APPLICATION OF A LOCAL AREA TRAFFIC MODEL IN AN INNER SUBURB OF MELBOURNE

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ABSTRACT: *The structure and development of a new traffic assignment procedure for use in small, detailed urban street networks is described. The model couples a probabilistic path selection procedure with a dynamic feedback system for delays, congestion and queueing in a network. It is intended for use with period travel demand data in the evaluation of network traffic and/or environmental management schemes, and the possible traffic impacts of urban redevelopment schemes.*

To evaluate the model, data regarding peak period traffic movements through an inner suburban area were collected. Included in the data collection were street traffic volumes and speed distributions, and cordon-line origin-destination data for the study area. The particular area (West Hawthorn) is subjected to large volumes of commuter traffic on its local street system during peak demand periods.

It is demonstrated that the proposed model was able to reproduce observed street traffic patterns to a high degree of accuracy. The model was subjected to a wide range of tests for its sensitivity to changes in model parameters, and for possible biases in its predictions. As a result of the study, the model stands as a potentially useful tool for the estimation of traffic impacts in small sections of an urban network.

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1. INTRODUCTION

In recent years a need has arisen for models and methods capable of analysing traffic movements through small, detailed networks. These networks would normally represent a small part of an urban area. The analysis might be required for, amongst other purposes:

(a) simulated tests of alternative traffic/environmental management schemes in urban areas, e.g. street closures to through traffic, or intersection control programs,

(b) local effects of new traffic generators, such as new regional shopping centres, new commercial or industrial developments, residential developments, and redevelopment schemes in established areas, and

(c) more general studies of congestion and dynamic travel demands.

One reason for the need for methods specifically designed for local area use was the general discovery of the unsuitability of strategic level capacity restraint traffic assignment procedures at the local area level (Chen Chu, 1971; Stephens and Cox, 1972). Several causes of deficiency have been cited, including:

(a) Conventional path selection procedures are inadequate when many alternative paths with small cost differentials exist.

(b) Travellers may have imperfect knowledge of the network and travel conditions on the network. Further, there may be wide variations in the perception and appraisal of network travel conditions over the traveller population.

(c) The scale of the local area network means that the movements through intersections (network nodes) become of prime importance. Strategic level travel cost functions are usually based on link (street) conditions and thus may be unsuitable.

(d) There is a need to consider dynamic travel demands and network conditions over short time periods (e.g. a peak hour).

For further discussion of these points, the reader could consult Chen Chu (1971), Stephens and Cox (1972) or Taylor (1976).

The subsequent sections of this paper describe the concepts of one model designed for local area use, and the application of the model to an inner suburban area of Melbourne. The model was tested and evaluated with traffic data collected in this area (West Hawthorn). So that the description of the model may be more appealing to a general audience, a deliberate attempt has been made to minimize the mathematical content of the description. Readers who would like to delve more deeply into the structure of the model could refer to Taylor (1976).

2. MODEL CONCEPTS

The basic concepts adopted for the traffic model were that the model should be dynamic, catering for variations in travel demand and network conditions over time, and that the path selection processes should be based on imperfect network knowledge. Trips could be split between competing paths with small path cost differentials between them. Special account should be taken of the capacity restrictions at intersections in the network, and of the relative difficulties involved in various turning and through movements at intersections.

2.1 PERCEPTIONS OF NETWORK CONDITIONS

One representation of imperfect network knowledge may be obtained by using a distribution of perceived costs for network elements. Over the population of travellers, variations in perceived element costs could be observed between individuals, so that a probability distribution is formed. If $f(z)$ is the relative frequency (probability density function) of the perceived cost z, then the probability that travellers perceive the travel cost on a network element to lie in the range $(z \pm \frac{1}{2}\delta z)$ is $f(z)\delta z$ for small δz.

Burrell (1968) and Wildermuth (1972) have both described traffic assignment procedures which use the concept of perceived link costs. These procedures sample a perceived travel cost for each link, and then route vehicles along minimum perceived cost paths. By repeating this process over all origins in the network, traffic could be split between alternative competing paths. One problem with this method is the definition of a suitable form for $f(z)$. Burrell (1968) used a uniform distribution, whilst Wildermuth (1972) selected a normal distribution. In both cases the mean of the perceived cost distribution was the actual link travel cost, while the spreads of the distributions were chosen arbitrarily.

Under an hypothesis that an individual traveller's perceptions of travel conditions depend on his experiences in the particular network, a functional form of $f(z)$ can be inferred from some recent studies of the variability of daily travel *times* for particular journeys (Richardson and Taylor, 1977). It was suggested that the distribution of day-to-day travel times for an individual on a segment of a route was log-normal. Further, if the travel times per unit distance on component sections of the route segment were independently and identically distributed, the standard deviation (s) of the distribution was directly proportional to the square root of the mean travel time (t)

$$\therefore \quad s = \gamma\sqrt{t} \tag{2.1}$$

where γ is a constant parameter, termed the "travel time variability ratio". (It follows immediately that the coefficient of variation of the distribution (s/t) is inversely proportional to $\sqrt{t}$.) Two important points arose from this study:

(a) the distribution of travel time variations is not symmetric, having a strong skew to the right, and

(b) the relationship between the spread and the mean of the distribution means that the percentage variation about the mean decreases as the mean increases. This is a reasonable result, if one considers that a $\pm$ 20% variation in a 5 minute trip yields travel times of 4-6 minutes while in a 50 minute trip the range is 40-60 minutes. Small time differences may not be significant, whereas the larger differences may well be noticeable.

The local area traffic model used log-normal distributions of perceived travel times, mean values being the actual travel times, and standard deviations given by equation (2.1). In the application of the model, travel time was used as a proxy for travel cost. However, the model could be used with more general cost definitions, provided that the form and shape of the perceived cost distribution might require further investigation. It was felt that the use of the log-normal distribution was more realistic than a symmetric distribution, for which both very long and very short travel time perceptions were equally likely. Further, the relative decrease of the spread of the distribution as the mean increased was also reasonable. The model could therefore include a fairly realistic interpretation of imperfect network knowledge.

2.2 PATH PROBABILITIES

Given a set of perceived network travel costs generated from the submodel of Section 2.1, a route selection procedure such as that given by Burrell (1968) or Wildermuth (1972) uses minimum perceived cost paths, i.e., a driver would attempt to minimize his perceived cost of travel through the network. It may be, however, that other factors enter into the path choice decision. A driver may seek to avoid intersections or bottlenecks which are *potential* sources of delay and frustration, even if these lie on otherwise acceptable paths. An individual's experiences of past events may introduce an irrational component into his route choice. For this reason the model was based on a concept of the existence of finite probabilities of use of alternative paths. In a dynamic system, a driver at one point in a network, at one point in time, would be unlikely to evaluate network conditions at subsequent points on his journey with great accuracy. Hence the model is based on a degree of uncertainty, coupling imperfect knowledge of travel conditions, differing perceptions of these conditions and a possible irrational element in the route choice decision. As will be seen later, the general model includes a number of special cases, by the choice of appropriate model parameters. The path probabilities were based on sampled sets of perceived travel costs on the network.

Finite probabilities of use of alternative paths for a given trip were found using a method similar to that proposed by

Dial (1973) for use in small-scale surface street networks[1]. The method is based on an hypothesis that the probability of use of path P, connecting origin h to destination d, is directly proportional to the "likelihood" of use of all of the movements m in the path. In mathematical terms, one may write

$$Pr\ \{P(h,d)\} = K \prod_{m \varepsilon P(h,d)} g(m) \tag{2.2}$$

$$= KG(P(h,d))$$

where K is a constant, g(m) is the "movement likelihood function" and G(P) is the "path likelihood function". The symbol Π means "the product of". A simple representation of the path is provided in Fig 1. By definition, g(m) is restricted to values between 0 and 1,

$$\text{i.e.}\quad 0 \leq g(m) \leq 1$$

and thus G(P(h,d)) is similarly constrained. A suitable form for g(m) analogous to that cited by Dial (1971) is

$$g(m) = \begin{cases} \exp\{-\theta u(m)\} & \text{if m is on an acceptable path} \\ 0 & \text{otherwise} \end{cases} \tag{2.3}$$

where $u(m) \geq 0$ is the difference between the travel cost[2] incurred in passing through m (i.e. moving directly from arc e to arc f, Fig 1) and the minimum cost path from e to f ($u(m) = 0$ implies that m is on the minimum path). The parameter θ is called the "path diversion factor". Its value dictates the spread of trips to paths more costly than the minimum path. The definition used for an acceptable path is a path on which every succeeding arc (f) is closer to the destination (d) than the previous arc (e) (Fig 1).

The desired output from any traffic assignment is the estimated traffic volume using each arc f in the network for a given travel demand. In the path probability model, this result may be found using Pr{f}, the probability that the trip from h to d uses arc f. The probability is found by locating all of the paths P(h,d) which use f, and summing the path probabilities, i.e.

$$Pr\{f\} = \sum_{P:f\varepsilon P} Pr\{P\} \tag{2.4}$$

where P:fεP means all of the paths from h to d which use arc f.

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1 Dial's 1973 method is a direct descendant of his strategic level probabilistic assignment model described in Dial (1971).

2 Note that the path probability submodel is applicable to a general definition of travel cost and is not restricted to perceived travel time alone. The local area model used perceived times as the cost input to the path probability submodel.

Despite the simplicity of this result, a serious practical problem arises because of the need to define explicitly all of the acceptable paths from h to d. This may be a very time consuming and wasteful process. However, the conditional probability Pr{fe} of a trip using arc f given that it enters intersection j from arc e can be found using an efficient recursive algorithm without the need to find all of the possible paths from h to d. In physical terms, Pr{fe} may be considered as the proportions of those drivers bound for a given destination, who make left or right turns at, or travel straight through, an intersection, depending on the relationship between f and e.

It can be shown (e.g. Taylor, 1976) that the conditional probability may be found recursively given a "movement weight function" w(m):

$$w(m) = \begin{cases} g(m) & \text{if } f = d\text{, the destination arc} \\ g(m) \sum\limits_{u \varepsilon \beta(f)} w(u) & \text{for all other } f \end{cases} \qquad (2.5)$$

The summation $\sum\limits_{u \varepsilon \beta(f)} w(u)$ means the sum of the weight functions of all of the movements u which can be used to leave arc f (i.e. the set $\beta(f)$). It can be shown that

$$\Pr\{fe\} = w(m) / \sum_{u \varepsilon \beta(e)} w(u) \qquad (2.6)$$

given that w(m) may be computed recursively by considering each arc f in order of increasing minimum travel cost to d. A full description of the model is given by Taylor (1976) derived from the strategic level model described by Dial (1971).

It should be noted that the model outlined above requires trips to be generated along the links in the network rather than at nodes representing zone centroids. This is perfectly acceptable, perhaps even essential, when one considers that the physical representation of a link in the local area model is a street. In the real world, trips are generated at individual locations along the streets. Secondly, the assignment algorithms are destination orientated. Trips are assigned from origins to a given destination. This is necessary in a dynamic system where the ultimate goal of a trip is to reach its destination rather than leave its origin. Knowledge of the intended destinations is required for vehicles held in queues. Once a trip has commenced, the origin is redundant information.

2.3 DYNAMIC DEMANDS

As well as the reduced geographic scale of the network for the local area traffic model compared to strategic level studies, the time scale was also reduced. The model was designed for use over short time periods (say 1-3 hours), typically for study of peak period demands. Changes in demand, and network conditions, over time were handled by dividing the total study period into subintervals ("computation intervals"). Fig 2 may prove useful in this regard. It shows, schematically, the trends of variation in demand over a day, at an arbitrary point in a transport system. Further, it shows possible variations in a short peak period interval from the daily profile. This short interval (T) is shown subdivided into a number of computation intervals (ΔT_i). These subintervals would be selected so that demands *within* each subinterval could be considered constant. The model was designed to use any number of subintervals, of arbitrary length.

2.4 CAPACITY, DELAYS AND QUEUEING

Capacity restraints were imposed on the movements of vehicles in each computation interval by giving finite capacities to each movement m at intersections in the network. Thus there were maximum limits on the numbers of vehicles able to pass through each movement in any computation interval. Any extra vehicles which tried to use a movement after its capacity was exhausted joined a queue on that movement, or were diverted to other movements through the intersection. (This latter diversion occurred when turning movement capacities were exhausted but the through movement still had excess capacity.)

The queueing-capacity submodel used in the traffic model was based on a storage-routing concept similar to that described by Rahmann (1972, 1973). Queues may exist on all permissible movements in the network. If there are N(t) vehicles in a given queue at time t, and if vehicles arrive at a rate I(t) and leave the queue at a rate Q(t), then the following continuity equation holds:

$$I(t) = \frac{dN}{dt} + Q(t) \qquad (2.7)$$

i.e. the rate at which vehicles enter the queue is equal to the rate at which they leave plus the rate of change of the queue length. For traffic flows, one can reasonably put the following constraints on the variables in equation (2.7):

(a) $N(t) \geq 0$,

(b) $Q(t) \leq C(t)$,

which define the existence of the queue, and place a capacity $C(t)$ as a maximum value of $Q(t)$,

(c) $Q(t) = C(t)$ if $N(t) > 0$ or $I(t) \geq C(t)$, and

(d) $Q(t) = I(t)$ if $I(t) < C(t)$ and $N(t) = 0$.

Thus "capacity" (C) is a maximum discharge rate of some traffic facility, and can vary with time.

For a finite time period Δt, equation (2.7) might be written as

$$\bar{I}\Delta t = \Delta N + \bar{Q}\Delta t \qquad (2.8)$$

where $\bar{I}$ is the mean arrival rate in the interval, $\bar{Q}$ is the mean departure rate, and $\Delta N = N(t+\Delta t) - N(t)$ is the change in queue size. The maximum number of vehicles able to pass through the facility in Δt is $\bar{C}\Delta t$. Average delays could be computed by considering the type of intersection (signalized, major/minor, "give-way to right") and the queues of vehicles on each approach to the intersection. These delays were applied as "turn penalties" in the computations of path lengths. For the different intersection types, various models were used to predict capacity ($\bar{C}$) and average delay for one computation interval given the conditions from the previous interval. $\bar{C}$ would depend on intersection type, controls and lane configurations, and the traffic volumes on other approaches to an intersection. In this way a dynamic feedback was established, with travel conditions generated in one interval directly influencing conditions in the next interval. A full description of the queueing and delay submodels for each intersection type was given by Taylor (1976).

The queueing submodels did not alter the path probabilities in a particular computation subinterval. Rather they prevented some vehicles from immediately following their intended paths. Such vehicles had to wait until the next interval, when new probabilities were computed based on the revised network travel conditions, and the movements had new available capacities. The model also included separate models for travel times and delays on various types of arterial roads and local streets. Details of these models are given in Taylor (1976).

2.5 SUMMARY

The model which has been briefly outlined in this section consisted on a probabilistic multiple path assignment procedure operating with dynamic trip demand inputs and feedback between the path selection process and network travel conditions.

The path selection process consisted of two components involving:

(a) varying perceptions of network conditions across the driver population, due to incomplete and imperfect knowledge of the network, and different appraisals of network conditions between individuals, and

(b) a mechanism for the estimation of probabilities of use of competing paths based on sampled perceived travel costs.

The two components were represented by two unknown parameters which were global to the model:

(a) the travel time variability ratio (γ) defined by equation (2.1), and

(b) the path diversion factor (θ) defined in equation (2.3).

The general path selection model may be reduced to a number of special submodels by taking appropriate values of these two parameters. If $\gamma \to 0$, the path selection process is a probabilistic model based on actual travel costs (the spread of the perceived cost distribution about its mean value vanishes). If

$\theta \to \infty$ in equation (2.3)[3], the probability of use of paths longer than the minimum path vanishes and drivers only choose the minimum cost paths. In this case, for finite γ, the path selection process becomes a minimization of perceived travel costs. If $\theta \to \infty$ and $\gamma \to 0$, the model becomes an "all-shortest-paths" model based on actual travel costs.

The dynamic components of the traffic model approximated conditions of time-dependent travel demands, and the finite capacities of network elements. These components were constructed to permit some comparisons of intersection control types, and surface street types (e.g. arterials, arterials with centre tram lines, and local streets).

The principal aim of the study was to evaluate the usefulness of the traffic model. This was attempted by applying the model with traffic data collected in a test area. By comparing model predictions of street traffic volumes over short time intervals with observed volumes, suitable values of the global parameters could be determined. Further, some idea of the success of the model in reproducing observed conditions could also be obtained. A detailed description of the model is available elsewhere (Taylor, 1976).

3. MODEL EVALUATION

The general method of model evaluation used in this study was suggested from some general results regarding the evaluation of hydrologic models, and recently summarized by Pilgrim (1975). A desirable outline for the general testing and evaluation of models may be given as the following four levels:

(a) a rational examination of model structures,

(b) an estimation of model parameters,

(c) a verification of the accuracy of the fitted model, and

(d) prediction of the possible range of applicability of a model.

On a conceptual basis these levels are distinct and sequential. Too often, however, model testing finishes at level (b) (Pilgrim, 1975) although this is not really satisfactory.

3.1 MODEL STRUCTURE

Model structure should be examined as a first check that a particular model performs reasonably, so that gross errors may be eliminated. Ranges of values of parameters may also be established. Structure examination may be attempted by an exploration of the model under a wide range of model parameter values.

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3 In practice, $\theta \to \infty$ means θ is about 5-10 (cost units)$^{-1}$.

3.2 ESTIMATION OF PARAMETERS

Parameter estimation is a necessary part of model evaluation. Two broad estimation procedures exist:

(a) rational techniques involving the direct measurement of a parameter, and

(b) techniques in which parameter values are inferred using theoretical relationships of system-type models, regression and other statistical techniques, or optimization of parameter values using operations research methods.

The rational techniques, if applicable, enable the parameter values to be included as exogenous inputs to the model evaluation process. The indirect techniques require the use of the model itself to predict parameter values. This can be done on the basis of the minimization of differences between observed events and model predictions of the events, expressed as an optimization problem involving an objective function (ψ) of the general form

$$\psi = \sum_{j=1}^{n} \psi(obs_j, pred_j(\ell_i, i=1,2,\ldots,k)) \qquad (3.1)$$

where obs_j is the observed value of the jth output, $pred_j$ is the corresponding model prediction and $\{\ell_i\}$ are the model parameters. The set $\{\ell_i^*, i=1,2,\ldots,k\}$ which minimized ψ could be selected as the parameter values for the application of the model. A common form of ψ would be the sum of squares of differences,

$$\psi = \sum_{j=1}^{n} (obs_j - pred_j)^2 \qquad (3.2)$$

as, for example, used in least squares regression.

3.3 VERIFICATION OF OUTPUT

The testing of a fitted model to verify the accuracy of its outputs should be a necessary part of any model evaluation. At the same time, it cannot be expected that a verified model will always be useful. Pilgrim (1975) maintained that validation must involve a degree of subjective appraisal, and that all models could be expected to fail on some occasions due to new conditions, unexpected in the construction of the models. Further, in systems with stochastic components exceptional events (those with very low probabilities of occurrence) could lead to apparent model failures.

For the evaluation of the proposed traffic model, a technique of "dual sample testing" was adopted. The technique required the collection of (at least) 2 *independent* data sets, each set consisting of observed street traffic volumes and matrices of trip interchanges across the test area over a number of short, successive time intervals. The idea of the dual sampling scheme was to test the model and evaluate its parameters on one data set, and then validate it by applying the calibrated model to the second data set. The process could then be reversed by testing and evaluating "best" parameters for the second data set with a validation of those parameters on the first data set. Comparisons of the results from both data sets enabled conclusions to be drawn about representative parameter values for the test network, the range of applicability of the model, and its robustness and possible deficiencies.

A scheme directed to the goal of useful model evaluation was required for two main reasons, one referring to models in general, the other to traffic assignment models in particular.

(a) In general, if any model is of some value, it would be expected that it should be able to reproduce the data with which it was calibrated. A validation based solely on these data is therefore an inadequate test of the general usefulness of the model and its parameters. Thus, we need to test a calibrated model on an independent data set.

(b) A particular problem with the validation of any traffic assignment procedure is that whereas assignment models are built on hypotheses about path choice criteria, seldom if ever can observed data about path choice be obtained for a given network to test the model. Commonly model outputs (assigned link volumes) are matched and compared to observed volumes, as the only available test. This is certainly a necessary condition for an assignment model, but it is not sufficient. It is possible for compensating errors to occur which may disguise the true performance of a model based on observed data. This may be particularly important if the model is intended for predictive use. Judge (1974) has discussed the problem. Again the dual sampling scheme should at least lessen the likelihood of this problem, by tending to remove data dependence from the test results.

Further evidence of model inadequacy and bias is available from examinations of the patterns of residual errors between observed and predicted outputs (see Nelder, 1972 and Aitken, 1973).

3.4 RANGE OF APPLICABILITY

A final stage of model evaluation could be considered as the estimation of the range of model applicability. This is particularly important if any regression relationships are included in a model. The situations to which a particular model would not usefully apply should be identified it this is at all possible.

4. THE WEST HAWTHORN TEST AREA

Traffic data were collected in a small area (of about 150 ha) at the western end of the City of Hawthorn, some 5 km from the Melbourne CBD. The area was bounded by the Yarra River, Barker's Road, Riversdale Road/Swan Street and Power Street. A map of the area is shown in Fig 3. The test area contains three bridges across the Yarra, at Victoria Street, Bridge Road and Swan Street. Other river crossings are well separated from the area, the nearest alternative crossings being at Johnston Street to the north, and on the South-Eastern Freeway to the south. Further the winding river course (see Fig 3) tends to isolate the area from adjacent areas. A total of four arterial roads converge into the three river crossings. A fifth arterial (Canterbury Road) feeds into the secondary street system about 1.5 km east of the test area. Canterbury Road runs parallel to Barker's Road and Burwood Road, approximately mid-way between the two (about 0.8 km separation). On Fig 3, Charles Street and Mary Street are the final secondary streets in the extension of Canterbury Road.

In the peaks there are considerable East-West tidal flow movements through the test area (principal flow directions are west-bound in the morning, and east-bound in the evening). A strong north-south flow also exists. In view of the restrictions on river crossing opportunities, and the number of major arterials converging on the area it had been suspected that considerable volumes of commuter traffic used the local street system inside the test area. This suspicion was confirmed by a recent study conducted for the City of Hawthorn (Loder and Bayly, 1974). This study provided a data base for the present work.

The principal land use in the test area was residential living, largely medium-density with a mixture of older single-unit dwellings and new blocks of flats. The test area may be divided into three well-defined environmental sub-areas. This was done, for example, by Loder and Bayly (1974). The three cohesive sub-areas were:

(a) the area bounded by Power Street, Burwood Road and the Yarra River,

(b) the area bounded by Power Street, Denmark Street, Church Street and Burwood Road, and

(c) the area bounded by Church Street, Barker's Road and the Yarra River.

From Fig 3 it may be seen that the street systems in sub-areas (b) and (c) together offer possibly attractive alternative routes to through traffic. The sub-area (a) does not provide for through traffic movements due to the presence of the railway, and the river on its western edge.

Observations were made of morning peak traffic flows in and across the test area. This was done because the predominant flows were then towards the river bridges, and the number of external trip destinations was minimized for the major flow direction. As the traffic model was destination orientated, a reduction of the number of destinations to be considered reduced model running times on the computer.

4.1 DATA COLLECTION

To apply the suggested dual-sampling technique for evaluation of the model, observations were taken for two separate morning peak periods in the study area. Data was collected over the time period 0700-0930 hours on Thursday, 5th and Friday, 6th December, 1974. On both days, the collected data comprised:

(a) traffic counts on streets inside the survey area, and on the cordon line, and

(b) the number-plates of two separate samples of vehicles entering and leaving the survey area.

The data observation posts are shown in Fig 3. At a later stage, measurements of vehicle speeds and flow rates on two local streets were taken, to calibrate simple speed-flow relationships for local streets in the test area.

The number plate observations were sorted to estimate vehicle movements across the area. A set of Origin-Destination matrices by time (15 minute intervals) were constructed based on a (nominal) 20% sample of all registration plates. Full details of the data analysis, including an innovative method of handling possible data errors, were given by Taylor (1976). Tables I and II show summary Origin-Destination matrices for total trip interchanges on the two survey days. The sets of Origin-Destination by time submatrices were used as inputs to the traffic model. Model predictions of street traffic volumes were then compared to the observed volumes, over 15 minute periods, at the volume observation stations shown on Fig 3.

5. EVALUATION OF THE TRAFFIC MODEL

5.1 OPTIMUM PARAMETERS

The traffic model was used with each data set in turn, to find the best-fit parameters (θ_*, γ_*) according to equation (3.2), using

(a) an initial grid search over a wide range of parameter values, and

(b) direct numerical function minimization techniques.

An immediate consequence of the investigation was that the stochastic components of the model (one of which was the sampling of perceived network arc and movement costs) required the adoption of a replication scheme. Under replication, the model was applied a number of times, with different random number sequences, for given values of θ and γ. Model outputs were then obtained by averaging the outputs obtained in each replication. (A further useful result of this procedure was that confidence intervals on each output could be estimated.) Estimated best-fit parameters for each of the two survey periods are shown in Table III, based on 15 minute vehicle counts at the 13 observation stations shown in Fig 3.

It can be seen from Table III that the values of θ_* for both data sets were very similar. However, the values of γ_* were quite different. Indeed the value of γ_* found for Friday 6/12/74 was not *practically* different from zero, whereas the value for Thursday 5/12/74 was significant in the model. Further

TABLE I

TOTAL MORNING PEAK PERIOD ORIGIN & DESTINATION MATRIX FOR THURSDAY 5/12/74

	DESTINATION							
ORIGIN	1	2	3	4	5	6	RESIDUAL	TOTAL
1	45 (14)	30 (14)	2760 (181)	0 (0)	110 (20)	0 (0)	0 (0)	2945 (183)
2	80 (22)	1670 (99)	120 (61)	15 (9)	45 (20)	0 (0)	435 (44)	2365 (128)
3	2240 (129)	275 (43)	110 (66)	20 (10)	430 (52)	20 (10)	415 (50)	3510 (168)
4	20 (10)	50 (17)	670 (77)	10 (7)	40 (12)	10 (7)	40 (26)	840 (85)
5	20 (10)	75 (21)	190 (31)	0 (0)	40 (14)	5 (5)	20 (12)	390 (43)
6	35 (13)	320 (39)	320 (60)	10 (7)	100 (18)	0 (0)	65 (28)	850 (80)
7	80 (18)	110 (20)	35 (36)	5 (5)	190 (26)	0 (0)	90 (18)	510 (55)
8	55 (15)	380 (36)	40 (35)	5 (5)	20 (10)	0 (0)	65 (14)	565 (55)
9	190 (29)	345 (39)	95 (55)	10 (7)	95 (21)	15 (8)	140 (24)	890 (81)
10	100 (20)	135 (23)	55 (44)	0 (0)	40 (11)	0 (0)	110 (22)	440 (59)
11	315 (46)	245 (36)	75 (44)	5 (5)	105 (20)	5 (5)	160 (28)	910 (81)
12	225 (26)	285 (32)	485 (96)	235 (32)	10 (10)	5 (5)	700 (72)	1945 (131)
13	1160 (73)	755 (63)	0 (0)	5 (5)	5 (5)	0 (0)	315 (44)	2240 (106)
14 (FINDON ST.)	675	-	-	-	-	-	-	675
RESIDUAL	805 (62)	485 (65)	380 (116)	130 (26)	380 (54)	95 (19)	? ?	2275 (160)
TOTAL	6045 (177)	5160 (168)	5335 (290)	455 (46)	1600 (94)	155 (26)	2650 (147)	21400 (421)

Note: Figures in parenthesis are standard errors of estimates.

investigation of the form of the response surface for ψ, for the Friday data, in the region of the optimum suggested the existence of a valley from $\gamma = 0$ to $\gamma = 0.50$ for $\theta \sim \theta_*$. There were only small variations in the values of ψ in this valley. For this reason, the representative model parameters for the test area were chosen as $\theta_* = 0.25$ (decimin)$^{-1}$ and $\gamma_* = 0.37$ (decimin)$^{\frac{1}{2}}$ where the units of travel time used in the model were deciminutes (tenths of minutes).

5.2 MODEL VALIDATIONS

Model fit was investigated by examining the degree to which the

TABLE II

TOTAL MORNING PEAK PERIOD ORIGIN & DESTINATION
MATRIX FOR FRIDAY 6/12/74

ORIGIN	DESTINATION 1	2	3	4	5	6	RESIDUAL	TOTAL
1	5	30	2990	0	80	5	0	3110
	(5)	(11)	(120)	(0)	(23)	(5)	(0)	(123)
2	85	1860	140	15	60	0	370	2530
	(19)	(92)	(71)	(9)	(19)	(0)	(43)	(127)
3	2675	270	50	20	460	50	225	3750
	(135)	(33)	(32)	(10)	(52)	(15)	(38)	(158)
4	0	40	610	0	70	0	30	750
	(0)	(15)	(57)	(0)	(20)	(0)	(11)	(63)
5	10	75	255	5	75	0	25	445
	(7)	(17)	(22)	(5)	(16)	(0)	(11)	(35)
6	10	325	340	15	110	0	100	900
	(7)	(34)	(37)	(9)	(24)	(0)	(23)	(61)
7	55	85	15	5	200	0	130	490
	(17)	(20)	(19)	(5)	(29)	(0)	(26)	(51)
8	50	295	60	0	15	0	155	575
	(15)	(37)	(36)	(0)	(8)	(0)	(28)	(61)
9	170	340	40	0	100	0	185	835
	(30)	(39)	(30)	(0)	(25)	(0)	(30)	(70)
10	205	75	30	0	40	5	80	435
	(33)	(26)	(30)	(0)	(17)	(5)	(17)	(57)
11	255	305	65	5	200	0	135	965
	(40)	(42)	(41)	(5)	(29)	(0)	(29)	(82)
12	175	300	395	145	35	0	760	1810
	(34)	(40)	(142)	(23)	(14)	(0)	(68)	(168)
13	1230	790	0	10	5	5	290	2330
	(76)	(65)	(0)	(7)	(5)	(5)	(40)	(108)
14 (FINDON ST.)	695	-	-	-	-	-	-	695
RESIDUAL	845	490	415	95	410	90	?	2345
	(61)	(59)	(173)	(20)	(45)	(25)	?	(200)
TOTAL	6465	5280	5405	315	1860	155	2480	21960
	(183)	(163)	(285)	(37)	(98)	(30)	(117)	(408)

Note: Figures in parentheses are standard errors of estimates.

model reproduced the observed station traffic volumes. Various statistical tests were used, primarily concerned with the hypothesized relationship that observed volumes (y) were equivalent to the model predictions (x), i.e.

$$y = x \tag{5.1}$$

The tests were based on volumes from all stations combined to form a single data set. This was felt necessary because the available ranges of data from the individual stations might be very limited. Further, only 10 data points were available at each station whereas 130 points (based on 15 minute traffic counts)

TABLE III

BEST-FIT PARAMETER VALUES FOR THE TRAFFIC MODEL APPLIED TO THE WEST HAWTHORN TEST AREA

	θ_* (deciminute)$^{-1}$	γ_* (deciminute)$^{\frac{1}{2}}$
Thursday, 5/12/74	0.249	0.371
Friday, 6/12/74	0.259	0.007
Selected representative values	0.25	0.37

were available for the combined data set. Results for longer counting periods (30, 60 and 150 minutes) could also be examined for the combined data set. (The total observation period for each day was 150 minutes.) Combination gave a good representation of observations over a full range of flow rates from 0 to 2200 vph. Later, some considerations of the performance of the model at individual stations were made in a search for possible model errors and biases.

The following tests were applied to help evaluate the performance of the model:

(a) Regression of observed volumes on model volumes to yield a a relationship

$$y = a + bx \tag{5.2}$$

where the expected values of a and b were 0 and 1 respectively. Further tests considered any possible differences between the means $\bar{y}$ and $\bar{x}$, and the variances s_y^2 and s_x^2.

(b) Measures of the degree of correlation between y and x;

(i) correlation coefficient (r),

(ii) coefficient of determination (r^2) which is the proportion of the variance of y explained by the regression relationship, and

(iii) residual variance about the regression relationship, given by $s_y^2(1-r^2)$.

These tests do not distinguish between random errors and systematic errors resulting from biases in the model. Aitken (1973) described a "coefficient of efficiency" (E) which may be used as a test of bias in a model:

$$E = \frac{\sum_{i=1}^{n} (y_i-\bar{y})^2 - \sum_{i=1}^{n} (y_i-x_i)^2}{\sum_{i=1}^{n} (y_i-\bar{y})^2} \tag{5.3}$$

E is similar in form to the coefficient of determination. If the results from a model are highly correlated but biased, then E is much less than r^2. If the model is completely unbiased, $E = r^2$.

Traffic volume observations were available in 15 minute intervals. The tests of observed and predicted volumes were conducted over the following time intervals, by aggregating consecutive period volumes where necessary: 15, 30, 60 minute and total period (2½ hours). In this way some idea of the usefulness of the model for predicting particular period volumes could be gained. Summary results of the evaluation tests are given in Tables IV and V. Figures 4, 5, 6 and 7 show scatter diagrams and regression lines for the data summarized by the tables. From these results it can be seen that the model performed well in the reproduction of the observed traffic volumes for both the Thursday and Friday data sets. One suggestion from Tables IV and V is that the observed traffic count mean ($\bar{y}$) and standard deviation (s_y) were consistently greater than the model values ($\bar{x}$ and s_x), although the differences were not statistically significant. This could indicate a possible bias in the model, or perhaps indicates errors in data collection such as a smaller sample size than that expected. On the basis of these (limited) tests, the model appears to be a useful tool for estimation of local street traffic volumes, for periods of 15 minutes upwards, given a trip interchange table for the test area. Longer periods (e.g. 30 or 60 minutes) were predicted with greater reliability (see Tables IV and V). This could be due to the use of a 15 minute computation interval in the model applications, and the subsequent averaging effects when longer period volumes were considered. Note, however, that none of the fitted linear relationships were significantly different from the postulated relationship $y = x$. It can also be seen from Tables IV and V that the optimum parameters found for Thursday, 5/12/74 performed better on both data sets together than did the Friday parameters, although the Friday parameters were still useful. Hence the choice of $\theta = 0.25$, $\gamma = 0.37$ as the representative parameters for the Hawthorn test area.

Further analyses of model performance and patterns of residual errors were made, and described by Taylor (1976). These tests were unable to locate any significant biases in the model results, although they did suggest some weaknesses at three observation stations. These weaknesses could be attributed to an inappropriate choice of travel time and delay functions for certain local streets in the test area, where unusual or different physical characteristics existed. As this discussion has not covered specific details of these functions, it would not seem appropriate to discuss this problem in great detail. In general it is sufficient to say that the model performed well over the test area, but some difficulties existed at particular stations. Readers interested in pursuing the slight problems in the model could refer to Taylor (1976) for a full discussion. Reference is also made to modifications which might further improve the performance of the model.

TABLE IV

RESULTS OF EVALUATION TESTS ON MODEL RESULTS FOR THURSDAY 5/12/74
(MORNING PEAK)

Model parameters		$\theta = 0.249$ (1) $\gamma = 0.371$				$\theta = 0.259$ (2) $\gamma = 0.007$			
Time Period	(min)	15	30	60	Total	15	30	60	Total
No. of Points	(n)	130	65	26	13	130	65	26	13
Observed Counts	$\bar{y}$	162.3	324.6	689.2	1623.1	162.3	324.6	689.2	1623.1
	s_y	135.4	269.2	553.8	1334.4	135.4	269.2	553.8	1334.4
Model Counts	$\bar{x}$	155.8	311.7	642.5	1558.3	156.5	312.5	660.3	1564.2
	s_x	117.3	229.4	469.7	1122.4	117.8	228.5	469.7	1080.4
Regression	a	4.0	-4.7	-8.1	-122.3	14.0	12.1	20.5	-98.1
	b	1.02	1.06	1.09	1.12	0.95	1.00	1.01	1.10
	t(3)	0.33	0.89	0.90	1.00	0.91	0.01	0.11	0.59
Correlation	r	0.881	0.900	0.921	0.942	0.825	0.848	0.859	0.891
	r^2	0.776	0.810	0.848	0.887	0.681	0.719	0.738	0.794
	E	0.773	0.806	0.835	0.875	0.677	0.717	0.735	0.785
	$s_y\sqrt{1-r^2}$	64.1	117.3	215.9	448.5	76.5	142.7	283.5	605.5

Notes:
1. Optimum parameters found for Thursday 5/12/74.
2. Optimum parameters found for Friday 6/12/74.
3. t statistic for regression coefficient b based on the hypothesis that E(b) = 1.0. Degrees of freedom are (n-2). None of the calculated t statistics were significant at the 5% level.

TABLE V

RESULTS OF EVALUATION TESTS ON MODEL RESULTS FOR FRIDAY 6/12/74
(MORNING PEAK)

Model parameters		θ = 0.249 (1)				θ = 0.259 (2)			
		γ = 0.371				γ = 0.007			
Time Period	(min)	15	30	60	Total	15	30	60	Total
No. of Points	(n)	130	65	26	13	130	65	26	13
Observed Counts	$\bar{y}$	168.3	336.6	703.3	1683.1	168.3	336.6	703.3	1683.1
	s_y	137.2	273.3	549.5	1367.4	137.2	273.3	549.5	1367.4
Model Counts	$\bar{x}$	157.7	315.4	653.3	1576.9	155.6	311.2	653.1	1555.9
	s_x	122.2	233.6	468.8	1111.0	124.8	243.3	496.1	1153.1
Regression	a	13.9	6.7	10.1	-150.1	20.5	25.4	40.1	-49.0
	b	0.98	1.05	1.06	1.16	0.95	1.00	1.02	1.11
	t(3)	0.42	0.70	0.60	1.34	-1.02	0.00	0.17	0.92
Correlation	r	0.865	0.894	0.905	0.945	0.864	0.891	0.917	0.939
	r^2	0.748	0.799	0.819	0.893	0.746	0.794	0.841	0.882
	E	0.742	0.792	0.808	0.868	0.736	0.784	0.832	0.863
	$s_y\sqrt{1-r^2}$	68.9	122.5	233.8	447.3	69.2	124.0	219.1	469.7

Notes:
1. Optimum parameters found for Thursday 5/12/74.
2. Optumum parameters found for Friday 6/12/74
3. t statistic for regression coefficient b based on the hypothesis that E(b) = 1.0. Degrees of freedom are (n-2). None of the calculated t statistics were significant at the 5% level.

6. CONCLUSIONS

The local area traffic model outlined in this paper, and described in detail elsewhere (Taylor, 1976) stands as a potentially useful tool for the evaluation of short period traffic movements through small parts of an urban area. Evaluation studies have suggested that the model is capable of reproducing observed street traffic volumes from supplied travel demand data. A rigorous scheme for model evaluation, involving the testing of a calibrated model with data independent of that used in the calibration, was applied to aid in the minimization of any effects of data dependence in the evaluation process.

It can be suggested that the model performed well in the evaluation. Some areas for future and related research would include the improvement of the elemental travel cost and delay functions in the model, methods for the estimation of peak period travel demands in a small part of an urban area, and the investigation of representative model parameters for other networks besides the one studied in this case.

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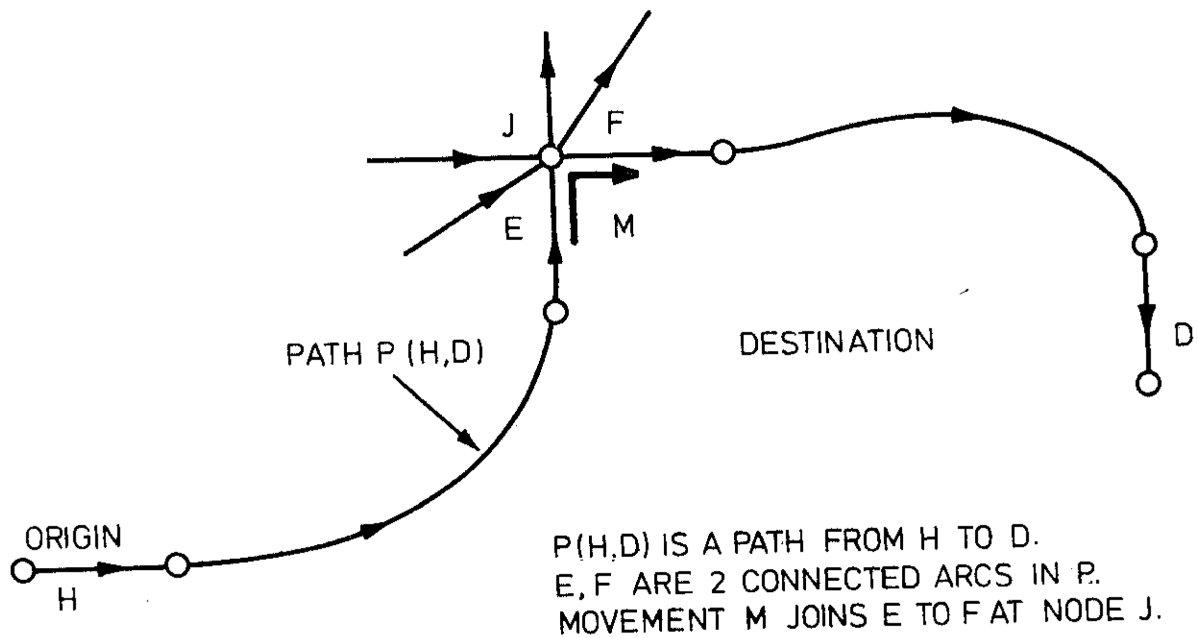

Fig 1 - Schematic representation of a network path

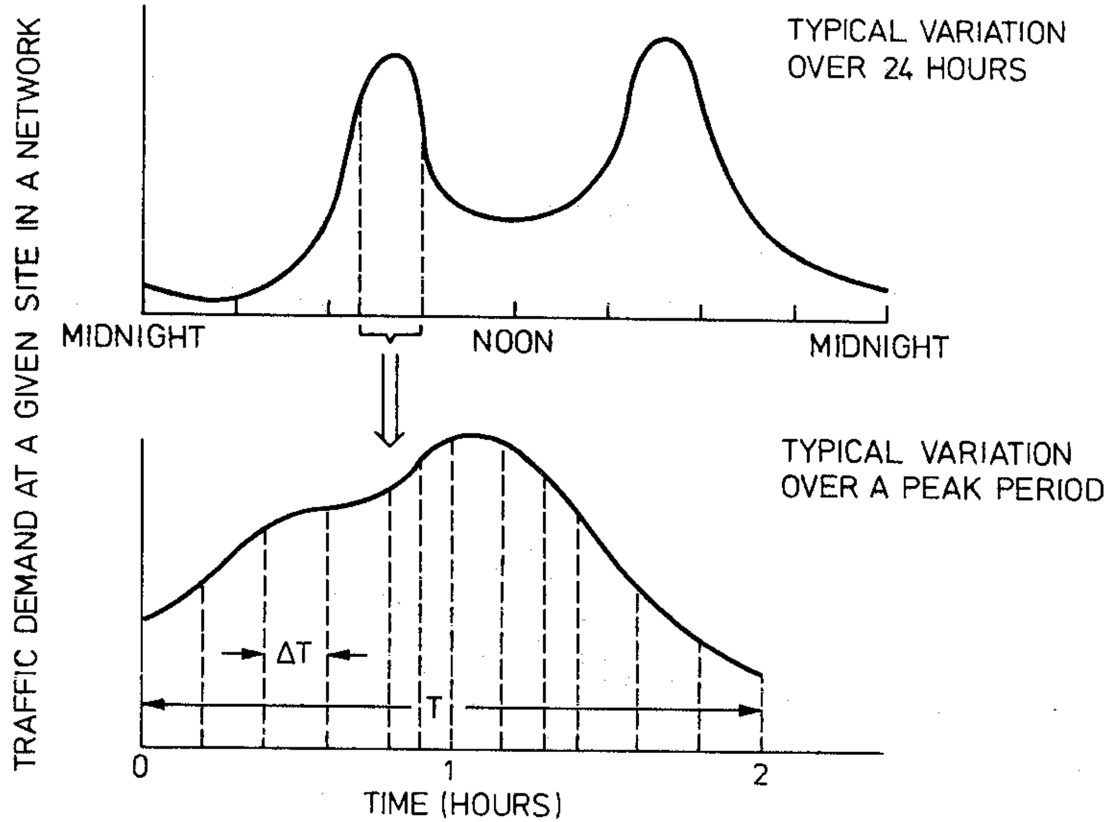

Fig 2 - Schematic representation of variations in traffic demands over time

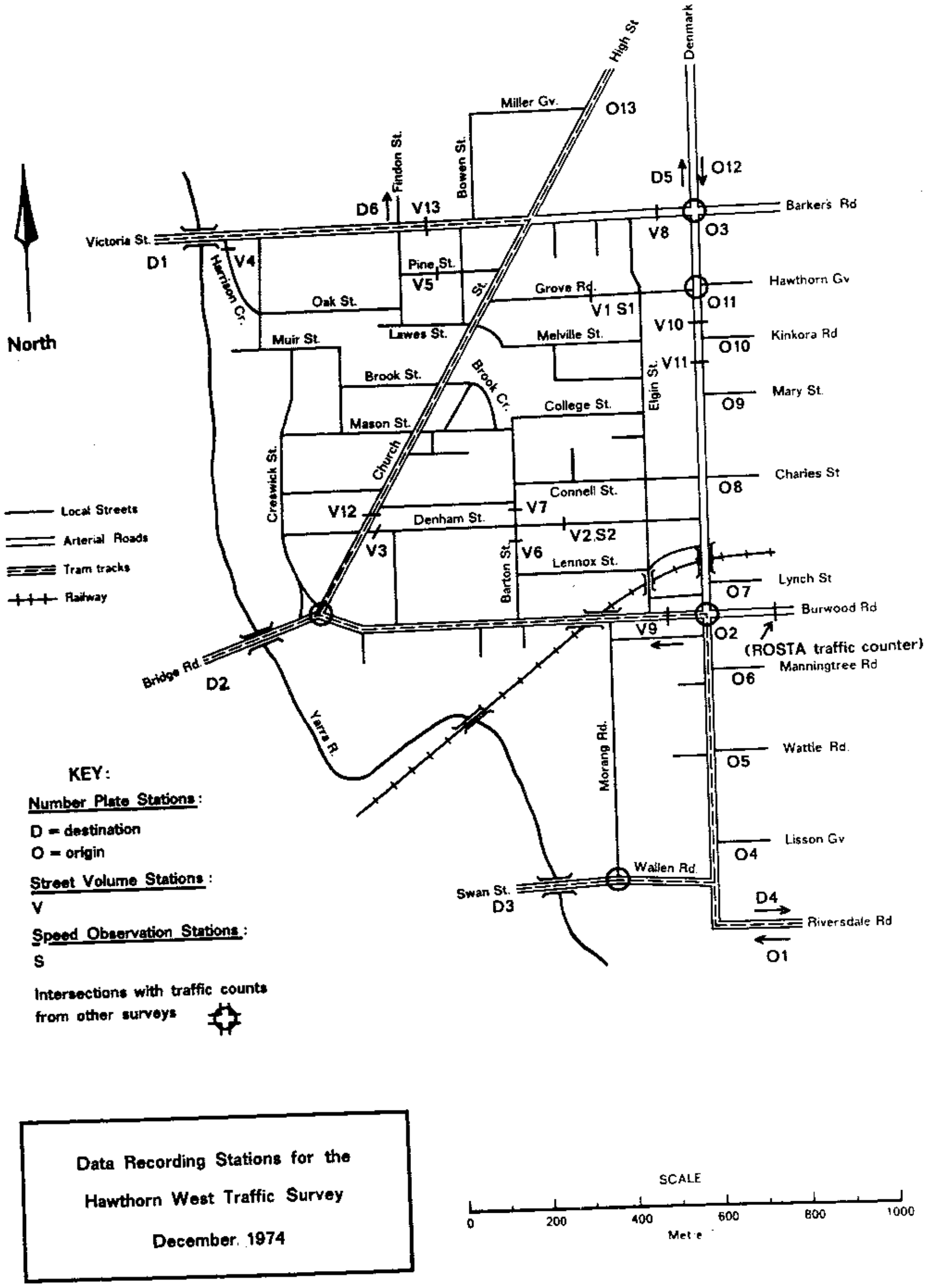

Fig 3 - Data recording stations for the Hawthorn
West traffic survey, December 1974

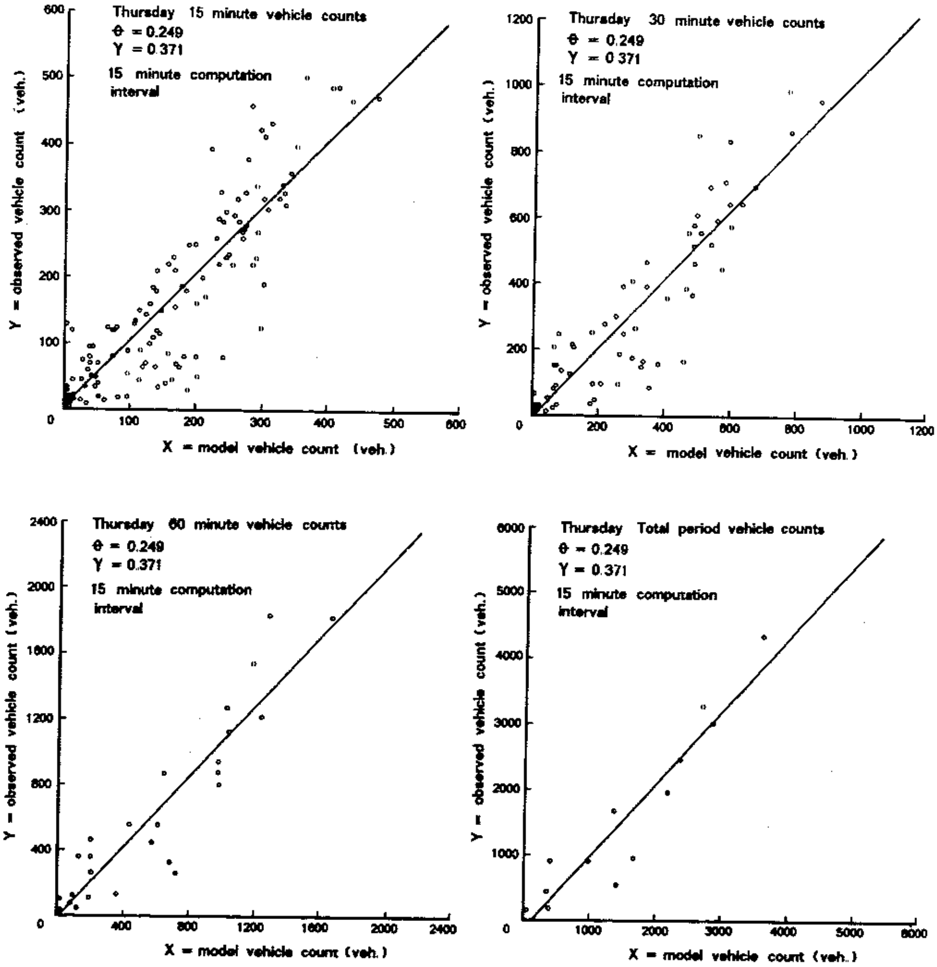

Fig 4 - Regression plots for Thursday, 5/12/74 based on optimum parameters for Thursday data

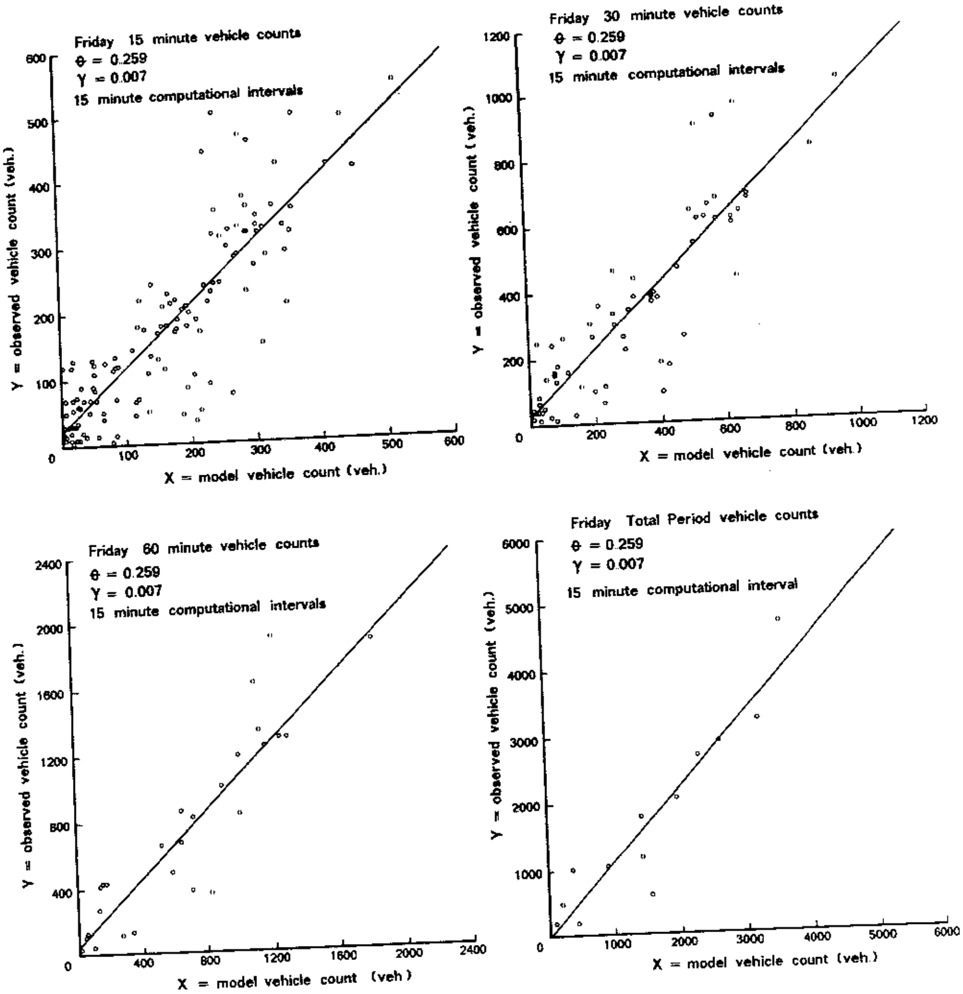

Fig 5 - Regression plots for Friday, 6/12/74 based on optimum parameters for Friday data

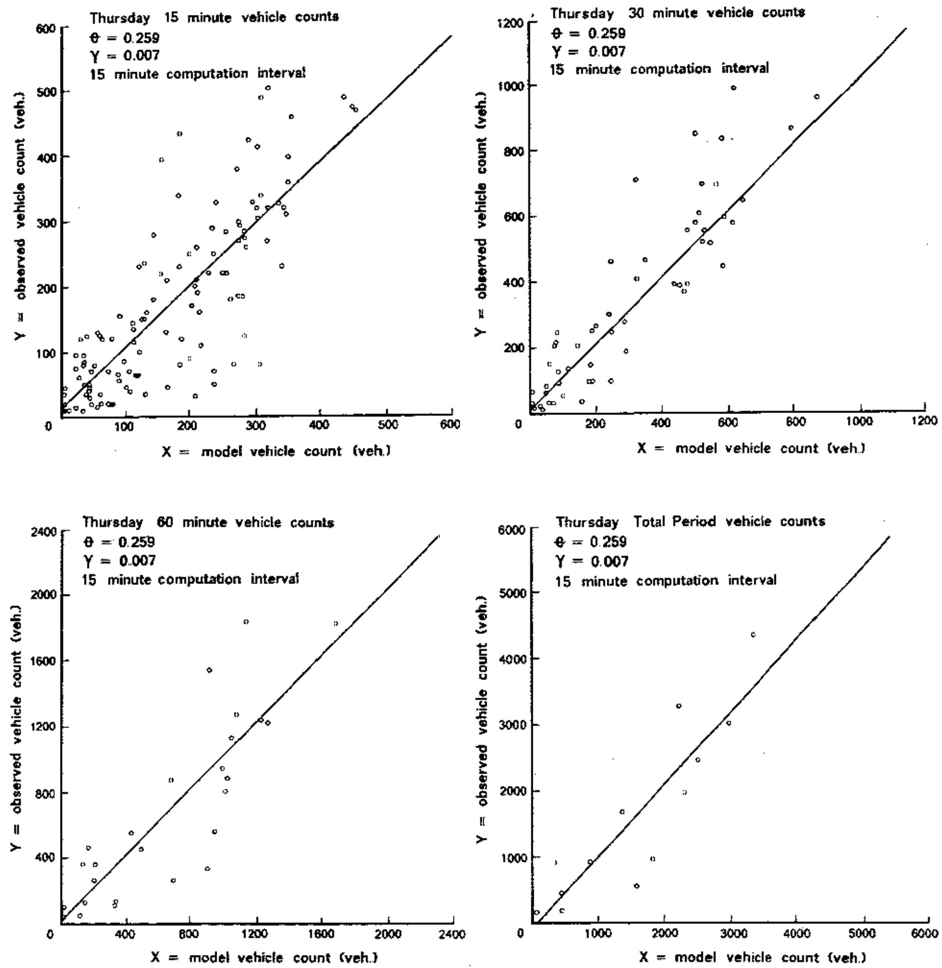

Fig 6 - Regression plots for Thursday, 5/12/74 based on optimum parameters for Friday data

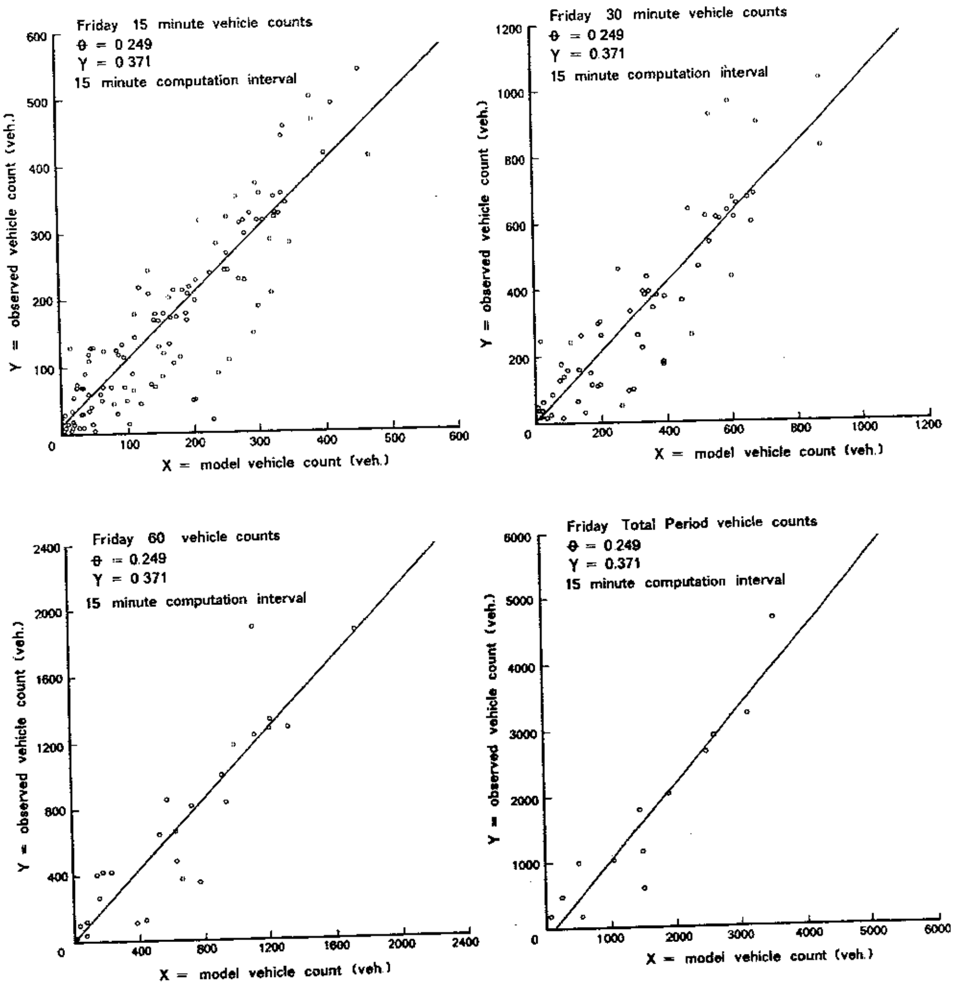

Fig 7 - Regression plots for Friday, 6/12/74 based on optimum parameters for Thursday data