ESTIMATING THE DEMAND FOR SHORT-HAUL AIR TRANSPORT SYSTEMS

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To evaluate the feasibility of novel systems for short-haul air transportation requires an estimation of the market share potential for various configurations of such systems. This paper deals with the development of a model for estimating the market share that various short take-off and landing (STOL) system configurations can be expected to capture in a high-density, short-haul air travel corridor. The process by which travelers in the corridor choose among different routes serving the corridor is studied. Variables such as line-haul travel times, schedule frequencies, and fares are studied. Traveler's choice is modeled in terms of these variables in a probabilistic manner. Such a formulation allows the aggregation of travelers into groups for the purpose of demand analysis. The model is calibrated on the basis of data on travel characteristics in the 500-mile corridor connecting the San Francisco Bay and Los Angeles metropolitan areas. System configurations include STOLports located at various points within the region and varying schedule frequencies and air fares. Alternative strategies of diverting short-haul air traffic from congested hub airports to STOLports are also studied. The calibrated choice model is combined with a total travel forecasting model to provide a forecasting procedure for estimating the demand potential for STOL transportation systems. The calibrated models are used to study various STOL system configurations and to estimate their market potential.

•THE objective of the research documented in this paper was to develop a procedure for forecasting the demand for alternative short take-off and landing (STOL) systems in the high-density, short-haul air travel corridor connecting San Francisco and Los Angeles.

The forecasting framework used has two stages. In the first stage total air travel demand in the corridor is forecast. This is followed by the second stage of estimating the choice among available air travel routes in the corridor. The combination of the two allows the estimation of the demand for any one route or type of service, including a variety of postulated STOL systems. This distinction between total air travel demand and the choice among available routes reflects a characteristic particular to short-haul air transportation. In short-haul air transportation (normally defined by a range of approximately 500 miles), line-haul travel time does not constitute the major portion of total travel time. The total quality of air service is, therefore, more sensitive to variations in ground access travel times and schedule delays than is the case in long-haul transport. Consequently, it is necessary to study the process of choice among alternative routes and to relate that process to such route characteristics as access times and schedule frequency.

Another characteristic peculiar to short-haul air transportation is that within its range high-speed ground transportation modes may pose significant competition. In principle, therefore, a forecasting procedure for short-haul air transportation should consider the interplay among all available air and ground modes. However, for this study of the California corridor, it was believed that ground transportation technology has not yet reached a point where significant interaction occurs between air and ground

transportation. Consequently, the forecasting process developed deals exclusively with air transportation. It is therefore clear that the forecasts obtained here are conditional on the fact that no significant changes occur in the ground transportation system in the corridor. Should a high-speed rail system, for example, become a reality for the California corridor, then the forecasts presented here would be false.

MODEL DESIGN

The modeling structure used in this study is shown in Figure 1. A number of travel routes are identified within the short-haul corridor, and for each route a number of attributes or transportation characteristics are identified. Two models are used to estimate the demand potential for STOL transport in the corridor. First, a generation model is used to estimate the total air travel demand, where it is postulated that this demand depends on the socioeconomic characteristics of the city pairs in the corridor as well as the best route attributes available for each city pair. Second, a choice model is used to estimate the split in the total demand among available routes in the corridor, where it is assumed that the split depends on the relative attributes of each of the routes. These two models are then combined to estimate the total market share for each route. When summed over routes that constitute STOL service, the total demand for STOL transportation is obtained.

The study corridor on which these models were to be applied was represented by a network consisting of origin and destination cities and origin and destination airports. As shown in Figure 2, the corridor joins two regions—I, San Francisco, and II, Los Angeles—with air transport among a number of airport pairs. For every origin-destination pair, a route is defined by a path along the network extending from the origin city to the origin airport, the destination airport, and finally the destination city. In Figure 2 ACDB and AEKB are examples of routes connecting cities A and B.

Figure 1. Model framework.

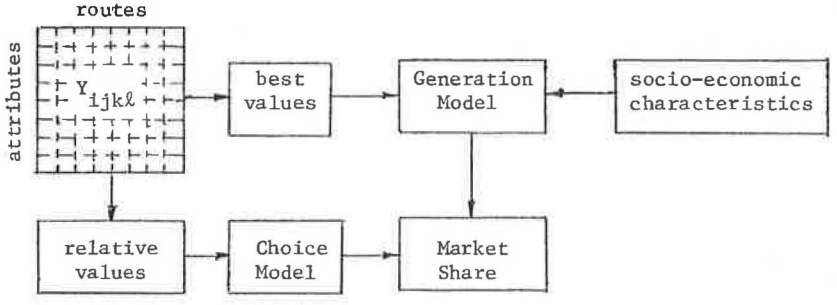
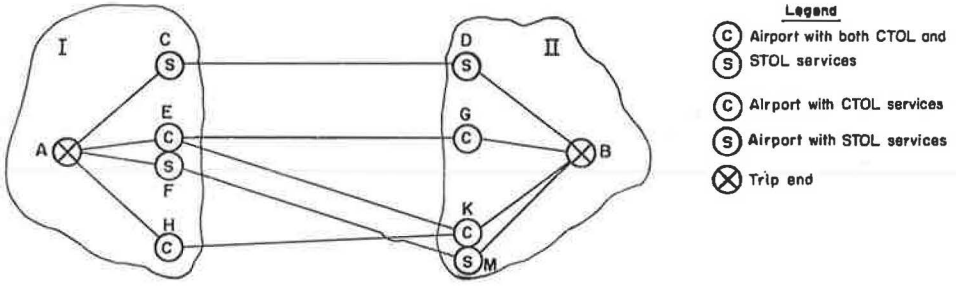


Figure 2. Graphical representation of corridor.



Air Travel Generation Model

A simple multiplicative model was used to estimate intercity air transport demand in the study corridor. This model included both socioeconomic (population, median income, and employment) and transportation (the best available schedule frequency, lowest travel time, and lowest travel cost) variables among all the available routes for each city pair. Three alternative model forms were specified and later statistically tested:

$$T_{ij} = \alpha_0 P_i^{\alpha_1} P_j^{\alpha_2} Y_i^{\alpha_3} Y_j^{\alpha_4} t_{ij}^{\alpha_5} \tag{1}$$

$$T_{ij} = \alpha_0 P_i^{\alpha_1} P_j^{\alpha_2} Y_{ij}^{\alpha_3} t_{ij}^{\alpha_4} \tag{2}$$

$$T_{ij} = \alpha_0 P_i^{\alpha_1} P_j^{\alpha_2} Y_{ij}^{\alpha_3} LS_{ij}^{\alpha_4} \tag{3}$$

where

T_{ij} = total traffic between cities i and j,
P = population,
Y = median income,
Y_{ij} = average median income for both cities,
t_{ij} = shortest travel time among all routes between i and j,
LS_{ij} = level-of-service variable defined as the average travel time between i and j over all routes and weighted by the cost and the schedule frequency for each route, and
α = parameter representing demand elasticities with respect to the variables.

Route Choice Model

The purpose of the choice model is to describe how a traveler in the corridor is likely to choose among the available routes serving the corridor. This description is then used to split the total travel demand generated by the previous model among these routes. The model specified in the study was a stochastic model that predicts the probability of choice conditional on values of the choice elasticities. By studying the random variations of these elasticities among individuals and using a procedure proposed by Kanafani (3), we can aggregate over the total study population.

Using the corridor notation of Figure 2, let P_{ijk} be the probability that a traveler between cities i and j chooses route k and let Y_{ijkl}, $l = 1, \ldots, m$, be m attributes of route k. The basic postulate of the model is specified by the following probability function:

$$P_{ijk} = g(Y_{ijk1}, Y_{ijk2}, Y_{ijk3}, \ldots, Y_{ijkm})$$

That is, the probability of choice is assigned on the basis of a set of m route attributes.

An individual is assumed to evaluate the characteristics of all routes one at a time. For each characteristic he ranks the routes available to him. This ranking is analogous to the probability that a route is chosen on the basis of this particular characteristic. Thus it is assumed that there is a unique correspondence between the ranking of a route on the basis of a characteristic and the probability of choosing the route on that basis. This correspondence is defined by a set of weights θ_l. Letting A_l be the event of choosing a route on the basis of characteristic l and postulating a sigmoidal relationship among the weight θ, the value Y_l of l, and the probability P give the choice probability P_{ijkl} as

$$P_{ijkl} = P[A_l] = \frac{Y_{ijkl}^{\theta_l}}{\sum_r Y_{ijrl}^{\theta_l}} \tag{4}$$

In Eq. 4 the probability of taking route k on the basis of attribute l is a function of

its value for route k relative to all available routes. It should be noted that P_{ijkl} in Eq. 4 is the probability based only on one attribute, l, and is independent of all the other attributes. That is, $P_{ijkl}, \ldots, P_{ijkm}$ are probabilities of independent events. The total choice probability P_{ijk}, which is based on all route attributes, is therefore

$$P_{ijk} = \prod_{l=1}^{m} P[A_l] = \prod_{l=1}^{m} \left[Y_{ijkl}^{\theta_l} \Big/ \sum_{Y} Y_{ijrl}^{\theta_l} \right] \tag{5}$$

subject to

$$0 \leq P_{ijk} \leq 1 \tag{6}$$

and

$$\sum_{k} P_{ijk} = 1 \tag{7}$$

Equation 7 is satisfied by introducing a factor K_{ij} in Eq. 5 to give

$$P_{ijk} = K_{ij} \prod_{l=1}^{m} \left[Y_{ijkl}^{\theta_l} \Big/ \sum_{Y} Y_{ijrl}^{\theta_l} \right] \tag{8}$$

With Eqs. 7 and 8 it should be possible to determine K_{ij}.

To facilitate the presentation of the remainder of the model, we assume without loss of generality that there are only three route attributes: total travel time H_{ijk}, schedule frequency F_{ijk}, and travel cost C_{ijk}. Equation 8 now becomes

$$P_{ijk} = K_{ij} \left[F_{ijk}^{\alpha} \Big/ \sum_{r} F_{ijr}^{\alpha} \right] \left[C_{ijk}^{\beta} \Big/ \sum_{r} C_{ijr}^{\beta} \right] \left[H_{ijk}^{\gamma} \Big/ \sum_{r} H_{ijr}^{\gamma} \right] \tag{9}$$

where α, β, and γ are the weights placed on each of the attributes. Combining Eqs. 7 and 9 gives

$$K_{ij} = \frac{\sum_{k} F_{ijk}^{\alpha} \sum_{k} C_{ijk}^{\beta} \sum_{k} H_{ijk}^{\gamma}}{\sum_{r} F_{ijr}^{\alpha} C_{ijr}^{\beta} H_{ijr}^{\gamma}} \tag{10}$$

Substituting this value in Eq. 9 gives the expression of the choice probability, which, because α, β, and γ are postulated as random variables, is stated as a conditional probability of choice given α, β, and γ:

$$P[ijk \mid \alpha, \beta, \gamma] = F_{ijk}^{\alpha} C_{ijk}^{\beta} H_{ijk}^{\gamma} \Big/ \sum_{r} F_{ijr}^{\alpha} C_{ijr}^{\beta} H_{ijr}^{\gamma} \tag{11}$$

To find the unconditional probability requires that this expression be integrated over the domains of the random variables α, β, and γ respectively, which gives

$$P[ijk] = \int_{R_1} \int_{R_2} \int_{R_3} P[ijk \mid \alpha, \beta, \gamma] f(\alpha, \beta, \gamma) \, d\alpha d\beta d\gamma \tag{12}$$

where $f(\alpha, \beta, \gamma)$ is the joint density function of the variables α, β, and γ. It was assumed and later statistically verified that a traveler assigns these weights independently of one another. This assumption yields a considerable simplification because it allows the representation of the joint density function as the product of the individual density functions for each weight. The choice model can now be specified in its complete form:

$$P[ijk] = \int_{R_1} \int_{R_2} \int_{R_3} \frac{F_{ijk}^{\alpha} C_{ijk}^{\beta} H_{ijk}^{\gamma}}{\sum_r F_{ijr}^{\alpha} C_{ijr}^{\beta} H_{ijr}^{\gamma}} f_1(\alpha) f_2(\beta) f_3(\gamma) d\alpha d\beta d\gamma \qquad (13)$$

STOL Share Model

Once both the travel generation model and the choice model are completely specified, we combine them into a model that will allow the estimation of the share of any route in a corridor. This will also allow the estimation of the demand potential for STOL transport. Combining the value T_{ij} of the demand for air travel between any O-D pair, as obtained from the generation model, with the choice probability P[ijk], as obtained from the choice model, gives the expected demand for a route k:

$$E[T_{ijk}] = T_{ij} P[ijk] \qquad (14)$$

If ψ denotes the subset of all routes k that are STOL routes, then the total demand potential for STOL transportation between any O-D pair i, j can be obtained from

$$E[ST_{ij}] = T_{ij} \sum_{k \in \psi} P[ijk] \qquad (15)$$

and the total STOL demand potential in the corridor is obtained by adding the demand values for all O-D pairs:

$$E[ST] = \sum_i \sum_j E[ST_{ij}] \qquad (16)$$

This model allows the estimation of the demand potential for STOL transportation for any STOL service configuration.

THE DATA BASE

Most of the data used in this study were derived from an on-board origin-destination survey conducted in 1970 by Daniel, Mann, Johnson, and Mendenhall (1). For each trip the following variables were observed:

1. Trip origin and destination,
2. Airport pair used,
3. Trip purpose, and
4. Reported ground access times at both trip ends.

A total of 1,637 business trips and 1,467 nonbusiness trips were included in the data base. This trip information was collected on 12 conventional take-off and landing (CTOL) routes in the study corridor:

1. Oakland-Hollywood/Burbank,
2. Oakland-Los Angeles International,
3. Oakland-Ontario,
4. Oakland-Santa Ana (Orange County),
5. San Francisco International-Hollywood/Burbank,
6. San Francisco International-Long Beach,
7. San Francisco International-Ontario,
8. San Francisco International-Santa Ana,

9. San Jose-Hollywood/Burbank,
10. San Jose-Los Angeles International,
11. San Jose-Ontario, and
12. San Jose-Santa Ana.

A major deficiency of the data source was that the survey did not include flights out of San Francisco International (SFO) and Los Angeles International (LAX). This, of course, reduces the accuracy of the estimation based on the remaining routes, for San Francisco International and Los Angeles International are by far the most important airports in the corridor. However, because the calibration technique uses a sample of travel records randomly selected from the trip file, it can be said that the loss of accuracy in the analysis is only to the extent that the sample used may be considered biased.

Inventory data including information on the socioeconomic characteristics of the study area and its population and information describing the air transport system in the study area were also acquired. The socioeconomic characteristics included were population, income characteristics, and employment levels, and the transportation variables were (a) schedule frequencies of service between airport pairs, (b) line-haul travel times between airport pairs, (c) air fares between airport pairs, and (d) ground access times between population centers and airports.

The socioeconomic variables were obtained from the 1970 census (10). The transportation characteristics were obtained from available sources such as the Official Airline Guide and available road maps of the study area.

MODEL CALIBRATION AND TESTING

Air Travel Generation Model

Multiple regression analysis was performed on the logarithmic forms shown in Eqs. 1, 2, and 3. The results of this analysis for both business and nonbusiness travel are given in Table 1, from which some interesting observations can be made.

1. In all regressions, population and median income seemed to be highly significant in explaining total travel generations. The positive signs of the elasticities were as expected.
2. In the case of business travel, shortest travel time t_{ij} did not seem to be so highly significant as the other variables, even though the parameters associated with it were all negative, as expected. This is probably due to the fact that there is very little variation in this variable among the zone pairs in the study corridor. In the case of nonbusiness travel, this variable is not significant. This result seems intuitively appealing inasmuch as it is reasonable to deduce that nonbusiness travelers, i.e., mainly recreational travelers, are not sensitive to travel time.
3. In all models tested, the total explanatory power was rather low. R^2 values fall in the range 0.26 to 0.36. Because the explanatory power of the variables in the models seemed sufficiently high as explained earlier, it seems likely that additional variables describing the socioeconomic nature of the various cities in the corridor should have been included.

Based mainly on these results, it was concluded that the models as calibrated were not suitable for forecasting travel demand. On the other hand, the explanatory power of the variables included in the model seemed sufficiently high to warrant use of the models. Because the demand elasticities of variables such as population and income were estimated with sufficiently high confidence, it should be possible to use them in relating changes in income and population to changes in travel demand.

The general structure of the travel generation model is

$$T_{ij} = \prod_k X_k^{\alpha_k}$$

where α_k is the elasticity of the travel demand with respect to variable X_k, the ratio of relative changes of T and X, and is given by

$$\alpha_k = \frac{\partial T_{ij}/T_{ij}}{\partial X_k/X_k} \tag{17}$$

for all k. The total relative change in T_{ij} that is brought about by changes in variable X_k can be calculated from the equation for the total derivative as follows:

$$dT_{ij} = \sum_k \frac{\partial T_{ij}}{\partial X_k} dx_k$$

from which

$$\frac{dT_{ij}}{T_{ij}} = \sum_k \alpha_k \frac{dX_k}{X_k} \tag{18}$$

For example, in model B4 (Table 1), if both population of the origin city and average median income simultaneously increase by 10 percent, then the total increases in travel generation will be as given in Eq. 18.

$$\frac{dT_{ij}}{T_{ij}} = 0.29 \frac{dP_i}{P_i} + 0.89 \frac{dY_{ij}}{Y_{ij}} = 11.80\%$$

This procedure is used to apply growth rates to the actual city pair volumes rather than to volumes obtained from the regression model. This avoids the forecasting difficulties caused by the weak explanatory power of the regression model.

The Choice Model

To determine the probabilities P[ijk] as shown in Eq. 13 required that the distribution functions $f_1(\alpha)$, $f_2(\beta)$, and $f_3(\gamma)$ be estimated. To do this we subdivided the data into randomly selected groups. For each group, estimates of α, β, and γ were obtained by regressing on the function:

$$T_{ijk} = F_{ijk}^{\alpha} C_{ijk}^{\beta} H_{ijk}^{\gamma} \tag{19}$$

where H_{ijk} is the access time at both ends of a trip between i and j by route k. The particular form of Eq. 19 was selected from a number of alternatives that were tested statistically.

This procedure is analogous to selecting random observations on the values of α, β, and γ. Although the sample subgroups were selected at random, there is no evidence that they do represent homogeneous subsets of the population and that the readings obtained for α, β, and γ are truly disaggregate estimates. On the other hand, this procedure provides a closer approximation to a completely disaggregate model than a deterministic model.

Estimated values for the three parameters were obtained for both business and nonbusiness travel. Both α and β have the correct sign. The parameter γ does not seem to have a consistent sign; however, the F-statistic associated with this parameter is very low in all cases, indicating that it is not significantly different from zero. This is not surprising for a number of reasons. First, it was found through an investigation of the data base that access time variations between the different trip data records were not very large. Second, when compared with the effect of schedule frequency, the access time effect seemed dwarfed. Variations in schedule frequencies among airport pairs were such that the resulting variations in expected schedule delays would be considerably larger than differences among access times.

The overall statistical goodness of fit was demonstrated by the high values of coefficients of multiple determination R^2, which were over 0.90 in all cases. These were corroborated by low values of the standard error of estimate—between 0.23 to 0.39.

Table 1. Results of regressions.

Variables	Business Models					Nonbusiness Models		
	B1	B2	B3	B4	B5	NB1	NB2	NB3
Constant	-6.2	-7.97	-4.39	-7.32	-13.44	-16.10	-15.65	-15.65
$\ln P_i$	0.31 (36.88)	0.29 (32.98)	0.31 (34.46)	0.29 (32.62)	0.30 (35.62)	0.32 (23.88)	0.31 (22.67	0.31 (22.67)
$\ln P_j$	0.31 (36.00)	0.37 (63.22)	0.34 (62.99)	0.37 (61.23)	0.40 (99.57)	0.40 (42.42)	0.42 (56.94)	0.42 (56.94)
$\ln Y_i$	1.02 (11.60)					1.05 (7.10)		
$\ln Y_j$	-0.12 (0.15)					0.45 (1.49)		
$\ln Y_{ij}$[a]		0.48 (4.70)	0.63 (2.23)	0.89 (4.20)	1.10 (7.50)		1.40 (7.37)	1.40 (7.37)
$\ln t_{ij}$	-0.46 (3.24)	-0.32 (1.54)	-0.41 (2.27)	-0.33 (1.70)		0.18 (0.32)	0.24 (0.63)	
$\ln LS_{ij}$					0.31 (0.99)			
R^2	0.3279	0.3128	0.3074	0.3117	0.3101	0.2619	0.3576	0.3558

Note: Numbers in parentheses are F-statistics.

[a]In model B2, $Y_{ij} = Y_i \times Y_j$; in model B3, $Y_{ij} = (P_i \times Y_i + P_j \times Y_j)/(P_i + P_j)$; in other models, $Y_{ij} = (Y_i + Y_j)/2$.

Figure 3. Cumulative distribution of departure frequency elasticity for business travelers.

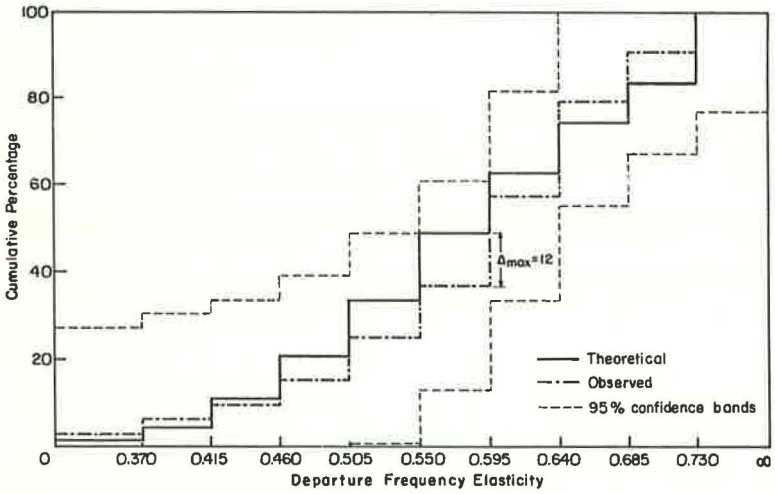


Table 2. Results of distributions and chi-square tests.

Trip Purpose	Variable	Gamma Distribution			Normal Distribution		Degrees of Freedom	χ^2 Calculated	P-Value
		K	λ	Γ(K)	μ	σ			
Business	α	23.72	38.96	1.05×10^{22}	—	—	5	6.042	0.3019
	β	4.28	14.43	8.63	—	—	4	3.925	0.4170
	γ	—	—	—	0.0136	0.1068	3	3.244	0.3592
Nonbusiness	α	4.64	13.43	14.13	—	—	2	1.596	0.4531
	β	5.33	10.69	40.19	—	—	2	1.033	0.5964
	γ	—	—	—	0.363	0.247	3	2.650	0.4520

Note: Gamma distribution: $f(x) = \frac{\lambda^K}{\Gamma(K)} x^{K-1} e^{-\lambda x}$. Normal distribution: $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}$

The next step was to estimate the density distribution of each of the estimates based on the values obtained in the regressions. This was done for α, β, and γ, in spite of the fact that γ was previously judged not significant. This allowed the investigation of any effect, regardless of its significance, of access time on the choice process. Furthermore, by including all parameters in the analysis, we could develop a process that is general enough to be used under other empirical conditions. This will only allow the corroboration of the rather limited results of this study.

Estimation of the density distribution functions of parameters α, β, and γ was performed by inspecting their graphical representations and then testing the fit to postulated statistical distribution functions. There is no obvious relationship between behavioral assumptions and specific statistical distribution functions. At this stage of knowledge regarding the behavioral implications of stochastic aggregation in travel demand models, the best that can be done is empirical analysis.

Graphical representations of the empirical distributions of α, β, and γ were obtained by constructing cumulative histograms for each parameter. An example of these histograms is shown in Figure 3 together with the theoretical distribution and the 95 percent confidence band. γ distributions were postulated for the parameters α and β, whereas a normal distribution was postulated for γ in both the business and nonbusiness cases. After the parameters of those hypothesized distributions were estimated from the respective data sets, statistical tests of goodness of fit were performed. Chi-square tests were performed on all six distributions and had high P-values, showing in all cases that the empirical distributions and the theoretical distributions were not significantly different.

To corroborate the results of the chi-square tests and to remove any doubt that may be precipitated because of the chi-square test's sensitivity to small sample sizes, we conducted Kolmogorov's D-test. This D-test result is shown in Figure 3 in the form of the 95 percent confidence band. As can be seen, the theoretical distribution falls within this band; therefore the postulated distribution is a valid representation of this random variable. The equations for the theoretical distributions as well as the results of the chi-square tests are given in Table 2. The assumption of the independence of α, β, and γ was checked by calculating the correlation coefficients. These were on the order of 0.3 to 0.4, which is significantly low for the sample sizes in question.

The final step in the calibration of the choice model is to evaluate the three-dimensional integral of Eq. 13. It was not possible to evaluate the integration analytically. However, it is always possible to evaluate a finite integral numerically with the aid of a high-speed computer. It is easy to tell from inspection of the integrand

$$\frac{F_{ijk}^{\alpha}\, C_{ijk}^{\beta}\, H_{ijk}^{\gamma}}{\sum_{r} F_{ijr}^{\alpha}\, C_{ijr}^{\beta}\, H_{ijr}^{\gamma}} f_1(\alpha) f_2(\beta) f_3(\gamma)$$

that it is indeed finite. The first part of the integrand is a ratio known to be less than unity and the second part is the joint density functions of three random variables that are also limited to unity.

The numerical analysis consisted of inputting characteristics of the 12 alternative routes in the study corridor and operating the model in an attempt to reproduce the observed data.

The overall goodness of fit of model results was then tested. Figures 4 and 5 show comparisons of model results with observed data for business and nonbusiness travel. Although a perfect fit was not achieved, in view of the results presented above and the imperfections of the data base used in calibrating the choice model, model results can generally be considered good and the calibrated model can be used for making travel forecasts.

DEMAND FORECASTING AND SENSITIVITY ANALYSIS

The first step in performing demand forecasting for STOL transportation is to postulate STOL system characteristics. Two basic assumptions are implicit in this ap-

proach: (a) that any transportation service can be represented by a number of attributes associated with it and that the decision process by which travelers choose among alternative services is essentially unchanged by the introduction of STOL or any other transportation service and (b) that the traveler's decision process remains unchanged over time. In other words, the values of the parameters and elasticities that reflect the traveler's response to exogenous influences will not change over the forecasting period. This latter assumption can be validated only after repeated applications of the forecasting models at different points in time.

STOL System Configurations

The specifications of STOL system configurations consist of the locations of STOLports, frequencies of service, travel costs, and travel times involved. There is a lack of precise data on STOLport locations and STOL aircraft characteristics. Therefore, the system variables are treated parametrically; i.e., a number of reasonable configurations are postulated and the resulting forecasts are presented. The purpose of this type of analysis is to demonstrate the use of the forecasting models and provide a procedure by which the demand potential of alternative STOL systems can be compared.

The only locations for STOLports considered in this study are existing military fields and general aviation fields. It is believed that such airports, by the mere fact of their existence, would be the first candidates for the introduction of STOL air transportation into any urban area. In the San Francisco Bay area, candidate airports include Crissy Field, Berkeley Marina, Concord Buchanan Field, and Palo Alto Airport, and, in the Los Angeles area, they include Hawthorne Airport, Fullerton Airport, Compton Airport, and Santa Monica Airport.

In the analysis, many configurations can be generated by selecting various airports from these two groups. In this presentation we show the results for only two configurations.

Postulate STOL fares were calculated from the formula

$$\text{Fare} = \frac{\text{total cost per available seat-mile} \times \text{stage length}}{\text{load factor}} + \text{tax}$$

The range of total cost per available seat-mile was taken as 2 to 4 cents for a stage length of 400 miles, which is an average range anticipated for STOL aircraft (7). The load factor range was 0.5 to 0.7.

The frequency of service was allowed to vary in two manners. First STOL service frequency was increased from 0 to 49 weekly flights, without adjusting the frequency of service of the CTOL airport pairs. Then it was postulated that some CTOL service will essentially be replaced by STOL service, so the increase in STOL frequency was accompanied by an equal decrease in CTOL frequency.

Forecasting STOL Market Share

The first model application consisted of varying STOL fares and departure frequencies without adjustment to CTOL frequency. For the STOL system chosen, Figure 6 shows its market shares of business and nonbusiness travel and the increase in STOL market share brought about by increasing service frequencies as well as decreasing the fare. Comparing the results for business and nonbusiness travel shows that business travel is more sensitive to departure frequency than nonbusiness travel; the curves for the former are steeper. Also, comparing the distances between the curves for different fares shows that nonbusiness travel is more sensitive to fare than business travel. In both cases, the market share for STOL does not exceed 8 percent of the total.

The next step in the analysis was to introduce adjustments in the CTOL schedule frequency simultaneous to increases in STOL frequencies. This was done in two manners. First, reductions in total CTOL frequencies ranging from 10 to 90 percent were obtained by distributing these flights equally among STOL routes in the configuration studied. Second, CTOL frequencies were reduced only at routes involving either SFO or LAX or both by switching flights to STOL and distributing them among STOL routes

Figure 4. Comparison of modeled and observed business trips on each route.

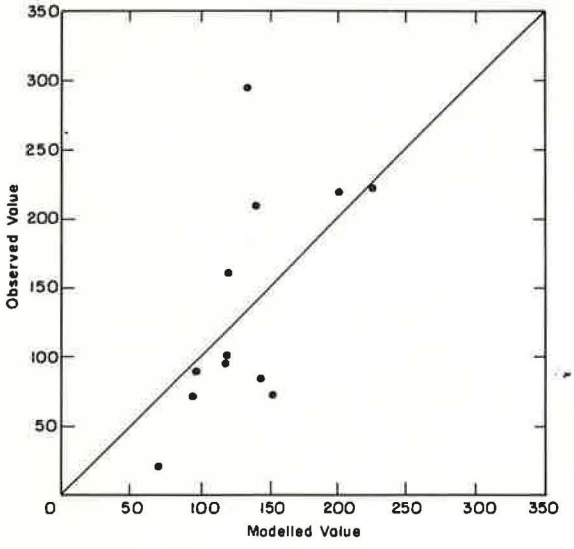


Figure 5. Comparison of modeled and observed nonbusiness trips on each route.

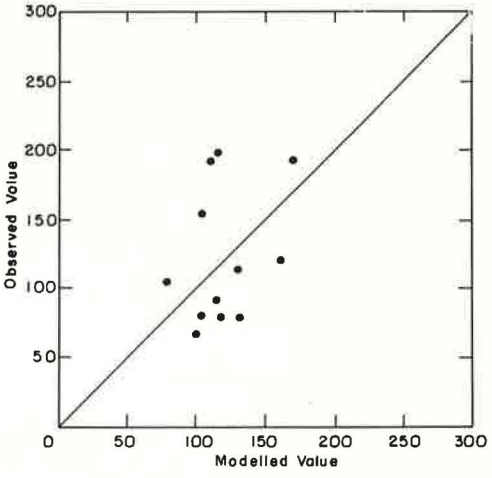


Figure 6. Sensitivity of STOL market share to departure frequency (configuration I).

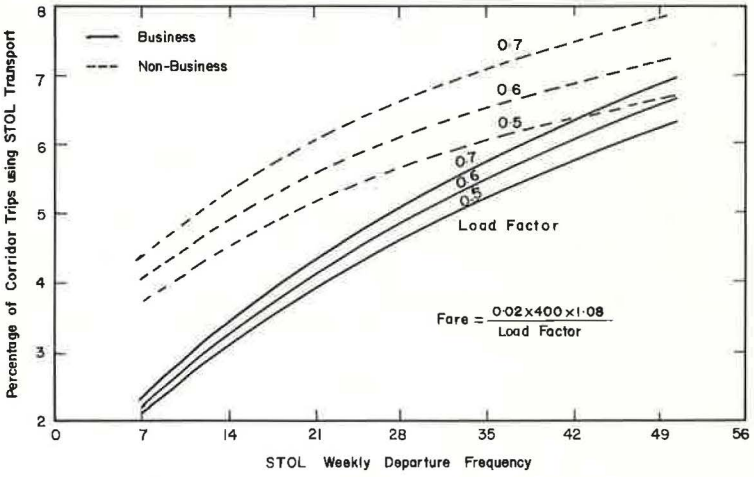
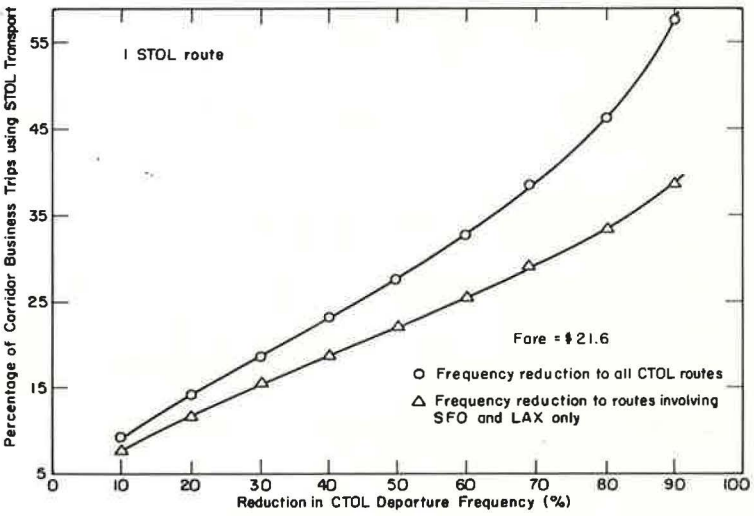


Figure 7. Sensitivity of STOL share of business travel market to changes in CTOL departure frequency (configuration I).



in the same manner as before. This second case was motivated by the idea that STOL service may be introduced to reduce congestion at major hub airports. Because only SFO and LAX may have volumes sufficiently high to cause congestion, it was assumed that reductions in CTOL service may be warranted at routes including either or both of these airports.

The results of this analysis are shown in Figure 7 for configuration I and in Figure 8 for configuration II. The figures show the increase in STOL market share related to the two types of CTOL frequency adjustments described. In configuration I a market share of more than 50 percent can be achieved; market share potential increases to a maximum of about 70 percent for configuration II. It should be noted that for both configurations the increase in business travel is larger than the increase in nonbusiness travel. This result follows from the fact that business travel is more sensitive to service frequency.

An interesting result is obtained when Figures 7 and 8 are compared. In spite of the fact that in both cases the number of flights switched from CTOL to STOL service is the same, the market share potential under configuration II is larger than under configuration I. This seems to indicate that market share increases as the number of STOL routes increases, even if the same service frequency is offered. Of course, this effect is due for the most part to the fact that a larger number of STOLports will yield a higher accessibility to STOL services.

The results obtained from applying the model to additional configurations indicated that the marginal increase in STOL market share decreases as the number of STOL routes increases. A result such as this is of vital importance when the cost-effectiveness of introducing additional STOL routes or STOLports into an urban area is analyzed.

Forecasting Total Air Travel

As was discussed, calibration results showed that the models were not sufficient to forecast the absolute levels of traffic between city pairs. However, the elasticities of demand with respect to the population, income, and travel time variables were estimated with high reliabilities. Therefore, they were used to relate the increase in travel volumes to varying growth rates in population and income and to the changes in travel times caused by the introduction of STOLports in the study area.

Based on the calibration results, the models selected were

$$\ln T_{ij} = -7.32 + 0.29 \ln P_i + 0.37 \ln P_j + 0.89 \ln Y_{ij} - 0.33 \ln t_{ij}$$

for business travel and

$$\ln T_{ij} = -15.65 + 0.31 \ln P_i + 0.42 \ln P_j + 1.40 \ln Y_{ij}$$

for nonbusiness travel. If we assume that population and income growth occurs in the same manner in all zones, simplifying Eq. 18 gives

$$\frac{\Delta T_{ij}}{T_{ij}} = (\alpha_1 + \alpha_2)W_p + \alpha_3 W_y + \alpha_4 W_t \qquad (20)$$

where

α_k = elasticity with respect to variable k, and
W_k = proportional change in variable k.

If $\Delta T_{ij}/T_{ij}$ is denoted by β and the number of years over which the forecast is performed by N, future traffic volumes T^*_{ij} can be obtained from present volume T_{ij} by

$$T^*_{ij} = (1 + \beta)^N T_{ij} \qquad (21)$$

The total corridor travel T^* at year N is then

Figure 8. Sensitivity of STOL share of business travel market to changes in CTOL departure frequency (configuration II).

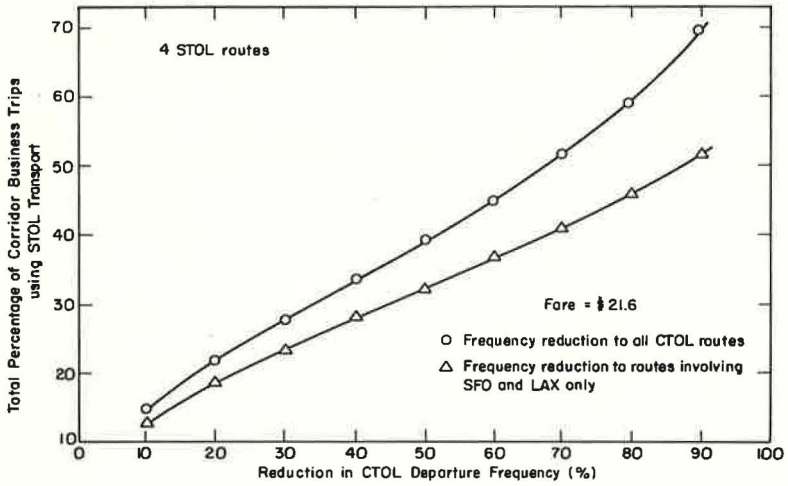


Figure 9. Sensitivity of business travel to changes in population and median family income.

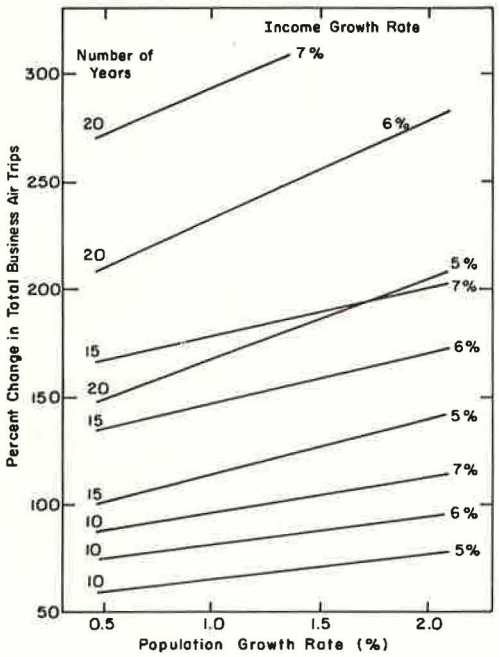
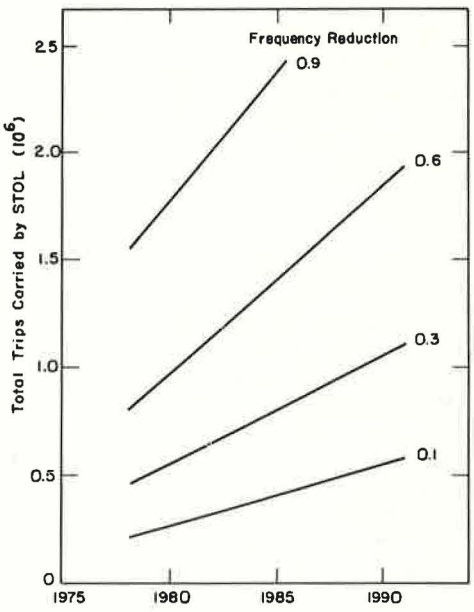


Figure 10. Forecast of STOL transport demand generated by configuration I with frequency reduction of all CTOL routes.



$$T^* = \sum_{ij} T_{ij}(1 + \beta)^N = T(1 + \beta)^N \qquad (22)$$

This procedure relates future travel volumes in each city pair to present volumes and thus avoids zone-by-zone errors that may be introduced if the volume levels are forecast directly from the model.

Annual population growth rates were varied from 0.5 to 2.0 percent. Median income was increased in the range 5.0 to 7.0 percent per year. The forecast was performed for values of N of 10, 15, and 20 years. For the STOL system configuration, the following assumptions are made. During the first 10 years, i.e., up to the year 1980, no service will be introduced at any of the STOLports. In 1980 service will be introduced according to configuration I. Travel times will then be modified but held unchanged throughout the rest of the forecasting period.

Results of model application to business travel are shown in Figure 9. It should be mentioned that these results are samples of the types of results that can be obtained from the application of the travel generation model. This application allows the estimation of the increase in total corridor air travel, as well as particular city pair volumes, under different population and income growth assumptions and for different air transport system alternatives.

Forecasting STOL Demand Potential

Forecasting STOL demand is done by combining the forecasts of the total corridor air travel demand with the forecasts of the STOL market share. This is a simple operation consisting of the multiplication of the STOL share and the total air travel volume. As an example, the forecast for configuration I was obtained, for business travel, for various levels of frequency switch from the CTOL airports to the STOLports. The forecast results (Fig. 10) are based on a population growth rate of 0.5 percent per year and a median income increase of 7 percent per year with a STOL fare of $21.60. The forecast extends from a 1970 base year total volume of 3.1 million passengers to 1990. Naturally, the validity of a forecast through 1990 depends on the validity of the assumed growth rates for population and income. These growth rates could be modified at intervals within the forecast period if this is deemed necessary.

CONCLUSIONS

The procedure presented in this paper is aimed at forecasting the demand potential for transport systems in short-haul air transportation. Particularly, the objective was to study market potentials for various STOL system configurations in a short-haul corridor, such as the Los Angeles-San Francisco corridor.

The framework used in forecasting consists of three stages: Forecast the total air travel demand in the corridor; estimate the market share for any given STOL configuration; and combine these two into a forecast of the market share for STOL. An aggregative choice model is developed for this purpose. This model is stochastic in nature and permits the aggregation of individual choice decisions across a study population. Because of the lack of suitable data, it was not possible to perform this aggregation strictly on an individual traveler basis. Therefore, it was necessary to perform the aggregation on small population subgroups, chosen at random. It is believed that such a procedure, though not strictly an aggregative procedure, is a step in the right direction, particularly based on the large amount of data required for calibrating a model to account for differences among all individuals in a population.

In the forecasting model used in this study, it is assumed that no significant changes will occur in high-speed ground transportation in the study corridor and that the air travel market and the ground travel market are essentially independent. This, of course, will not be true if technological changes occur that create competition in the corridor between air and high-speed ground transportation. Therefore, it is essential to note that the validity of the forecasts obtained by the procedure developed in this study is conditional on this assumption.

The uncertainties inherent in forecasting socioeconomic indicators such as income and population are accounted for by forecasting in a sensitivity manner. That is, the forecasts are provided for ranges in growth rates for such variables. In a long-range planning situation it is always prudent to revise such forecasting inputs and modify the forecasts if necessary.

An interesting finding of this analysis is that the demand potential for STOL transportation in a corridor served by CTOL airports is strongly dependent on the level to which corridor traffic is diverted from the CTOL airports to STOLports. This is due to the strong impact of schedule frequency on the attractiveness of any particular airport pair and the initial frequency advantage that the large CTOL airports have. It was also found in the analysis that adding STOLport pairs in the system increases the market share but at a decreasing rate. This is a finding that would be important in assessing the cost-effectiveness of introducing STOL service in a short-haul air travel corridor.

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