45.62	40.14	44.64	43.49	45.68
07:50	48.41	48.52	47.85	58.95	61.90
07:55	65.34	71.94	69.77	68.21	66.94
08:00	50.42	71.32	68.68	56.39	54.94
08:05	40.06	59.25	53.30	50.48	47.97
08:10	54.49	74.07	74.35	62.45	56.41
08:15	91.65	76.70	76.16	74.99	67.04
08:20	99.01	92.98	106.63	93.25	92.54
08:25	99.38	99.02	95.69	96.78	98.06
08:30	88.78	106.60	104.41	98.40	100.10
08:35	91.07	80.99	73.60	83.70	82.26
08:40	92.26	88.92	99.91	90.47	91.76
08:45	88.87	96.02	93.48	96.00	97.53
08:50	64.18	71.30	67.10	67.90	67.14
08:55	44.30	55.59	55.46	49.32	48.13
09:00	44.31	41.09	39.25	39.53	37.65
09:05	46.25	36.20	41.88	37.12	37.24
09:10	34.50	35.55	38.39	34.87	37.52
09:15	42.02	36.67	32.35	36.49	38.32
09:20	39.39	33.60	36.18	35.21	38.04
09:25	33.19	35.89	36.17	36.41	39.76
09:30	39.61	34.81	31.47	35.38	36.71
09:35	30.14	35.49	38.48	33.72	35.82
09:40	32.56	35.31	31.28	31.88	32.26
09:45	32.57	32.25	33.20	30.92	31.37
09:50	34.87	34.23	35.43	32.85	33.72
09:55	35.72	30.10	30.23	30.18	31.29
10:00	36.11	32.12	34.16	32.01	34.59

Table B.3 Route1 - Journey Time Forecasts on 14-6-91

Time	Observed	BJ-Model		HS-Model	
		Forecasts	Updated	Forecasts	Updated
07:05	202.12	200.91	200.91	204.91	204.91
07:10	197.30	215.22	215.22	213.29	212.42
07:15	205.49	231.31	221.06	226.63	220.89
07:20	208.90	226.21	216.37	224.41	214.15
07:25	213.86	224.26	221.11	222.05	210.34
07:30	227.11	229.91	228.47	221.74	211.10
07:35	222.32	229.67	230.71	228.60	222.58
07:40	268.17	241.41	238.04	239.74	233.34
07:45	248.98	251.32	268.01	265.33	269.82
07:50	256.00	264.25	256.26	279.72	277.86
07:55	263.72	283.41	279.41	280.25	271.81
08:00	236.44	269.29	260.43	255.10	245.21
08:05	216.33	249.22	235.91	245.35	233.30
08:10	253.99	276.18	266.14	272.60	253.56
08:15	309.74	285.21	281.12	295.54	275.04
08:20	312.78	315.82	334.98	322.68	311.67
08:25	327.15	332.43	324.61	330.83	319.88
08:30	311.04	334.78	332.61	328.23	319.53
08:35	315.42	327.29	315.44	324.70	313.57
08:40	303.11	315.25	314.60	316.06	305.77
08:45	303.41	332.81	329.04	326.87	315.40
08:50	280.17	345.25	331.96	320.27	305.51
08:55	246.77	312.04	283.27	285.95	265.98
09:00	253.68	278.33	258.38	258.29	235.05
09:05	235.56	254.55	257.18	243.48	226.83
09:10	226.25	246.22	241.85	235.49	221.93
09:15	237.92	232.67	226.34	227.25	215.41
09:20	240.67	225.49	233.39	223.07	218.07
09:25	226.16	224.74	231.85	224.44	226.23
09:30	212.06	226.69	223.68	224.27	226.05
09:35	218.46	227.43	218.96	221.38	218.99
09:40	208.50	226.22	224.90	216.32	213.82
09:45	198.81	220.12	212.52	211.35	207.35
09:50	213.27	223.74	216.35	218.21	211.43
09:55	238.77	213.98	213.49	208.39	202.45
10:00	214.07	206.64	223.02	206.29	211.20

Appendix C

Computer Programs to implement BJ and HS Models

C.1 BJ-Model Updating Program

```
      PROGRAM UPDATE_BJ
      INCLUDE 'JVAR.FOR'

*     ---------------------------------------------------------------
*     This program reads Journey Time forecasts generated by BOX-JENKINS
*     procedures of STATGRAPHICS package and update the forecasts for
*     every time period by reading the current day observations. Program also
*     calculates forecast-error statistics.
*     ---------------------------------------------------------------
*
      WRITE(*,*)
*
      CALL READ_FCAST
      CALL READ_NDATA
*
      WRITE(*,*) 'Enter the model number = '
      READ(*,*) NO
*
      IF(NO.EQ.35) THEN
       CALL MODEL_35
      ELSE
       WRITE(*,*) ' This model can not be updated.'
       GOTO 99
      ENDIF
*
      CALL WRITE_FCAST
      CALL ERROR_STAT
*
 99   END


      COMMON/PAR/ NO,SERR,SAERR,SSERR,SPERR,

1SAPERR,SE1,SE2,ME1,ME2,SAE1,SAE2,SSE1,SSE2,MAD1,MAD2,MSE1,MSE2,
     2CHISUM1,CHISUM2,CHISQ1,CHISQ2,PSUM1,PSUM2,MAPE1,MAPE2
*
      COMMON/DIM1/ OBSER,ERR1,ERR2,ME,MAE,MSE,MPE,MAPE
*
      COMMON/DIM1/ FCAST,UPDATE
*
      COMMON/CHAR/ TIME
*
*
      INTEGER NO
```

```
      REAL OBSER(36),ERR1(36),ERR2(36)
      REAL FCAST(36),UPDATE(36)
      REAL SERR,SAERR,SSERR,SPERR,SAPERR
      REAL ME(36),MAE(36),MSE(36),MPE(36),MAPE(36)
      REAL SE1,ME1,SAE1,SSE1,MAD1,MSE1,CHISUM1,CHISQ1,PSUM1,MAPE1
      REAL SE2,ME2,SAE2,SSE2,MAD2,MSE2,CHISUM2,CHISQ2,PSUM2,MAPE2
      CHARACTER*5 TIME(36)


      SUBROUTINE READ_FCAST
      INCLUDE 'JVAR.FOR'
      INTEGER I
      CHARACTER*15 FFILE
      WRITE(*,*) 'Enter the FORECASTS file name : '
      READ(*,16) FFILE
 16   FORMAT(A10)
      OPEN (UNIT=1,FILE=FFILE,STATUS='OLD')
      DO 10 I=1,36
        READ(1,11,END=100) FCAST(I)
 11     FORMAT(F10.5)
 10   CONTINUE
 100  END
*
*
      SUBROUTINE READ_NDATA
      INCLUDE 'JVAR.FOR'
      INTEGER K,CT
      REAL DELAY(36),FLOW(36)
      CHARACTER*15 NDFILE
      WRITE(*,*) 'Enter the NEW DATA filename : '
      READ(*,25) NDFILE
 25   FORMAT(A15)
      OPEN (UNIT=2, FILE=NDFILE,STATUS='OLD')
      WRITE(*,*) 'Enter the CRUISE TIME = '
      READ(*,*) CT
      DO 21 K=1,36
       READ(2,22,END=200) TIME(K),DELAY(K),FLOW(K)
 22    FORMAT(A5,F5.0,F6.0)
       OBSER(K)=((DELAY(K)/FLOW(K))*360.0)+FLOAT(CT)
 21   CONTINUE
 200  END
*
*

      SUBROUTINE MODEL_35
*     ======  ARIMA (0,1,2)(0,1,1)  ========
      INCLUDE 'JVAR.FOR'
```

```
      INTEGER I,J
      REAL THETA1,THETA2
*
      WRITE(*,*) 'Enter the value of THETA1 = '
      READ(*,*) THETA1
*
      WRITE(*,*) 'Enter the value of THETA2 = '
      READ(*,*) THETA2
*
        UPDATE(1)=FCAST(1)
        UPDATE(2)=FCAST(2)
*
       DO 341 I=3,36
           UPDATE(I)=FCAST(I)-FCAST(I-1)+OBSER(I-1)-
     1     THETA1*(OBSER(I-1)-FCAST(I-1))-
     2     THETA2*(OBSER(I-2)-FCAST(I-2))
 342    CONTINUE
 341   CONTINUE
      END
*
*
      SUBROUTINE WRITE_FCAST
      INCLUDE 'JVAR.FOR'
      INTEGER I
      CHARACTER*15 UPFILE
      WRITE(*,*) ' Enter the UPDATED FORECASTS file name : '
      READ(*,56) UPFILE
 56    FORMAT(A10)
      OPEN (UNIT=9,FILE=UPFILE,STATUS='NEW')
      DO 51 I=1,36
       WRITE(9,52) I,FCAST(I),OBSER(I),UPDATE(I)
 52     FORMAT(1X,I2,2X,3(1X,F8.2))
 51    CONTINUE
 500   END
*
*
      SUBROUTINE ERROR_STAT
      INCLUDE 'JVAR.FOR'
      CHARACTER*15 ESFILE
      WRITE(*,*) ' Enter ERROR STATISTICS file name : '
      READ(*,70) ESFILE
 70    FORMAT(A10)
      OPEN (UNIT=8,FILE=ESFILE,STATUS='NEW')
      SE1=0.0
      SAE1=0.0
      SSE1=0.0
      CHISUM1=0.0
      PSUM1=0.0
```

```
      DO 71 I=1,36
       ERR1(I)=OBSER(I)-FCAST(I)
       SE1=SE1+ERR1(I)
       SAE1=SAE1+ABS(ERR1(I))
       SSE1=SSE1+ERR1(I)**2
       CHISUM1=CHISUM1+(ERR1(I)/OBSER(I))
       PSUM1=PSUM1+ABS(ERR1(I)/OBSER(I))
71    CONTINUE
      ME1=SE1/36.0
      MAD1=SAE1/36.0
      MSE1=SSE1/36.0
      CHISQ1=(100.0/36.0)*CHISUM1
      MAPE1=(100.0/36.0)*PSUM1
      SE2=0.0
      SAE2=0.0
      SSE2=0.0
      CHISUM2=0.0
      PSUM2=0.0
      DO 72 J=1,36
       ERR2(J)=OBSER(J)-UPDATE(J)
       SE2=SE2+ERR2(J)
       SAE2=SAE2+ABS(ERR2(J))
       SSE2=SSE2+ERR2(J)**2
       CHISUM2=CHISUM2+(ERR2(J)/OBSER(J))
       PSUM2=PSUM2+ABS(ERR2(J)/OBSER(J))
72    CONTINUE
      ME2=SE2/36.0
      MAD2=SAE2/36.0
      MSE2=SSE2/36.0
      CHISQ2=(100.0/36.0)*CHISUM2
      MAPE2=(100.0/36.0)*PSUM2
      WRITE(8,73) ME1, ME2, MAD1, MAD2, MSE1, MSE2, CHISQ1, CHISQ2,
      MAPE1, MAPE2
73    FORMAT(8X///,8X,'FORECAST',38X,'UPDATE',1X////,
     17X,'ME = ',F12.2,28X,'ME = ',F12.2////,
     26X,'MAE = ' ,F12.2,28X,'MAE = ',F12.2////,
     37X,'MSE = ',F12.2,26X,'MSE = ',F12.2////,
     47X,'MPE = ',F12.2,26X,'MPE = ',F12.2////,
     57X,'MAPE = ',F12.2,26X,'MAPE = ',F12.2)
      WRITE(*,*) 'THIS IS END OF THE PROGRAM'
      END
```

```
      PROGRAM MODEL
      INCLUDE 'HSVARS.FOR'
      CHARACTER*10 FRFILE

*     --------------------------------------------------------
*     This program implement HORIZONTAL SEASONAL MODEL.
*
*     INPUT:
*
*     Number of days.
*     Number of time periods in each day.
*     Data file containing specified number of days data.
*     Data file containing current day data for updating.
*     Values of smoothing parameters.
*
*     OUTPUT:
*
*     36-steps ahead not-updated forecasts.
*     1-step ahead updated forecasts.
*     Forecast-Error statistics.
*
*     --------------------------------------------------------
*
      WRITE(*,*)
      WRITE(*,*) 'Enter '
      WRITE(*,*)
      WRITE(*,*) 'DAYS = '
      READ*,DAYS
      WRITE(*,*) 'TIME PERIODS = '
      READ*,PERIODS
      WRITE(*,*) 'ALPHA = '
      READ(*,*) ALPHA
      WRITE(*,*) 'GAMMA = '
      READ(*,*) GAMMA
      WRITE(*,*) 'Cruise Time = '
      READ(*,*) CT
      WRITE(*,*)
      CALL STEP1
      CALL STEP2
      CALL STEP3
      CALL STEP4
      CALL STEP5
      CALL STEP6
      CALL FC
      CALL NDATA
```

```
      PRINT*
       CALL UPDATE
      PRINT*
      WRITE(*,*) ' Enter the FORECAST RESULTS  file name :'
      READ(*,106) FRFILE
  106 FORMAT(A10)
      OPEN (UNIT=13,FILE=FRFILE,STATUS='NEW')
      DO 96 I=1,PERIODS
       WRITE(13,93) I,FORECAST(I),NEWDATA(I),UPCAST(I)
   93  FORMAT(1X,I2,2X,3(1X,F8.2))
   96 CONTINUE
      PRINT*
      CALL ANALYSIS
      PRINT*
      CALL WP
      PRINT*
      END


      COMMON/DIM2/ DATA,RTILD,AHAT,RHAT
      COMMON/DIM1/ MEAN,RFINAL,FORECAST,NEWDATA,UPCAST
      COMMON/PAR/DAYS,PERIODS,ALPHA,GAMMA,CT
      COMMON/CHAR/TIME
*
      REAL DATA(11,36),RTILD(11,36),AHAT(11,0:36),RHAT(11,0:36)
      REAL MEAN(36),RFINAL(36),FORECAST(36),NEWDATA(36),UPCAST(36)
      INTEGER DAYS,PERIODS
      REAL ALPHA,GAMMA,CT
      CHARACTER*5 TIME(36)


      SUBROUTINE STEP1
*
      INCLUDE 'HSVARS.FOR'
      REAL DELAY(10,36),FLOW(10,36)
      CHARACTER*10 DFILE
*
      WRITE(*,*) ' Enter the DATA file name :'
      READ(*,16) DFILE
   16 FORMAT(A10)
      OPEN (UNIT=11,FILE=DFILE,STATUS='OLD')
      DO 10 I=1,DAYS
       DO 11 J=1,PERIODS
         READ(11,12,END=100) DELAY(I,J),FLOW(I,J)
   12    FORMAT(5X,F4.0,F5.0)
         DATA(I,J)=((DELAY(I,J)/FLOW(I,J))*360.0)+CT
   11  CONTINUE
   10 CONTINUE
```

```
 100  RETURN
      END
*
*
      SUBROUTINE STEP2
*
      REAL SUM(36)
      INCLUDE 'HSVARS.FOR'
      DO 20 I=1,DAYS
       SUM(I)=0
         DO 21 J=1,PERIODS
          SUM(I)=SUM(I)+DATA(I,J)
  21     CONTINUE
       MEAN(I)=SUM(I)/FLOAT(PERIODS)
  20   CONTINUE
      RETURN
      END
*
*
      SUBROUTINE STEP3
*
      INCLUDE 'HSVARS.FOR'
      DO 30 I=1,DAYS
       DO 31 J=1,PERIODS
          RTILD(I,J)=DATA(I,J)/MEAN(I)
  31    CONTINUE
  30   CONTINUE
      RETURN
      END
*
*
      SUBROUTINE STEP4
*
      REAL SRTILD(36)
      INCLUDE 'HSVARS.FOR'
      DO 40 J=1,PERIODS
       SRTILD(J)=0
         DO 41 I=1,DAYS
          SRTILD(J)=SRTILD(J)+RTILD(I,J)
  41     CONTINUE
       RHAT(1,J)=SRTILD(J)/FLOAT(DAYS)
  40   CONTINUE
      RETURN
      END
*
*
      SUBROUTINE STEP5
*
```

```
      INCLUDE 'HSVARS.FOR'
       DO 50 I=1,DAYS
       IF(I.EQ.1)THEN
         AHAT(I,0)=MEAN(I)
       ELSE
         AHAT(I,0)=AHAT(I-1,PERIODS)
       ENDIF
         DO 51 J=1,PERIODS
          IF(J.EQ.1)THEN
           RHAT(I+1,0)=RHAT(I,PERIODS)
          ENDIF
          AHAT(I,J)=ALPHA*(DATA(I,J)/RHAT(I,J))+(1.0-ALPHA)*AHAT(I,J-1)
          RHAT(I+1,J)=GAMMA*(DATA(I,J)/AHAT(I,J))+(1.0-GAMMA)*RHAT(I,J)
 51       CONTINUE
 50     CONTINUE
      RETURN
      END
*
*
      SUBROUTINE STEP6
*
      REAL RSUM,RMEAN
      INCLUDE 'HSVARS.FOR'
      RSUM=0.0
      DO 61 I=1,PERIODS
       RSUM=RSUM+RHAT(DAYS+1,I)
 61    CONTINUE
       RMEAN=RSUM/FLOAT(PERIODS)
      DO 62 J=1,PERIODS
        RFINAL(J)=RHAT(DAYS+1,J)/RMEAN
 62    CONTINUE
      RETURN
      END
*
*
      SUBROUTINE FC
*
      INCLUDE 'HSVARS.FOR'
        DO 71 I=1,PERIODS
         FORECAST(I)=AHAT(DAYS,PERIODS)*RFINAL(I)
 71      CONTINUE
       RETURN
      END
*
*
      SUBROUTINE NDATA
*
      INCLUDE 'HSVARS.FOR'
```

```
      REAL NDELAY(36),NFLOW(36)
      CHARACTER*10 NDFILE
      WRITE(*,*) ' Enter the NEW DATA file name :'
      READ(*,79) NDFILE
   79 FORMAT(A10)
      OPEN (UNIT=12,FILE=NDFILE,STATUS='OLD')
      DO 75 I=1,PERIODS
       READ(12,76,END=200) TIME(I),NDELAY(I),NFLOW(I)
   76  FORMAT(A5,F4.0,F5.0)
       NEWDATA(I)=((NDELAY(I)/NFLOW(I))*360.0)+CT
   75 CONTINUE
  200 RETURN
      END
*
*
      SUBROUTINE UPDATE
*
      REAL AHATNEW(0:36),RNEW(36)
      INCLUDE 'HSVARS.FOR'
      AHATNEW(0)=AHAT(DAYS,PERIODS)
       DO 81 I=1,PERIODS

AHATNEW(I)=ALPHA*(NEWDATA(I)/RFINAL(I))+(1.0-ALPHA)*AHATNEW(I-1)
        RNEW(I)=GAMMA*(NEWDATA(I)/AHATNEW(I))+GAMMA*RFINAL(I)
   81   CONTINUE
        DO 82 J=2,PERIODS
         UPCAST(J)=AHATNEW(J-1)*RFINAL(J)
   82   CONTINUE
        UPCAST(1)=FORECAST(1)
       RETURN
      END
*
*
      SUBROUTINE ANALYSIS
*
      INCLUDE 'HSVARS.FOR'
      REAL ERR1(36),ERR2(36)
      REAL SE1,SAE1,SSE1,ME1,MAD1,MSE1,CHISUM1,CHISQ1,PSUM1,MAPE1
      REAL SE2,SAE2,SSE2,ME2,MAD2,MSE2,CHISUM2,CHISQ2,PSUM2,MAPE2
      CHARACTER*10 FEFILE
      SE1=0.0
      SAE1=0.0
      SSE1=0.0
      CHISUM1=0.0
      PSUM1=0.0
      DO 101 I=1,PERIODS
       ERR1(I)=NEWDATA(I)-FORECAST(I)
       SE1=SE1+ERR1(I)
```

```
      SAE1=SAE1+ABS(ERR1(I))
      SSE1=SSE1+ERR1(I)**2
      CHISUM1=CHISUM1+(ERR1(I)/NEWDATA(I))
      PSUM1=PSUM1+ABS(ERR1(I)/NEWDATA(I))
 101  CONTINUE
      ME1=SE1/FLOAT(PERIODS)
      MAD1=SAE1/FLOAT(PERIODS)
      MSE1=(SSE1/FLOAT(PERIODS))
      CHISQ1=(100.0/36.0)*CHISUM1
      MAPE1=(100.0/36.0)*PSUM1
      SE2=0.0
      SAE2=0.0
      SSE2=0.0
      CHISUM2=0.0
      PSUM2=0.0
     DO 103 J=1,PERIODS
      ERR2(J)=NEWDATA(J)-UPCAST(J)
      SE2=SE2+ERR2(J)
      SAE2=SAE2+ABS(ERR2(J))
      SSE2=SSE2+ERR2(J)**2
      CHISUM2=CHISUM2+(ERR2(J)/NEWDATA(J))
      PSUM2=PSUM2+ABS(ERR2(J)/NEWDATA(J))
 103  CONTINUE
      ME2=SE2/FLOAT(PERIODS)
      MAD2=SAE2/FLOAT(PERIODS)
      MSE2=(SSE2/FLOAT(PERIODS))
      CHISQ2=(100.0/36.0)*CHISUM2
      MAPE2=(100.0/36.0)*PSUM2
*
     WRITE(*,*) ' Enter the FORECAST ERROR file name :'
     READ(*,107) FEFILE
 107  FORMAT(A10)
     OPEN (UNIT=18,FILE=FEFILE,STATUS='NEW')
     WRITE(18,102)
ME1,ME2,MAD1,MAD2,MSE1,MSE2,CHISQ1,CHISQ2,MAPE1,
    1MAPE2
 102  FORMAT(8X///,8X,'FORECAST',38X,'UPDATE',1X////,
    18X,'ME = ',F8.2,34X,'ME = ',F8.2////,
    27X,'MAE = ',F8.2,33X,'MAE = ',F8.2///,
    37X,'MSE = ',F8.2,30X,'MSE = ',F8.2///,
    47X,'MPE = ',F8.2,33X,'MPE = ',F8.2///,
    57X,'MAPE = ',F8.2,33X,'MAPE = ',F8.2)
     RETURN
     END
*
*
     SUBROUTINE WP
*
```

```
      INCLUDE 'HSVARS.FOR'
      CHARACTER*10 RFILE
      WRITE(*,*) ' Enter the WP-RESULTS file name :'
      READ(*,119) RFILE
119   FORMAT(A10)
      OPEN (UNIT=15,FILE=RFILE,STATUS='NEW')
      WRITE(15,*) 'AHAT(6,36) = ',AHAT(DAYS,PERIODS)
      WRITE(15,*)
      DO 109 I=1,DAYS
      WRITE(15,112) I,MEAN(I)
112   FORMAT(2X,I2,2X,F5.2)
109   CONTINUE
      WRITE(15,*)
      DO 110 I=1,12
      WRITE(15,111) TIME(I),RFINAL(I),TIME(I+12),RFINAL(I+12),TIME(I+24)
     1,RFINAL(I+24)
111   FORMAT(3(3X,A5,2X,F8.2))
110   CONTINUE
      RETURN
      END
```

Appendix D

Traffic Characteristics of the links studied.

Table D.1 Congestion Index values for Non-Incident case (Simulated)

Time	* K-714	K-730	B-1494	B-1692	L-3232
8:05	1.29	1.00	1.85	2.80	1.75
8:10	1.57	1.51	2.45	2.98	1.75
8:15	2.06	1.96	2.92	2.97	1.93
8:20	2.84	1.93	3.19	3.18	2.25
8:25	4.44	2.21	3.92	3.19	2.42
8:30	6.50	2.78	5.20	3.17	3.24
8:35	6.07	2.94	5.62	2.95	3.28
8:40	6.22	3.06	5.10	3.00	3.03
8:45	6.63	2.78	4.22	2.97	3.49
8:50	5.91	2.69	4.12	3.18	3.21
8:55	2.65	2.05	4.49	3.20	2.52
9:00	1.81	2.17	5.11	3.17	2.89

Table D.2 Degree of Saturation values for Non-Incident case (Simulated)

Time	K-714	K-730	B-1494	B-1692
8:05	0.06	0.00	0.35	0.13
8:10	0.51	0.24	0.95	0.23
8:15	0.77	0.17	0.95	0.33
8:20	0.95	0.51	0.98	0.36
8:25	1.13	0.53	1.16	0.33
8:30	0.94	0.86	1.05	0.34
8:35	1.01	0.78	0.98	0.23
8:40	1.02	0.89	0.85	0.24
8:45	0.98	0.78	0.93	0.33
8:50	0.87	0.75	0.97	0.36
8:55	0.76	0.50	1.09	0.34
9:00	0.71	0.57	0.97	0.37

*	K-714	Kingston Network Link 714
	K-730	Kingston Network Link 730
	B-1494	Boscombe Network Link 1494
	B-1692	Boscombe Network Link 1692
	L-3232	London Network Link 3232

Table D.3 Delay (sec/veh) values for Non-Incident case (simulated)

Time	K-714	K-730	B-1494	B-1692	L-3232
8:05	4	0	27	9	21
8:10	6	11	45	10	21
8:15	11	20	60	10	26
8:20	19	17	69	11	35
8:25	37	22	95	11	40
8:30	57	31	135	11	40
8:35	49	34	144	10	63
8:40	53	36	121	10	62
8:45	57	31	99	10	56
8:50	47	29	97	11	72
8:55	15	18	111	11	60
9:00	8	20	129	11	41

Appendix E

Simulated Number of Links Affected

Table E.1 Number of links affected with incident on link K-714 (Simulated)

Time	* I1	I2	I3	I4	I5	I6
8:05	0	0	0	1	1	1
8:10	0	1	1	1	1	1
8:15	0	1	1	2	2	2
8:20	0	2	2	3	4	5
8:25	0	5	4	3	9	9
8:30	0	8	8	2	26	27
8:35	0	9	11	4	33	38
8:40	0	9	15	4	33	46
8:45	0	8	17	4	31	51
8:50	0	9	15	3	26	53
8:55	0	6	12	3	23	54
9:00	0	3	10	1	18	51

Time	I7	I8	I9	I10	I11	I12
8:05	1	1	1	1	1	1
8:10	2	2	2	3	3	3
8:15	4	4	4	9	9	9
8:20	4	10	10	10	20	20
8:25	9	23	23	12	34	34
8:30	7	37	38	12	51	51
8:35	8	46	52	18	56	55
8:40	8	51	54	19	55	57
8:45	8	49	58	17	56	57
8:50	9	48	58	18	56	57
8:55	7	43	59	14	58	60
9:00	2	20	59	11	57	60

* Incident categories I1 .. I12 are defined as:

Severity	Duration		
	15-min	30-min	45-min
20%	I1	I2	I3
50%	I4	I5	I6
70%	I7	I8	I9
99%	I10	I11	I12

Table E.2 Number of links affected with incident on link K-730 (Simulated)

Time	I1	I2	I3	I4	I5	I6
8:05	0	0	0	0	0	0
8:10	0	0	0	0	1	1
8:15	0	0	0	0	1	1
8:20	0	0	1	0	1	1
8:25	0	0	1	0	1	1
8:30	0	0	1	0	1	3
8:35	0	0	1	0	1	3
8:40	0	0	1	0	1	5
8:45	0	0	1	0	1	5
8:50	0	0	1	0	1	5
8:55	0	0	0	0	0	4
9:00	0	0	0	0	0	3

Time	I7	I8	I9	I10	I11	I12
8:05	0	0	0	0	0	0
8:10	0	1	1	1	1	1
8:15	0	1	1	1	1	1
8:20	0	1	1	1	3	3
8:25	0	3	3	0	5	5
8:30	0	5	6	0	6	7
8:35	0	4	5	0	5	11
8:40	0	3	6	1	6	14
8:45	0	3	12	1	7	19
8:50	0	3	11	1	6	22
8:55	0	1	10	1	5	22
9:00	0	0	9	0	6	23

Table E.3 Number of links affected with incident on link B-1692 (Simulated)

Time	I1	I2	I3	I4	I5	I6
8:05	0	0	0	0	0	0
8:10	0	0	0	0	1	1
8:15	0	0	0	0	1	1
8:20	0	0	0	0	1	1
8:25	0	0	0	0	1	1
8:30	0	0	0	0	1	1
8:35	0	0	0	0	0	1
8:40	0	0	0	0	0	1
8:45	0	0	0	0	0	1
8:50	0	0	0	0	0	0
8:55	0	0	0	0	0	0
9:00	0	0	0	0	0	0

Time	I7	I8	I9	I10	I11	I12
8:05	1	1	1	1	1	1
8:10	1	1	1	2	2	2
8:15	2	1	2	2	2	2
8:20	0	1	1	3	4	4
8:25	0	1	1	1	6	6
8:30	0	1	1	2	6	6
8:35	0	1	1	1	9	7
8:40	0	0	1	1	5	7
8:45	0	0	1	0	3	10
8:50	0	0	1	0	1	13
8:55	0	0	0	0	1	13
9:00	0	0	0	0	1	10

Table E.4 Number of links affected with incident on link B-1494 (Simulated)

Time	I1	I2	I3	I4	I5	I6
8:05	0	0	0	1	1	1
8:10	1	1	1	1	1	1
8:15	1	1	1	1	1	1
8:20	1	1	1	1	3	3
8:25	1	1	1	1	8	8
8:30	1	1	2	1	13	13
8:35	1	1	3	1	16	20
8:40	1	1	3	1	12	21
8:45	1	1	4	1	12	24
8:50	1	1	4	1	12	27
8:55	1	1	5	1	13	26
9:00	0	1	5	1	13	26

Time	I7	I8	I9	I10	I11	I12
8:05	1	1	1	1	1	1
8:10	1	1	1	3	3	3
8:15	3	3	3	9	9	9
8:20	5	9	9	9	17	17
8:25	5	17	17	11	27	26
8:30	5	22	22	11	33	33
8:35	6	25	28	15	38	38
8:40	5	24	30	11	36	39
8:45	5	23	35	10	37	42
8:50	4	22	33	10	34	48
8:55	4	22	35	11	34	49
9:00	5	22	36	11	35	52

Table E.5 Number of links affected with incident on link L-3232 (Simulated)

Time	I3	I6	I9
8:05	0	1	1
8:10	0	1	1
8:15	2	3	3
8:20	6	6	7
8:25	5	6	7
8:30	8	10	11
8:35	16	21	21
8:40	26	31	30
8:45	39	43	42
8:50	40	45	43
8:55	38	41	38
9:00	17	46	41

Appendix F

Simulated Journey Times

Table F.1 Simulated Journey Times for Link K-714

Time	Non [1]	I1	I2	I3	I4	I5	I6
8:05	14	14	14	14	15	15	15
8:10	16	17	17	17	33	33	33
8:15	21	30	31	31	68	87	87
8:20	29	32	59	59	68	123	123
8:25	47	49	76	76	63	118	118
8:30	67	60	78	79	62	116	116
8:35	59	59	68	80	62	61	105
8:40	63	64	64	78	64	60	109
8:45	67	69	58	73	68	61	106
8:50	57	57	59	63	66	67	61
8:55	25	25	61	57	48	59	58
9:00	18	18	50	57	22	53	60

Time	I7	I8	I9	I10	I11	I12
8:05	15	15	15	626	1204	1204
8:10	90	90	90	587	1422	1798
8:15	184	185	185	327	1216	2108
8:20	63	180	180	82	934	1825
8:25	56	189	189	58	646	1538
8:30	62	195	195	64	371	1262
8:35	60	65	174	63	94	960
8:40	58	67	203	67	63	663
8:45	63	57	166	63	63	399
8:50	62	57	64	59	64	126
8:55	58	60	60	62	72	74
9:00	50	56	56	64	60	59

1 Non — Non-incident case.
I1 .. I12 — Incident categories as defined on page 213.

Table F.2 Simulated Journey Times for Link K-730

Time	Non	I1	I2	I3	I4	I5	I6
8:05	17	17	17	17	17	17	17
8:10	28	28	28	28	32	32	32
8:15	37	37	37	37	41	41	41
8:20	34	34	37	37	34	55	55
8:25	39	39	43	43	39	103	103
8:30	48	48	68	71	48	162	206
8:35	51	51	59	91	51	149	320
8:40	53	54	55	115	54	112	367
8:45	48	51	51	129	51	79	271
8:50	46	48	49	91	48	48	179
8:55	35	36	36	35	36	35	174
9:00	37	37	37	37	37	37	148

Time	I7	I8	I9	I10	I11	I12
8:05	17	17	17	17	17	17
8:10	43	43	43	583	981	1096
8:15	61	61	61	294	1186	2075
8:20	35	97	97	109	991	1880
8:25	39	359	390	39	692	1578
8:30	48	329	489	48	510	1395
8:35	51	177	557	51	272	1072
8:40	54	171	593	54	190	771
8:45	51	156	311	51	165	609
8:50	48	154	178	48	170	331
8:55	36	84	178	36	172	192
9:00	37	37	179	37	159	165

Table F.3 Simulated Journey Times for Link B-1494

Time	Non	I1	I2	I3	I4	I5	I6
8:05	58	60	60	60	72	72	72
8:10	76	102	102	102	208	208	208
8:15	91	159	166	166	331	477	477
8:20	100	170	231	231	339	665	668
8:25	126	193	327	328	353	652	753
8:30	166	227	381	429	375	503	755
8:35	175	238	386	469	384	399	747
8:40	152	216	376	478	373	389	647
8:45	130	194	354	432	349	391	501
8:50	128	188	341	391	336	392	406
8:55	142	199	345	391	340	394	391
9:00	160	168	209	251	209	251	251

Time	I7	I8	I9	I10	I11	I12
8:05	136	136	136	767	1658	2548
8:10	377	464	464	703	1593	2484
8:15	440	941	962	648	1538	2428
8:20	403	962	1243	411	1242	2131
8:25	390	750	1239	392	873	1763
8:30	392	535	1164	394	680	1569
8:35	394	407	969	391	429	1279
8:40	391	392	744	390	394	985
8:45	390	393	525	392	399	703
8:50	391	391	416	393	402	445
8:55	392	390	398	391	404	398
9:00	244	253	239	250	242	227

Table F.4 Simulated Journey Times for Link B-1692

Time	Non	I1	I2	I3	I4	I5	I6
8:05	14	14	14	14	16	16	16
8:10	15	15	15	15	19	19	19
8:15	15	17	17	17	24	24	24
8:20	16	16	17	17	16	27	27
8:25	16	16	17	17	16	27	27
8:30	16	16	17	17	16	27	27
8:35	15	15	15	15	15	15	20
8:40	15	15	15	16	15	15	20
8:45	15	15	15	17	15	15	24
8:50	16	16	16	16	16	16	16
8:55	16	16	16	16	16	16	16
9:00	16	16	16	16	16	16	16

Time	I7	I8	I9	I10	I11	I12
8:05	21	21	21	694	1585	2363
8:10	35	35	35	578	1469	2360
8:15	57	68	68	337	1228	2119
8:20	19	125	125	53	933	1824
8:25	16	158	158	17	535	1426
8:30	16	137	159	16	287	1178
8:35	15	25	159	15	75	791
8:40	15	15	159	15	56	605
8:45	15	15	134	15	23	385
8:50	16	16	22	16	16	98
8:55	16	16	16	16	16	58
9:00	16	16	16	16	16	53

Table F.5 Simulated Journey Times for link L-3232

Time	Non	I3	I6	I9
8:05	49	52	67	137
8:10	49	52	69	189
8:15	54	62	119	379
8:20	63	93	269	606
8:25	68	100	379	769
8:30	68	125	446	1051
8:35	91	184	506	970
8:40	90	233	501	736
8:45	84	237	422	537
8:50	100	228	361	357
8:55	88	160	307	357
9:00	69	113	201	221

Appendix G

Databases Compiled from Simulation Runs

Table G.1 Database for slope M1

Duration *	Severity	LCI	M1	Link
15	0.20	1.64	0.00	714
15	0.50	1.64	0.20	714
15	0.70	1.64	0.40	714
15	0.99	1.64	1.20	714
30	0.20	3.12	0.28	714
30	0.50	3.12	1.14	714
30	0.70	3.12	1.72	714
30	0.99	3.12	2.38	714
45	0.20	4.18	0.42	714
45	0.50	4.18	1.60	714
45	0.70	4.18	1.86	714
45	0.99	4.18	1.77	714
15	0.20	2.40	0.00	1494
15	0.50	2.40	0.00	1494
15	0.70	2.40	0.40	1494
15	0.99	2.40	1.20	1494
30	0.20	3.26	0.00	1494
30	0.50	3.26	0.62	1494
30	0.70	3.26	1.12	1494
30	0.99	3.26	1.56	1494
45	0.20	3.83	0.09	1494
45	0.50	3.83	0.76	1494
45	0.70	3.83	1.04	1494
45	0.99	3.83	1.17	1494
30	0.50	1.73	0.06	730
30	0.70	1.73	0.18	730
30	0.99	1.73	0.28	730
45	0.20	2.13	0.04	730
45	0.50	2.13	0.13	730
45	0.70	2.13	0.25	730
45	0.99	2.13	0.48	730

*	Duration	Duration of the incident in minutes
	Severity	Severity of the incident (between 0 to 1)
	LCI	Link congestion index
	M1	slope calculated by using equation 6.1
	Link	Link number

Table G.2 Database for Slope M2

Time	* Duration	Severity	M2	LCI	Link
8:20	15	0.5	0.2	2.84	714
8:30	15	0.5	-0.2	6.50	714
8:35	15	0.5	0.4	6.07	714
8:50	15	0.5	-0.2	5.91	714
9:00	15	0.5	-0.4	1.81	714
8:25	15	0.7	1.0	4.44	714
8:30	15	0.7	-0.4	6.50	714
8:35	15	0.7	0.2	6.07	714
8:50	15	0.7	0.2	5.91	714
8:55	15	0.7	-0.4	2.65	714
9:00	15	0.7	-1.0	1.81	714
8:35	30	0.2	0.2	6.07	714
8:45	30	0.2	-0.2	6.63	714
8:50	30	0.2	0.2	5.91	714
8:55	30	0.2	-0.6	2.65	714
9:00	30	0.2	-0.6	1.81	714
8:35	30	0.5	1.4	6.07	714
8:45	30	0.5	-0.4	6.63	714
8:50	30	0.5	-1.0	5.91	714
8:55	30	0.5	-0.6	2.65	714
9:00	30	0.5	-1.0	1.81	714
8:35	30	0.7	1.8	6.07	714
8:40	30	0.7	1.0	6.22	714
8:45	30	0.7	-0.4	6.63	714
8:50	30	0.7	-0.2	5.91	714
8:55	30	0.7	-1.0	2.65	714
8:50	45	0.2	-0.4	5.91	714
8:55	45	0.2	-0.6	2.65	714
9:00	45	0.2	-0.4	1.81	714
8:50	45	0.5	0.4	5.91	714
8:55	45	0.5	0.2	2.65	714
9:00	45	0.5	-0.6	1.81	714
8:55	45	0.7	0.2	2.65	714
8:55	30	0.5	-0.2	2.05	730
8:35	30	0.7	-0.2	2.94	730
8:40	30	0.7	-0.2	3.06	730
8:55	30	0.7	-0.4	2.05	730
9:00	30	0.7	-0.2	2.17	730

Table G.2 (Contd) Database for Slope M2

Time	Duration	Severity	M2	LCI	Link
8:55	45	0.2	-0.2	2.05	730
8:55	45	0.5	-0.2	2.05	730
9:00	45	0.5	-0.2	2.17	730
8:50	45	0.7	-0.2	2.69	730
8:55	45	0.7	-0.2	2.05	730
9:00	45	0.7	-0.2	2.17	730
9:00	15	0.2	-0.2	5.11	1494
8:20	15	0.7	0.4	3.19	1494
8:35	15	0.7	0.2	5.62	1494
8:40	15	0.7	-0.2	5.10	1494
8:50	15	0.7	-0.2	4.12	1494
9:00	15	0.7	0.2	5.11	1494
8:35	30	0.5	0.6	5.62	1494
8:40	30	0.5	-0.8	5.10	1494
8:55	30	0.5	0.2	4.49	1494
8:35	30	0.7	0.6	5.62	1494
8:40	30	0.7	-0.2	5.10	1494
8:45	30	0.7	-0.2	4.22	1494
8:50	30	0.7	-0.2	4.12	1494
8:55	45	0.2	0.2	4.49	1494
8:50	45	0.5	0.6	4.12	1494
8:55	45	0.5	-0.2	4.49	1494
8:50	45	0.7	-0.4	4.12	1494
8:55	45	0.7	0.4	4.49	1494
9:00	45	0.7	0.2	5.11	1494

*	Duration	Duration of the incident in minutes
	Severity	Severity of the incident (between 0 to 1)
	LCI	Link congestion index
	M2	slope calculated by using equation 6.4
	Link	Link number

Table G.3 Database for Slope S1

Severity	LCI	S1	DSat	CT	Delay	Link
0.2	1.57	0.6	0.51	10	6	714
0.5	1.57	3.6	0.51	10	6	714
0.7	1.57	15.0	0.51	10	6	714
0.2	1.57	0.6	0.51	10	6	714
0.5	1.57	3.6	0.51	10	6	714
0.7	1.57	15.0	0.51	10	6	714
0.2	1.57	0.6	0.51	10	6	714
0.5	1.57	3.6	0.51	10	6	714
0.7	1.57	15.0	0.51	10	6	714
0.2	1.51	2.2	0.24	17	11	730
0.5	1.51	3.0	0.24	17	11	730
0.7	1.51	5.2	0.24	17	11	730
0.2	1.51	2.2	0.24	17	11	730
0.5	1.51	3.0	0.24	17	11	730
0.7	1.51	5.2	0.24	17	11	730
0.2	1.51	2.2	0.24	17	11	730
0.5	1.51	3.0	0.24	17	11	730
0.7	1.51	5.2	0.24	17	11	730
0.2	2.45	8.4	0.95	31	45	1494
0.5	2.45	27.2	0.95	31	45	1494
0.7	2.45	48.2	0.95	31	45	1494
0.2	2.45	8.4	0.95	31	45	1494
0.5	2.45	27.2	0.95	31	45	1494
0.7	2.45	65.6	0.95	31	45	1494
0.2	2.45	8.4	0.95	31	45	1494
0.5	2.45	27.2	0.95	31	45	1494
0.7	2.45	65.6	0.95	31	45	1494
0.2	2.98	0.2	0.23	5	10	1692
0.5	2.98	0.6	0.23	5	10	1692
0.7	2.98	2.8	0.23	5	10	1692
0.2	2.98	0.2	0.23	5	10	1692
0.5	2.98	0.6	0.23	5	10	1692
0.7	2.98	2.8	0.23	5	10	1692
0.2	2.98	0.2	0.23	5	10	1692
0.5	2.98	0.6	0.23	5	10	1692
0.7	2.98	2.8	0.23	5	10	1692
0.2	2.06	2.6	0.77	10	11	714
0.5	2.06	7.0	0.77	10	11	714
0.2	2.06	2.8	0.77	10	11	714

Table G.3 (Contd) Database for Slope S1

Severity *	LCI	S1	DSat	CT	Delay	Link
0.5	2.06	10.8	0.77	10	11	714
0.2	2.06	2.8	0.77	10	11	714
0.5	2.06	10.8	0.77	10	11	714
0.2	1.96	1.8	0.17	17	20	730
0.5	1.96	1.8	0.17	17	20	730
0.7	1.96	3.6	0.17	17	20	730
0.2	1.96	1.8	0.17	17	20	730
0.5	1.96	1.8	0.17	17	20	730
0.7	1.96	3.6	0.17	17	20	730
0.2	2.92	11.4	0.95	31	60	1494
0.5	2.92	24.6	0.95	31	60	1494
0.2	2.92	12.8	0.95	31	60	1494
0.5	2.92	53.8	0.95	31	60	1494
0.2	2.92	12.8	0.95	31	60	1494
0.5	2.92	53.8	0.95	31	60	1494
0.2	2.97	0.4	0.33	5	10	1692
0.5	2.97	1.0	0.33	5	10	1692
0.7	2.97	6.6	0.33	5	10	1692
0.2	2.97	0.4	0.33	5	10	1692
0.5	2.97	1.0	0.33	5	10	1692
0.7	2.97	6.6	0.33	5	10	1692
0.2	2.84	5.6	0.95	10	19	714
0.2	2.84	5.6	0.95	10	19	714
0.5	1.93	2.8	0.51	17	17	730
0.7	1.93	7.2	0.51	17	17	730
0.2	1.93	0.0	0.51	17	17	730
0.5	1.93	2.8	0.51	17	17	730
0.7	1.93	7.2	0.51	17	17	730
0.2	1.93	0.0	0.51	17	17	730
0.2	3.19	13.0	0.98	31	69	1494
0.2	3.19	13.0	0.98	31	69	1494
0.5	3.19	38.2	0.98	31	69	1494
0.7	3.18	11.4	0.35	5	11	1692
0.7	3.18	11.4	0.35	5	11	1692
0.2	2.21	1.2	0.53	17	22	730
0.5	2.21	9.6	0.53	17	22	730
0.2	2.21	1.2	0.53	17	22	730
0.5	2.21	9.6	0.53	17	22	730
0.7	2.21	58.6	0.53	17	22	730

Table G.3 (Contd) Database for Slope S1

Severity	LCI	S1	DSat	CT	Delay	Link
0.2	3.92	19.2	1.16	31	95	1494
0.2	3.92	19.4	1.16	31	95	1494
0.2	2.78	5.6	0.86	17	31	730
0.5	2.78	20.6	0.86	17	31	730
0.7	2.78	19.8	0.86	17	31	730
0.2	5.20	20.2	1.05	31	135	1494
0.2	2.94	4.0	0.78	17	34	730
0.5	2.94	22.8	0.78	17	34	730
0.7	2.94	13.6	0.78	17	34	730
0.2	3.06	4.8	0.89	17	34	730

*	Severity	Severity of the incident (between 0 to 1)
	LCI	Link congestion index
	S1	slope calculated by using equation 6.6
	DSat	Degree of saturation
	CT	Cruise Time on the link in secs
	Delay	Delay in secs/veh
	Link	Link number

Table G.4 Database for MaxJt

Duration	Severity	MaxJt	CT	MaxJtNon	Link
15	0.2	69	10	67	714
15	0.5	68	10	67	714
15	0.7	184	10	67	714
30	0.2	78	10	67	714
30	0.5	123	10	67	714
30	0.7	195	10	67	714
45	0.2	80	10	67	714
45	0.5	118	10	67	714
45	0.7	203	10	67	714
15	0.2	54	17	53	730
15	0.5	54	17	53	730
15	0.7	61	17	53	730
30	0.2	68	17	53	730
30	0.5	162	17	53	730
30	0.7	359	17	53	730
45	0.2	129	17	53	730
45	0.5	367	17	53	730
45	0.7	593	17	53	730
15	0.2	238	31	175	1494
15	0.5	384	31	175	1494
15	0.7	440	31	175	1494
30	0.2	386	31	175	1494
30	0.5	665	31	175	1494
30	0.7	962	31	175	1494
45	0.2	478	31	175	1494
45	0.5	755	31	175	1494
45	0.7	1243	31	175	1494
15	0.2	17	5	16	1692
15	0.5	24	5	16	1692
15	0.7	57	5	16	1692
30	0.2	17	5	16	1692
30	0.5	27	5	16	1692
30	0.7	158	5	16	1692
45	0.2	17	5	16	1692
45	0.5	27	5	16	1692
45	0.7	159	5	16	1692

* MaxJT — Maximum journey time on the link after an incident in secs
CT — Cruise time on the link in secs
MaxJtNon — Maximum journey time on the link during non-incident conditions in secs

Table G.5 Database for slope S2

Duration	Severity	CT	LCI	Delay	MaxJt	S2	Link
15	0.7	10	2.84	19	184	-24.2	714
30	0.2	10	6.07	49	78	-2.0	714
30	0.5	10	6.07	49	123	-11.0	714
30	0.7	10	6.07	49	195	-26.0	714
45	0.2	10	5.91	47	80	-2.0	714
45	0.5	10	5.91	47	118	-9.0	714
45	0.7	10	5.91	47	203	-20.5	714
15	0.2	17	1.93	17	54	-0.6	730
15	0.5	17	1.93	17	54	-1.4	730
15	0.7	17	1.93	17	61	-5.2	730
30	0.2	17	2.94	34	68	-1.8	730
30	0.5	17	2.94	34	162	-2.6	730
30	0.7	17	2.94	34	359	-30.4	730
45	0.2	17	2.69	29	129	-7.6	730
45	0.5	17	2.69	29	367	-18.4	730
45	0.7	17	2.69	29	593	-26.6	730
15	0.7	31	3.19	69	440	-7.4	1494
30	0.5	31	5.62	144	665	-20.8	1494
30	0.7	31	5.62	144	962	-25.6	1494
45	0.2	31	4.12	97	478	-8.2	1494
45	0.5	31	4.12	97	755	-19.0	1494
45	0.7	31	4.12	97	1243	-21.8	1494
15	0.5	5	3.18	11	24	-1.6	1692
15	0.7	5	3.18	11	57	-7.6	1692
30	0.5	5	2.95	10	27	-2.4	1692
30	0.7	5	2.95	10	158	-22.4	1692
45	0.5	5	3.18	11	27	-1.6	1692
45	0.7	5	3.18	11	159	-22.4	1692

*	Duration	Duration of the incident in minutes
	Severity	Severity of the incident (0 to 1)
	CT	Cruise time on the link in secs
	LCI	Link congestion index
	Delay	Delay in secs/veh
	MaxJT	Maximum journey time on the link after an incident in secs
	CT	Cruise time on the link in secs
	S2	slope calculated by using equation 6.10

Table G.6 Database for MaxJt on affected links

Incident Link	Severity	Affected Links	CT	Distance	MaxJt Non	MaxJt
714	0.2	519	15	74	15	116
	0.2	520	15	59	15	157
	0.2	535	9	9	20	47
	0.2	707	25	59	36	318
	0.2	708	23	57	50	280
	0.2	710	10	34	15	82
	0.2	711	15	24	25	127
	0.2	712	21	45	27	186
	0.2	731	25	99	48	119
	0.2	732	25	99	45	77
	0.5	520	15	59	15	353
	0.5	535	9	9	20	116
	0.5	707	25	59	36	650
	0.5	708	23	57	50	676
	0.5	710	10	34	15	169
	0.5	711	15	24	25	266
	0.5	712	21	45	27	614
	0.5	724	10	44	32	181
	0.7	520	15	59	15	636
	0.7	535	9	9	20	304
	0.7	707	25	59	36	1122
	0.7	708	23	57	50	1191
	0.7	710	10	34	15	349
	0.7	711	15	24	25	468
	0.7	712	21	45	27	1169
	0.7	724	10	44	32	281
1494	0.2	2014	3	3	10	36
	0.2	1474	10	13	10	71
	0.5	1424	16	49	16	307
	0.5	1434	4	33	4	71
	0.5	1444	6	29	6	149
	0.5	1454	4	23	4	108
	0.5	1464	6	19	6	151
	0.5	1474	10	13	10	277
	0.5	2014	3	3	11	88
	0.7	1424	16	49	16	525
	0.7	1434	4	33	4	121
	0.7	1444	6	29	6	238
	0.7	1454	4	23	4	171

Table G.6 (Contd) Database for MaxJt on affected links

Incident Link	Severity	Affected Links	CT	Distance	MaxJt Non	MaxJt
1494	0.7	1464	6	19	6	259
	0.7	1474	10	13	10	457
	0.7	2014	3	3	11	188
730	0.5	518	15	15	17	296
	0.5	603	41	41	52	333
	0.7	517	4	19	5	291
	0.7	518	15	15	17	734
	0.7	603	41	41	52	661
	0.7	703	19	38	28	444
	0.7	706	15	53	24	131

* Affected links — Links which are affected by the incident (20% increase in journey time

CT — Cruise time on the link in secs

Distance — Distance of affected link from incident link in meters

MaxJT — Maximum journey time on the link after an incident in secs

MaxJtNon — Maximum journey time on the link during non-incident conditions in secs

Appendix H

Predictive Models

Table H.1 Predictive Models for Slope M1

Equation	R^2	SE(r)
M1 = 0.37 * Sev * LCI	0.51	0.47
M1 = 0.24 * Sev * LCI * NCI	0.51	0.47
M1 = 0.70 * Sev * LCI -1.19*NCI	0.63	0.42
M1 = 0.14 * Sev * LCI * NCI + 1.15	0.51	0.47
M1 = 0.08 * Sev * $(LCI)^2$	0.61	0.43

Table H.2 Predictive Models for Slope M2

Equation	R^2	SE(r)
M2 = 0.44 - 1.75*(1/LCI)	0.20	0.48
M2 = -0.9*(NCI/LCI) - 0.44	0.22	0.47
M2 = -0.62 + 0.13*LCI	0.17	0.49

Table H.3 Predictive Models for Slope S1

Equation	R^2	SE(r)
Additive Models		
S1 = -24.7 + 8.5 CI + 38.7 Sev	0.21	17.4
S1 = 1.6 CI + 23.5 Sev	0.40	18.2
S1 = -31.7 + 40.6 DSat + 47.5 Sev	0.51	13.6
S1 = 17.8 DSat + 12.1 Sev	0.50	16.6
Multiplicative Models		
S1 = 1.8 * CT * Sev	0.58	9.6
S1 = 0.8 * CT * Sev * CI	0.69	8.1
S1 = 0.05 * Sev * CT * Delay	0.70	8.2
S1 = 0.41 * Sev * CI * Delay	0.56	9.9
S1 = 1.25 * Sev * Delay	0.69	8.2
Power Function Models		
S1 = (1.45 * CI) * $(15.96)^{sev}$	0.22	17.3
S1 = (4.51 * DSat) * $(36.23)^{sev}$	0.62	11.8
S1 = 10.29 * $CI^{1.38}$ * $Sev^{1.19}$	0.22	17.2
S1 = 146.4 * $DSat^{3.17}$ * $Sev^{1.72}$	0.76	9.4
S1 = (0.08 * CT * CI) * $(21)^{sev}$	0.70	8.0
S1 = (0.50* CT * CI * Sev) * $(2.28)^{sev}$	0.71	8.0

Table H.4 Predictive Models for Slope S2

Equation	R^2	SE(r)
S2 = -1.46*(MaxJT/Delay) + 2.25	0.52	6.9
S2 = -1.78*(MaxJT/Delay)	0.47	7.1
S2 = -0.79*(MaxJT/CT)	0.75	5.0
S2 = -0.09*Delay + 96.5	0.11	9.4

Table H.5 Predictive Models for MaxJT

Equation	R^2	SE(r)
MaxJT = MaxJtNon + (27.34 * Sev * CT)	0.73	147
MaxJT = MaxJtNon + (2.24 *Sev * LL)	0.75	143
MaxJT = 2.87 * MaxJtNon + 128.06 * Sev	0.75	189
MaxJT = 12.94 * CI * CT * Sev	0.87	101
MaxJT = 50.12 * DSat * CT * Sev	0.84	114
MaxJT = -584.2 + 98.3 CI + 21.5 CT + 483 Sev	0.74	145
MaxJT = -23.8 CI + 17.1 CT + 162 Sev	0.73	197
MaxJT = -395 + 304.5 DSat +16.4 CT + 483 Sev	0.71	154
MaxJT = 67 DSat + 14.3 CT + 59.5 Sev	0.73	199
$MaxJT = 4.08 * CI^{1.24} * CT^{1.23} * Sev^{0.81}$	0.89	92
$MaxJT = 55.2 * DSat^{0.98} * CT^{0.94} * Sev^{0.8}$	0.85	112

Appendix I

Detailed information used for the simulation of incidents in CONTRAMI programme.

Card type 100 (added into the network file)

Card type 100 is used to introduce an incident on a specific link. e.g. on Kingston link 714, for an incident lasting for 30 minutes with a severity of 50%; card 100 in Network file is inserted as:

100 714 4 1325 1325 1325 1325 1325 1325 2650 2650 2650 2650 2650 2650

where

- parameter 1 is the card type number;
- parameter 2 is the number of the incident link;
- parameter 3 is the iteration number when the incident is to be introduced;
- The following parameters are the new saturation flows for each time slice. In this example, the initial link saturation flow was 2650. During the incident (which lasts here for 30 min = 6 time slices) the saturation flow is reduced to 50% of the initial saturation flow:
$$50\% \times 2650 = 1325 \text{ (pcu/h)}$$
After the end of the incident the new capacity of the link is 1325 pcu/h (from time slice 7).

Card type 93 (added in Control file)

This card is used to define the diversion strategy. As fixed route strategy is used in this study, card 93 has same parameters for all the incidents simulated in this study, i.e.

93 0 20 100 100

where

- parameter 1 is the card type number;
- parameter 2 is the maximum number of diversions allowed;
- parameter 3 is the coefficient of diversion (10 * the maximum acceptable ratio of new over usual cruise time);
- parameter 4 is the percentage of packets which will not divert;
- parameter 5 is the percentage of occupancy which will trigger diversions.

Card 101 (added in Control file)

This card is used to define iterations, for all the incidents simulated in this study, the card has fixed parameters as :

101 3 1 3

where

- parameter 1 is the card type number;
- parameter 2 is the number of iterations to load the network;
- parameter 3 is the number of iterations allowing diversions;
- parameter 4 is the number of iterations keeping the routes fixed.

Appendix J

Description of the ANALYSE Program.

The ANALYSE program compares Journey times on links before and after an incident. The input for this program are the result file from CONTRAMI standard run (non-incident), and CONTRAMI result file of incident run.

It then compares the two files and output a file which contains all the links that have been affected as a result of the incident, the JTM (journey time multiplier) for each link and the number of links affected per 5 minute time intervals.

Links affected by incident are selected by comparing their TJT (total journey time) during the incident that without the incident. Varying degrees of affected links could be selected by choosing only those links which have been affected by a specified percentage (for this study it is 20%) of their TJT without incident.

```
      PROGRAM ANALYSE
*
*     --------------------------------------------------------------------
*     This program reads CONTRAM result files and compare the journey
*     time on every link before and after the incident and output those
*     links where journey time has changed for more than 20% for the
*     current time interval.
*
*     INPUT  :  Non-Incident Result File.
*               Incident Result File.
*               OutPut file name.
*
*     OUTPUT :  Number of links which are affected by an incident.
*     --------------------------------------------------------------------
*
      INTEGER LNO,TS,NAL
      INTEGER NOLA(13),TJT(1700),TJTI(1700)
      INTEGER JT(1700,13),JTI(1700,13)
      REAL CL
      REAL JTM(1700,15)
      CHARACTER*7 LINK(1700)
      CHARACTER*7 ALINK(1700,13)
      CHARACTER*15 DATAFILE1,DATAFILE2,RESFILE
      CHARACTER*90 LINE,TLINE
*
*
      TLINE='1                    LINK-BY-LINK ALL-TIME-SLICES  - MEAN
     1TRAVEL  TIMES PER VEHICLE (SEC)'
*
 101  WRITE(*,*) ' Enter the name of first data file : '
      READ(*,'(A)',ERR=101) DATAFILE1
      OPEN(UNIT=8,FILE=DATAFILE1,STATUS='OLD')
*
  64  READ(8,62) LINE
```

```
 62  FORMAT(A90)
     IF(LINE.EQ.TLINE) THEN
     GO TO 63
     ELSE
     GO TO 64
     ENDIF
*
*----------------------------------------------
*    Reading data line by line from first file.
*----------------------------------------------
 63  READ(8,59)
 59  FORMAT(12(/))
     LNO=1
 21  READ(8,31,ERR=100) LINK(LNO),(JT(LNO,TS),TS=1,13)
 31  FORMAT(A7,3X,13(I8))
      LNO=LNO+1
      GO TO 21
 100  LNO=LNO-1
*----------------------------------------------------
 102 WRITE(*,*) ' Enter the name of second data file : '
     READ(*,'(A)',ERR=102) DATAFILE2
     OPEN(UNIT=9,FILE=DATAFILE2,STATUS='OLD')
*
 74  READ(9,72) LINE
 72  FORMAT(A90)
     IF(LINE.EQ.TLINE) THEN
     GO TO 73
     ELSE
     GO TO 74
     ENDIF
*-----------------------------------------------
*    Reading data line by line from second file.
*-----------------------------------------------
 73  READ(9,49)
 49  FORMAT(12(/))
     DO 22 K=1,LNO
     READ(9,41) (JTI(K,TS),TS=1,13)
 41  FORMAT(10X,13(I8))
 22  CONTINUE
*------------------------------------------------
*    Reading output file name.
*------------------------------------------------
 103 WRITE(*,*) ' Enter the name of result file : '
     READ(*,'(A)',ERR=103) RESFILE
     OPEN(UNIT=7,FILE=RESFILE,STATUS='NEW')
*------------------------------------------------
     DO 23 I=1,LNO
      TJT(I)=0
```

```
    TJTI(I)=0
    DO 24 K=1,13
     TJT(I)=TJT(I)+JT(I,K)
     TJTI(I)=TJTI(I)+JTI(I,K)
24   CONTINUE
   IF(TJTI(I).NE.0) THEN
     CL=(1.2)*(FLOAT(TJT(I)))
     IF(TJTI(I).GT.CL) THEN
      DO 27 L=1,13
      IF (JT(I,L).NE.0) THEN
       JTM(I,L)=FLOAT(JTI(I,L))/FLOAT(JT(I,L))
      ELSE
       JTM(I,L)=0.0
     ENDIF
27    CONTINUE
     WRITE (7,39) LINK(I),(JTM(I,L),L=1,13)
39   FORMAT(A8,13(2X,F5.1))
     ENDIF
    ENDIF
23  CONTINUE
   DO 91 L=1,13
    NOLA(L)=0
    NAL=1
    DO 92 I=1,LNO
    IF (JTM(I,L).GE.1.2) THEN
      NOLA(L)=NOLA(L)+1
      ALINK(NAL,L)=LINK(I)
      NAL=NAL+1
    ENDIF
92   CONTINUE
91  CONTINUE
   WRITE(7,*)
   WRITE(7,*)'------------------------------------------------------
  1-------------------------'
   WRITE(7,84) (NOLA(L),L=1,13)
84  FORMAT(8X,13(2X,I5))
   WRITE(7,*) '-----------------------------------------------------
  1-------------------------'
   DO 86 I=1,LNO
   WRITE(7,85) (ALINK(I,TS),TS=1,13)
85  FORMAT(8X,13(A7))
86  CONTINUE
   WRITE(*,*) 'This is the end of the program.'
   END
```

<u>Example of output file from ANALYSE program</u>

1454 1464 1474 1494 2014	1.0 1.0 1.0 1.0 1.0	1.0 1.0 1.0 1.3 1.0	1.0 1.0 1.0 1.8 1.0	1.0 1.0 1.0 2.3 1.0	1.0 1.0 1.0 2.6 1.0	1.0 1.0 1.0 2.6 1.4	1.0 1.0 3.5 2.7 2.9	1.0 1.0 5.1 3.1 2.7	1.0 2.7 7.1 3.3 3.6	1.0 3.3 5.9 3.1 2.1	2.3 3.3 6.5 2.8 2.4	3.5 3.3 6.8 1.6 2.6	1.3 1.2 1.5 1.0 1.0
	0	1	1	1	1	2	3	3	4	4	5	5	2
		1494	1494	1494	1494	1474 2014	1474 1494 2014	1474 1494 2014	1464 1474 1494 2014	1464 1474 1494 2014	1454 1464 1474 1494 2014	1454 1464 1474 1494 2014	1454 1474

Appendix K

Network Connection Files

Table K.1 Kingston Network Connections File

Link No.	Upstream Links			Junc1	Junc2	
100	201			42	41	0
101				42	43	0
102				40	41	1
103				19	3	0
104				18	20	1
105				21	4	1
106				57	55	1
107	203			53	55	0
108	202			53	51	0
109				50	6	1
110				13	12	1
111				23	24	0
112				37	36	1
113				31	29	0
114				33	34	1
115				48	45	0
116				68	47	0
117				16	5	1
118	200			11	28	0
119				11	9	0
120				26	27	1
200		310	541	9	11	0
201	501	500		43	42	0
202	510	601		55	53	0
203	516	515		51	53	0
300				69	49	0
301				67	1	1
302	405	404	403	56	1	0
303	405	404	402	56	2	0
304	405	403	402	56	55	0
305	402	403	404	56	62	0
306				63	62	0
307	408			64	62	0
308				66	65	0
309				59	58	0
310	413			10	9	0
311	411			10	29	0
312	412			30	29	0
313	401			46	29	0
314	412	414		30	47	1
315	415			46	47	0
400	714	718		49	69	0
401	528	116	612	47	46	0
402	700			1	56	0
403	508			2	56	0

Table K.1 (Contd)

404						55	56	0
405	512	307				62	56	0
406	512	305				62	63	0
407	600	512	305			62	64	0
408	727	308				65	64	1
409	727	725				65	66	0
410	715	728				58	59	0
411	541					9	10	0
412	541					9	30	1
413	113	504				29	10	0
414	504					29	30	0
415	113					29	46	0
500	717					49	43	1
501	716	713				44	43	1
502	501	500				43	41	1
503	302	301				1	41	0
504	543					28	29	0
505	102	503				41	39	1
506	301					1	2	0
507	506	303				2	3	0
508	509	103				3	2	0
509	704					17	3	1
510	705	702				4	55	1
511	510	601	304	107	106	55	54	0
512	723	719				61	62	0
513	721	723				61	54	0
514	513	540				54	52	1
515	514					52	51	1
516	519	604	518			7	51	0
517	703	117				5	6	0
518	517					6	7	0
519	731	732				8	7	0
520	519					7	6	0
521	539					32	34	1
522	519	603				7	12	0
523	532	111				24	12	0
524	709					14	24	1
525	524	111	605			24	25	0
526	525					25	35	0
527	526	610				35	45	0
528	527					45	47	0
529	315	116	314			47	45	0
530	529	115				45	35	0
531	609	530				35	25	0
532	531					25	24	0
533						35	36	0
534						38	36	1
535	711					22	38	1
536	722	720				61	60	0
537	308	727				65	60	0
538	312	311	313			29	28	0
539	538					28	32	1
540	304	107	106			55	54	0

Table K.1 (Contd)

541	730	729			8	9	0
542	729				8	27	0
543	542	543			27	28	0
544	538				28	27	0
600	510	106	107		55	62	0
601	306	307			62	55	0
602	309	728	715		58	60	1
603	515	108			51	7	0
604	523				12	7	0
605	522	110			12	24	0
606	5340				36	35	0
607	531	525			25	27	0
608	525				27	25	0
609	521				34	35	0
610	521				35	34	0
611	116	528	315	314	47	32	0
612	539				32	47	0
700	502	102			41	1	0
701	508				2	1	0
702	507	103			3	4	0
703	702	706	105		4	5	0
704	734				20	17	1
705	734	104			4	20	0
706	734	104			20	4	0
707	702	706	105		5	4	0
708	514				52	5	1
709	707	708	117		5	14	1
710	708	724	707		5	15	1
711	710	712			15	22	1
712	532	111	605		24	15	1
713	535				38	44	1
714	535				38	49	1
715	308	726			65	58	0
716	300				49	44	1
717	529				49	45	0
718	529				45	49	0
719	511				54	61	0
720	511				54	61	0
721	306	307	305		62	61	0
722	306	305	307		62	61	0
723	537	602			60	61	0
724	520				6	5	0
725	536				60	65	0
726	536				65	60	0
727	309	728			58	65	0
728	732	730			8	58	0
729	715	309			58	8	0
730	518	603	604		7	8	0
731	310				9	8	0
732	544				27	8	0
733	501	500			43	39	1
734	733	505			39	20	1

Table K.2 Boscombe Network Connections File

Link No.	Upstream Links			Junc1	Junc2	
1132	1142	1143		5	4	0
1134	1172	1173		12	4	0
1142	1153	1152		6	5	0
1143	1903			14	5	0
1144	1134			4	5	0
1151	1144	1143		5	6	0
1152	1163			7	6	0
1153	1182	1183		9	6	0
1163	1203			10	7	0
1164	1151	1153		6	7	0
1171	1132			4	12	0
1172	1282	1284		32	12	0
1173	1262			30	12	0
1181	1151	1152		6	9	0
1182	1201	1203		10	9	0
1183	1303			15	9	0
1201	1164			7	10	0
1203	1343	1344	1342	17	10	0
1261	1171	1172		12	30	0
1262	1272	1273		31	30	0
1272	1282	1281		32	31	0
1273	1682	1681		74	31	0
1274	1261			30	31	0
1281	1171	1173		12	32	0
1282	1292	1293	1291	33	32	0
1284	1274	1273		31	32	0
1291	2061	2062		23	33	0
1292	2052	2051		34	33	0
1293	1533	1532		57	33	0
1294	1284	1281		32	33	0
1301	1181	1182		9	15	0
1303	1312	1313		24	15	0
1311	1301			15	24	0
1312	2542			25	24	0
1313	1324	1322		35	24	0
1321	1311	1312		24	35	0
1322	1332			36	35	0
1324	2054	2051		34	35	0
1332	2002			37	36	0
1334	1324	1321		35	36	0
1341	1201			10	17	0
1342	1353			18	17	0
1343	1383			26	17	0
1344	2554			16	17	0
1353	1392	1394	1393	27	18	0
1362				20	19	0
1363	1403			28	19	0

Table K.2 (Contd)

1364	1353			18	19	0
1373	1462	1464		43	20	0
1374	1364			19	20	0
1381	1341	1344	1342	17	26	0
1383	1413	1412	1414	38	26	0
1391				18	27	0
1392	1401	1403		28	27	0
1393	1422	1424		39	27	0
1394	1381			26	27	0
1401	1362			19	28	0
1403				42	28	0
1411	1381			26	38	0
1412	1422	1421		39	38	0
1413	1572	1574	1573	51	38	0
1414	2004			37	38	0
1421	1392	1394		27	39	0
1422	1432	1433		40	39	0
1424	1414	1411	1413	38	39	0
1432	1442	1443		41	40	0
1433				52	40	0
1434	1424	1421		39	40	0
1442	1452	1451		42	41	0
1443	2033			60	41	0
1444	1434	1433		40	41	0
1451	1401			28	42	0
1452	1462	1461		43	42	0
1454	1444			41	42	0
1461				20	43	0
1462	1472	1473		44	43	0
1464	1454			42	43	0
1472	2012			45	44	0
1473	2023			62	44	0
1474	1464	1461		43	44	0
1492	5023			47	46	0
1493	1613			54	46	0
1494	2014			45	46	0
1531	1291	1294	1292	33	57	0
1532	1551	1553		58	57	0
1533	1682	1684	1683	74	57	0
1541	1332			36	49	0
1542	2562			50	49	0
1543	1554	1553		58	49	0
1551	1542	1541		49	58	0
1553	1563	1562		66	58	0
1554	1531	1533		57	58	0
1561	1551	1554		58	66	0
1562	1582	1581		67	66	0
1563	1693			75	66	0
1571	1411	1412	1414	38	51	0
1572	1593	1591		52	51	0
1573	1582			67	51	0
1574	2564			50	51	0

Table K.2 (Contd)

1581	1571	1572	1574	51	67	0
1582	1603			68	67	0
1584				66	67	0
1591	1432	1434		40	52	0
1593	1603			68	52	0
1594	1574	1571	1573	51	52	0
1601	1591	1594		52	68	0
1603	1722			78	68	0
1604				67	68	0
1611	1492	1494		46	54	0
1613	1643	1644		64	54	0
1641	1611			54	64	0
1643	1773			69	64	0
1644	1664	1661	1663	72	64	0
1661	2021			62	72	0
1662	1641	1643		64	72	0
1663	1793	1791		73	72	0
1664	1754	1752		81	72	0
1681	1531	1532		57	74	0
1682	1692			75	74	0
1683	1833	1831		90	74	0
1684	1274	1272		31	74	0
1691	1561	1562		66	75	0
1692	1702			76	75	0
1693	1833	1834		90	75	0
1694	1684	1681	1683	74	75	0
1702	1712	1713		77	76	0
1703	1922	1923		91	76	0
1704	1694			75	76	0
1712	1722			78	77	0
1713	1852			92	77	0
1714	1704	1703		76	77	0
1721	1601	1604		68	78	0
1722	1732			79	78	0
1724	1714	1713		77	78	0
1732	1742	1743	1741	80	79	0
1734	1724	1721		78	79	0
1741	2031			60	80	0
1742	1752	1751		81	80	0
1743	1872	1874		94	80	0
1744	1734			79	80	0
1751	1661	1662	1663	72	81	0
1752	1762			82	81	0
1754	1744	1743	1741	80	81	0
1762	1801			83	82	0
1764	1754	1751		81	82	0
1771	1641	1644		64	69	0
1773	1793	1794		73	69	0
1791	1771			69	73	0
1793	1804			83	73	0
1794	1661	1664	1662	72	73	0
1801	1794	1791		73	83	0

Table K.2 (Contd)

1804	1764			82	83	0
1831	1691			75	90	0
1833	1912			97	90	0
1834	1684	1681	1682	74	90	0
1851	1714	1712		77	92	0
1852	1862			93	92	0
1854	1923	1921		91	92	0
1862	1872			94	93	0
1864	1851	1854		92	93	0
1871	1742	1741	1744	80	94	0
1872	5029			95	94	0
1874	1864			93	94	0
1884	1874	1871		94	95	0
1901	1142	1144		5	14	0
1903	2064	2062		23	14	0
1911	1834	1831		90	97	0
1912	1921	1922		91	97	0
1921	1702			76	91	0
1922	1852	1851		92	91	0
1923	1911			97	91	0
2002	1412	1411	1413	38	37	0
2004	1334			36	37	0
2012	1492	1493		46	45	0
2014	1474			44	45	0
2021	1474	1472		44	62	0
2023	1662	1663	1664	72	62	0
2031	1444	1442		41	60	0
2033	1743	1742	1744	80	60	0
2044	1494	1493		46	47	0
2051	2061	2064		23	34	0
2052	1322	1321		35	34	0
2054	1294			33	34	0
2061	1901			14	23	0
2062	2052	2054		34	23	0
2064	1294	1293		33	23	0
2542	1383	1381		26	25	0
2554	1301	1303		15	16	0
2562	1572	1571	1573	51	50	0
2564	1543	1541		49	50	0

Appendix L

Network Plotting Programs

```
      PROGRAM TREE

      INTEGER LINK1,LINK2,LINK3,LINK4,LINK5
      INTEGER SEV,UPSTREAM,INCLNK,TAL
      INTEGER*1 FLAG(1132:2565)
      INTEGER LINK(1132:2565,0:4),ALINK(0:190)
      CHARACTER OUTFILE*15,TAIL*20
      PARAMETER(TOTAL=190,UPSTREAM=4)
      OPEN(UNIT=2,FILE='BOS2.LST',STATUS='OLD')
*
 33   FORMAT(I6)
 51   FORMAT(2X,I6,1X,4(1X,I5))
 52   FORMAT(5(I8))
*
      CALL GETCOM(TAIL)
      READ(TAIL,71) INCLNK,SEV
 71   FORMAT(1X,I4,1X,I2)
      OUTFILE=TAIL(10:18)
*
      OPEN(UNIT=3,FILE=OUTFILE,STATUS='NEW')
*
 101  READ(2,51,END=102) LINK1,LINK2,LINK3,LINK4,LINK5
      LINK(LINK1,0)=LINK1
      LINK(LINK1,1)=LINK2
      LINK(LINK1,2)=LINK3
      LINK(LINK1,3)=LINK4
      LINK(LINK1,4)=LINK5
      FLAG(LINK1)=0
      FLAG(LINK2)=0
      FLAG(LINK3)=0
      FLAG(LINK4)=0
      FLAG(LINK5)=0
      GO TO 101
*
 102  CONTINUE
*
      TAL=0
      DO 21 I=1,SEV
        IF(I.EQ.1) THEN
              ALINK(0)=LINK(INCLNK,0)
              WRITE(3,33) ALINK(0)
        ELSE
 41           DO 22 J=1,4
                 TAL=TAL+1
                 ALINK(TAL)=LINK(ALINK(I-2),J)
```

```
          IF((ALINK(TAL).EQ.0).OR.(FLAG(ALINK(TAL)).EQ.1)) THEN
             TAL=TAL-1
             GO TO 22
          ENDIF
             WRITE(3,33) ALINK(TAL)
             FLAG(ALINK(TAL))=1
22        CONTINUE
    ENDIF
21 CONTINUE
   WRITE(*,*) ' TAL = ',TAL
   WRITE(*,*) ' This is END of the program.'
   END
```

L.2 Description of Graph Program

This program plots the given network on the screen with incident link and affected links shown in different colours (darker on black & white screen).

Input
1. Incident link number
2. NODES.LST - File with junction co-ordinates file
3. LINKS.LST - File with link numbers and start/end nodes
4. File which contain affected link numbers (from output of ANALYSE program)

Output — Graph to screen, printer or file

Facilities
1. One line per road
2. Zoom in/out, move graph etc

Appendix M

Comparison of Simulated vs Predicted results

Table M.1 Number of links affected with incident link K-714 (Sim vs Pre [1])

Time	[2] I3		I6		I9	
	Sim	Pre	Sim	Pre	Sim	Pre
8:05	0	0	1	1	1	2
8:10	1	1	1	3	2	4
8:15	1	2	2	5	4	6
8:20	2	3	5	7	10	10
8:25	4	5	9	11	23	16
8:30	8	7	27	17	38	24
8:35	11	9	38	23	52	32
8:40	15	11	46	29	54	40
8:45	17	14	51	35	58	49
8:50	15	15	53	36	58	50
8:55	12	14	54	35	59	49
9:00	10	11	51	32	59	46
[3] ME	0		9		7	
MAE	1		10		8	
MAPE	31		55		37	

1 Sim Simulated
Pre Predicted

2 I3 Incident with Duration = 45 min Severity = 20%
I6 Incident with Duration = 45 min Severity = 50%
I9 Incident with Duration = 45 min Severity = 70%

3 ME Mean Error
MAE Mean Absolute Error
MAPE Mean Absolute Percentage Error

Table M.2 Number of links affected with incident link B-1494 (Sim vs Pre)

Time	I3		I6		I9	
	Sim	Pre	Sim	Pre	Sim	Pre
8:05	0	0	1	2	1	2
8:10	1	1	1	4	1	5
8:15	1	3	1	7	3	9
8:20	1	4	3	10	9	13
8:25	1	5	8	13	17	18
8:30	2	7	13	18	22	25
8:35	3	9	20	23	28	32
8:40	3	11	21	28	30	39
8:45	4	12	24	32	35	44
8:50	4	12	27	32	33	44
8:55	5	12	26	32	35	44
9:00	5	13	26	33	36	45
ME	-5		-5		-6	
MAE	5		5		6	
MAPE	201		123		76	

Table M.3 Number of links affected with incident link L-3232 (Sim vs Pre)

Time	I3		I6		I9	
	Sim	Pre	Sim	Pre	Sim	Pre
8:05	0	1	1	2	1	2
8:10	0	1	1	3	1	4
8:15	2	2	3	5	3	7
8:20	6	3	6	7	7	10
8:25	5	4	6	9	7	13
8:30	8	5	10	12	11	17
8:35	16	6	21	15	21	21
8:40	26	7	30	18	30	25
8:45	39	8	42	21	42	30
8:50	40	7	45	20	43	29
8:55	38	6	41	19	38	28
9:00	42	5	46	18	41	27
ME	14		9		3	
MAE	14		10		6	
MAPE	58		62		71	

Table M.4 Comparison of Predicted vs Simulated JT at Link K-714

Time	I3		I6		I9	
	Sim	Pre	Sim	Pre	Sim	Pre
8:05	14	19	15	26	15	31
8:10	17	26	33	45	90	58
8:15	31	40	87	79	185	106
8:20	59	64	123	139	180	189
8:25	76	110	118	204	189	258
8:30	79	122	116	204	195	258
8:35	80	122	105	204	174	258
8:40	78	122	109	204	203	258
8:45	73	122	106	204	166	258
8:50	63	114	61	183	64	229
8:55	57	66	58	95	60	115
9:00	57	18	60	18	56	18
ME	-22		-51		-38	
MAE	28		59		63	
MAPE	47		74		68	

Table M.5 Comparison of Predicted vs Simulated JT at Link B-1494

Time	I3		I6		I9	
	Sim	Pre	Sim	Pre	Sim	Pre
8:05	60	92	72	142	136	176
8:10	102	148	208	283	464	373
8:15	166	223	477	470	962	635
8:20	231	309	668	599	1243	768
8:25	328	344	753	599	1239	768
8:30	429	344	755	599	1164	768
8:35	469	344	747	599	969	768
8:40	478	344	647	599	744	768
8:45	432	344	501	599	525	768
8:50	391	330	406	565	416	722
8:55	391	319	391	537	398	682
9:00	251	310	251	514	239	650
ME	23		-19		54	
MAE	71		116		272	
MAPE	27		34		48	

Table M.6 Comparison of Predicted vs Simulated JT at Link L-3232

Time	I3		I6		I9	
	Sim	Pre	Sim	Pre	Sim	Pre
8:05	52	75	67	114	137	140
8:10	52	101	69	179	189	232
8:15	62	133	119	260	379	346
8:20	93	176	269	369	606	499
8:25	100	226	379	483	769	636
8:30	125	253	446	483	1051	636
8:35	184	253	506	483	970	636
8:40	233	253	501	483	736	636
8:45	237	253	422	483	537	636
8:50	228	238	361	445	357	583
8:55	160	218	307	397	357	517
9:00	113	184	201	322	221	415
ME	-60		-71		33	
MAE	60		78		153	
MAPE	60		46		30	

Appendix N

Updated Forecasts

Table N.1 Updated forecasts for 'Number of links affected' with incident link K-714

Time	LCI	5*M1 5*M2	Forecasts	Observed	Update
8:05	1.29	1.2	1	1	1
8:10	1.57	1.5	3	1	3
8:15	2.06	1.9	5	2	3
8:20	2.84	2.5	7	4	5
8:25	4.44	4.1	11	9	8
8:30	6.50	6.0	17	26	15
8:35	6.07	0.7	18	33	27
8:40	6.22	0.8	19	33	34
8:45	6.63	0.9	20	31	34
8:50	5.91	0.7	21	26	32
8:55	2.65	-1.1	20	26	25
9:00	1.81	-2.6	17	18	23
ME			4		- 0.25
MAE			6		3
MAPE			54		35

Table N.2 Updated forecasts of Journey Time (16) on Link B-1494

Time	Delay	5*S1 5*S2	Forecasts	Observed	Update
8:05	27	84	142	72	142
8:10	45	141	282	208	213
8:15	60	187	470	477	395
8:20	69	216	599	668	599
8:25	95	297	599	753	668
8:30	135	422	599	755	753
8:35	144	450	599	747	755
8:40	121	378	599	647	755
8:45	99	309	599	501	755
8:50	97	-34	565	406	467
8:55	111	-28	537	391	378
9:00	129	-23	514	251	368
ME			- 19		- 31
MAE			116		73
MSE			17772		9788
MAPE			34		23

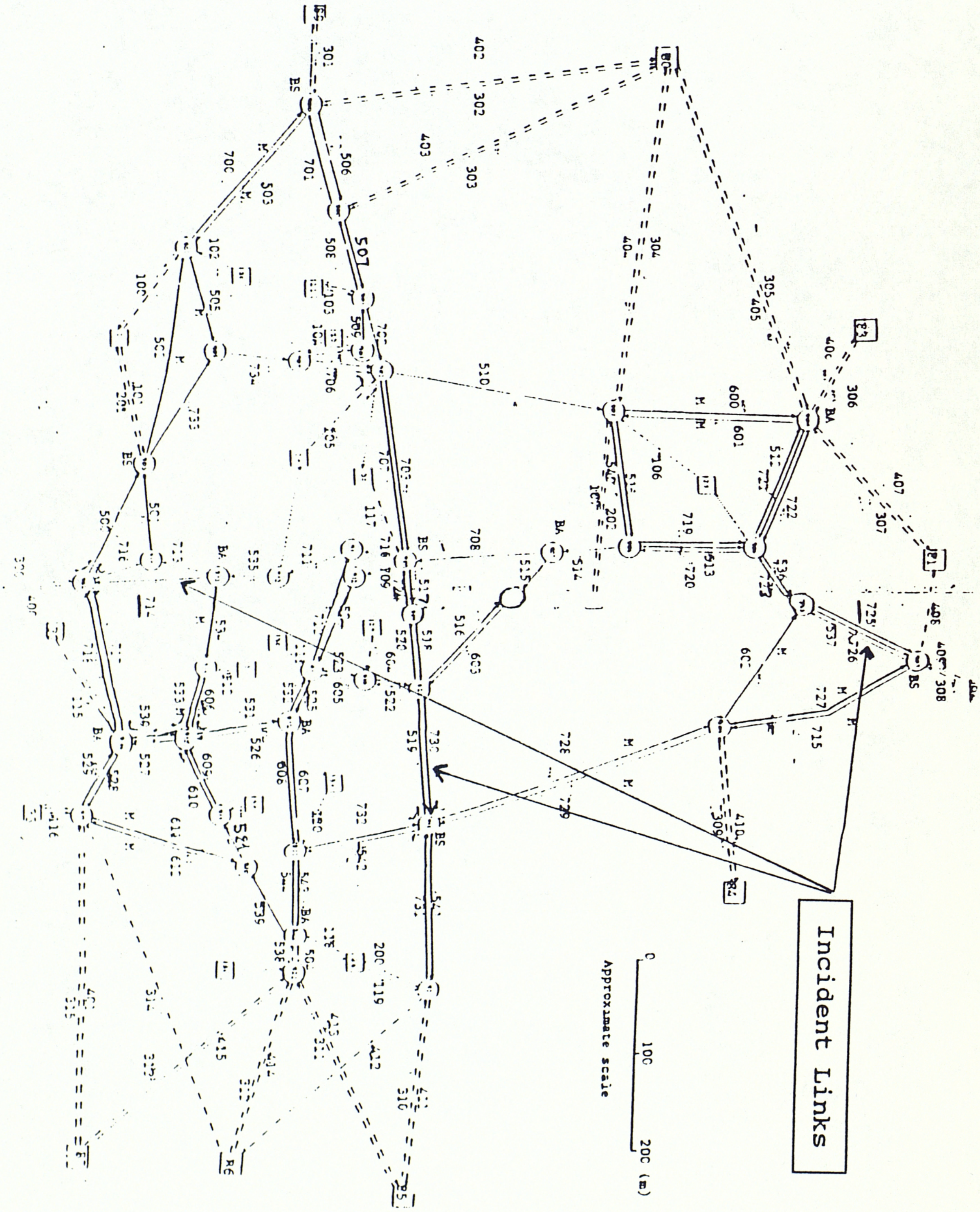
Table N.3 Updated forecasts of increased Journey Time (19) on Link 1494

Time	Delay	5*S1 5*S2	Forecasts	Observed	Update
8:05	27	118	176	136	176
8:10	45	197	373	464	333
8:15	60	262	635	962	726
8:20	69	302	768	1243	962
8:25	95	416	768	1239	1243
8:30	135	591	768	1164	1243
8:35	144	630	768	969	1243
8:40	121	529	768	744	1243
8:45	99	433	768	525	1177
8:50	97	-47	721	416	478
8:55	111	-39	682	398	377
9:00	129	-32	650	239	366
ME			54		- 89
MAE			272		200
MAPE			48		34

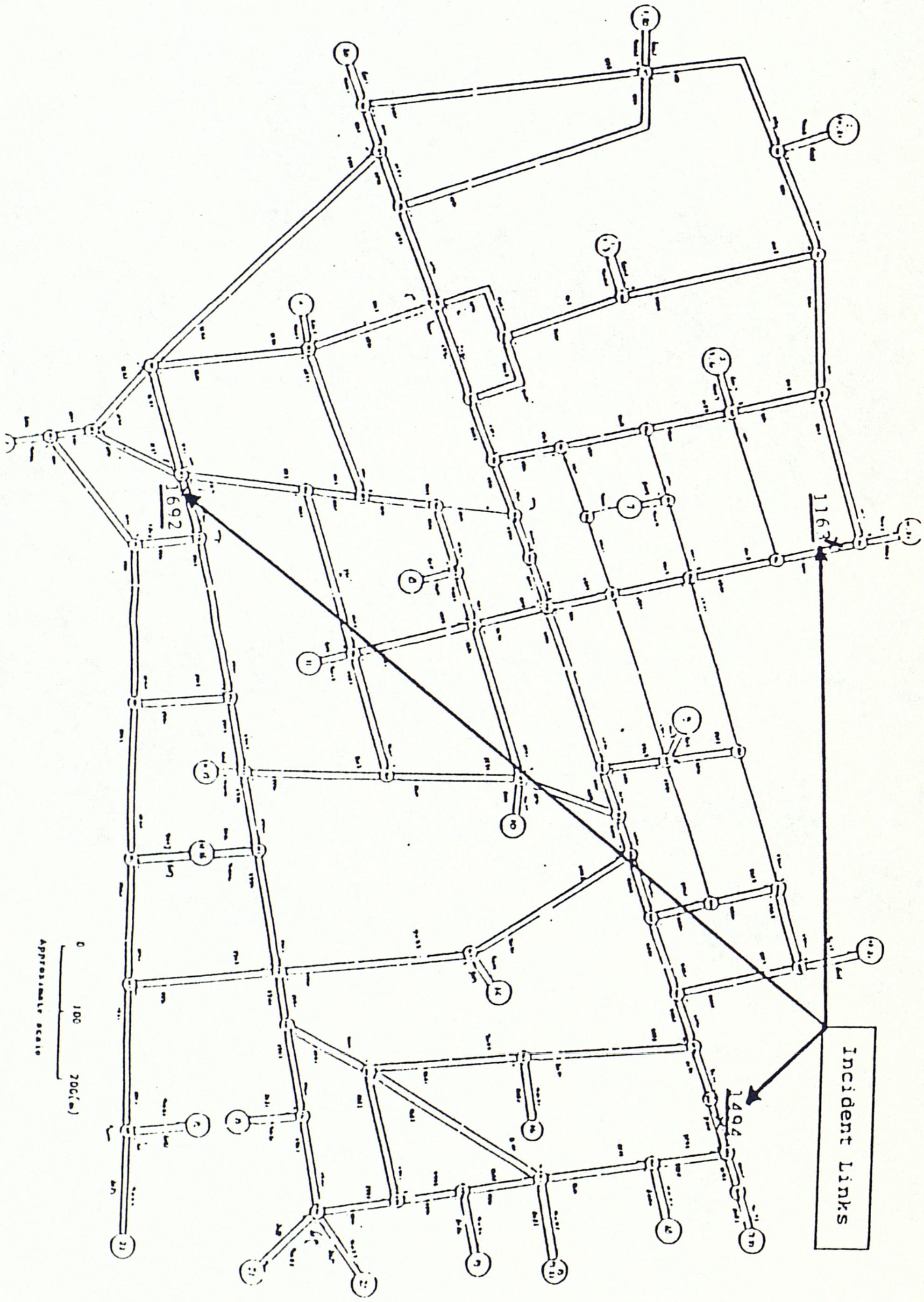
Appendix O

Study Network Maps

O.1 Kingston Network Map



O.2 Boscombe Network Map



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