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Studies in the Demand for Short Haul Air Transportation

Adib Kanafani, Geoffrey Gosling, Seyfollah Taghavi

October 1975

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THE INSTITUTE OF TRANSPORTATION
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UNIVERSITY OF CALIFORNIA

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STUDIES IN THE DEMAND FOR SHORT HAUL AIR TRANSPORTATION

by

Adib Kanafani
Geoffrey Gosling
Seyfollah Taghavi

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INSTITUTE OF TRANSPORTATION AND TRAFFIC ENGINEERING

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PREFACE

This report represents the second of two reports concerned with the study of demand and supply in short haul air transportation. The study was conducted at the Institute of Transportation and Traffic Engineering of the University of California at Berkeley under the sponsorship of the Ames Research Center of the National Aeronautics and Space Administration. This report deals with an analysis of demand in a short haul air transportation corridor, namely the California Corridor between the San Francisco and the Los Angeles Metropolitan Regions. The study is an extension of an earlier study of a similar nature conducted on the same corridor. It includes extensions in terms of model formulations, estimation techniques, and traffic data handling.

The main concern of this study of demand is the process by which travelers in the corridor appear to choose among the available routes. There are 12 routes connecting the two metropolitan areas constituted by connections between three airports in the San Francisco area and five in the Los Angeles area. Multinomia type choice models appear to be a powerful tool to explain the traveler choice behaviour. Calibrated separately for business and nonbusiness traffic, these models exhibit good explanatory power. On the other hand, abstract mode type models that attempt to explain the demand generation and the choice process simultaneously do not appear to be as successful. The reasons for this can be mainly due to deficiencies in the data base, and to the absence of sufficient socio-economic information regarding the travelers. It is believed that an effort to collect traveler data in a short haul corridor is an essential step that should precede any further attempts to model the demand behaviour in a short haul air travel corridor.

Throughout the conduct of the study valuable assistance to the authors was given by a number of their colleagues at the Institute. The authors wish to extend their appreciation to Professor R. Horonjeff, Elisabeth Sadoulet, and Marvin Tsao. The authors also wish to extend their appreciation to Messrs. George Kenyon and Mark Waters of the Ames Research Center and their staff.

CONTENTS

LIST OF FIGURES

COMPARISON OF MODELLED AND OBSERVED TRAFFIC PROPORTIONS

COMPARISON OF MODELLED AND OBSERVED TRAFFIC ON EACH ROUTE

1. INTRODUCTION

In considering the demand for short haul air travel in a given market, there are two aspects that must be addressed. The first concerns the size of the total market and the second is the way this travel is distributed over the available services. The extent to which these two aspects are related must depend on the market under consideration, in particular on the geographical distribution of origins and destinations within the communities that comprise the market and the pattern of air services regarding both the extent of the route network and the frequency of flights. The extent of competition from other modes of transport may also be important.

In some situations the consumer is not presented with any real choice of routes. The decision to travel by air therefore is either a choice of air versus other modes or of air versus not making the trip. Seen from the standpoint of air travel then, the total market is merely the summation of the demand on each route, and both aspects can be considered as one.. However, in the general case, the consumer does have a choice of routes and so the two aspects may be characterised as the total demand and the route choice.

These aspects have been investigated in two ways by attempting to construct models that replicate observed patterns of demand in the California corridor. The first model, termed the Choice Model, assumes that the total demand is known and attempts to determine how travellers choose by which route to fly by calculating the proportion of the total traffic that uses each route. The second model calculates the actual magnitude of the traffic on each route from a consideration of the distribution of population and income in the market and user-perceived characteristics of each route such as cost and travel time. Since these parameters are not specific to any given mode, this type of model has traditionally been termed an Abstract Mode Model.

Three parameters have been selected for incorporation in the choice process inherent in the two models. They are travel time, departure frequency and cost. In reality, travel time consists of airport access time (i.e. time from actual trip origin to the airport chosen), processing and wait time at the terminals, the line-haul time (i.e. time spent travelling by air including any stop-over time en-route) and the airport egress time (i.e. time from leaving the final airport to reaching actual trip destination). Previous studies have suggested that in such a market in view of the similarity of flight times on different routes, people are more influenced by the access and egress time than by the total time from door to door. Accordingly, the sum of access and egress time (termed access time hereafter) has been used as a measure of travel time. Departure frequency obviously varies during the day and from day to day. Total weekly departures was felt to be a reasonable measure of perceived frequency. Perceived cost was measured by the economy class fare on each route.

Some features of the California corridor that are pertinent to the assumptions underlying the model should be noted. The corridor consists of two large metropolitan areas about 400 miles apart (Figure 1-1). They are connected by a single freeway, the journey by auto usually taking some eight hours. There is a conventional rail service which is even slower and extremely infrequent, being of the order of one or two trains a day. By contrast, the flight time is about one hour for direct flights. Intrastate air travel in California is somewhat less expensive than domestic fare levels generally, and in 1970 the one-way fare was of the order of $20. Both metropolitan areas, but particularly Los Angeles, have well developed urban freeway systems providing fairly rapid access to airports. However, the presence of the San Francisco Bay in the San Francisco metropolitan area and the consequent presence of a limited number of toll crossings affects access. The principal airport in each metropolitan area, San Francisco International and Los Angeles International (LAX) are major airports on both the U.S. domestic and international air route networks, sharing the bulk of West Coast long-range traffic including direct European and trans-Pacific flights. In consequence, they dominate the air market for their respective areas.

Figure 1-1 California Corridor Showing Metropolitan Areas and Airports

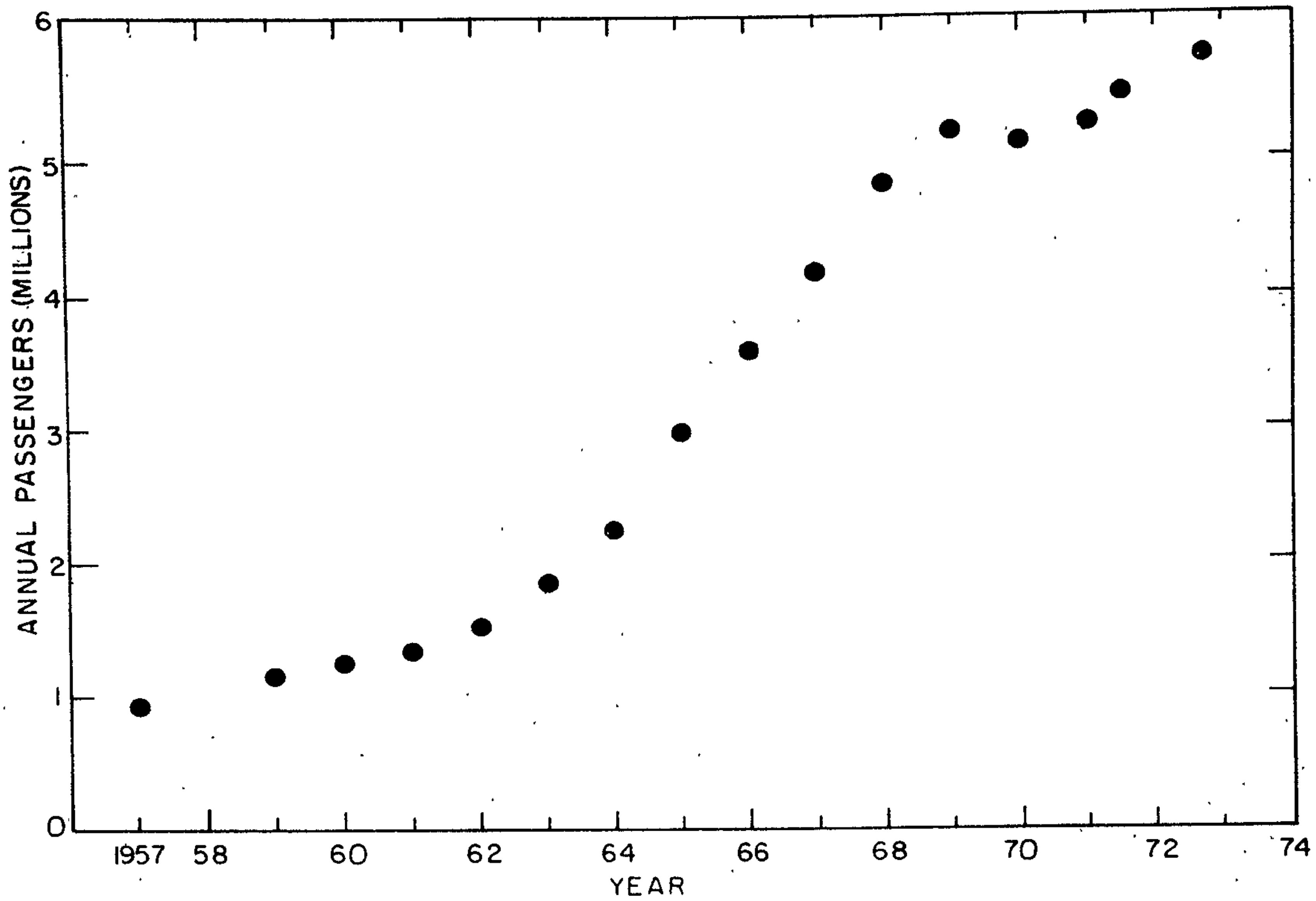

Figure 1-2 Growth of Traffic in the California Corrido

The significance of the above comments will be discussed below in considering the data base and the formulation and results of the individual models.

Data on the total annual traffic in the corridor was obtained for a period of 15 years from publications of the California Public Utilities Commission (see Chapter 3). This has been plotted in Figure 1-2 for traffic between the two metropolitan areas. It shows a characteristic growth curve with the increase in traffic growing each year until around 1964 when it stabilized. From 1968 the rate of increase has been declining with strong signs that saturation of the market is being approached, with annual traffic of around 6 million passengers. Thus, the California Corridor may be considered a mature market as far as air travel is concerned. It can also be concluded from this that the analysis of the segmentation of total traffic among the available services can be done without a need to feed back to total traffic, at least in the short run.

2. MODEL DESIGN

ANALYTICAL FRAMEWORK

Both models use essentially the same analytical framework. Each of the two metropolitan areas that the corridor serves are divided into several zones. In each area there are more zones than airports and no zone has more than one airport. The models calculate the traffic (propportional or absolute) between each zone pair by each available route, routes being defined in terms of airport pairs in the two areas between which air service is provided.

Summing the traffic over each route for any zone pair gives the total zone to zone traffic. Summing the total zone to zone traffic over all zone pairs gives the total traffic.

Parameters relate either to zone characteristics such as population, route characteristics such as fare, or zone-route interrelationships such as access time from a given zone to a given airport (or route).

The choice of zone boundaries is described in Chapter 3, and shown on Figures 2-1 and 2-2. These figures also show the location of the airports incorporated in this study.

LIMITATION

This structure clearly only relates to traffic generated in one metropolitan area with a destination in the other. This is termed local traffic. Of course, the air carriers in the corridor also carry other traffic, both people originating in one area and flying to the other enroute for some other destination (or returning to one via the other) and people enroute from an origin outside the corridor to a destination outside the corridor whose flight calls at both metropolitan areas. These two categories are termed through traffic. There is negligable traffic between airports within each area and little, if any, goes by flights that serve the corridor. The models do not calculate either through traffic or zone to zone traffic within each area.

For practical and computational reasons, the zones are fairly large. This introduces considerable approximation in determining zone parameters which must necessarily be very aggregate measures.

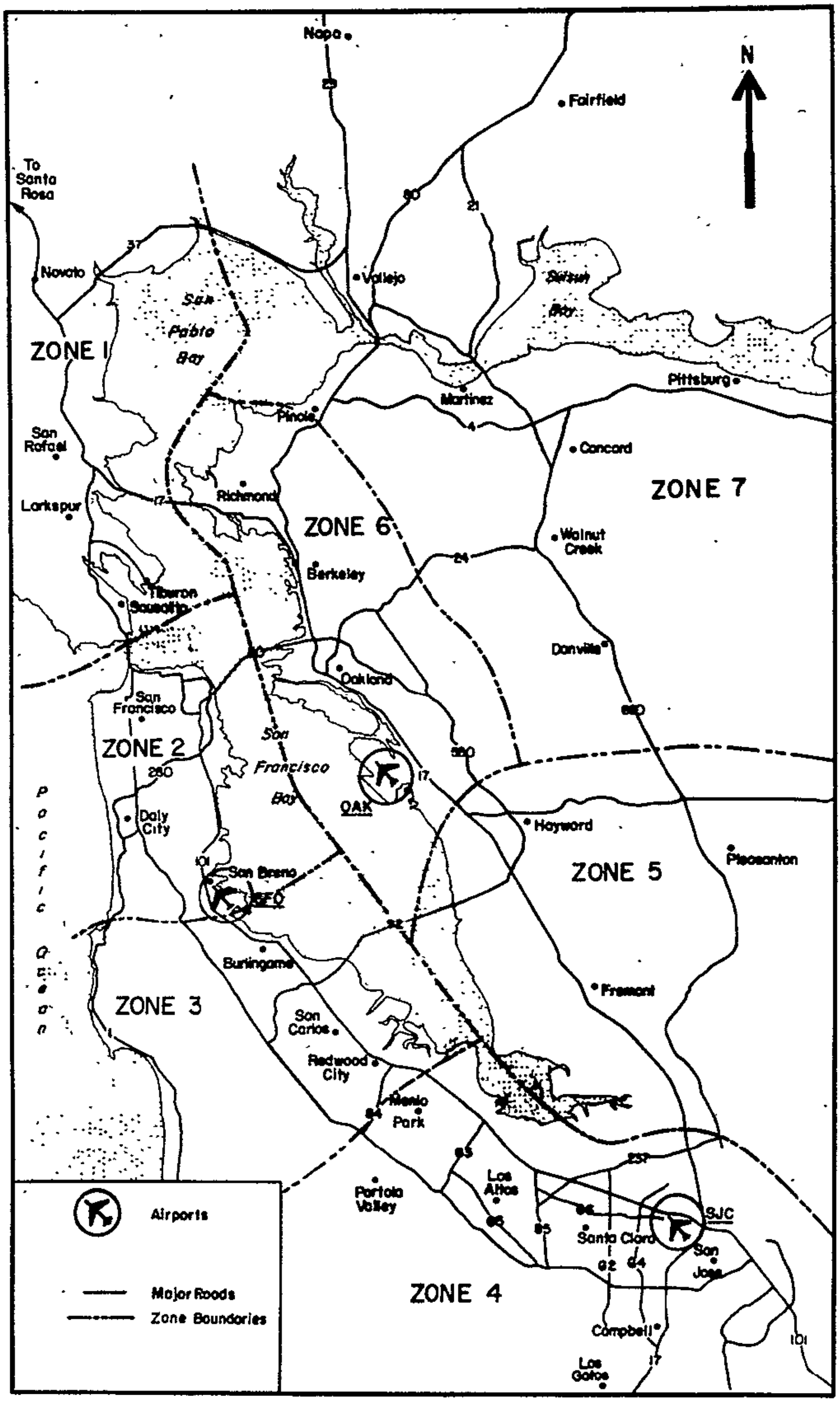

Figure 2-1 San Francisco Bay Area. Zone Boundaries and Airport Locations.

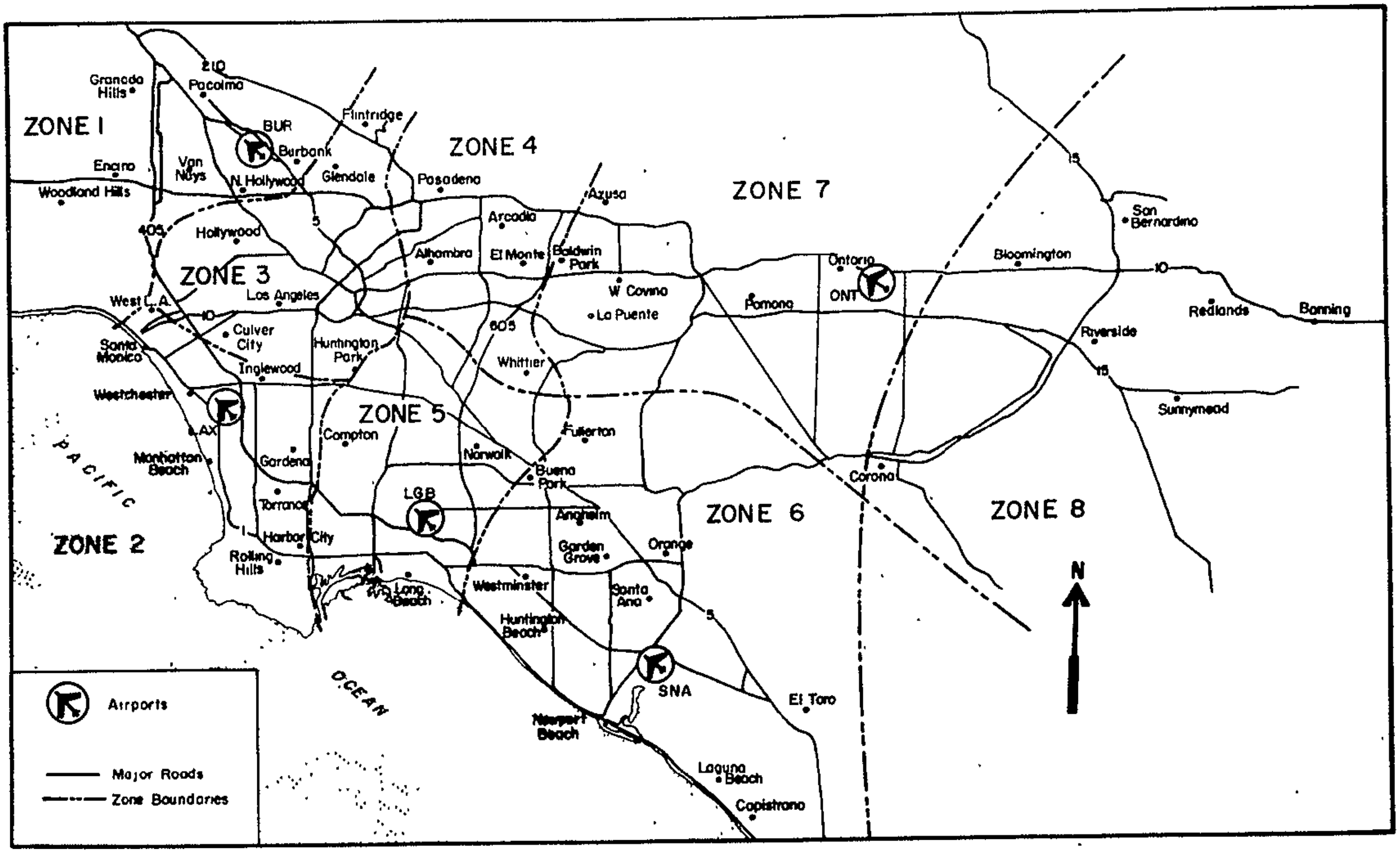

Figure 2-2 Los Angeles Area. Zone Boundaries and Airport Locations

CHOICE MODEL

The choice model assumes a logit form

$$P_{ijk} = \frac{e^{U_{ijk}}}{\sum_k e^{U_{ijk}}}$$

where P_{ijk} = proportion of traffic between zones i and j using route k

U_{ijk} = measure of the utility of using route k derived by passengers between zones i and j expressed in terms of objective parameter

The form chosen for the utility function was

$$U_{ijk} = \alpha_1 T_{ijk} + \alpha_2 F_k + \alpha_3 C_k$$

where T_{ijk} = sum of average access times from zones i and j to the respective airports defined by route k

F_k = frequency of service on route k expressed in terms of total flights per week

C_k = fare on route k in dollars

$\alpha_1, \alpha_2, \alpha_3$ = coefficients determined by calibration

The model was calibrated by maximum likelihood method as follows: For any zone pair ij the probability of a traveller between i and j choosing route k is P_{ijk} determined as above. If t_{ij} is the total number of travellers between i and j and t_{ijk} is the number using route k, multinominal probability theory states that the probability of getting exactly t_{ijk} on route k for every route is:

$$\frac{t_{ij}!}{t_{ij1}!\ t_{ij2}!\ \ldots . t_{ijn}!}\ P_{ij1}^{\ t_{ij1}}\ .P_{ij2}^{\ t_{ij2}}\ \ldots . P_{ijn}^{\ t_{ijn}}$$

where n is the number of routes. The likelihood function ℓ is defined as the probability of obtaining the observed traffic distribution for all zone pairs and is the product of the probabilities of obtaining the observed traffic on each, or

$$\ell = \prod_{ij} \frac{t_{ij}!}{t_{ij1}!\ t_{ij2}!\ \ldots t_{ijn}!}\ P_{ij1}^{\ t_{ij1}}\ P_{ij2}^{\ t_{ij2}} \ldots . P_{ijn}^{\ t_{ijn}}$$

Values of the coefficients, α, are chosen to maximize ℓ. It is more convenient to use the logarithm of the likelihood function and since a function and its logarithm are monotonic, the result is not affected by maximizing the logarithm.

$$\log \ell = \sum_{ij} \log \left(\frac{t_{ij}!}{t_{ij_1}!\, t_{ij_2}! \ldots t_{ijn}!}\, P_{ij_1}^{\,t_{ij_1}}\, P_{ij_2}^{\,t_{ij_2}} \ldots P_{ijn}^{\,t_{ijn}} \right)$$

$$= \sum_{ij} \sum_{k} t_{ijk} \log P_{ijk} + K$$

$$\text{where } K = \sum_{ij} \log \frac{t_{ij}!}{t_{ij_1}!\, t_{ij_2}! \ldots t_{ijn}!}$$

Since the t_{ij} and t_{ijk} terms are observed traffic, they are not influenced by the values of the coefficients α and therefore the term K is constant with respect to the α terms and its omission will not effect the values of α to give a maximum.

$$L = \log \ell - K = \sum_{ij} \sum_{k} t_{ijk} \log P_{ijk}$$

Initial values of zero are assigned to the coefficients and the log likelihood function L is maximized iteratively using a modified Newton-Raphson algorithm to obtain the α values that produce zero values for the first derivative of L with respect to each α, subject to a negative second derivative.

ABSTRACT MODE MODEL

The second model follows a fairly common formulation:

$$\hat{t}_{ijk} = e^{\Theta_1} \left[\frac{P_i\ P_j}{10^{12}}\right]^{\Theta_2} \left[\frac{I_i I_j}{10^{8}}\right]^{\Theta_3} T_b^{\Theta_4}\ C_b^{\Theta_5}\ F_b^{\Theta_6} \left[\frac{T_k}{T_b}\right]^{\Theta_7} \left[\frac{C_k}{C_b}\right]^{\Theta_8} \cdot \left[\frac{F_k}{F_b}\right]^{\Theta_9}$$

where $\hat{t}_{ijk}$ = traffic between zones i and j by route k

P_i, P_j = population of zones i and j respectively

I_i, I_j = median income of families in zones i and j respectively, expressed in dollars

T, C, F = access time, cost and frequency parameters defined as for the Choice Model in Section 2.2.3 above. T_b, C_b, F_b are the best or most favorable values of each parameter available to a traveller between zones i and j. T_k, C_k, F_k are the values on route k. The best values do not necessarily occur on the same route.

$\Theta_1\ \Theta_2 \ldots \Theta_9$ = coefficients determined by calibration

The introduction of the factors of powers of ten to the population and income groups is simply to avoid the need to deal with excessively large numbers in data preparation and for computational reasons.

Because of the formulation of the model, calibration by maximum likelihood is not possible and the method of least squares was used instead.

$$\text{squared error } E = \sum_{ij} \sum_{k} \left[\hat{t}_{ijk} - t_{ijk}\right]^2$$

where $\hat{t}_{ijk}$ = computed traffic between zones i and j by route k

t_{ijk} = observed traffic between zones i and j by route k

An iterative method similar to the Choice Model is used to obtain parameter values that minimize the squared error.

However, it was found that it is not possible to converge to a solution from assumed coefficients of zero. Therefore initial values of the coefficients were determined by carrying out a log linear regression on the data.

3. DATA BASE

SOURCES OF DATA

In order to calibrate the two models, data are required for both the dependent variable, the zone to zone traffic flows, and the independent variables, access time, frequency, fare, population and income.

Preparation of the data base was simplified by selecting the zones to correspond to those used for a previous study ("Forecasting the Demand Potential for STOL Air Transportation") (1). This enabled some of the data collected for that study to be used without requiring extensive modification.

The traffic data was based on the results of a three-day on-board survey conducted in October 1970 as part of the studies for the California Master Plan of Aviation by Daniel, Mann, Johnson and Mendenhall (2). This survey provided zone to zone flows segregated by airport pair used, for both business and non-business traffic. It covered all airport pair routes in the study corridor except between San Francisco International and Los Angeles International (SFO/LAX). Unfortunately, this is the link with the heaviest traffic, a deficiency which it was attempted to remedy as discussed below.

In addition to the survey data, traffic flows on an annual and quarterly basis are available from California Public Utilities Commission reports (3 & 4). These, however, are only concerned with traffic between airports and do not provide any data on origin or destination within the metropolitan area. The PUC reports give two different measures of the traffic. One series of reports (PUC form 1504) gives the total traffic on board (both through and local passengers, as defined in Chapter 2) for aircraft flying between airport pairs. No data is given for traffic between airport pairs in the same metropolitan area. The other series of reports (form 1511) gives the traffic with an origin at one airport of a pair and a destination at the other. It therefore only measures local passengers. A further important difference between the reports is that the former essentially only measures the combination of direct traffic between the airport pair considered and indirect traffic between other airport pairs that uses that leg as part of the route, while the latter measures both direct and indirect traffic between the airport pair, however routed.

The average acess time from each zone to all the airports in the area was obtained from the STOL study. They had been obtained from road maps of the areas, assuming speeds of 25 mph for city streets, 40 mph for urban highways and 50 mph for freeways. The zone value was obtained by considering each city in the zone and then combining these results. Terminal times were not included as they were assumed to be equal for all cases.

Frequency and fare data were obtained from the October 1970 Official Airline Guide. Frequency was defined as the total number of scheduled non-stop and one-stop flights per week between each pair. Coach air fare was used, including tax. Where different carriers had slightly different fares, a composite fare was used reflecting relative frequency of flights by each.

Population and median family income for each zone in the two areas was also obtained from the STOL study. Data for individual cities had been obtained from the 1970 Census Report of the U.S. Bureau of the Census and aggregated into the fifteen zones.

USE OF SYNTHETIC DATA

In addition to the problem of the absence of data for the SFO/LAX route, comparison of the traffic figures from the survey with the PUC figures for the corresponding quarter suggested that the survey sampling rate had varied from route to route. It was therefore decided to investigate the effect of using a synthetic data base constructed by combining the survey data and PUC data. It was assumed that although the sampling rate may have varied, the data obtained still represented an unbiased sample of the total traffic on that route. It was further assumed that the zonal distribution of destinations for passengers using routes to either SFO or LAX that were included in the survey represented the trip end distribution of all passengers through those airports, including those on the SFO/LAX link.

The total traffic on each route was adjusted to correspond to the PUC figures and distributed among the zone pairs according to the survey proportions.

The SFO/LAX traffic was synthesized by taking the PUC figures and assigning the trip ends to zones according to the overall proportions determined in the survey for routes ending at the particular airport.

In order to obtain zone to zone traffic, it was necessary to further assume that the proportional distribution of destination zones also represented the distribution of origin zones for traffic originating at SFO or LAX, and that this distribution of destination zones was constant for traffic from all origin zones. This final assumption is easily the weakest.

DATA MODIFICATION TO RESTRICT CHOICE

The models as designed calculate the traffic between any zone pair by all possible routes. Although over 15,000 sample points were obtained in the survey, when broken down into the large number of data sets (56 zone pairs, 13 routes, 2 trip purpose categories) many cells of the resulting trip tables have very few entries. It was felt that the calibration process might be unduly influenced by a spurious entry or the values of the coefficients distorted by the need to accomodate many zero entries.

An algorithm was devised which defined non-feasible route choices based on whether it seemed reasonable for a given airport to attract traffic from a particular zone. For any zone pair a route was considered feasible if (and only if) both airports were considered possible choices for the respective zones.

Trip cells for non-feasible routes were set to zero and these routes were excluded from the summations for the zone pair.

The determination of the possible airport choices for each zone was based partly on access time and partly on a subjective assessment from a knowledge of the two metropolitan areas. An initial assessment was compared to the survey traffic and some choices were revised where it was felt the data showed a clear departure from the assumed choice process.

4. CHOICE MODEL

CALIBRATION

The model was calibrated for business and non-business trip purposes. For each purpose parameter values were determined using both the original traffic data uncorrected for variation in sampling density and the synthetic data which included the SFO/LAX route. Both original and synthetic data were run, using both full choice of routes and restricted choice options as described in Chapter 3. The results are given in Table 4-1 and 4-2 for business and non-business traffic respectively.

RESULTS AND ANALYSIS

The values of the parameters obtained in the calibration are related to the elasticity of proportional demand with respect to the independent variable and have the same sign. It would be expected that the elasticity of demand with respect to both access time and fare should be negative, and with respect to frequency be positive. With the exception of the fare elasticity of the business model when using the original data, this is the outcome. Tables 4-1 and 4-2 also give the R^2 values for each calibration and the Beta coefficient and t-value for each parameter. The Beta coefficient is a measure of the relative importance of that variable in explaining the variability of the dependent variable (the traffic). The larger the Beta coefficient, the greater the relative importance. The t-statistic measures the significance of the value obtained for the parameter; small values of the statistic indicate that the parameter value is not significantly different from zero. Only the fare parameter for the non-business model using original data and unrestricted route choice should be rejected on this basis.

The results show that the effect of restricting the route choice is fairly minor and tends to decrease the access time and frequency parameters and increase the fare parameter. The business model fare parameter with the original data does not conform, but this has the wrong sign and is suspect anyway.

TABLE 4-1

Choice Model Parameters - Business Traffic

	Access Time	Frequency	Fare
Original data full route choice R^2 = 0.7336	-0.108 (β= -13.93) (t = 51)	0.0222 (β= 4.191) (t = 30)	0.225 (β= 2.503) (t = 13)
Original data restricted route choice R^2 = 0.6948	-0.108 (β= -6.067) (t = 36)	0.0221 (β= 3.337) (t = 27)	0.211 (β= 1.461) (t = 10)
Synthetic data full route choice R^2 = 0.5659	-0.100 (β -14.09) (t = 220)	0.0029 (β= 2.897) (t = 140)	-0.038 (β= -0.447) (t = 11)
Synthetic data restricted route choice R^2 = 0.5942	-0.095 (β= -5.55) (t = 160)	0.0027 (β= 2.243) (t = 140)	-0.041 (β= -0.278) (t = 10)

TABLE 4-2

Choice Model Parameters - Non-business Traffic

	Access Time	Frequency	Fare
Original data full route choice $R^2 = 0.7013$	-0.108 (β= -13.20) (t = 49)	0.0165 (β= 2.945) (t = 26)	-0.015 (β= -0.154) (t = 0.97)
Original data restricted route choice $R^2 = 0.6024$	-0.107 (β= -5.538) (t = 36)	0.0165 (β= 2.307) (t = 24)	-0.064 (β= -0.406) (t = 3.8)
Synthetic data full route choice $R^2 = 0.6618$	-0.105 (β= -14.08) (t = 210)	0.0022 (β= 2.103) (t = 110)	-0.065 (β= -0.725) (t = 16)
Synthetic data restricted route choice $R^2 = 0.6728$	-0.101 (β= -5.657) (t = 150)	0.0021 (β= 1.620) (t = 100)	-0.080 (β= 0.517) (t = 17)

Figures 4-1 to 4-8 show a comparison of modelled values of the proportion of total traffic on each route against the observed values. The figures for business and non-business traffic with original data show a fairly even spread with no isolated points very far from the line. The restricted route choice results appear to give a closer agreement than the full route choice, especially for non-business traffic.

The figures for synthetic data do not show such a satisfactory pattern with the point representing the SFO/LAX route well isolated from the rest and the remaining points clustered in the low value region of the diagrams. The clusters for business traffic show considerable scatter, although they retain a linear trend, however the results for non-business traffic show little linearity in the cluster. It seems likely that the parameter values of these particular calibrations may have been largely determined by the presence of the SFO/LAX link.

Comparing the results from the synthetic data with those from the original shows a slight reduction in access time parameter and a considerable drop in frequency parameter. Ignoring the business model original data results, it appears that fare parameter may be somewhat higher with the synthetic data.

Of the four sets of parameter values for each trip purpose, the results for the business model with original data have to be rejected because the fare parameter has the wrong sign. Rejecting the results for the non-business model using original data and unrestricted route choice because of the low significance of fare parameter, the parameter set with the highest R^2 value that remains is from the synthetic data and restricted route choice in both models. This gives parameter values as follows:

	Access Time	Frequency	Fare
Business	-0.10	0.003	-0.04
Non-business	-0.10	0.002	-0.08

This suggests that business travel is more sensitive to frequency and less sensitive to fare than non-business travel, a result which agrees with 'a priori' reasoning. The Beta coefficients imply that demand is more sensitive to access time than frequency and more sensitive to frequency than fare for both business and non-business traffic. They also confirm that business traffic places higher importance on frequency and a lower importance on fare than does non-business traffic.

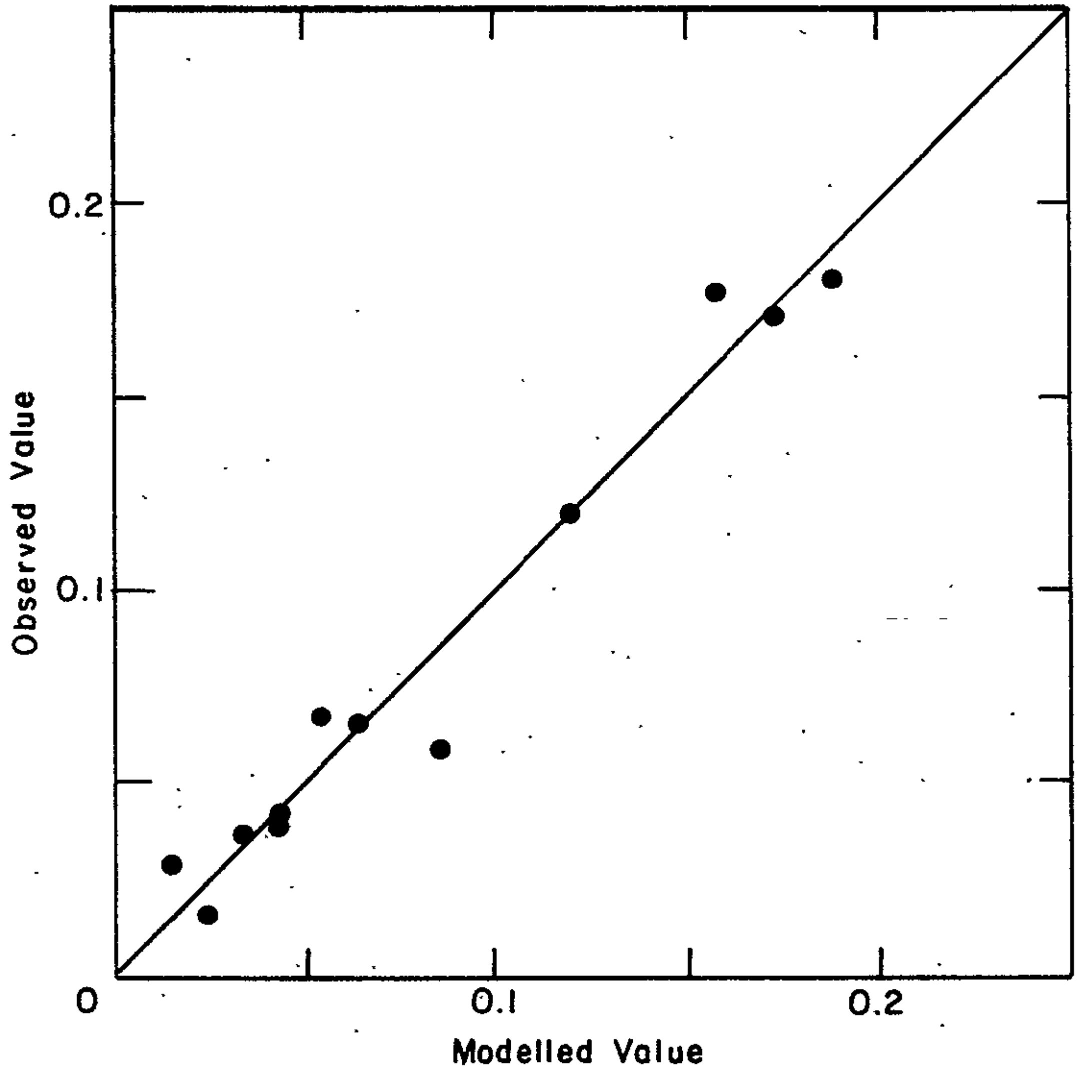

Figure 4-1 Comparison of Modelled and Observed Traffic Proportions

Choice Model: Business Traffic, Original Data, Full Route Choice.

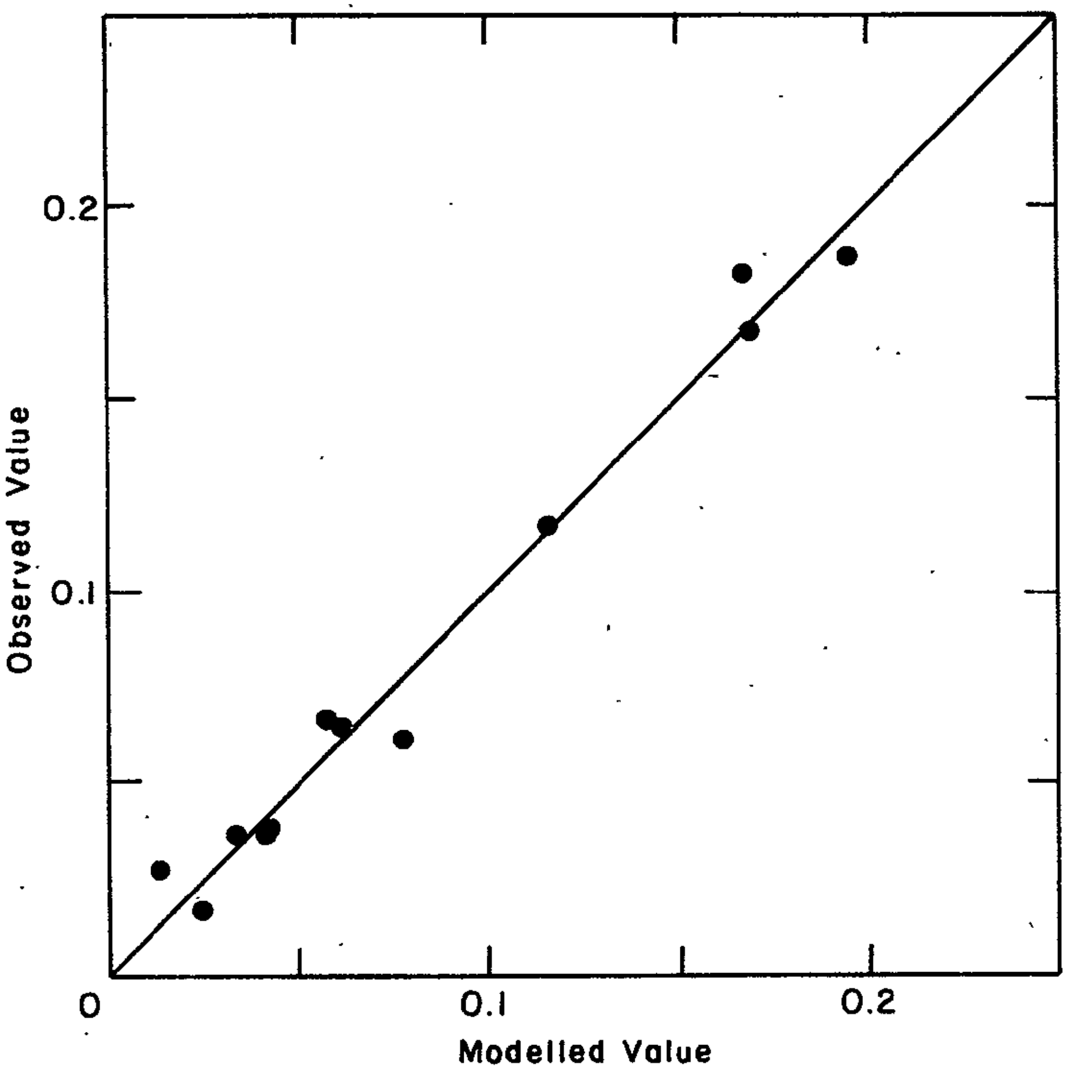

Figure 4-2 Comparison of Modelled and Observed Traffic Proportions

Choice Model: Business Traffic, Original Data, Restricted Route Choice

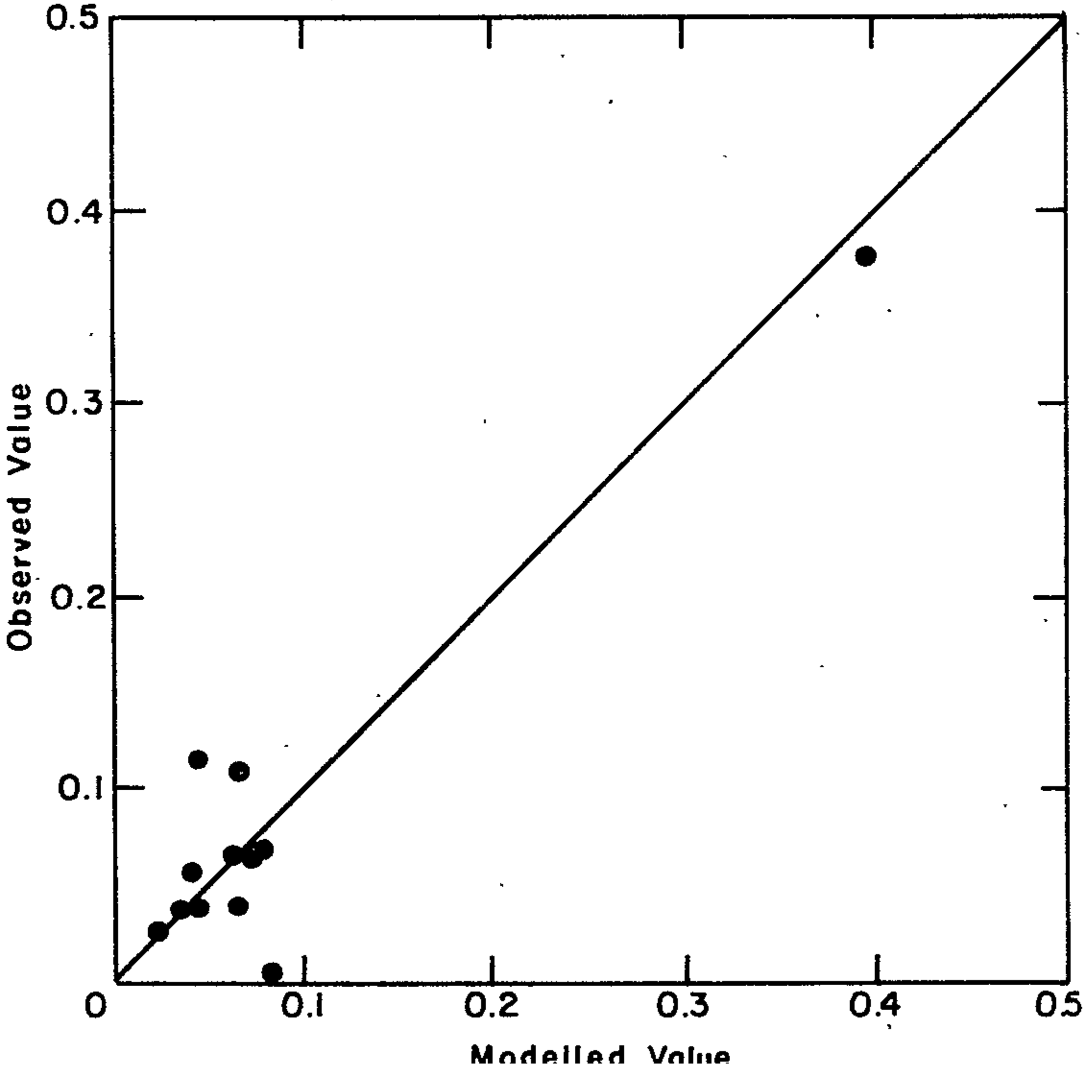

Figure 4-3 Comparison of Modelled and Observed Traffic Proportions

Choice Model: Business Traffic, Synthetic Data, Full Route Choice

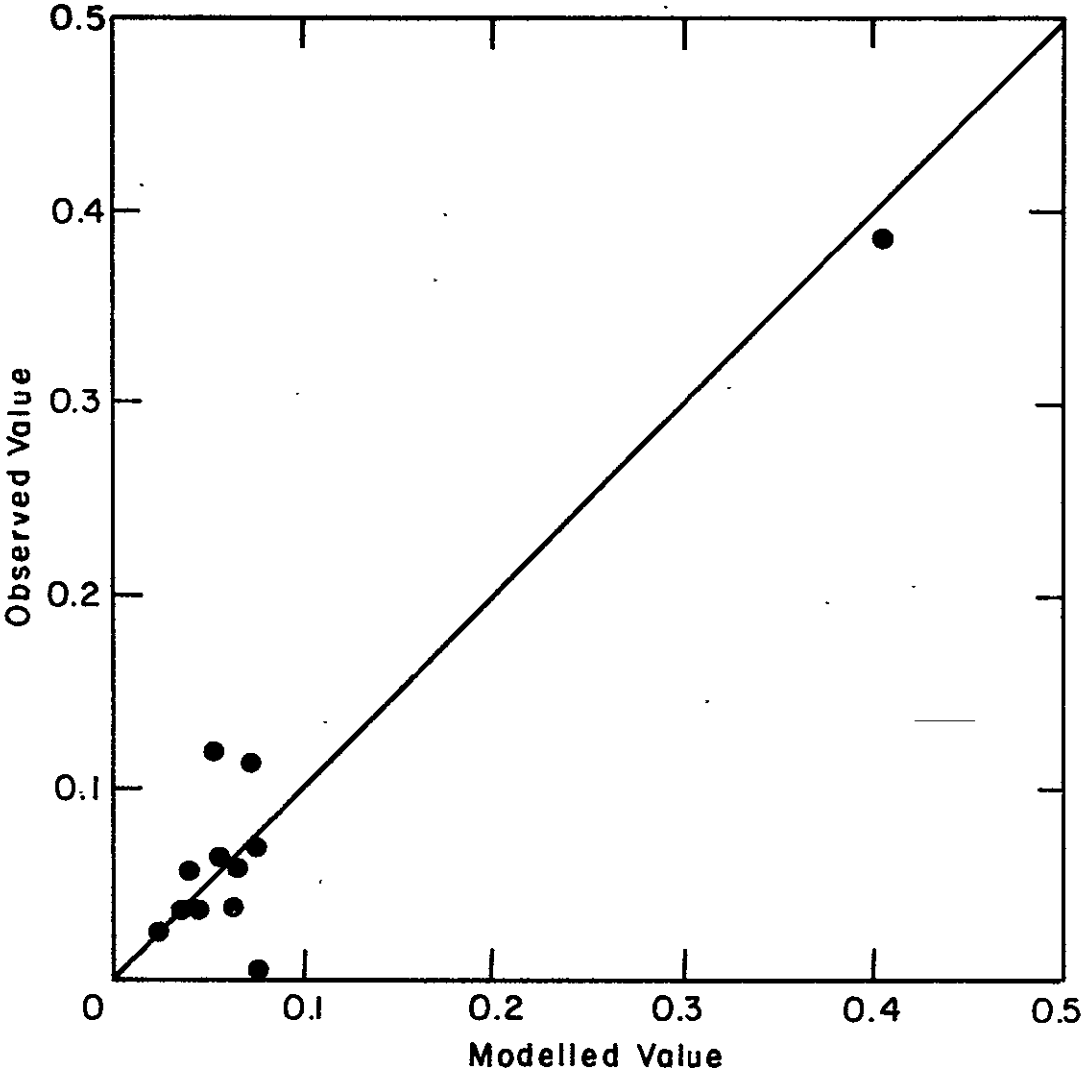

Figure 4-4 Comparison of Modelled and Observed Traffic Proportions

Choice Model: Business Traffic, Synthetic Data, Restricted Route Choice

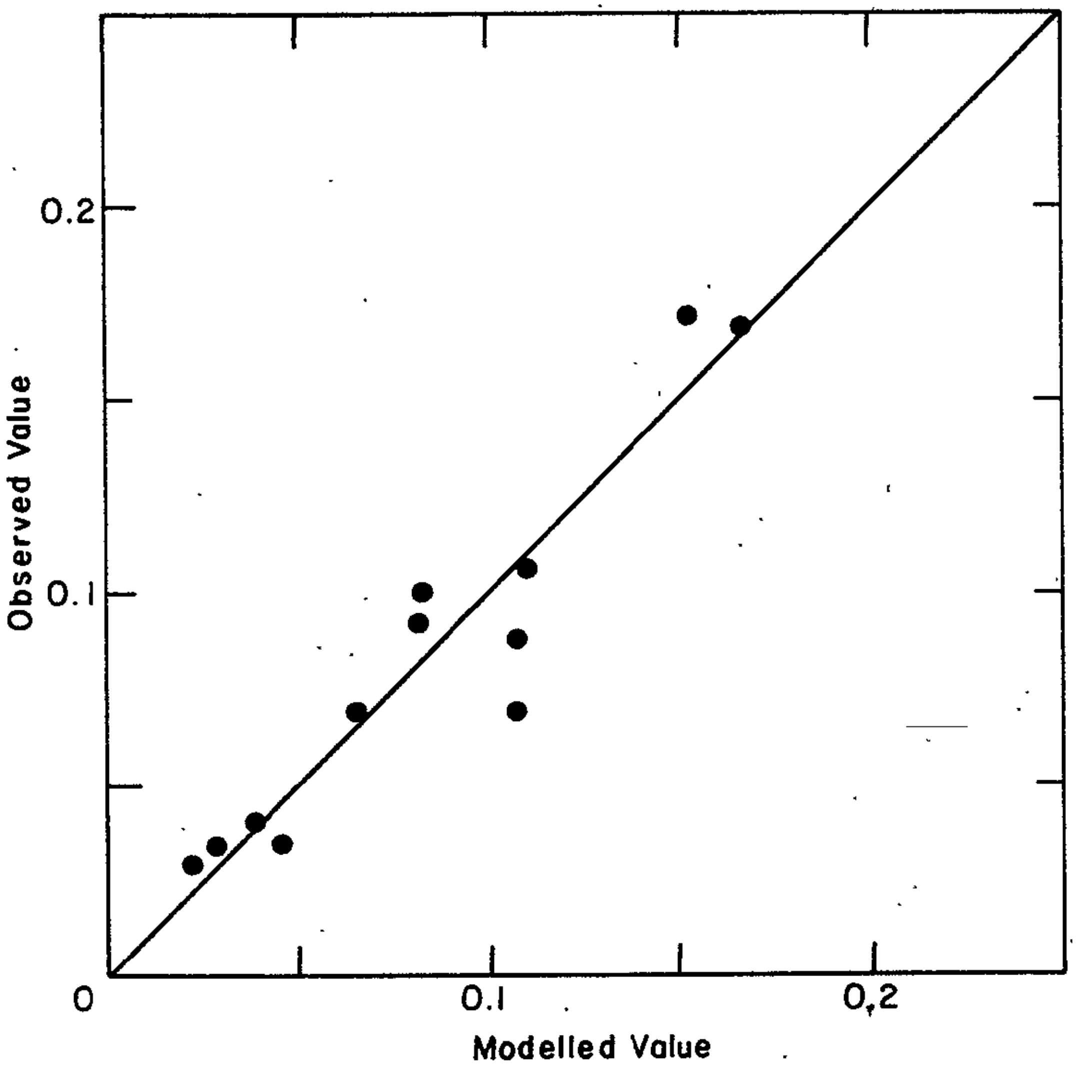

Figure 4-5 Comparison of Modelled and Observed Traffic Proportions

Choice Model: Nonbusiness Traffic, Original Data, Full Route Choice

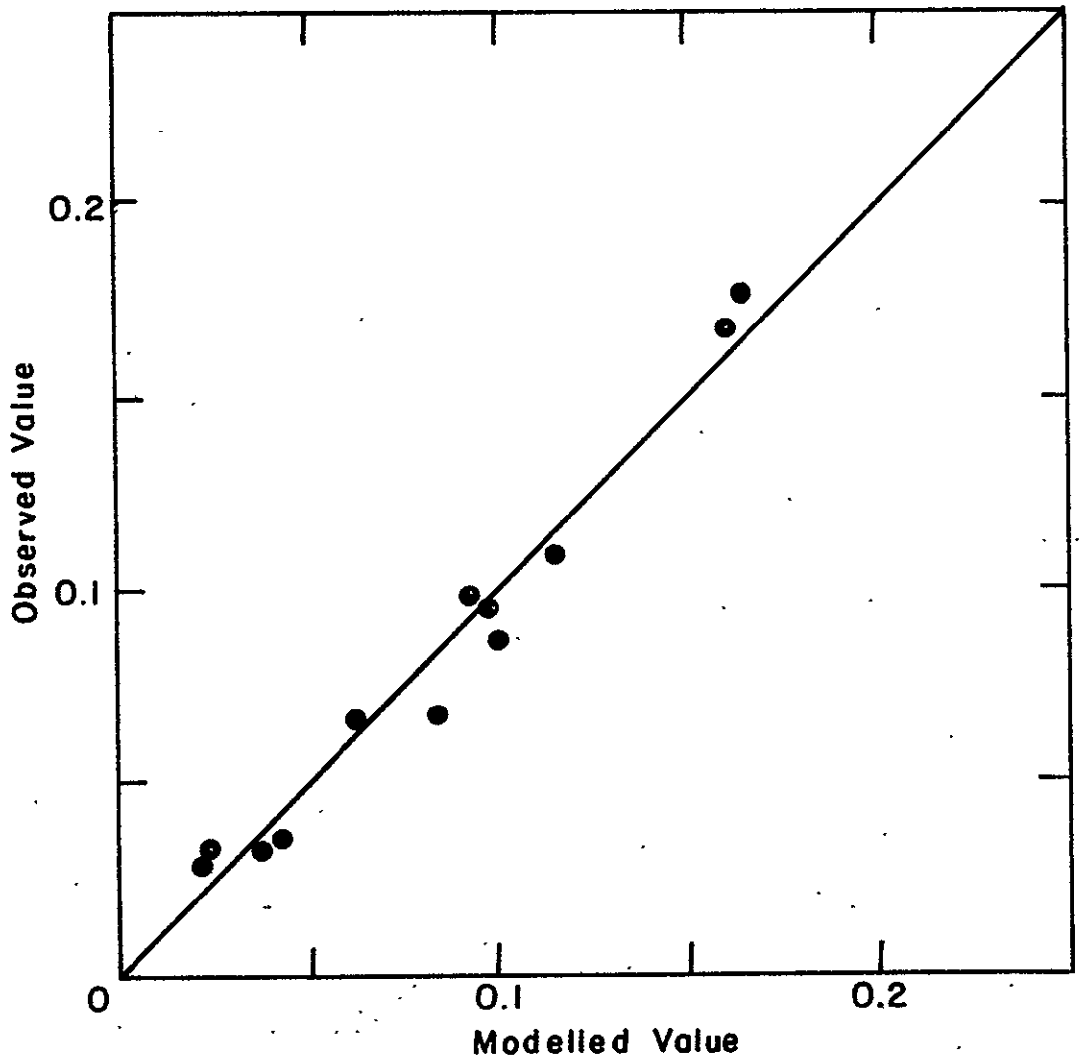

Figure 4-6 Comparison of Modelled and Observed Traffic Proportions

Choice Model: Nonbusiness Traffic, Original Data, Restricted Route Choice

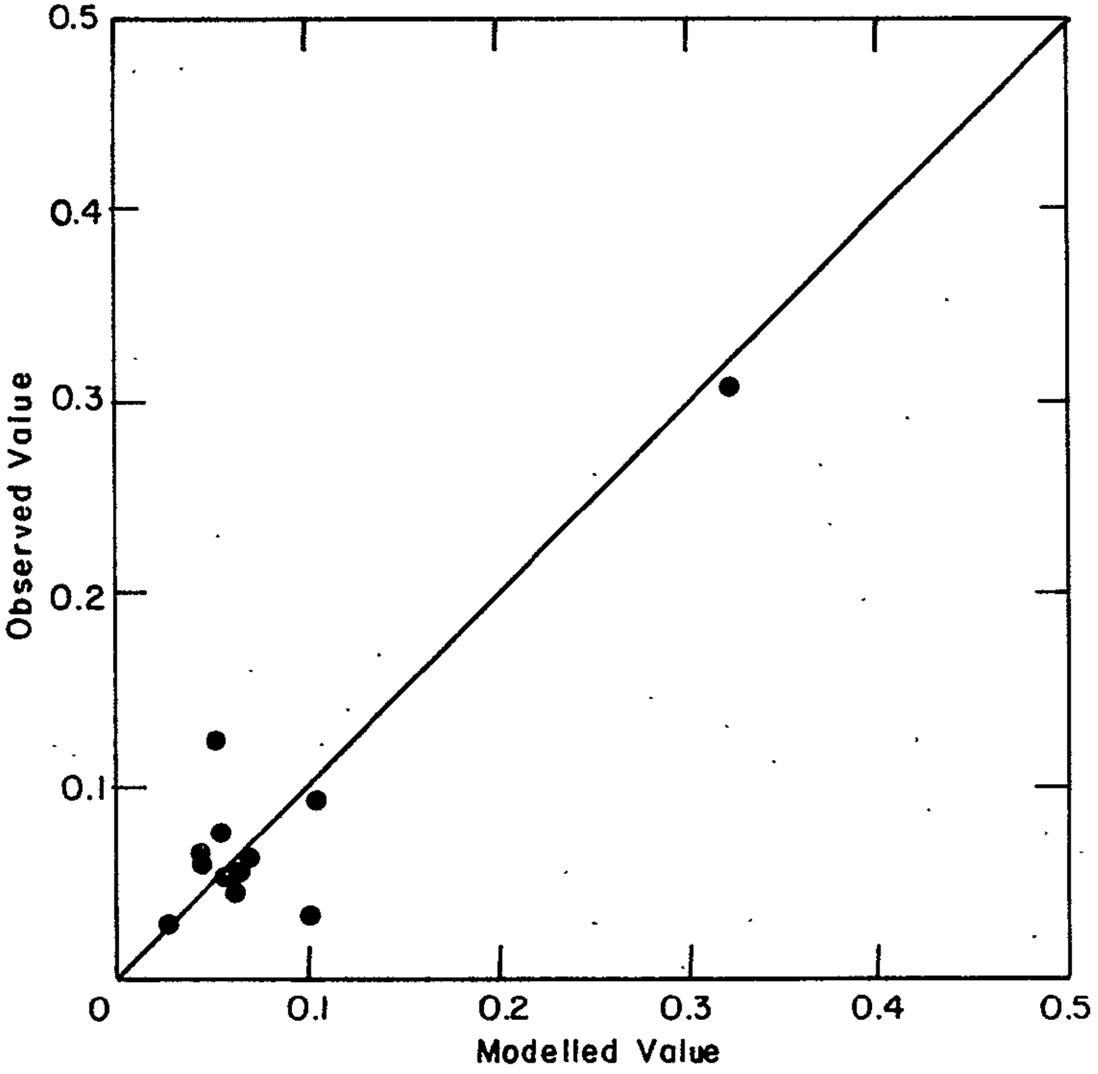

Figure 4-7 Comparison of Modelled and Observed Traffic Proportions

Choice Model: Nonbusiness Traffic, Synthetic Data, Full Route Choice

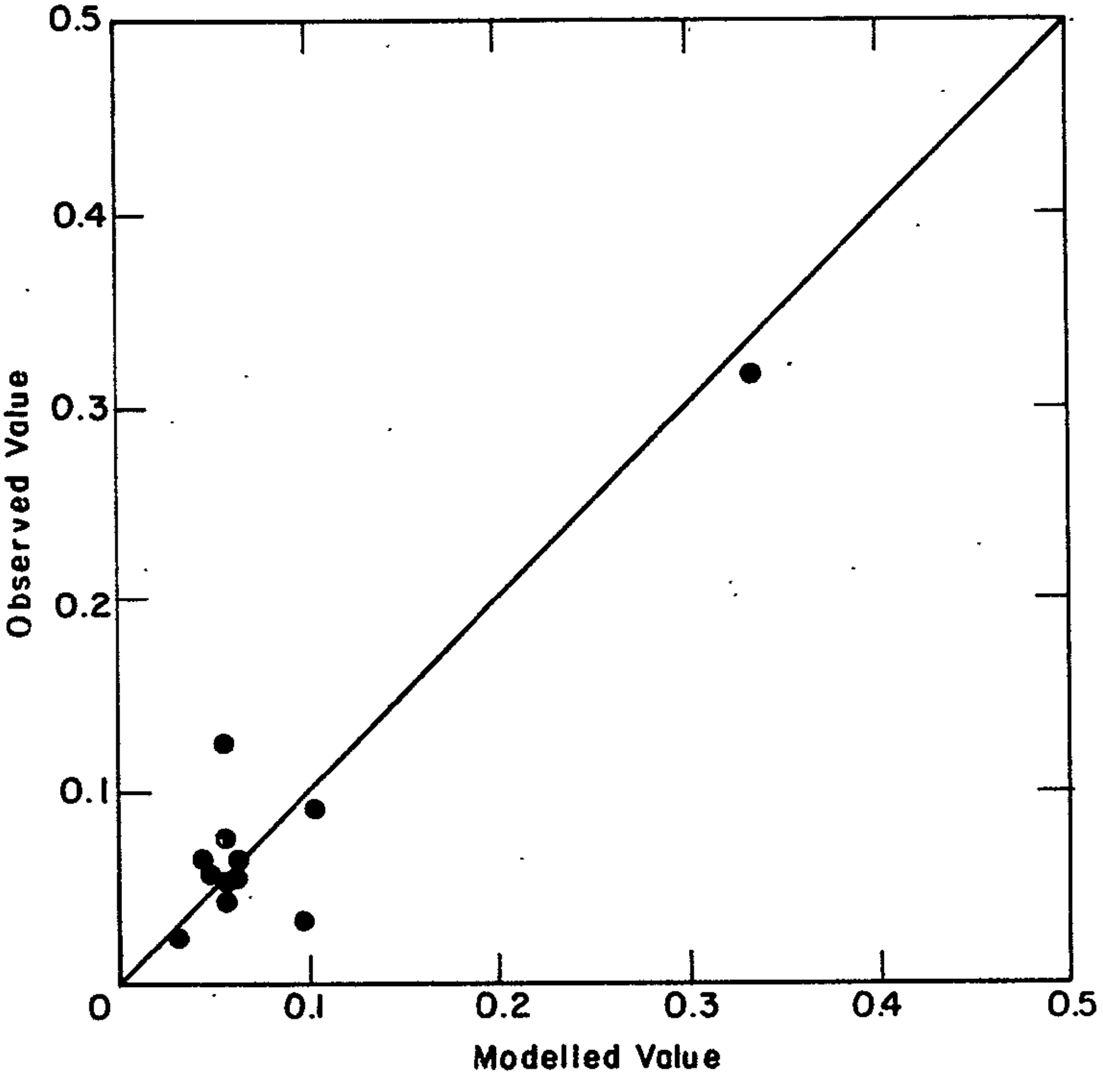

Figure 4-8 Comparison of Modelled and Observed Traffic Proportions

Choice Model: Nonbusiness Traffic, Synthetic Data, Full Route Choice

5. ABSTRACT MODE MODEL

CALIBRATION

This model was also calibrated for business and non-business trip purposes, using both original and synthetic traffic data. In view of the results of the Choice Model, all calibrations were performed using the restricted route choice option. This reduced the number of calibrations required whilst the differences between the two options in the Choice Model were not felt to be significant enough to justify the additional runs.

Three runs were performed on each trip purpose model for both the original and synthetic data. These runs were to investigate the effect of omitting some of the variables from the model. Variables were omitted on the criteria of either wrong sign or lack of significance of the parameter value as measured by the t-statistic as discussed in Chapter 4. The results, together with the t-statistics, are given in Tables 5-1 and 5-2.

RESULTS

Unlike the Choice Model, the values of the parameters with the exception of the constant, are actually the elasticities of demand with respect to the relevant variable. Values greatly in excess of unity should therefore be suspect. As in the Choice Model, the parameters of access time and fare should be negative and the frequency parameters should be positive. This holds whether the variable is the best or relative expression of the attribute. In addition, it would be expected that the elasticities of population and income would be positive.

In the business calibration with original data, the parameter values for best frequency and relative fare have the wrong sign for the first run. The best frequency parameter has the lowest significance and is omitted from the second calibration. This fails to correct the sign of the relative fare parameter and that parameter is then omitted from the third run. However, the best fare parameter in the third calibration assumes the wrong sign and an absurdly large value (85.6). All the attribute parameters have apparently large values with the exception of the best fare parameter, which has the wrong sign as discussed. The elasticities decrease on the second calibration except for the relative fare and all increase, some to absurd levels, on the third run.

The first run of the business model with synthetic data produced the wrong sign for both the best fare and relative fare. In addition, the value of the constant was insignificant. The values of the demand elasticities appear more reasonable than the calibration with the original data. The value for best fare was large but of low significance. The second run omitted the best fare parameter but failed to change the sign of the relative fare elasticity. The constant changed sign and its significance was greatly improved but no great changes occured to the other parameters. The relative fare parameter was omitted from the third run. All elasticities now have the correct sign and apparently reasonable values. The relative access time and frequency parameter values have a much higher significance than those for the best value of these attributes.

As might be expected, the R^2 value of the calibrations declined as variables were omitted. The synthetic data calibrations had a generally lower R^2 than the original data runs. However, the value for the final synthetic data calibration of 0.75 shows good explanation of the variation in the traffic.

The first calibration of the non-business model with original data produced the wrong sign for best fare and frequency and relative fare. In addition, the parameter value for income was not significant and the parameter values for population and access time appear rather large. Best frequency and relative fare were omitted from the second run. The sign of the best fare parameter remained unchanged and the value became ridiculous. The significance of the income parameter improved but still remained unsatisfactory and values of the population and best access time parameters, already large, increased.

TABLE 5-1

Abstract Mode Model Parameters - Business Traffic

	Constant	Population	Income	Best Access Time	Best Fare	Best Frequency	Relative Access Time	Relative Fare	Relative Frequency
Original data R^2 = 0.8917	63.987 (t=5.7)	2.435 (t=15)	2.359 (t=11)	-6.102 (t=7.7)	-10.398 (t=3.3)	-1.579 (3.0)	-7.017 (t=13)	8.985 (t=13)	3.993 (t=13)
Original data R^2 = 0.8887	38.968 (t=4.1)	2.111 (t=18)	2.226 (t=10.4)	-3.658 (t=8.8)	-7.595 (t=2.4)	--	-6.867 (t=13)	9.108 (t=14)	3.759 (t=14)
Original data R^2 = 0.7657	-142.469 (t=2.9)	13.191 (t=8.2)	4.572 (t=6.5)	-26.665 (t=6.0)	85.574 (t=5.0)	--	-9.389 (t=8.3)	--	5.289 (t=6.8)
Synthetic data R^2 = 0.7670	-15.695 (t=0.70)	2.078 (t=15)	1.947 (t=4.8)	-1.935 (t=3.6)	8.475 (t=1.1)	0.986 (t=3.0)	-4.267 (t=14)	1.918 (t=3.5)	0.845 (t=15)
Synthetic data R^2 = 0.7657	8.963 (t=3.1)	2.072 (t=15)	1.958 (t=4.8)	-1.939 (t=3.6)	--	0.829 (t=3.4)	-4.266 (t=14)	1.912 (t=3.5)	0.845 (t=15)
Synthetic data R^2 = 0.7536	11.424 (t=3.5)	2.038 (t=14)	2.134 (t=5.3)	-2.609 (t=4.3)	--	0.824 (t=2.9)	-4.187 (t=14)	--	0.786 (t=16)

TABLE 5-2

Abstract Mode Model Parameters - Nonbusiness Traffic

	Constant	Population	Income	Best Access Time	Best Fare	Best Frequency	Relative Access Time	Relative Fare	Relative Frequency
Original data R^2 = 0.7778	65.191 (t=5.3)	3.017 (t=11)	0.007 (t=0.02)	-10.844 (t=9.0)	2.829 (t=1.25)	-5.732 (t=6.4)	-5.930 (t=12)	4.097 (t=9.4)	1.102 (t=6.8)
Original data R^2 = 0.6894	-45.223 (t=4.0)	5.256 (t=10.4)	0.618 (t=1.47)	-14.177 (t=10.5)	35.718 (t=8.5)	--	-5.685 (t=11)	--	1.390 (t=7.5)
Original data R^2 = 0.5449	39.726 (t=7.9)	2.534 (t=7.7)	--	-9.632 (t=7.0)	--	--	-5.182 (t=8.3)	--	0.958 (t=5.1)
Synthetic data R^2 = 0.7725	-11.610 (t=0.71)	1.876 (t=15)	0.512 (t=1.36)	-1.865 (t=3.9)	7.351 (t=1.36)	0.858 (t=3.4)	-5.015 (t=14)	2.085 (t=4.1)	0.797 (t=16)
Synthetic data R^2 = 0.7706	9.724 (t=4.1)	1.845 (t=15)	0.561 (t=1.5)	-1.848 (t=3.9)	--	0.718 (t=3.9)	-5.009 (t=14)	2.060 (t=4.0)	0.795 (t=16)
Synthetic data R^2 = 0.7558	12.329 (t=4.6)	1.801 (t=14)	0.672 (t=1.8)	-2.509 (t=4.8)	--	0.688 (t=3.2)	-4.849 (t=14)	--	0.669 (t=18)

For the third run, the income and best fare variables were also omitted. All parameters have the correct sign. The value of the population parameter assumed a more reasonable value and the other parameters values also decreased although the access time parameters remained unreasonably large. As might be expected with four variables omitted, the R^2 value was relatively low at 0.54.

Calibrating the non-business model with synthetic data produced the wrong sign for the fare parameters and low significance for the constant and income parameter values. Both fare parameter values had low significance compared to the other variables of the type (best or relative attributes). The second run omitted the best fare variable. The significance of the constant and income parameter values improved, but the sign of the relative fare parameter remained incorrect. Both fare parameters were then omitted from the third run. All parameters had the correct sign and the parameter values appear reasonable. The significance of the income parameter value improved again, but still remained low. As with the business model, the parameter values for the relative attributes were much more significant than for the best attributes. The R^2 value of 0.76 is similar to that for the final business calibration and shows good explanations of the traffic variation.

A comparison of the observed and modelled values of the total traffic on each link for the size calibration of each traffic category, business and non-business, has been plotted as Figures 5-1 to 5-12. These show a general tendency of the model to underestimate the actual traffic. This appears to be worse with the original data than with the synthetic data.

The first two calibrations for business traffic with original data (Figures 5-1 and 5-2) show reasonable linearity and moderate dispersion. The extent of the underestimation does not appear to depend on the volume of the link traffic. However, the third calibration (Figure 5-3) produced massive underestimation and dispersion. Although it appears that the error tends to increase with higher values of link traffic, this may well be due to the fact the model does not permit negative traffic values thus restricting the extent of underestimation possible with smaller values. The three calibrations for business traffic with synthetic data (Figures 5-4 to 5-6)show good linearity with very little dispersion and slight underestimation which appears to be unrelated to link traffic. The dispersion appears to increase slightly as variables are omitted. The effect of the large traffic volume on the SFO/LAX link does not appear to be unduly influencing the calibration.

The three non-business calibrations with original data (Figures 5-7 to 5-9) show considerable scatter and major underestimation. The errors in the first and second appear to tend to increase with higher link traffic values. This is not so clear in the third calibration and the extent of underestimation appears less although the scatter is still considerable. The three calibrations with synthetic data (Figures 5-10 to 5-12) show good linearity with little dispersion and a slight underestimation. As with the business calibrations, the SFO/LAX link does not appear to have unduly influenced the result.

It would appear that final calibrations of the two models, business and non-business, represent the most reasonable values of the parameters. These are summarized as follows:

	Constant	Population	Income	Best Access Time	Best Frequency	Relative Access Time	Relative Frequency
Business	11.4	2.0	2.1	-2.6	0.82	-4.2	0.74
Non-business	12.3	1.8	0.7	-2.5	0.69	-4.8	0.67

ANALYSIS OF RESULTS

These results suggest that fare is not a major factor in determining traffic. This is perhaps not surprising since the fare levels are really not very high and the fare spread is not wide. This point will be expanded in Chapter 6. They also suggest that travel demand is more sensitive to access time than frequency. The differences in the elasticity of demand with respect to the perceived attributes (access time and frequency) between the business and non-business traffic is not so marked as might have been expected.

The population elasticity of demand appears higher than might have been expected on 'a priore' grounds. The population term is a product of the populations of the two zones in the generalized zone pair ij. An increase in the population of zone i of δ% will cause an increase in the population term of the same amount. Since no change has occurred in zone j, the attraction of zone j remains as before and we might expect that proportion of the traffic generated in zone i to increase by the order of δ% assuming no other changes in the socio-economic base beside the population increase. If we assume that the number of trips generated in zone j increases by the order of δ% for a population increase in zone i of δ%, i.e., near unit elasticity of attracted trips with respect to population, we obtain an increase of total trips of the order of δ%, or in other words, a population elasticity of demand near unity. If both populations change, the argument becomes more involved but produces the same result.

The low significance of the non-business income elasticity of demand should perhaps be not unexpected in view of the use of median income as a variable. With large areas, median income does not so much measure the size of the wealthy and poor sections of the populations as the general level of income in the middle range. It may be argued that non-business air travel is more a cultural attribute that is only loosely connected with income over the wide middle income range. For example, a major element of non-business traffic may be students at college outside their home area or military personne on leave. The apparently strong business income elasticity of demand may be due to median income in large zones being a measure of prevailing industrial or commercial activity. High activity generates business travel and also increases wage levels. If the zones are large enough most workers probably live in their zone of employment.

Consideration of the elasticities with respect to the travel attributes may be simplified by reformulating the model to separate the relative attribute into best attribute and the route attribute, or

$$\hat{t}_{ijk} = e^{\Theta_1} \{\text{population}\}^{\Theta_2} \{\text{income}\}^{\Theta_3} \, T_b^{(\Theta_4-\Theta_7)} \, F_b^{(\Theta_6-\Theta_9)} \, T_k^{\Theta_7} \, F_k^{\Theta_9}$$

This gives elasticities as follows:

	Best Access Time	Best Frequency	Route Access Time	Route Frequency
Business	1.6	0.08	-4.2	0.74
Non-Business	2.3	0.02	-4.8	0.67

At first sight the best frequency elasticity appears to have the wrong sign. Since increasing the frequency on the best frequency route should capture traffic from other routes one might expect the traffic on route k to decline and hence the elasticity to be negative. However, it is just possible that there is a counteracting trip generation effect, with more air travel being demanded generally due to the greater apparent availability of air service and some of this spilling over onto the other routes. However, this highlights a serious weakness of the Abstract Mode Model as formulated, namely that any changes in the attributes of other routes, that are not the best route for the attribute, will have no affect whatever on the route considered. This is clearly illogical. In any event, it can be argued that the capture effect is likely to be small since those persons travelling by a route that does not have the best value of an attribute are clearly more influenced by other things. Thus changing the best value of that attribute will not influence them greatly. On the other hand, in a well-developed market such as the California Corridor, it would be surprising if increasing the frequency of service would have much of a generation effect. Therefore, the counteracting effects of capture and trip generation are both fairly small and their combined effect therefore close to zero. This agrees with the magnitude of the best frequency elasticity. With such small values, the sign may be spurious.

The access time elasticities appear larger than might have been expected. That the non-business access time elasticities are larger than the business ones may be a reflection of non-business traffic tending to use the most convenient airport, being able to adjust departure times to suit schedules more easily than business traffic. Probably for the same reason, the business route frequency elasticity is greater than that for non-business traffic.

The link traffic comparisons suggest that the calibrations with original data are inherently unreliable. This accords with the unusually large magnitudes of some of the parameters that were obtained. The wide scatter may reflect a variation in data sampling rate on the different links which the model attempts to explain by means of the attribute variables rather than by having a different constant for each link.

The underestimation is probably due to a combination of data characteristics and the nature of the estimation process. Detailed investigation of some of the estimates suggest that the data may have inherent heteroscedastic tendencies when used in a model of the form adopted. The least square estimation process achieves a better fit of the large value cells at the price of underestimating the larger number of small value cells. This process is aggravated by the formulation of the model which prevents negative traffic values being estimated. This restraint also violates some of the assumptions (such as constant variance) that are inherent in the statistical justification for use of least squares as an estimating technique.

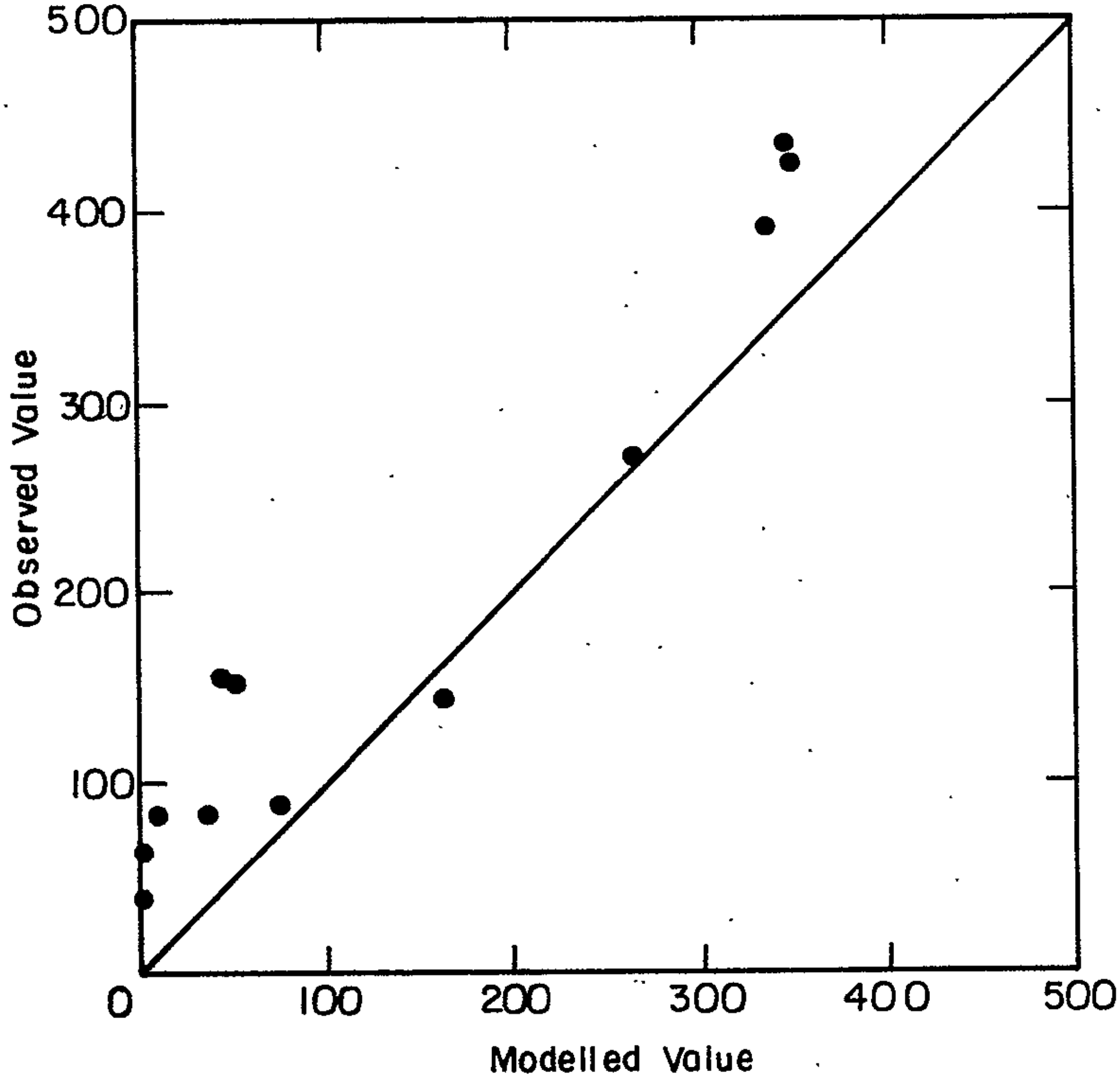

Figure 5-1 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Business Traffic, Original Data, All Variables

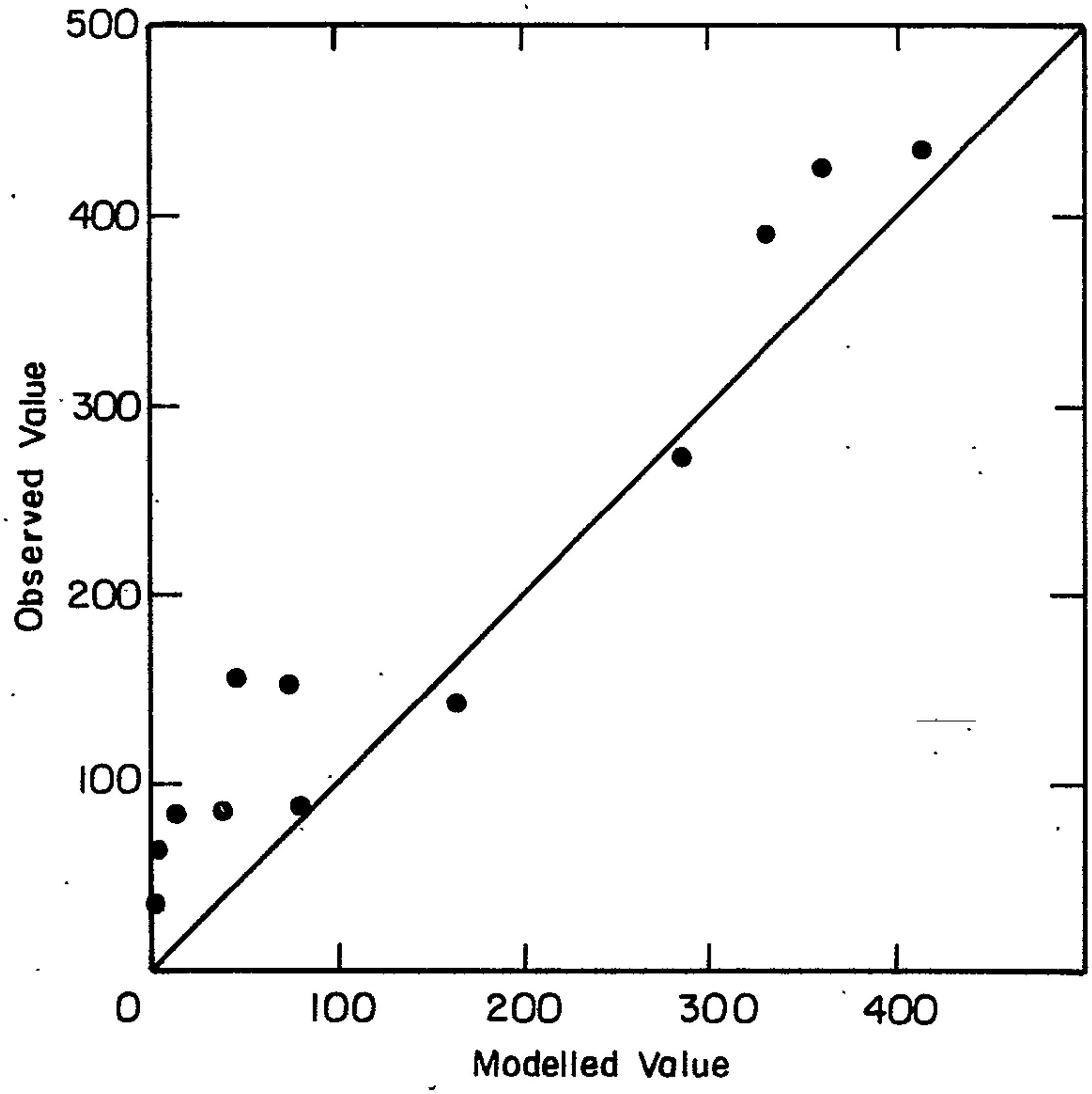

Figure 5-2 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode; Business Traffic, Original Data, Best Frequency Omitted

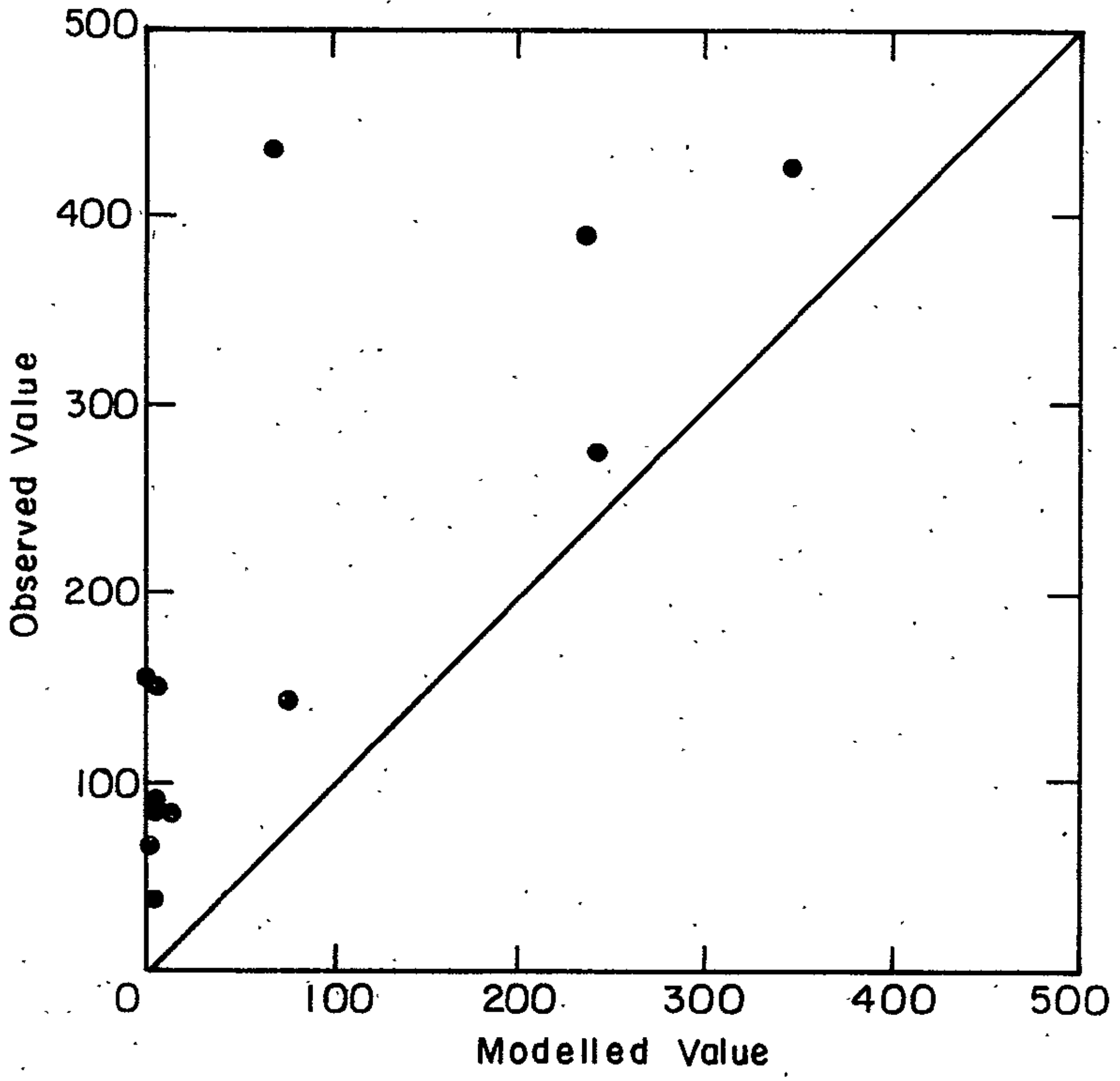

Figure 5-3 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Business Traffic, Original Data, Best Frequency and Relative Cost Omitted.

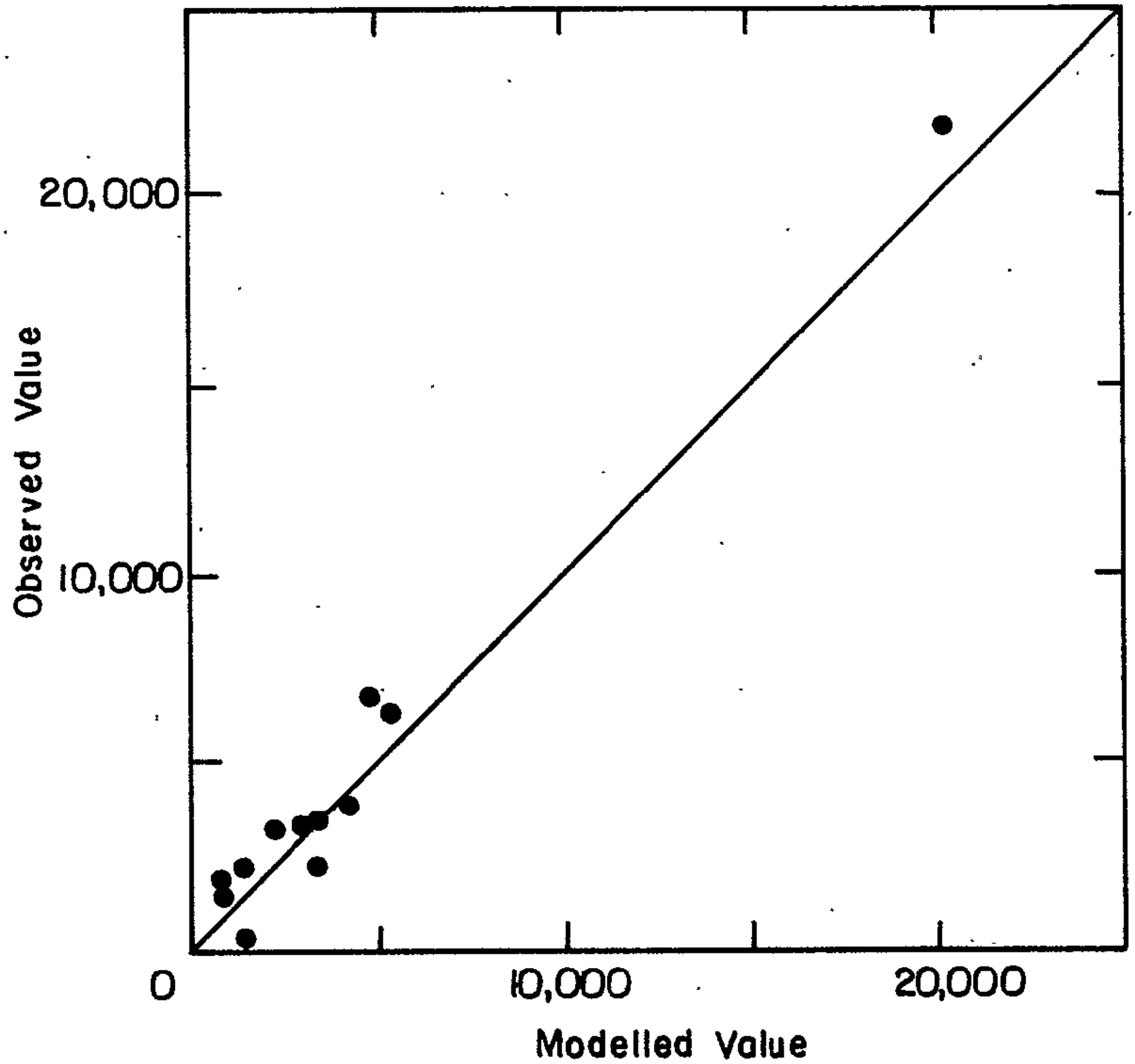

Figure 5-4 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Business Traffic, Synthetic Data, All Variables

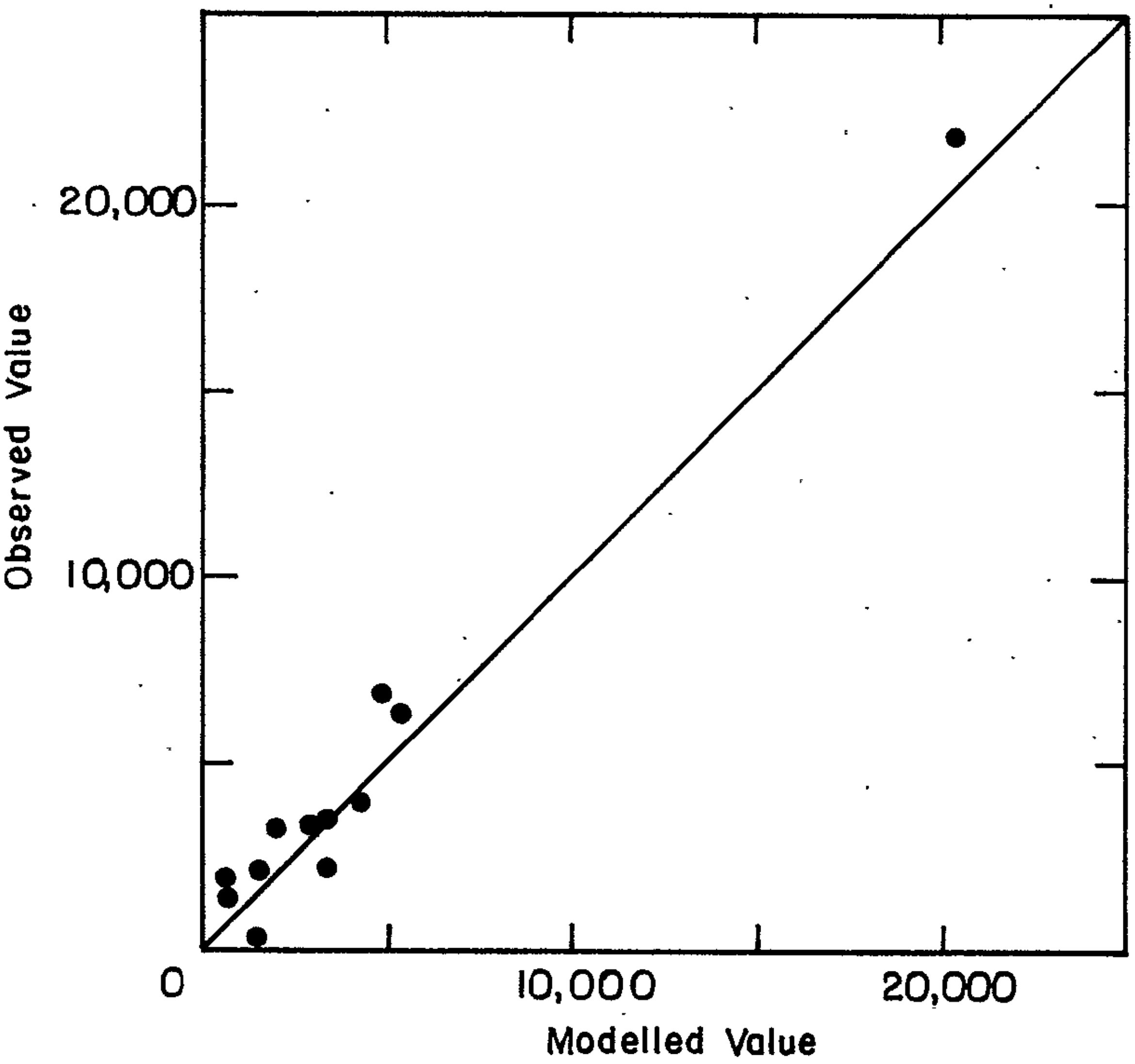

Figure 5-5 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Business Traffic, Synthetic Data, Best Cost Omitted

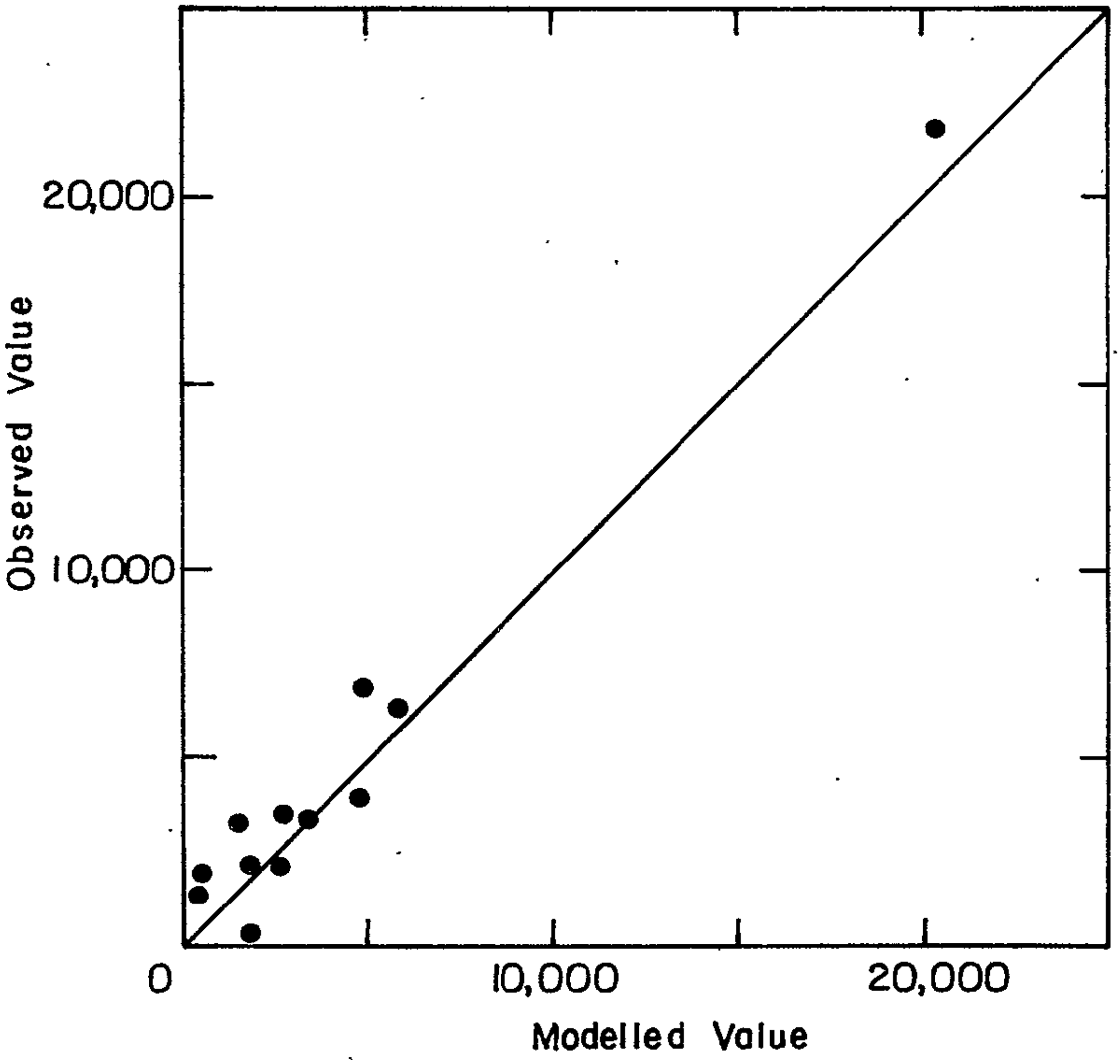

Figure 5-6 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Business Traffic, Synthetic Data, Best Cost and
Relative Cost Omitted.

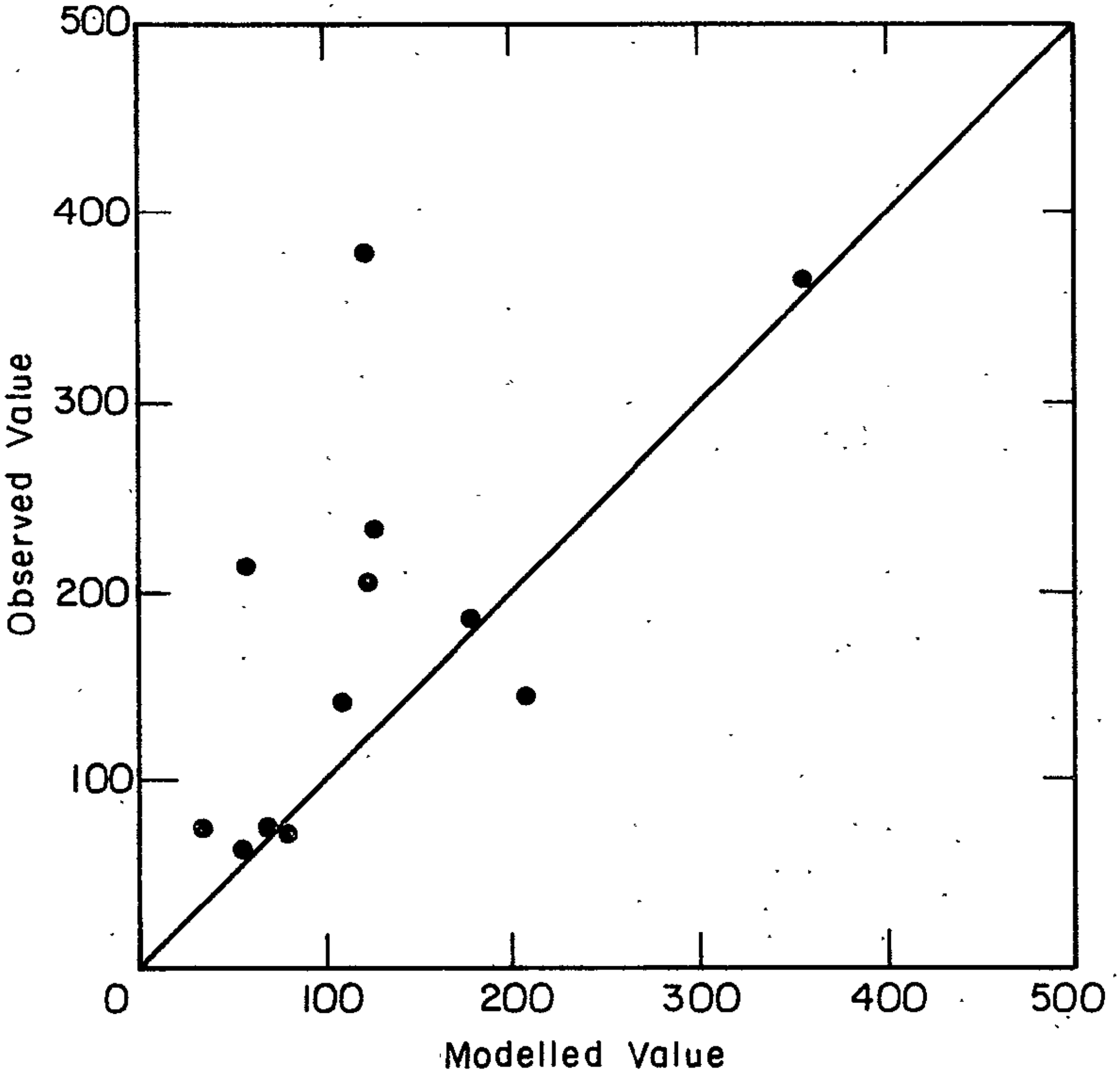

Figure 5-7 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Nonbusiness Traffic, Original Data, All Variables

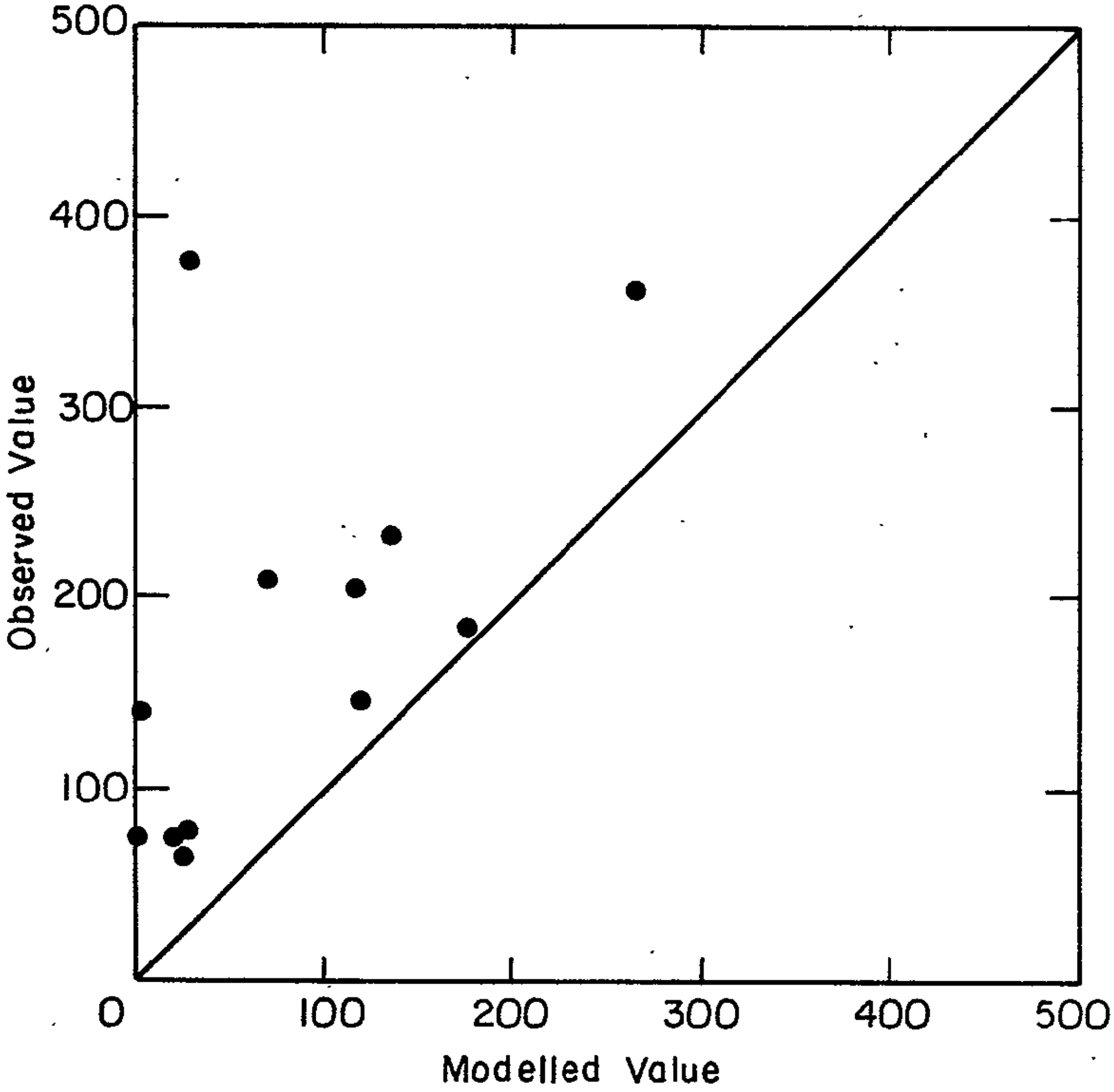

Figure 5-8 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Nonbusiness Traffic, Original Data, Best Frequency
and Relative Cost Omitted

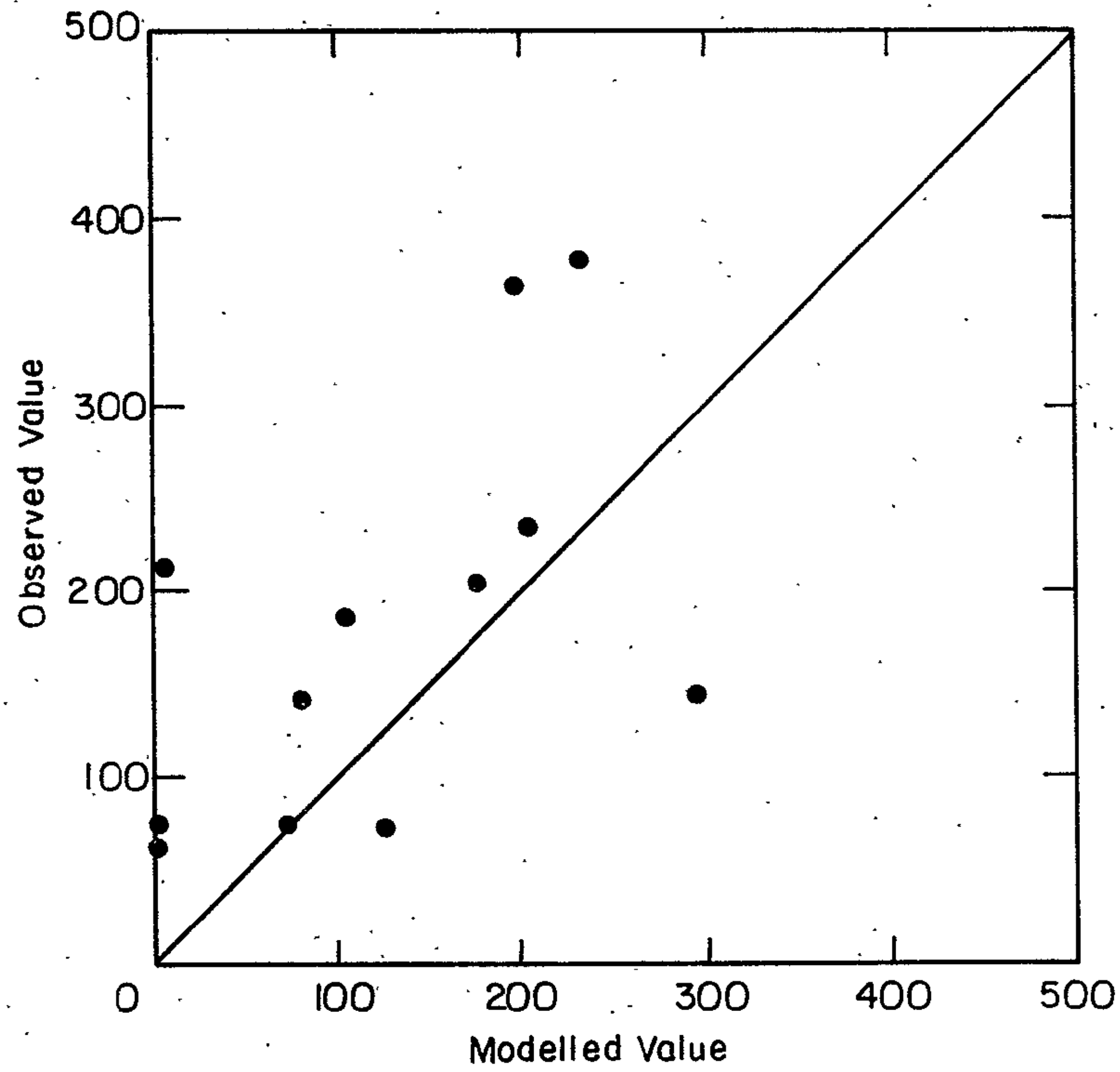

Figure 5-9 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Nonbusiness Traffic, Original Data, Income, Best Cost, Best Frequency and Relative Cost Omitted

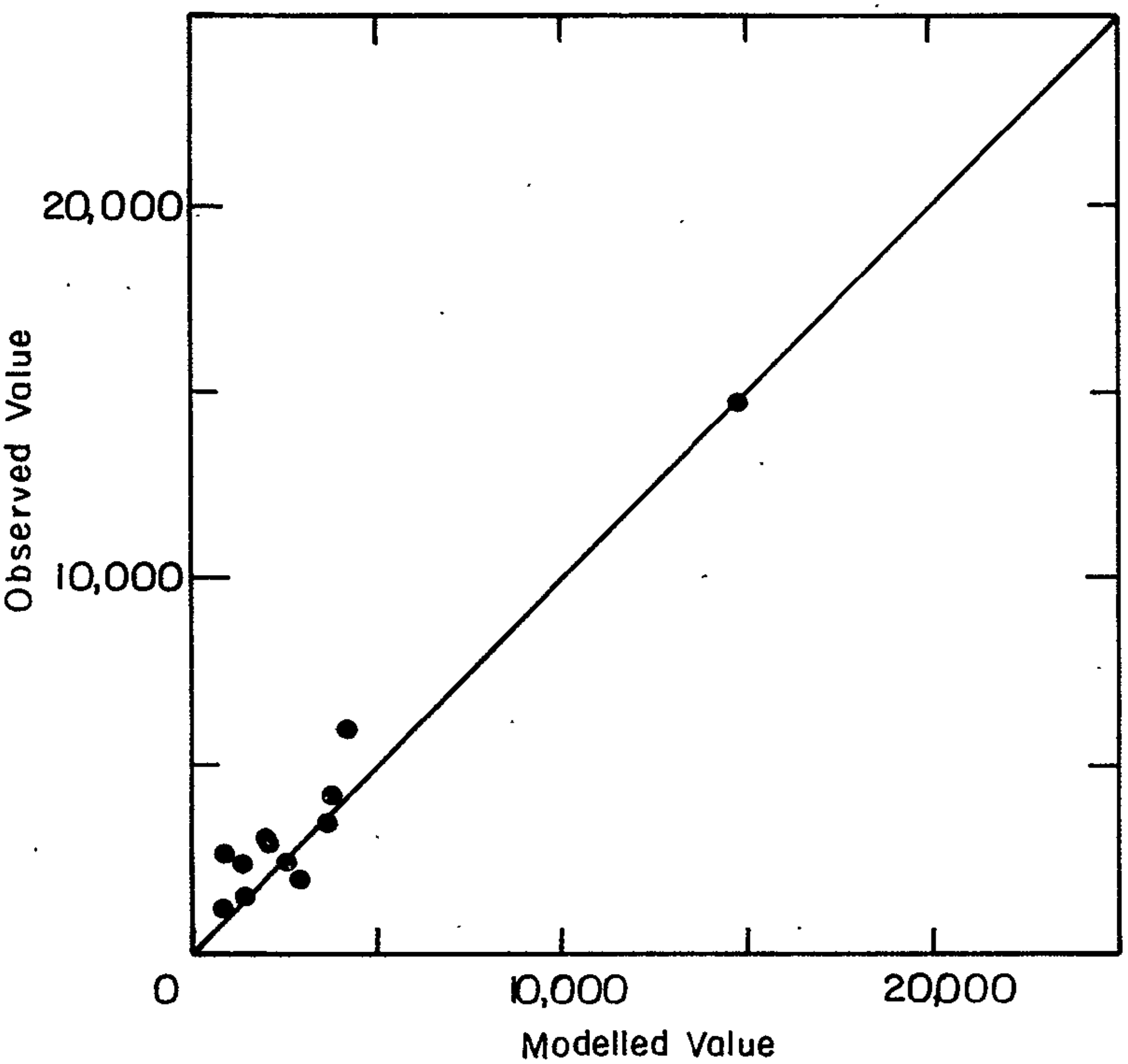

Figure 5-10 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Nonbusiness Traffic, Synthetic Data, All Variables

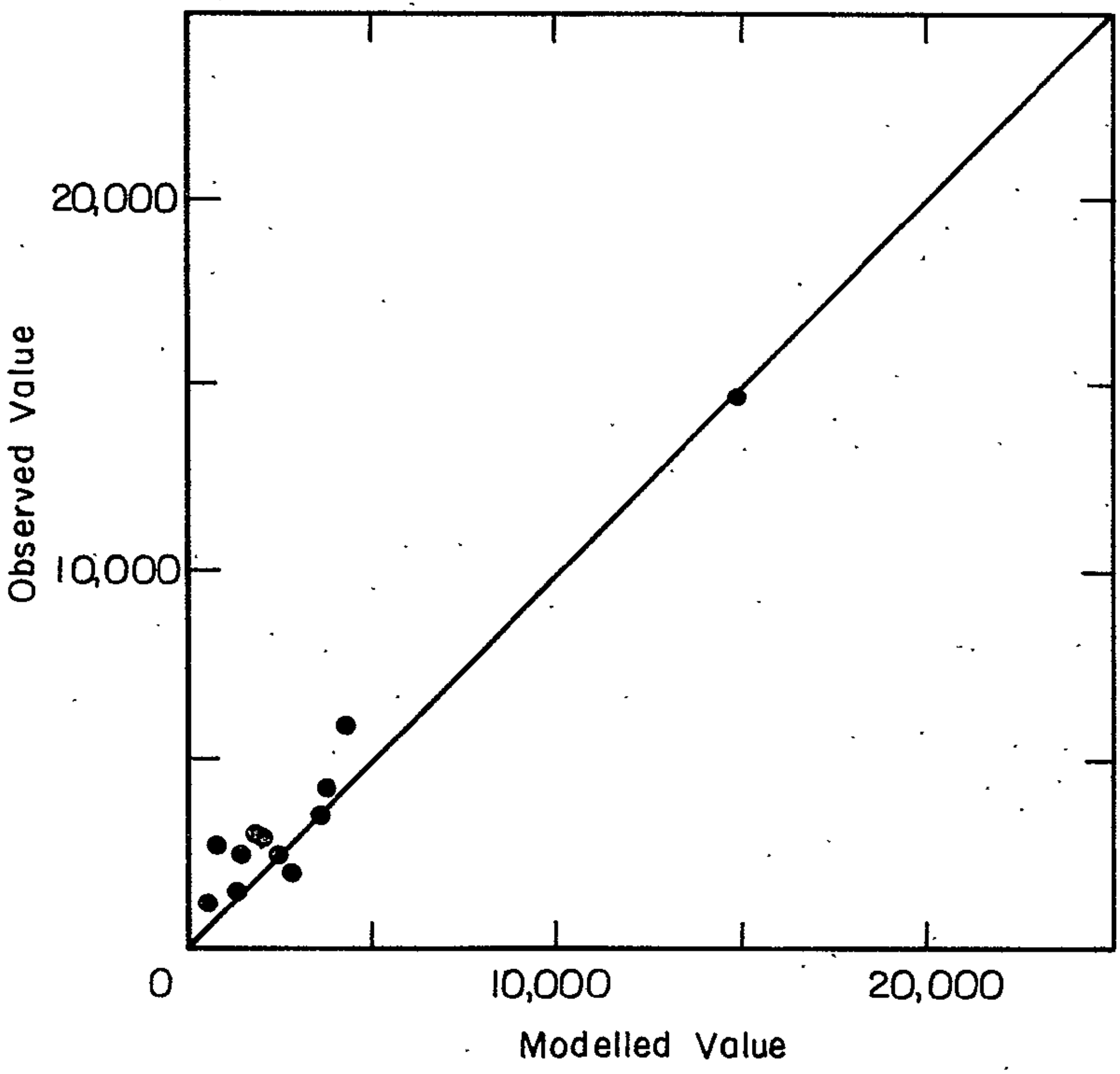

Figure 5-11 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Nonbusiness Traffic, Synthetic Data, Best Cost Omitted

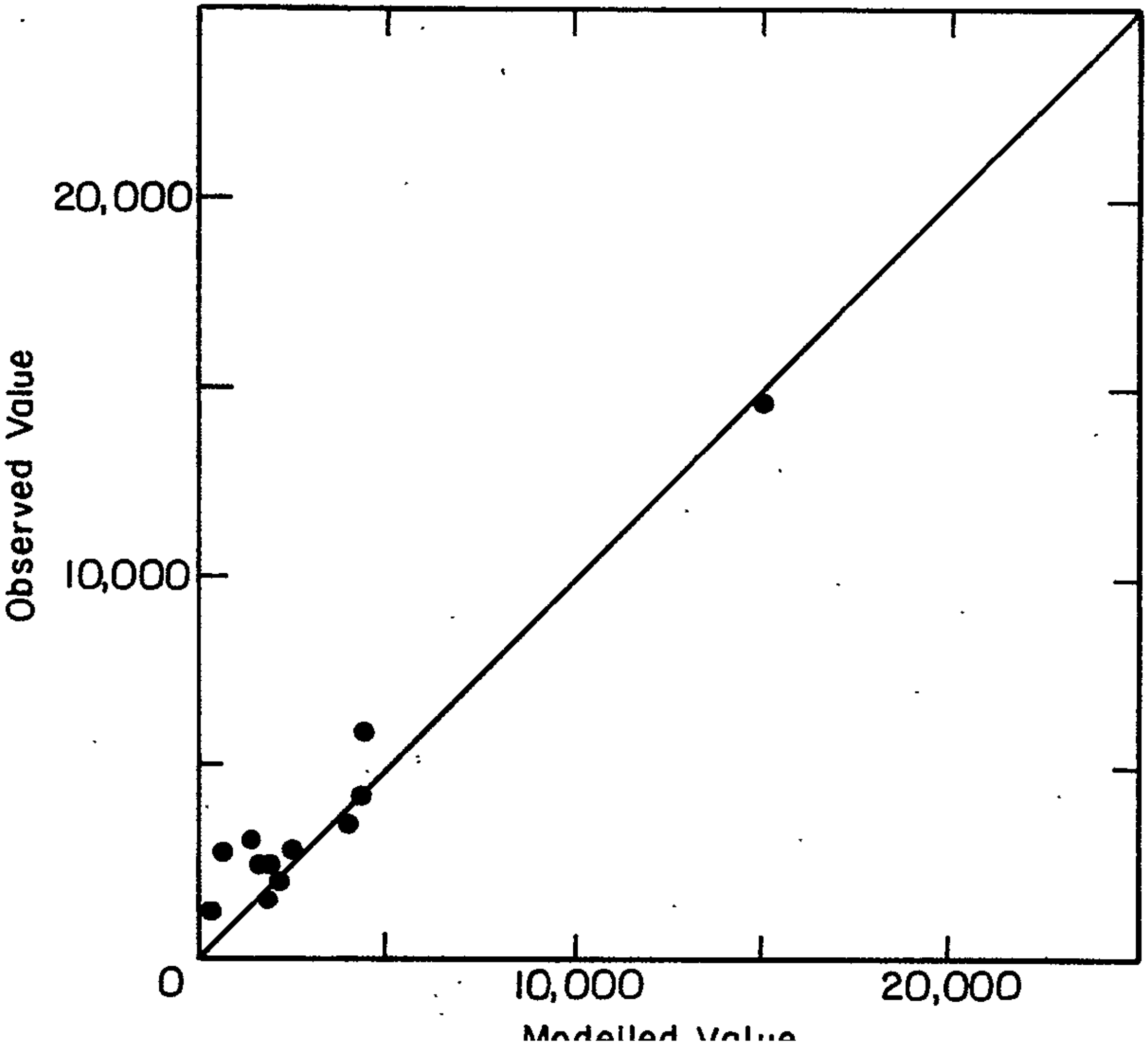

Figure 5-12 Comparison of Modelled and Observed Traffic on Each Route

Abstract Mode: Nonbusiness Traffic, Synthetic Data, Best Cost and
Relative Cost Omitted.

6. COMPARISON OF MODELS

A direct comparison between the parameter values of the two models is not possible because while the parameters of the Abstract Mode Model give constant elasticities of demand, it can be shown that the elasticities of demand obtained from the Choice Model are not constant but depend on the value of the attribute and the proportion of the traffic choosing the route in question as well as the parameter. If $\varepsilon_{ijk\ell}$ is the elasticity of demand on route k for traffic between zones i and j with respect to attribute ℓ, then the elasticity is given by

$$\varepsilon_{ijk\ell} = \alpha_\ell X_{ijk\ell} (1 - P_{ijk})$$

where α_ℓ = parameter value for attribute ℓ

$X_{ijk\ell}$ = attribute value for attribute ℓ on route k between zones i and j

P_{ijk} = proportion of traffic between zones i and j using route k (from model)

The presence of the X and P terms need some discussion. The term $(1 - P_{ijk})$ is the proportion of the zone to zone traffic on all the other links. It therefore represents the potential traffic that could be captured by relative improvements in the attributes on the link k. In other words, this suggests a mechanism of diminishing returns; as a link obtains a larger share of the market, the elasticity declines. This appears intuitively reasonable. Ineed, without such a mechanism it would be possible to obtain a proportion in excess of unity, which is clearly ridiculous.

The presence of the X term appears to suggest that the larger the actual value of the attribute, the greater the impact of a given proportional change in the attribute, or in other words, the <u>proportional</u> change in the proportion of traffic using a link depends upon the <u>actual</u> value of the change in the attribute. Thus, people perceive the advantages of changes in an attribute in terms of the magnitude of the change, minutes of access time, flights per week or dollars, rather than in terms of the relative change.

It should be noted that these characteristics are a consequence of the formulation of the model and are not a result of the data. Therefore they should be borne in mind when interpreting the results of the Choice Model but in no way does this imply that they are in reality characteristic of travel patterns in the California corridor, one way or the other.

In spite of the above qualifications concerning the variability of the Choice Model elasticities, orders of magnitude may be obtained by assuming typical values for the X and P terms. Two cases have been chosen, one where the zone pair route choice is dominated by the single major route, namely San Francisco to soutwest Los Angeles (SF zone 2 to LA zone 2, with most traffic going via SFO/LAX) and the second where the route choice is neither dominated by any single route nor involves the major route in the corridor. Such a zone pair is the Fremont area to the Pasadena/Arcadia area. In the first case, elasticities were calculated for SFO/LAX, which attracts 88% of the zone to zone business traffic and 87% of the non-business traffic, and in the second case for OAK/BUR which attracts 37% of the zone to zone business traffic and 26% of the non-business traffic.

CASE 1 - SF zone 2 to LA zone 2. Demand elasticities on route SFO/LAX.

	Access Time	Frequency	Fare
Business	-0.45	0.26	-0.08
Non-business	-0.66	0.28	-0.22

CASE 2 - SF zone 5 to LA zone 4. Demand elasticities on route OAK/BUR.

	Access Time	Frequency	Fare
Business	-3.1	0.08	-0.41
Non-Business	-3.1	0.05	-0.75

Comparison of the route access time and route frequency elasticities from the Abstract Mode Model with the above results shows no clear correspondence with either case with respect to magnitude, the access time elasticity being larger than the case 2 values while the frequency is larger than the case 1 value. However, the relative size of business and non-business values for each attribute follow similar patterns.

The results for the two cases given above may be recalculated to given marginal elasticities rather than true elasticities, or in other words, the proportional change in traffic for a unit change in the attribute (one minute of access time, on flight per week, or one dollar in fare).

CASE 1 - SF zone 2 to LA zone 2. Marginal elasticities on route SFO/LAX.

	Access Time	Frequency	Fare
Business	-0.012	0.0003	-0.005
Non-business	-0.017	0.0004	-0.014

CASE 2 - SF zone 5 to LA zone 4. Marginal elasticities on route OAK/BUR.

	Access Time	Frequency	Fare
Business	-0.058	0.0016	-0.025
Non-business	-0.056	0.0012	-0.046

These results show that any given improvement in an attribute has a far greater effect in a situation such as case 2 than on the dominant route. Business traffic appears to be less influenced by fare than non-business traffic, which is to be expected. The fact that the access time and frequency marginal elasticities are lower for business traffic in case 1 but higher in case 2 probably is a reflection of the tendency for business traffic to use the route with most departures while non-business traffic uses the nearest airport, as discussed in Chapter 5.

In comparing the results of the two models, the essential difference between their formulation should be remembered, as this gives a clue to many of the apparent contradictions. The Choice Model assumes a constant total traffic between a zone pair and interaction between all routes serving the pair. Improve the attributes of one route and it will capture traffic from all other routes. Clearly as the market share of one route increases, the traffic available for capture from other routes declines and it becomes harder and harder to attract more traffic, hence elasticities decline. On the other hand, the Abstract Mode Model assumes no interaction between routes, save in the case of the best value for an attribute. In general, improving an attribute on a route will increase traffic on that route without affecting the traffic on other routes. All the increase in traffic has been generated by the improvement.

In the California corridor, for reasons given in Chapter 1, it seems likely that the air travel market is mature and the traffic growth largely a result of rising income rather than improvements in the service as measured by the perceived attributes. The assumption of constant demand is therefore probably fairly close to reality in the short run. In the longer run, improvements in service are bound to generate some additional traffic. However, it should not be forgotten that the calibration of both models was performed on cross sectional data collected over a period of three days rather than on time-series data.

Thus, one might expect that the Choice Model with its variable elasticities reproduces route choice patterns better than the Abstract Mode Model. However, the Choice Model gives no guidance on absolute levels of demand, for this one must turn to the Abstract Mode Model.

The Choice Model appears to be able to handle the original data much better than the Abstract Mode Model particularly for non-business traffic. This may be due to the generational rather than distributional aspects of the Abstract Mode Model, that is the importance of population and income. Variations in zone to zone traffic due to demographic aspects not explained by the very aggregate measures used are excluded from the formulation of the Choice Model by the use of proportional traffic. The Abstract Mode Model may have attempted to explain some of this variation in terms of the perceived attributes. Variation in the sampling rates on different links would effect the zone totals where there is a dominant link for a zone pair.

7. CONCLUSIONS

The results of these studies represent two complementary ways of explaining the pattern of air travel in the California corridor. In so far as neither fully explains all the variation observed in the data base, it is relevant to consider possible sources of this variation and to indicate directions for further improvement in the understanding of the processes at work. This improvement could come from two directions, refinement of the data base and improvement of the models.

The traffic data used in the studies is deficient in several respects, apart from the fact that the survey from which it was obtained was conducted over five years ago. Inadequate knowledge about variation in sampling rates and the omission of the SFO/LAX link are major difficulties, as is the bias that is inherent in data obtained from a survey of only three days duration. Both for technical reasons and simply the passage of time, a new survey is needed of air travel in the corridor. None the less, even with the original survey data, there is scope for further analysis. The aggregation that was adopted may have been insensitive to important factors that determine the pattern of demand. Based on the experience with these studies, the methodology for generating synthetic data could be refined. The models could be recalibrated excluding particularly suspect data.

As far as the models are concerned, further study of the estimation techniques used for the Abstract Mode Model is required in order to better identify the cause of the underestimation problem. Further explanatory work with the causal structure in the travel choice process may lead to better formulated models, or even new approaches. However, without better data, improvements in the models themselves may be difficult to achieve or impossible to measure.

REFERENCES

1. Fan, Shing-Leung, et al. Forecasting the Demand Potential for STOL Air Transportation. Special Report 103. Institute of Transportation and Traffic Engineering, University of California, Berkeley, 1973.

2. Daniel, Mann, Johnson and Mendenhall. Statewide Master Plan of Aviation, State of California. Interior Progress Report. 1971.

3. California Public Utilities Commission. Passengers on Board and Load Factors for Scheduled Carriers on Nonstop Flights Between California Airports. (PUC Form 1504). Quarterly.

4. California Public Utilities Commission. Intrastate Passengers of Scheduled Air Carriers (PUC Form 1511). Twice yearly.