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An Analysis of Long and Medium-Haul

Air Passenger Demand

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DEPARTMENT OF AERONAUTICS & ASTRONAUTICS

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AN ANALYSIS OF LONG AND MEDIUM-HAUL AIR PASSENGER DEMAND
Volume I

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MASSACHUSETTS INSTITUTE OF TECHNOLOGY

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Section 1. INTRODUCTION TO THE INTEGRATED AIR TRANSPORT MODEL

This report reviews a series of interrelated research tasks conducted between December 1975 and November 1977 by an MIT research team under the sponsorship of the National Aeronautics and Space Administration - Ames Research Center (Grant No. NSG-2129). The tasks were carried out under the general title of "The Impact of Changing Technology on the Demand for Air Transportation" with Professor Nawal K. Taneja of MIT as Principal Investigator. Senior members of the research team consisted of Professor Robert W. Simpson, Dr. James T. Kneafsey and Dr. Steven E. Eriksen. In addition, several graduate students and members of the Flight Transportation Laboratory participated during different stages of the research program.

The initial purpose of this research grant was to develop demand models for air transportation that are sensitive to the impact of changing technology. In order to satisfy this requirement, the models not only had to be responsive to potential changes in technology, but also to changing economic, social, and political factors as well. While these models were developed to conform with past history, they also went beyond simple projections of historical trends, carefully incorporating the important basic variables that explain these trends. In addition to anticipating the wide differences in the factors influencing the demand for long haul and short haul air travel, the models were designed to clearly distinguish between these markets.

The initial proposal was submitted with research to be carried out in three phases. The first phase focused on the development of the relationship between past and current aviation technology and current aviation demand and was completed according to plan. The second phase was to investigate the relationship between future aviation technology and future aviation demand, while the final phase was to produce projections of fleet requirements.

However, the scope of the second and third phases changed in light of the results of the first phase and the NASA-Ames in-house research project entitled, "Development of a Methodology for Assessing the Benefits of Aeronautical R & T". The objective of this NASA work was to provide an in-house capability to evaluate the potential benefits/costs for using advanced technology in air transportation. In-depth discussions between the research team and the Ames technical monitors during Autumn 1976 had narrowed the scope of the second phase in order to integrate more effectively the research at MIT with the projects being carried out in-house at the Ames Research Center. Selected members of the research team under the supervision of Professor Simpson contributed to the development of NASA's Benefit/Cost Model of Aeronautical R & T.

In conducting the tasks under the NASA grant during the past two years, the MIT research team has investigated several economic and technological issues that bear directly on the interrelationships between aviation technology and future aviation demand. While some of these investigations are more elaborate extensions of prior work, others represent exploratory efforts in demand modeling and the economics of technological change. It is hoped that these research results will extend the frontiers of econometric model applications as well as enhance the understanding of the principal determinants of transportation demand, aircraft technology and their interactions.

The research project was carried out under the technical monitorship of Mr. Louis Williams and Mr. Mark Waters of NASA-Ames Research Center.

Section 2. TECHNICAL BACKGROUND

2.1 Overall Objectives of the Research Program

The ultimate objective in the research program was the projection of passenger and cargo traffic growth for the air transport industry with clear distinctions for the short haul, intermediate haul and long haul markets. These traffic growth projections and the models used to evaluate the technological impacts of plausible future scenarios can be implemented in the overall technology cost-benefit evaluation models under development at NASA. The driving force in the whole integrated air transport modeling process is a national macroeconometric model (domestic). Relatively little effort was devoted to developing this model, except to the extent that a modified version of a commercially available,* large macromodel was considered for future research programs.

During the progress of the MIT research, the scope of the effort has expanded from that originally contemplated. Based on consultations with industry and NASA representatives, the MIT research team concluded during the initial year that the research program should involve several links between macroeconomic events and air transport factors, some of which ultimately involved a more intensified modeling effort. In light of the changed scope of the research program the total modeling process was labeled, "An Integrated Air Transport Model," and its generalized format is presented in Figure 1.

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*The leading prognosticating firms with whom we have had contact include Chase Econometrics Associates, Inc., Data Resources, Inc., and a university-based source, the Wharton Economic Forecasting Service, Inc.

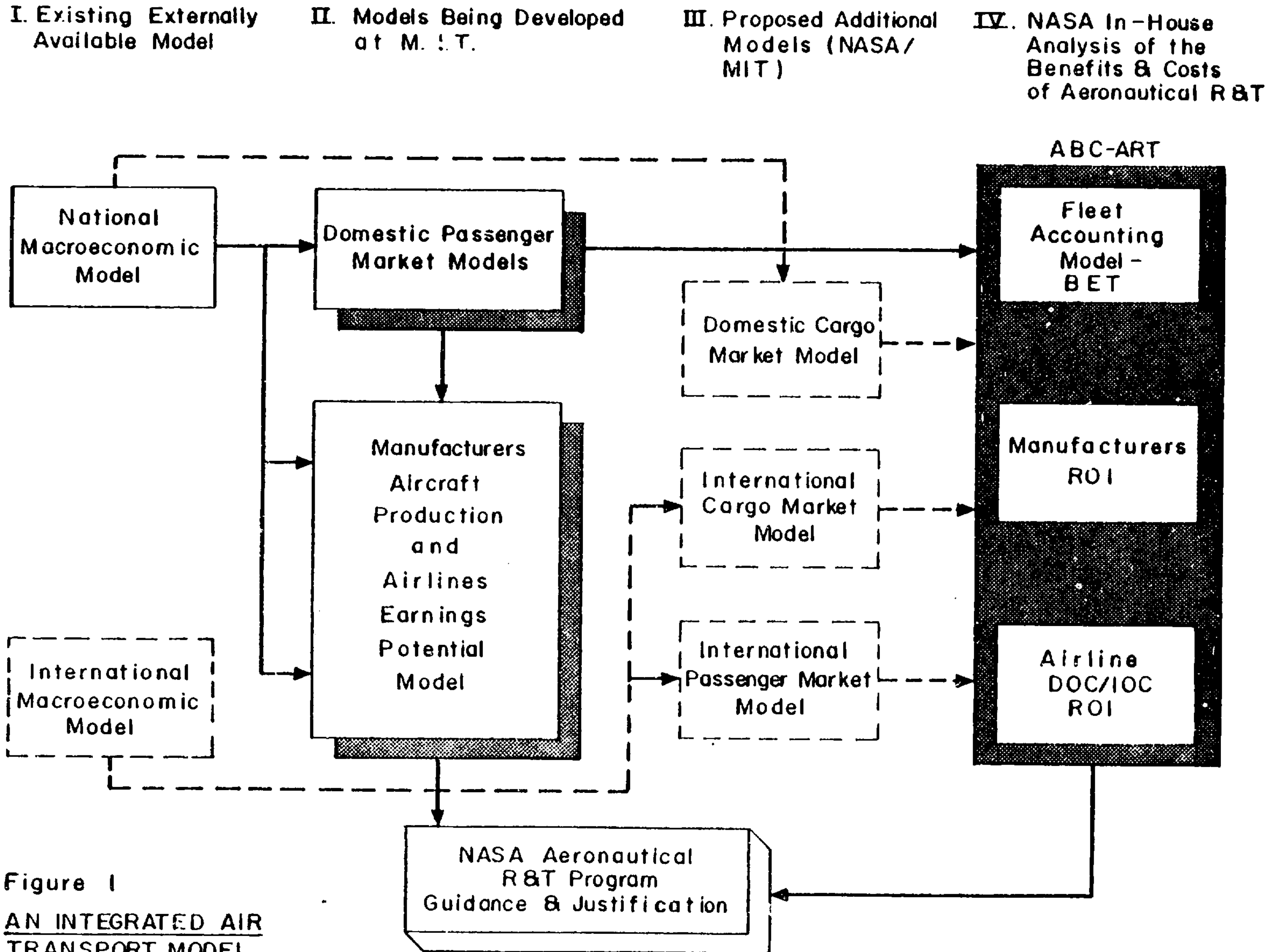


Figure 1

AN INTEGRATED AIR TRANSPORT MODEL

The interactive process shown in this figure is described below and is particularly important in light of the current research into the methodologies for performing cost-benefit studies of advanced aeronautical technology that is being performed in the Research Aircraft Technology Office at NASA Ames Research Center. Note that both passenger and cargo market models are included in this integrated air transport model. The current work includes only domestic passenger market models with domestic cargo and international passenger and cargo models proposed for future work.

A desirable feature of an integrated approach is that the sensitivities of key variables can be determined very clearly. The integrated model allows for the examination of the impact on air transport demand resulting from a change in technology and vice versa. The model also allows the estimation of the effects on either air transport demand or technology resulting from higher or lower estimates of GNP, population, or inflation. In addition, the model can be used to estimate how high GNP must be for a sufficient growth in passenger demand to occur that would warrant launching a "new" technolog aircraft, for adequate airline profitability so that the airlines would purchase it, and for sufficient attraction for the manufacturers to promote and construct it.

In summary, the integrated modeling approach represents the most comprehensive attempt presently available to analyze the appropriate interactions between demand and technological characteristics in the air transport industry.

2.2 Model Output and Interrelationships

The structure of the integrated air transport model depicted in Figure 1 is intentionally separated into four columns to distinguish among: (1) existing and externally determined models (to the NASA/MIT research program) that can be used to drive the integrated systems; (2) models developed under the NASA/MIT grant; (3) future models that will be required to continue the research on an optimal path; and finally (4) subsequent integration with the models of the in-house research program.

Concerning the NASA studies labeled in column four as "Benefits and Costs of Aeronautical R & T", these models consider the benefits that would be derived through the introduction of new technology aircraft into the existing air transport fleet (e.g., reduced energy consumption or reduced noise). The aircraft replacement sequence develops a market for the postulated new aircraft over time, and separate models evaluate the improved airline economics that may result and the prospect for the aircraft manufacturer(s) to sell the new aircraft at a price necessary to realize a successful production program. If the airline economics are not significantly improved with the introduction of the new aircraft, then the market will be reduced and the profit picture of the manufacturer weakened.

These models are driven by an input of projected growth in air transport revenue passenger miles. Hence, the major link with NASA/MIT study program is through the passenger market model which develops passenger demand growth projections for short, medium and long range markets. Provision is made for a feedback loop to evaluate the interaction between passenger demand for travel, fleet requirements and the profitability of both the manufacturers and airlines. Figure 2 is an expanded block diagram of the ABC-ART models and the domestic passenger market models. The direct tie between the two is the assumed level of fares. A fare structure is used to examine airline profitability in the ABC-ART model; air fare is a major factor in the market model which will predict the growth in passenger demand. This in turn is a major input to the fleet accounting model in ABC-ART. Thus, the loop is complete, and a solution to balance both growth and profitability for a given level of fares is solved in an iterative fashion.

Also shown in Figure 1 is a model developed in this research program to address the purchase potential of the airlines and the production potential of the manufacturer. This combined model receives input from the National Macroeconomic model and from the Market models in Figure 1. Distinction must be made between this model and those in the NASA cost-benefit analysis. In the NASA models, a single or series of new aircraft programs are addressed, and the relative economic merit to both the airline and manufacturer is assessed. In the NASA/MIT model, a broader evaluation of the U.S. airlines and aircraft manufacturers is made, based on the historical growth in air transportation and their own financial status. Recent concern over new aircraft development risk is well documented, and even though many factors might appear promising -- high projected growth, improved seat-mile costs and an apparent large market for the aircraft -- companies (airlines, manufacturers, and their financiers) may be reluctant to undertake a new airplane development because of the risk associated with the introduction of new technology.

In some respects, this analysis is the bottom line for NASA in this

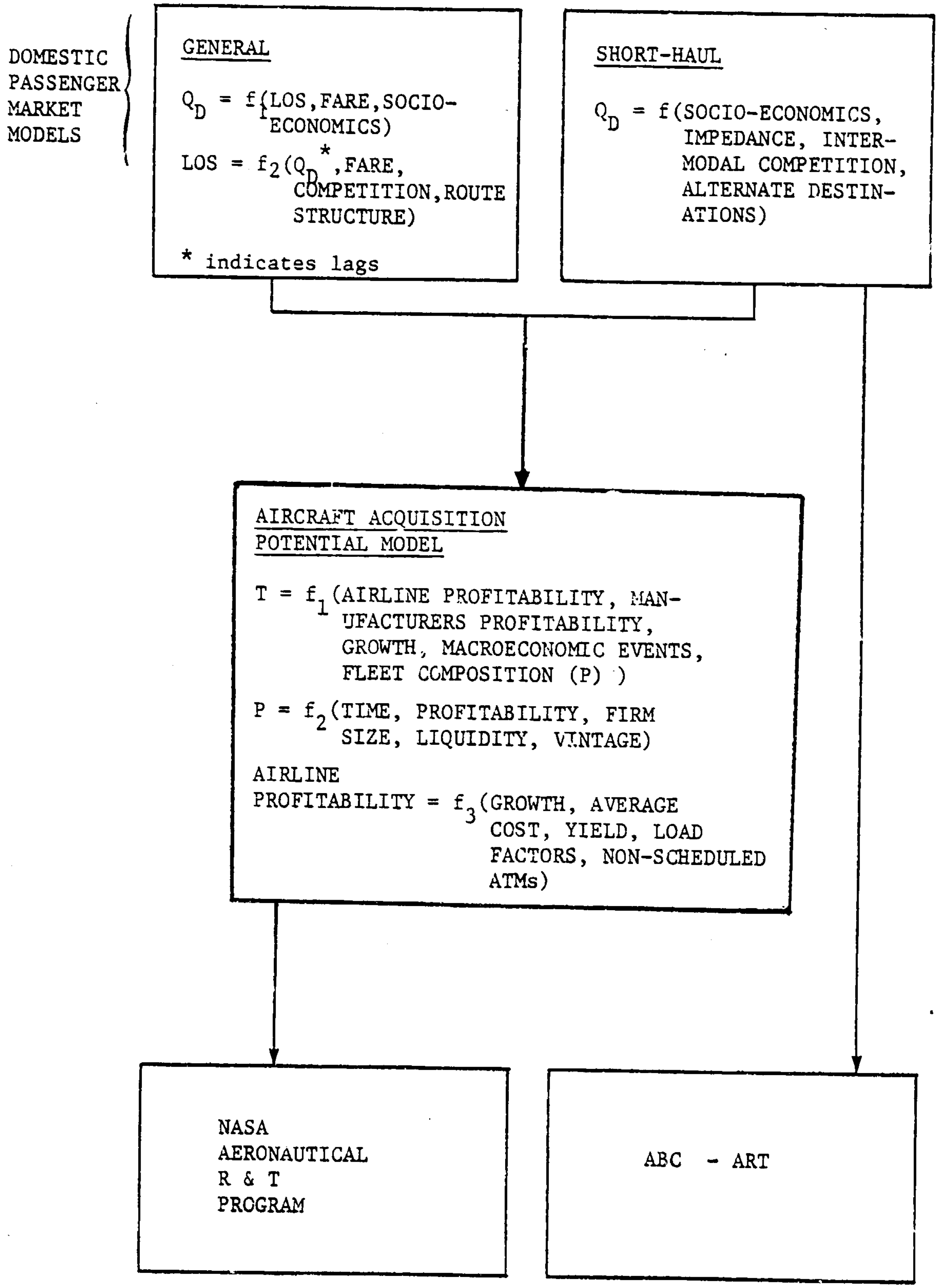


FIGURE 2: MODELS BEING DEVELOPED AT MIT

project because, through their aeronautics program, this agency is in a unique position to reduce the risk of introducing new technology into air transportation.

The following sections of this report summarize the progress to date in each model that provided the initial foundation for this integrated approach. Specifically, these models include: (a) the General Passenger Market Model; (b) the Short Haul Passenger Demand Model for Air Transportation; and (c) the Manufacturers Model of Aircraft Production and Airlines Earnings Potential. Separate volumes describing each of these models in detail have been prepared by the research team. These volumes are the following:

Volume I -- Analysis of Long and Medium Haul Air Passenger Demand

Volume II -- Analysis of Short Haul Air Passenger Demand

Volume III -- Economic Model of the Manufacturers Aircraft Production and Airlines Earnings Potential

Section 3. SYNOPSES OF ACCOMPANYING RESEARCH REPORTS (VOLUMES I-III)

3.1 Analysis of Long and Medium Haul Air Passenger Demand (Volume I)

The main variant in the structure of transportation demand models is level of aggregation. A totally disaggregate model specifies the optimization problem for each consumer (or group of equivalent consumers) in the population. The decision of how many air trips from each consumer's origin to a specific destination in a given time period would be a function of not only the characteristics and prices of these trips, but also of the characteristics and prices of all other transportation services available to this consumer. These other services include trips to all other destinations and trips to the same destination by alternative modes. Summing over all consumers would yield estimates of total demand in all markets and by all modes.

Figure 3 is a schematic representation of the development of demand models as the formulation is modified from total disaggregation to total aggregation. Reference is made in the figure to existing models of each type. Details of each of these models are given in Volume I.

A totally disaggregated model of the demand for transportation service is depicted at the top of the figure. Such a model would, for each market, consider the response of each income level group of consumers, to not only changes in characteristics and price of air service in that market, but also to changes in characteristics and price of services in competing markets and by competing modes. Since this analysis is obviously intractable, the researcher is forced to aggregate some or all of these factors.

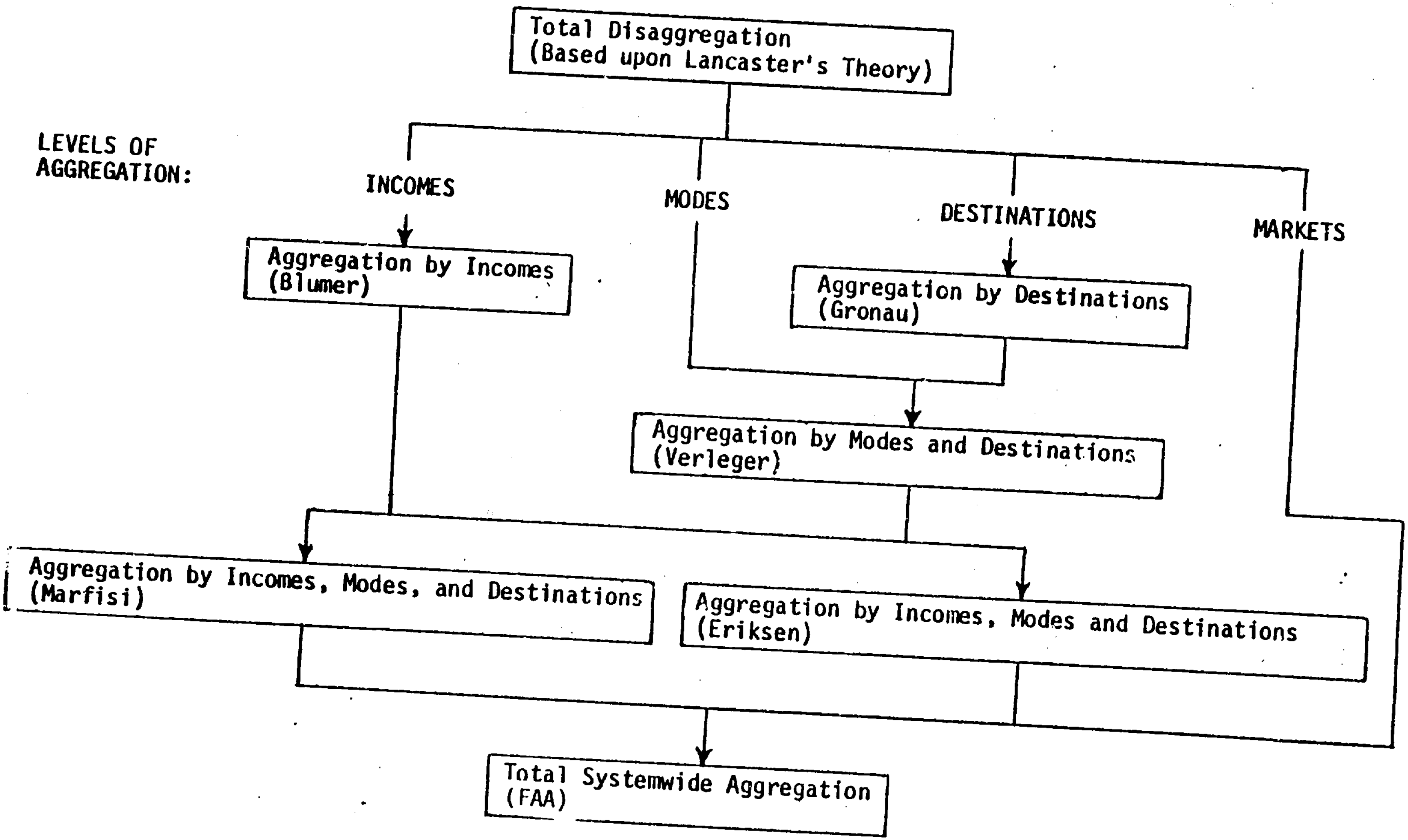


Figure 3 Levels of Aggregation for Air Transportation Demand Models

The extreme case of aggregation is the macroeconomic model at the bottom of Figure 3. In this setting a single parameter, revenue passenger miles (RPM), is generated for the entire industry. Since this parameter is of little value as a planning tool, it is clear that forecasting models must necessarily be geared to a more microeconomic level.

In this project, a theory and a set of models have been developed which focus on individual domestic U.S. long haul and medium haul air passenger markets. Short haul passenger demand was also investigated, and it was concluded that a much different formulation is necessary to address the unique problems of short haul travel, particularly the need to consider alternative modes of travel. Due to data limitations, aggregation by destinations and income groups is necessary; therefore this set of models fits next to Marfisi's model in Figure 3. Great emphasis has been placed on the definition of a realistic set of variables to formulate the models and a representative sampling procedure to calibrate it.

3.1.1 Model Objectives

The goal of this model is to identify a set of mathematical relationships which will accurately indicate how the levels of origin-to-destination air passenger traffic between region pairs vary as functions of their determining factors. This set of relationships will not only predict future levels of demand between region pairs, but will also be sufficiently sensitive to measure the impact of decisions upon demand. In particular, the impact of decisions regarding individual causal attributes such as the level-of-service, technology, pricing, and regulatory factors can be assessed.

While most of the published air transportation econometric models are reasonably adequate for forecasting aggregate demand if the transportation system continues in the same direction, they are inadequate for planning and analysis purposes, such as determining the impact of route awards, fare changes, alterations in quality of service, frequency of service, and acquisition of new equipment. Since decisions regarding factors such as these will have different effects on different markets, a truly sensitive model must necessarily be microeconomic rather than macroeconomic. Therefore, a general passenger market model has been calibrated on sets of "region pairs" that are representative of the U.S. domestic system. The concept of "region pairs" rather than "city pairs" has been adopted to appropriately accommodate the fact that a major airport serves a greater surrounding area than merely the home city. Therefore, the included variables are descriptive of regional economics rather than focused on the central urban area.

One of the unique features of this model is its explicit inclusion of a composite proxy to measure level of service. Many existing models adopt a frequency variable (for example, number of daily departures) as such a measure. However, frequency alone does not consider the time of day distribution of these departures, nor does it consider the number of intermediate stops and/or connections, the speed of the aircraft, or expected delays due to congestion. A non-dimensional generalized trip time, scaled from zero to one, which accounts for all of these factors is developed and implemented as the level-of-service variable for the analysis of long and medium haul air passenger demand.

The selection of a region pair formulation rather than an aggregate model presents a statistical problem in that a mutual causality between demand and level-of-service exists. Therefore, in a single equation model with demand as the dependent variable, the level-of-service and the residual variables will be correlated, and the ordinary least squares estimation procedure is inappropriate. This problem is rectified in the long and medium haul passenger air travel models by specifying a multi-equation system.

3.1.2 Model Formulation

The basic model is a two equation region pair econometric system in which air passenger demand and airline level-of-service are the endogenous variables. The objective of the model is to identify the causal relationship between each of these two variables and its determining factors, and to also identify the interaction of demand and level-of-service with each other.

The specification of the basic model is as follows:

(Demand equation) $Q_D = f_1(LOS, F, SE)$

(Service equation) $LOS = f_2\ (TRAFL, F, COMP)$

where

Q_D = Origin to destination (local) passenger demand

LOS = Level-of-service

F = Standard coach fare

SE = Level of regional socio-economic activity

COMP = Level of competition

TRAFL = Total traffic (local and non-local) in the previous time period

The selected variable for the measure of air passenger traffic activity in a given region pair market, Q_D, is defined as the number of passengers in a given time period that originate in one region and fly to the other region for purposes other than to make a connection to a third region. This variable is declared the true origin to destination passenger traffic, using the passenger intent criterion. The best source for these data is Table 8 of the Civil Aeronautics Board's Origin to Destination Survey.

An unfortunate limitation of employing Table 8 data is that the decision rules selected by the Board for Tabulation do not in all cases accurately reflect passenger intent. The net result is that Table 8 have a tendency to be biased by understating true origin to destination traffic flows in long haul markets and overstating them in short haul markets. However, since the bias is slight and unmeasurable , it is assumed to be negligible for the purpose of calibrating this model.

The level-of-service variable, LOS, is an index scaled from zero (no service offered) to one ("perfect" service). This measure is a function not only of the number of flights or seats that are scheduled in the market, but also whether these flights are direct or connecting, the number of intermediate stops, and how well the departure times match the time of day demand fluctuations.

One of the inputs to the computation of the level-of-service variable is a time of day demand distribution for each direction in a given market. Empirical data on the time of day distribution is for most markets difficult to find since actual passenger flow is dependent upon imperfect scheduling.

However, some markets with very frequent and regular service (such as the Boston-New York shuttle) have provided such data. A time of day demand distribution for Boston-New York is shown in Figure 4. A procedure for estimating the time of day distribution of demand for any segment based upon these data and some behavioral assumptions has been developed. Examples of the output are shown in Figure 5 (Boston to San Francisco) and Figure 6 (San Francisco to Boston). The expected decline in passenger demand in the early evening and increase late in the evening for the night flights in transcontinental west-to-east markets can be observed in Figure 6.

Without discussing in detail the theoretical background of the derivation of the level-of-service index (see Volume I), the index can best be explained by going through an example of its computation. Consider the schedule of flights from Chicago to Philadelphia shown in Figure 7. The departure and arrival times are expressed in the local time zones and in the decimal equivalent of military time (for example, the departure time of the twentieth flight, shown as "19.50" is 7:30 p.m. Central time). The adjusted flight time is the flight time plus one-half hour if the flight is an online connection or one hour if it is an interline connection (for a justification of this adjustment see Volume II). The status column indicates whether the flight is direct or an online or interline connection.

In Figure 8 the traveling day is divided into 41 discrete time points separated by half-hour intervals starting at 4:00 a.m. and ending at midnight. The PI(J) column is the time of day demand distribution. The major behavioral assumption in the level-of-service derivation is that a passenger who desires to depart at some given time of day will select that flight which minimizes trip time, defined as the sum of the displacement time and

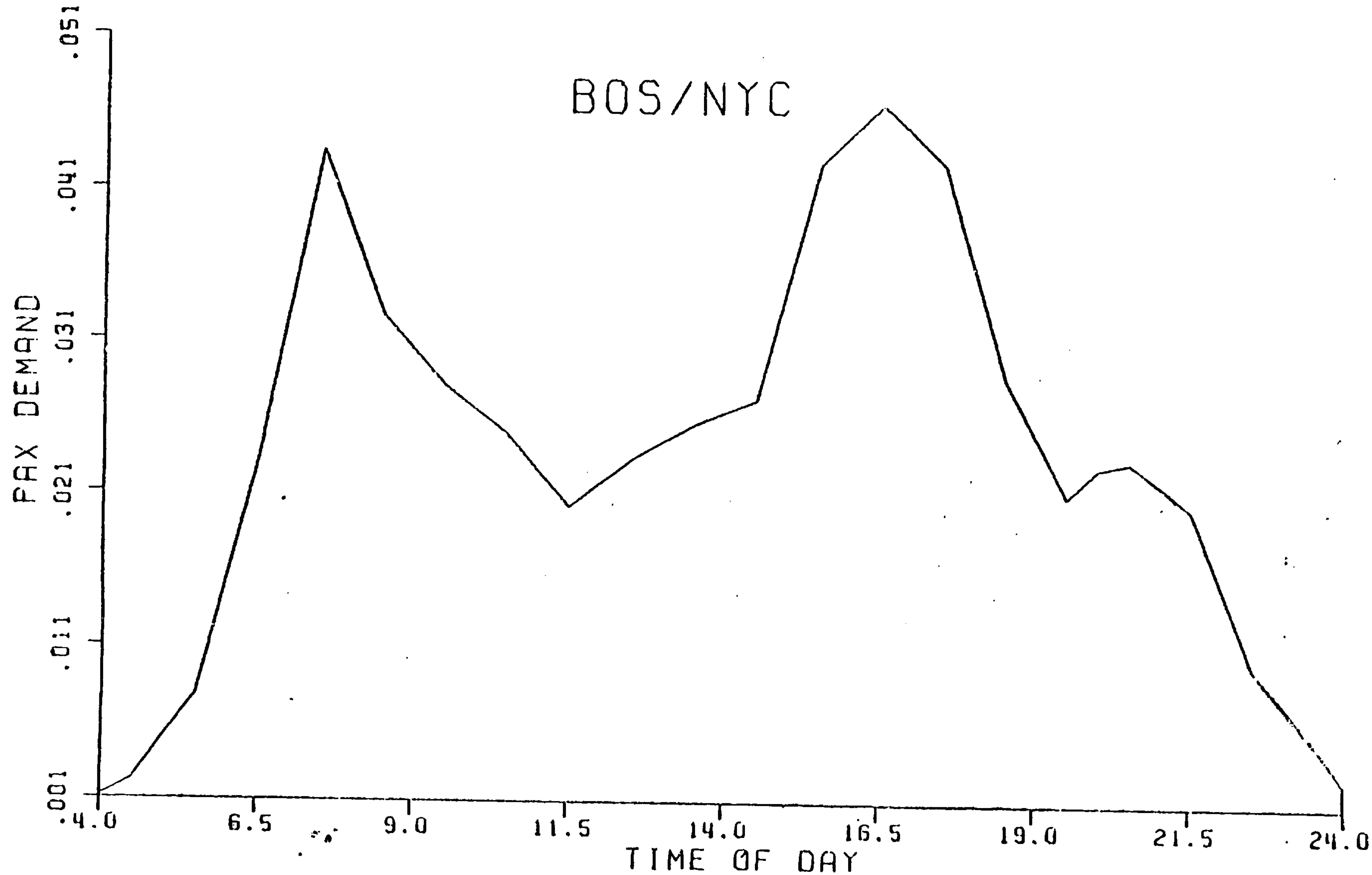


Figure 4 Empirical Time of Day Demand Distribution for Eastern Airlines' Boston/New York Air Shuttle

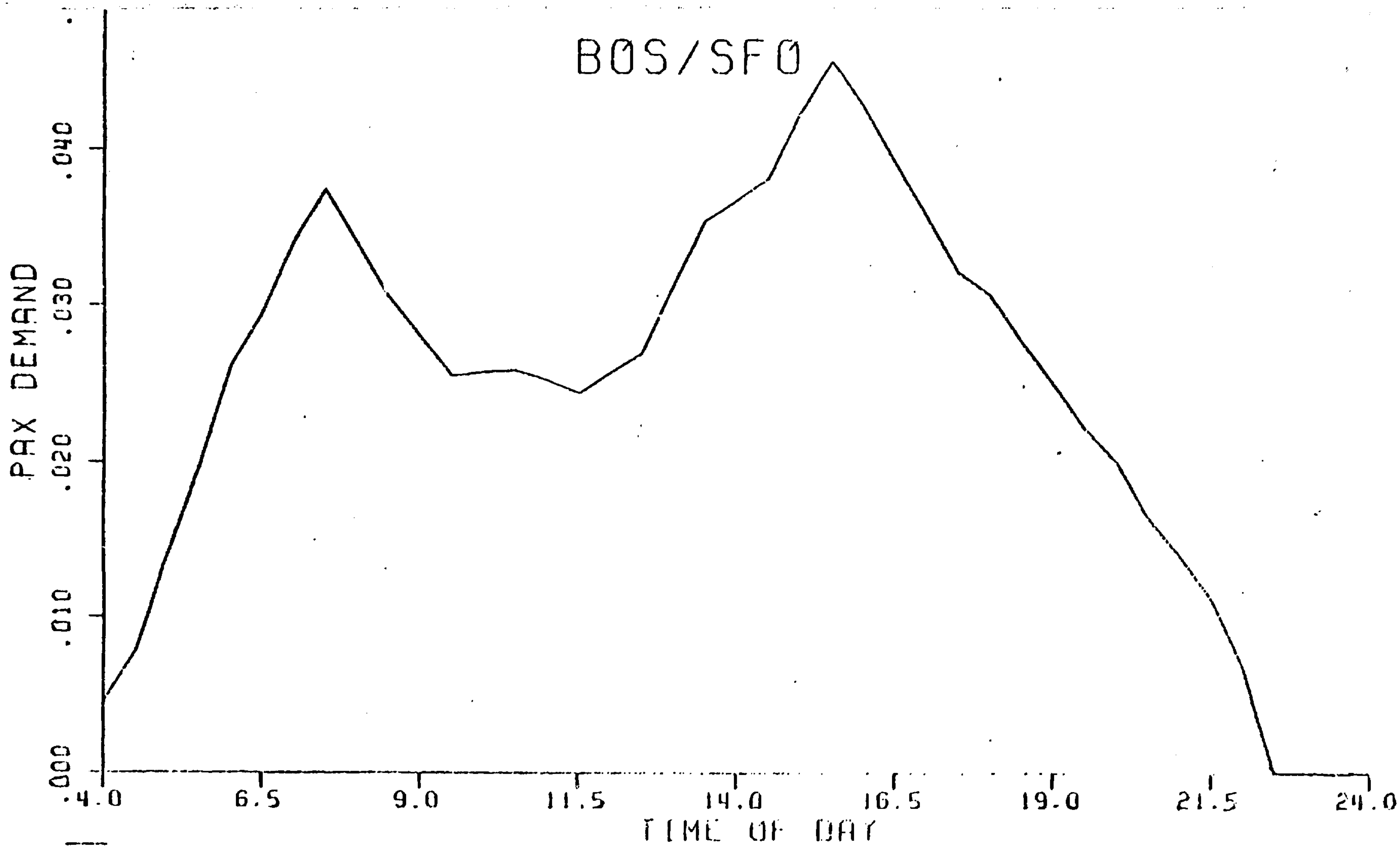


Figure 5 Theoretical Time of Day Demand Distribution for Boston to San Francisco

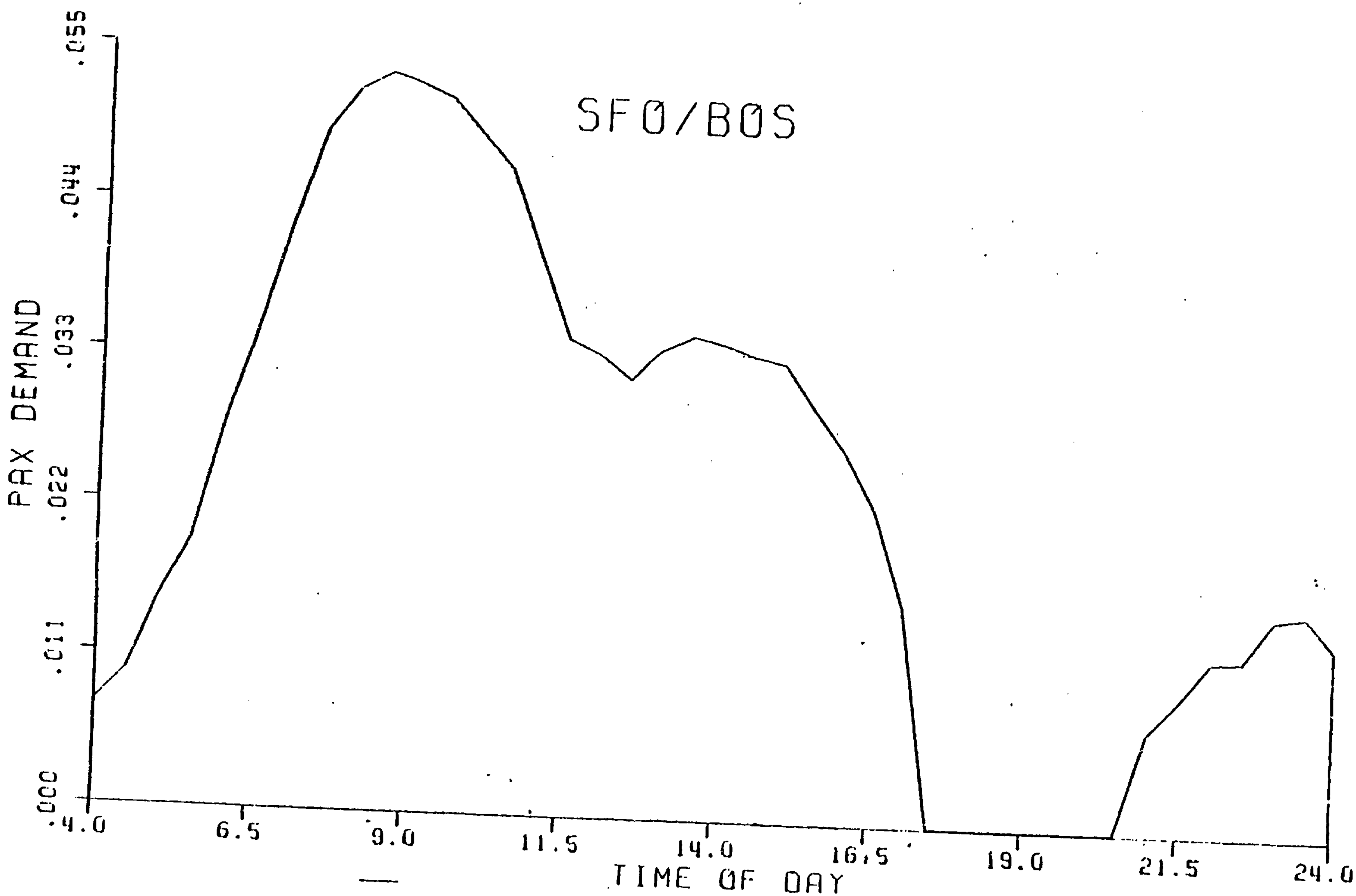


Figure 6 Theoretical Time of Day Demand Distribution for San Francisco to Boston

igure 7 Flight Schedule for Chicago to Philadelphia

FLIGHT SCHEDULE CHI PHL

FLIGHT	DEPART	ARRIVE	ADJUSTED FLIGHT TIME	STATUS	CARRIER(S)
1	7.00	9.83	1.83	DIRECT	TW
2	7.00	10.92	3.42	ONLINE	AL/AL
3	7.25	10.08	1.83	DIRECT	UA
4	8.75	12.87	3.12	DIRECT	UA
5	9.75	13.83	3.58	ONLINE	AL/AL
6	10.50	13.37	1.87	DIRECT	TW
7	10.75	15.32	4.07	ONLINE	AL/AL
8	11.67	14.50	1.83	DIRECT	UA
9	12.00	16.93	4.43	ONLINE	AL/AL
10	13.58	17.33	2.75	DIRECT	NW
11	13.75	18.33	4.08	ONLINE	AL/AL
12	14.00	16.83	1.83	DIRECT	TW
13	14.92	17.78	1.87	DIRECT	TW
14	15.17	19.92	4.25	ONLINE	AL/AL
15	15.58	18.47	1.88	DIRECT	UA
16	17.08	20.03	1.95	DIRECT	UA
17	17.75	21.57	3.32	ONLINE	AL/AL
18	17.75	21.78	3.03	DIRECT	NW
19	17.83	20.77	1.93	DIRECT	TW
20	19.50	22.35	1.85	DIRECT	TW
21	20.00	23.98	3.48	ONLINE	AL/AL
22	20.08	22.95	1.87	DIRECT	UA
23	22.07	25.43	2.37	DIRECT	UA

COMPUTATION OF AVERAGE TOTAL TRIP TIME

J	T(J)	PI(J)	FLIGHT BOARDED	DISPLACE-MENT TIME	ADJUSTED FLIGHT TIME	TRIP TIME	CONTRIBUTION TO TOTAL TRIP TIME
1	4.00	0.003	1	3.00	1.83	4.83	0.015
2	4.50	0.006	1	2.50	1.83	4.33	0.027
3	5.00	0.011	1	2.00	1.83	3.83	0.044
4	5.50	0.017	1	1.50	1.83	3.33	0.056
5	6.00	0.027	1	1.00	1.83	2.83	0.077
6	6.50	0.031	1	0.50	1.83	2.33	0.073
7	7.00	0.034	1	0.00	1.83	1.83	0.063
8	7.50	0.038	3	0.25	1.83	2.08	0.079
9	8.00	0.034	3	0.75	1.83	2.58	0.088
10	8.50	0.031	3	1.25	1.83	3.08	0.094
11	9.00	0.029	4	0.25	3.12	3.37	0.097
12	9.50	0.026	6	1.00	1.87	2.87	0.075
13	10.00	0.024	6	0.50	1.87	2.37	0.057
14	10.50	0.024	6	0.00	1.87	1.87	0.045
15	11.00	0.024	6	0.50	1.87	2.37	0.057
16	11.50	0.023	8	0.17	1.83	2.00	0.046
17	12.00	0.025	8	0.33	1.83	2.17	0.053
18	12.50	0.026	8	0.83	1.83	2.67	0.069
19	13.00	0.027	12	1.00	1.83	2.83	0.076
20	13.50	0.031	12	0.50	1.83	2.33	0.073

Figure 8 (continued)

J	T(J)	PI(J)	FLIGHT BOARDED	DISPLACE-MENT TIME	ADJUSTED FLIGHT TIME	TRIP TIME	CONTRIBUTION TO TOTAL TRIP TIME
21	14.00	0.035	12	0.00	1.83	1.83	0.064
22	14.50	0.036	13	0.42	1.87	2.28	0.083
23	15.00	0.042	13	0.08	1.87	1.95	0.082
24	15.50	0.046	15	0.08	1.88	1.97	0.090
25	16.00	0.046	15	0.42	1.88	2.30	0.105
26	16.50	0.043	16	0.58	1.95	2.53	0.108
27	17.00	0.037	16	0.08	1.95	2.03	0.076
28	17.50	0.034	19	0.33	1.93	2.27	0.077
29	18.00	0.029	19	0.17	1.93	2.10	0.060
30	18.50	0.027	19	0.67	1.93	2.60	0.070
31	19.00	0.025	20	0.50	1.85	2.35	0.059
32	19.50	0.022	20	0.00	1.85	1.85	0.041
33	20.00	0.022	22	0.08	1.87	1.95	0.044
34	20.50	0.020	22	0.42	1.87	2.28	0.045
35	21.00	0.015	22	0.92	1.87	2.78	0.043
36	21.50	0.013	23	0.57	2.37	2.93	0.038
37	22.00	0.009	23	0.07	2.37	2.43	0.023
38	22.50	0.005	23	0.43	2.37	2.80	0.015
39	23.00	0.000	23	0.93	2.37	3.30	0.000
40	23.50	0.000	23	1.43	2.37	3.80	0.000
41	24.00	0.000	23	1.93	2.37	4.30	0.000

TEAR = 2.390

LOS = TNJ/TEAR = 1.55/2.39 = 0.648

the adjusted flight time. The displacement time is the absolute difference between the time when the traveler desires to depart and when the flight actually does depart. For example, those passengers desiring to depart from Chicago at 11:00 a.m. (time point 15) will select the sixth flight which actually departs at 10:30. Hence, their displacement time is 0.50 hours, and adding the flight time of 1.87 hours yields a trip time of 2.37 hours. None of the remaining 22 flights would provide them with a shorter trip time.

The average total trip time, TBAR, shown in the lower right corner of Figure 8, is a weighted (by the time of day demand distribution) average of the trip time column. The level-of-service variable, LOS, is the ratio of the nonstop jet time, in this case 1.55 hours, to the average total trip time. The interpretation of the value of LOS, 0.648, is that if "perfect" service, a nonstop jet departing at every time point, were offered, the average total trip time would be 64.8% of its current value.

Two socio-economic, SE, variables have been defined and these will be combined in some manner for the calibration in the model. The first of these is personal income, which is hypothesized to be a factor for generating travel demand, particularly for personal and pleasure purposes. The second is the total income in service related industries, which is hypothesized to be a factor for attracting passenger traffic. Regions such as New York, Miami, and Las Vegas, which have a large service oriented economy, seem to attract greater levels of traffic in comparison to the more industrial regions than would be implied if an indicator such as total income or population were used to measure the size of a region.

The competition variable, COMP, is a function not only of the number of carriers competing in a given market but also of their relative competitive strengths. The value of COMP in a purely monopolistic market would be one, while in a market that consists of two equally strong competitors (and no other carriers) the value of COMP would be equal to two, etc. However, in a market in which there are two carriers operating but one carries a major portion of the traffic, the value of COMP would be between one and two. The greater the market share of the major carrier becomes, the more monopolistic the market becomes, and the closer COMP is to one. The value of COMP is computed in the same computer program as LOS.

Two measures of competition were developed. Both have the value of 1.0 in strictly monopolistic markets and greater values as the amount of competition increases. It was originally uncertain which of these values would produce a better fit in the service equation; both were investigated in separate regression analyses.

The two variables COMP1 and COMP2, are defined as follows:

$$\text{COMP1} = \frac{1}{\max\limits_{i \in I} MS_i}$$

$$\text{COMP2} = \frac{1}{\sum\limits_{i \in I} MS_i^2}$$

where

I = the set of carriers competing in the market

i = a generic carrier, $i \in I$

and MS_i = market share of carrier i

The market shares are estimated in conjunction with the level-of-service computation. Since, as was shown in Figure 8, the passengers desiring to depart at each time point are assigned to a given flight, the PI(J) values corresponding to each time point are allocated to the particular airline producing the flight. Summing these over all time points yields the estimated market shares, and the competition values are then computed as indicated above. Figure 9 is the computer output for the Chicago-Philadelphia example used in the level-of-service description.

The traffic variable, TRAFL, in the service equation accounts for the fact that service is provided to accommodate not only local (origin to destination) demand, but also non-local demand. Many low density (in terms of local demand) markets receive a very high level of service because of their location within the route structure. For example, there are currently sixteen nonstop flights offered daily from Birmingham, Alabama, to Atlanta, Georgia. Obviously, the volume of origin to destination demand that exists in this market could adequately be served by a far lower frequency. This high level of service is provided to feed into the complex in Atlanta. A passenger desiring to travel from Birmingham to virtually anywhere in the world would fly to Atlanta and connect outward.

The number of non-local (either continuing or connecting) passengers traveling on a segment in a given time period is not readily available. They can only be extracted from the Civil Aeronautics Board's service segment flow data. The acquisition and processing of these data are very expensive, both in terms of cost and time requirements. As a surrogate to the number of non-local passengers, the selected measure of the network effects is the number of connecting passengers. These data are extracted from Table 10 of the CAB Origin to Destination Survey.

CARRIER	MARKET SHARE
TW	0.538
UA	0.462

COMP 1 = 1.859

COMP 2 = 1.989

Figure 9. Estimates of Market Shares for Chicago to Philadelphia and Evaluation of the Competition Variables

The rationale behind the lagging of the traffic varaible in the service equation is discussed in the following section.

3.1.3 Functional Forms of the Demand and Service Equations

The exact specification of the demand equation is as follows:

$$Q_{D_t} = \beta'_{10} \, LOS_t^{\beta_{11}} \, F_t^{\beta_{12}} \, SE_t^{\beta_{13}} \, \varepsilon'_1$$

In this formulation, the subscript t refers to the current year and ε'_1 is an error term.

The rationale behind this specification is that in any time period t there exists a total potential local demand in a region pair market which is determined by socio-economic factors (populations, incomes, amount of recreational facilities, etc.). The flow of this total potential demand is impeded by positive fare levels and less than perfect level of service.

A multiplicative (instead of, say, an additive) form was selected for two reasons. With respect to level of service, this specification satisfies the necessary boundary conditions in that, if no service were offered (LOS=0) there would be no traffic, and if perfect service were offered (LOS=1) the local demand would be finite. With respect to fare, the multiplicative, more specifically the log-linear, form was selected to allow for the estimation of the various price elasticities. Since it is assumed that β_{12} is negative, if fare values go to zero this specification implies that demand will go to infinity, which is in violation of a boundary condition (see Volume I, Section 3.3.1). However, since the model considers only positive fare values, both in calibration and prediction, this violation is of no consequence.

Since a mutual causality exists between demand and level of service, the demand model as shown cannot appropriately be calibrated using ordinary least squares estimation. In an effort to rectify this problem, a second equation, the "service equation", is developed. The specification of the service equation is as follows:

$$LOS_t = \beta'_{20}\ TRAFL^{\beta_{21}}\ F_t^{\beta_{22}}\ COMP_t^{\beta_{23}}\ \varepsilon'_2$$

The level of service on a given route segment is determined not only by the level of local demand, but also by the level of non-local passenger flow over the segment. The Birmingham to Atlanta route segment example previously cited is a classic example of a market in which the amount of service offered is far in excess of what the local demand requires. Therefore, LOS is specified in the service equation as being a function of the total traffic over a route segment.

The total segment traffic is lagged in the service equation for two reasons. It is not unreasonable to assume that if traffic (whether local or otherwise) were to increase or decrease in a given route segment, the airlines' response (improving or reducing service) would not be immediate. There would probably be a lag due to the time lapse before the carriers perceive the change in traffic as being significant, and since schedules are normally altered only twice per year, there would certainly be a lag before they could operationalize the schedule change. The second reason for the lag is statistical. The lagged variables are "predetermined", and therefore the simultaneity condition present in the demand equation does not exist in the service equation, and ordinary least squares estimation is appropriate.

The fare variable is included in the service equation to account for the fact that if fares were to increase, it would economically be in the best interests of the suppliers to increase service. This follows from Simpson's and Marfisi's theories and from the theoretical development of Chapter III of Volume I.

The competition variable has been included in the service equation to account for the commonly held belief that more competition stimulates improved service.

Assuming that the specification of the service equation is valid, the predicted values of level of service, $\hat{LOS}$, will be highly correlated with the observed values of LOS. Furthermore, since $\hat{LOS}$ is a (log) linear combination of predetermined variables, it should be uncorrelated with ε'_1 in the demand equation. Therefore, $\hat{LOS}$ should serve as a valid instrumental variable in the demand equation. Substituting $\hat{LOS}$ for LOS in the demand equation renders ordinary least squares estimation appropriate.

Figure 10 is a schematic representation of the interaction of the variables in the demand and service equations.

3.1.4 Model Calibration

The demand models have been calibrated based upon a sample of 180 domestic region pair markets for six years (1969-1974). The sample procedure is explained in detail in Volume I. The models have been calibrated with data evenly distributed over short (less than 400 miles), medium (400 to 999

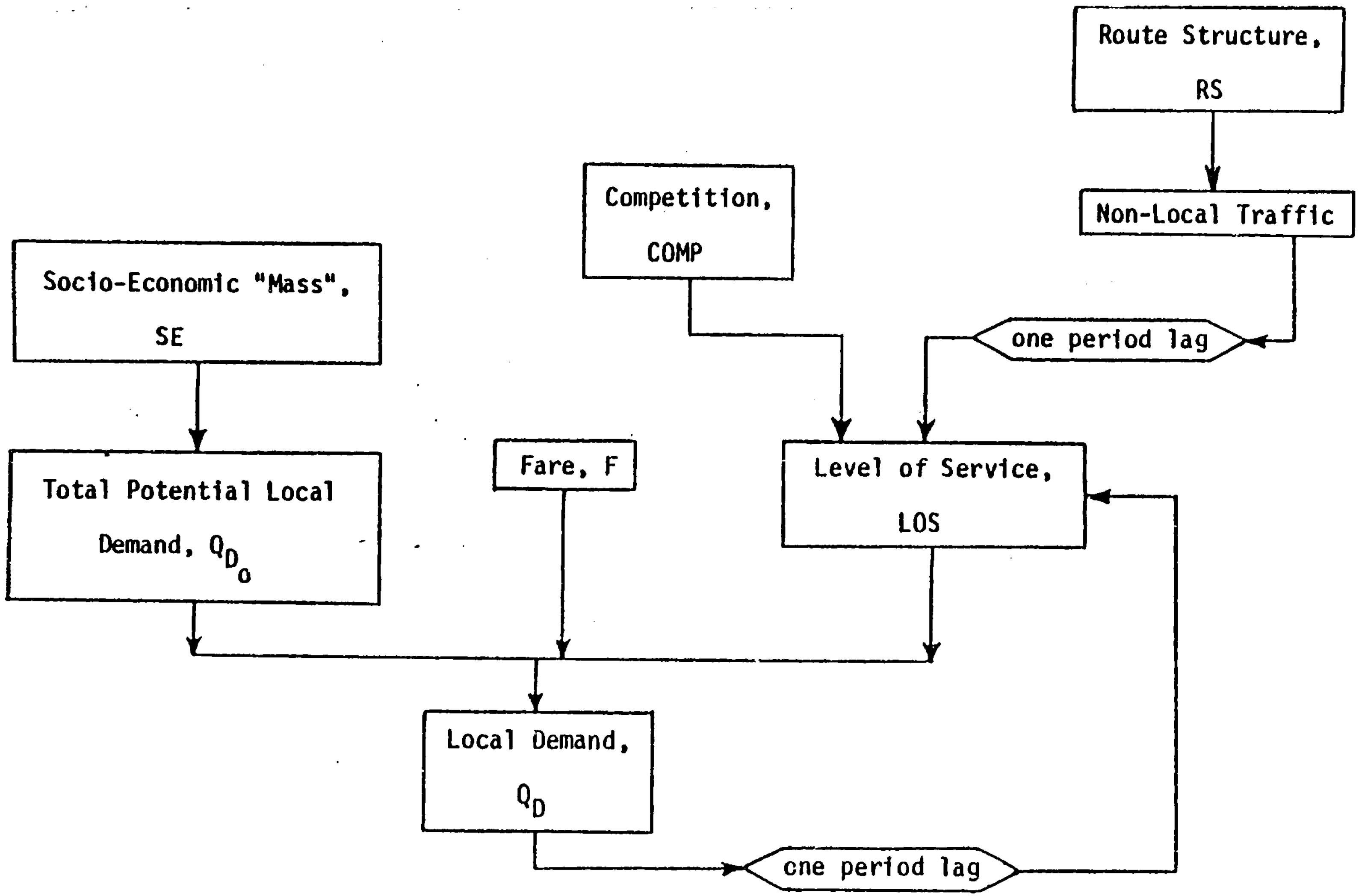


Figure 10 Flow Diagram of Interaction of the Variables

miles) and long (greater than 1000 miles) haul ranges. Figures 10a, b, and c indicate the location of these markets. However, it appears that a specification error exists for short-haul markets. In view of this limitation, a separate model to forecast short-haul passenger traffic growth rates has been developed. This model is summarized in Section 3.2 and described in detail in Volume II.

3.1.4.1 The Concept of Region Pairs

An airport generally attracts passengers from a larger area than its respective city or SMSA. Several characteristics of passenger behavior related to this fact are as follows:

(1) Airline passengers may be drawn from cities with air carrier service to more distant airports depending upon the relative levels of service available. For example, consider a passenger desiring to travel from Providence to Cleveland sometime after the only direct flight which leaves at 8:50 a.m. While several connections are available during the rest of the day, a number of nonstops depart from Boston, 60 miles away, and may be as convenient in terms of total trip time. Thus, some of the Providence-Cleveland demand can be expected to spill over into the Boston-Cleveland statistics solely because of the schedule offered.

(2) Commuter airlines, while becoming a more integral part of the air transportation system since their beginning in the late 1960's, do not report traffic statistics to the C.A.B. in the same detail as do the trunk and local service carriers. While recent C.A.B. actions have attempted to bring the

commuters closer to the mainstream of air transportation activity by the introduction of joint fares and airline ticketing, the unregulated commuters began operations in an environment virtually disjoint from the rest of the airline system. Under these conditions, a ticket written from New York to Los Angeles with a connection to Palm Springs on Golden West Airlines would statistically have represented an origin to destination trip in the New York-Los Angeles city pair, while in fact it would be more accurate to consider this the New York-Los Angeles <u>region</u> pair with Palm Springs included within the Los Angeles region.

(3) Due to economic pressures brought before the Board by the airlines, the C.A.B. approved suspensions and deletions of service to a large number of small communities, forcing those passengers formerly served by the suspended flights to use airports further away. If the replacement airport is within the same region as the abandoned one, working with city pairs will show a decline to almost nothing at the abandoned airport and an increase at the replacement airport.

These points support use of regions rather than cities to insure more accurate modeling and analysis of the level of passenger movements. However, this reasoning is highly dependent upon the quality and accuracy of the delineation of the regions themselves. In 1972, the Bureau of Economic Analysis (BEA) of the Department of Commerce investigated the use of geographical regions delineated by criteria based upon transportation data. By using the journey-to-work data from the 1960 Census of Population, the Bureau divided the country into the 173 self-sufficient regions by minimizing the routine commuting across region boundaries so that labor supply and demand were located in the same region. Region boundaries were restricted to county boundaries and, for the purposes of this work, there is at least one air carrier airport serving each region. Since other geographical delineations considered were not based upon transportation criteria, the BEA regions were adopted for this investigation.

Each region pair is comprised of a set of airport pairs found by enumerating the airports in one region with those in the other. Even if there is more than one airport within a metropolitan area, all airports must be counted and matched with all airports in the other region. The Official Airline Guide aggregates airports within the same city, but for purposes of this research, each airport is considered separately. The demand in a region pair is the sum of the demands of the component airport pairs; the supply of service in a region pair is the aggregate of flights offered in each of the component airport pairs.

3.1.4.2 Sampling Design and Criteria

The criteria used in the process of selecting a representative sample of region pair markets for this analysis are as follows:

(1) The sample size should be larger than that of most other econometric analyses in this area, preferably on the order of 200 markets.

(2) The stage lengths should be evenly distributed over short (less than 400 miles), medium (400 to 999 miles), and long (1000 miles and longer) haul markets.

(3) To facilitate data collection the total number of distinct regions should be held to a reasonably manageable number (on the order of 50).

(4) A mix of economic levels of the region pairs should be selected within each of the length of haul strata. There should be selections of two large regions, a large and a medium size region, a large and a small region, two medium size regions, etc.

(5) The markets should be distributed as evenly as possible with respect to geographical location and market type.

The initial step in the sampling procedure was to select fifty distinct regions which were quite evenly distributed across the country. It was hoped that the entire selection of region pairs could be taken using these regions. It turned out to be necessary to add two additional regions, bringing the total number to fifty-two. The regions are listed in alphabetical order in Figure 11. For data manipulation reasons, it was necessary to assign each region a two digit code number. These and the standard three letter city codes are included in Figure 4.11.

The second stage of the sampling procedure was to design a two way stratification using length of haul and economic activity as the stratified variables. The economic variable used was the 1974 Buying Power Index (BPI) for each region. The Buying Power Index is a function of a region's retail sales, population, and total income, and is published annually in the "Survey of Buying Power" edition of Sales Management magazine. The regions were divided into five economic strata, with number 1 being the low BPI regions (e.g., Erie, Reno), and number 5 being the high BPI regions (e.g., New York, San Francisco). This resulted in fifteen economic strata for region pairs:

1-1	2-2	3-4
1-2	2-3	3-5
1-3	2-4	4-4
1-4	2-5	4-5
1-5	3-3	5-5

Figure 11. List of Regions

Region	Codes No.	Codes Letters
Albany	01	ALB
Atlanta	02	ATL
Bismarck	03	BIS
Boston	04	BOS
Chicago	05	CHI
Cincinnati	06	CVG
Cleveland	07	CLE
Dallas	08	DAL
Dayton	09	DAY
Denver	10	DEN
Detroit	11	DTT
Erie	12	ERI
Fargo	13	FAR
Houston	14	HOU
Jackson	15	JAN
Jacksonville	16	JAX
Kansas City	17	MKC
Knoxville	18	TYS
Las Vegas	19	LAS
Lexington	20	LEX
Lincoln	21	LNK
Los Angeles	22	LAX
Lubbock	23	LBB
Memphis	24	MEM
Miami	25	MIA
Milwaukee	26	MKE

Region	Codes No	Codes Letters
Minneapolis	27	MSP
Minot	28	MOT
Nashville	29	BNA
New Orleans	30	MSY
New York	31	NYC
Norfolk	32	ORF
Oklahoma City	33	OKC
Omaha	34	OMA
Philadelphia	35	PHL
Pittsburgh	36	PIT
Portland, Maine	37	PWM
Portland, Oregon	38	PDX
Raleigh	39	RDU
Reno	40	RNO
Richmond	41	RIC
Rochester	42	ROC
Sacramento	43	SAC
St. Louis	44	STL
Salt Lake City	45	SLC
San Antonio	46	SAT
San Diego	47	SAN
San Francisco	48	SFO
Seattle	49	SEA
Tucson	50	TUS
Washington	51	WAS
Wichita	52	ICT

The lowest economic markets are in the "1-1" category (e.g., Erie-Reno) and highest are the "5-5" markets (e.g., New York-San Francisco).

This two dimensional stratification yields a 3 x 15 matrix with the three rows representing length of haul and the fifteen columns representing economic level. Four regions were selected for each of the forty-five blocks, yielding a total sample of 180 region pairs. The markets were carefully hand-picked in an effort to geographically vary the markets within each block as much as possible.

The markets in the sample are listed by stratification in Appendix A.

3.1.4.3 Pooling of Entire Data Set

It is generally agreed that pooling data containing observations over all lengths of haul to calibrate a single equation or set of equations is inappropriate. The inappropriateness is due to the very different market characteristics between length of haul strata (i.e., the model coefficients are functions of length of haul). This effect was a major conclusion of Marfisi's empirical work and is also discussed in detail in Blumer's thesis.

Four separate regression analyses were conducted: all data, long, medium, and short lengths of haul. The results are shown in Figure 12. The test statistic, F, for the Chow test, is equal to 35.3, which greatly exceeds the critical value, 2.53 at the one percent level of significance.

The conclusion to this is, as expected, that indeed pooling data over length of haul is not appropriate. The implication of this conclusion is that at least one length of haul stratum has different market characteristics (demand equation parameters) than the other two, and it is possible that all

Figure 12 Estimates of Demand Equation Parameters for All, Long Haul, Medium Haul, and Short Haul Markets

ALL MARKETS

Carrier	Coefficient	Standard Error	t-ratio
Constant	14.6	0.283	51.7
Level of Service	4.38	0.0651	67.3
Fare	-1.13	0.0217	-52.0
Socio-Economics	0.171	0.0254	6.73

n = 820 R^2 = 0.944 F(8/816) = 4610

std. error = 0.339 R^2 adj = 0.944 SSR = 93.8

LONG HAUL MARKETS

Carrier	Coefficient	Standard Error	t-ratio
Constant	15.2	0.375	40.5
Level of Service	4.15	0.0900	46.2
Fare	-1.41	0.0514	-27.4
Socio-Economics	0.238	0.0372	6.39

n = 232 R^2 = 0.980 F(3/228) = 3730

std. error = 0.182 R^2 adj = 0.980 SSR = 7.56

Figure 12 (continued)

MEDIUM HAUL MARKETS

Carrier	Coefficient	Standard Error	t-ratio
Constant	13.9	0.429	32.5
Level of Service	4.07	0.0751	54.2
Fare	-1.07	0.0670	-15.9
Socio-Economics	0.207	0.0311	6.67

n = 283 R^2 = 0.971 F(3/279) = 3140

std error = 0.217 R^2 adj = 0.971 SSR = 13.2

SHORT HAUL MARKETS

Carrier	Coefficient	Standard Error	t-ratio
Constant	10.6	0.606	17.6
Level of Service	4.23	0.115	36.9
Fare	-0.182	0.0973	-1.87
Socio-Economics	0.265	0.0416	6.38

n = 305 R^2 = 0.942 F(3/301) = 1601

std error = 0.402 R^2adj = 0.041 SSR = 48.6

Figure 13 Chow Test for Pooling Markets by Length of Haul

Pooled Sample: All markets

Subsamples:
1. Long haul markets
2. Medium haul markets
3. Short haul markets

Total number of observations: $n = 820$

Number of estimated parameters: $p = 4$

Number of subsamples: $k = 3$

$$SSR_{pooled} = 93.8$$

$$SSR_l = 7.56$$
$$SSR_m = 13.2$$
$$SSR_s = \underline{48.6}$$

$$SSR_{ind} = 69.4$$

$$F = \frac{\dfrac{SSR_{pooled} - SSR_{ind}}{p(k-1)}}{\dfrac{SSR_{ind}}{n - pk}} = \frac{\dfrac{24.8}{8}}{\dfrac{69.4}{808}} = 35.5$$

$$F_{crit} = (8, 808, 0.01) = 2.53$$

three are mutually different. Pairwise Chow tests could be conducted to verify the latter case, but it was assumed a priori that indeed each is different, and so separate models were calibrated for each length of haul grouping. As will be indicated by the results that follow, the coefficient estimates do vary dramatically by length of haul, so this assumption appears to have been very reasonable.

3.1.4.4 Analysis of Long and Medium Haul Markets

The first order of business in the analysis of long haul markets was to determine whether pooling over levels of socio-economic activity (within the length of haul grouping) was appropriate. The method of analysis is identical to that of the previous section, where a Chow test was used to ascertain that pooling over length of haul is unacceptable.

The markets were separated into three socio-economic strata -- large, medium, and small. The assignment procedure was somewhat arbitrary. Using the socio-economic labels of Section 3.1.4.2, the assignment is as follows:

Large socio-economic: 3-4, 3-5, 4-4, 4-5, 5-5

Medium socio-economic: 2-2, 2-3, 2-4, 2-5, 3-3

Small socio-economic: 1-1, 1-2, 1-3, 1-4, 1-5

It was discovered that this arbitrary assignment was, at least for long haul markets, not as representative as had been hoped, and corrective measures have been applied. For example, four separate regression analyses were conducted: all long haul, long/large, long/medium, and long/small, markets. The Chow test statistic for the regression is equal to 3.29, which exceeds the critical value of F, 2.59, at the one percent level of significance. It is therefore concluded that the characteristics of long haul markets vary by size of market (as measured by socioeconomic levels). The implication of this is that separate long haul models must be estimated for large, medium, and small demographic region pairs.

Detailed sensitivity studies were performed to finally arrive at final demand and service equations. These studies are documented in Volume I, and the final results are given in Figures 14 and 15 for long haul and medium haul markets.

3.1.5 Applications of the Models

The purpose of this research, as was stated earlier, was to develop a set of demand models which are sufficiently sensitive so as to measure the impacts upon market demand of policy decisions. Examples provided here show how the models may be applied to the analysis of demand variations due to changes in quality of service and fare. These changes may be the effects of the introduction of new aircraft technology or of the implementation of managerial strategies within the framework of existing technology. Also included is an outline of how the models may be applied for aggregate forecasting purposes.

3.1.5.1 Derivation of Demand vs. Frequency Relationships

The concept of the "demand vs. frequency" relationship has been developed in this study (see Volume I, Section 3.2.1). The motivation for the determination of accurate demand vs. frequency relationships is related to

Figure 14 Service and Demand Equations Parameters for Long Haul Markets

Large Long Haul Markets

DEMAND EQUATION

$$\ln(Q_{D_t}) = -0.859 + .429\ \ln(LOS_t) - 1.26\ \ln(F_t) + 1.73\ \ln(SE_t)$$

SERVICE EQUATION

$$\ln(LOS_t) = -2.95 + .112\ \ln(TRAFL_{t-1}) + .309\ \ln(F_t) - .0122\ \ln(COMP_t)$$

Medium Size Long Haul Markets

DEMAND EQUATION

$$\ln(Q_{D_t}) = -.0338 + .452\ \ln(LOS_t) - 2.07\ \ln(F_t) + 2.20\ \ln(SE_t)$$

SERVICE EQUATION

$$\ln(LOS_t) = -3.32 + .097\ \ln(TRAFL_{t-1}) + .421\ \ln(F_t) - .0440\ \ln(COMP_t)$$

Small Long Haul Markets

DEMAND EQUATION

$$\ln(Q_{D_t}) = -.105 + .575\ \ln(LOS_t) - .45\ \ln(F_t) + 1.27\ \ln(SE_t)$$

SERVICE EQUATION

$$\ln(LOS_t) = -4.89 + .171\ \ln(TRAFL_{t-1}) + .622\ \ln(F_t) + .0286\ \ln(COMP_t)$$

Figure 15 Service and Demand Equation Parameters for Medium Haul Markets

Large Medium Haul Markets

DEMAND EQUATION

$$\ln(Q_{D_t}) = -.0822 + .534\ \ln(LOS_t) - .583\ \ln(F_t) + 1.4\ \ln(SE_t)$$

SERVICE EQUATION

$$\ln(LOS_t) = -3.24 + .233\ \ln(TRAFL_{t-1}) + .134\ \ln(F_t) - .140\ \ln(COMP_t)$$

Medium Size Medium Haul Markets

DEMAND EQUATION

$$\ln(Q_{D_t}) = .0144 + .991\ \ln(LOS_t) - .89\ \ln(F_t) + 1.56\ \ln(SE_t)$$

SERVICE EQUATION

$$\ln(LOS_t) = -3.94 + .217\ \ln(TRAFL_{t-1}) + .338\ \ln(F_t) - .0948\ \ln(COMP_t)$$

Small Medium Haul Markets

DEMAND EQUATION

$$\ln(Q_{D_t}) = -.0277 + .57\ \ln(LOS_t) - .597\ \ln(F_t) + 1.44\ \ln(SE_t)$$

SERVICE EQUATION

$$\ln(LOS_t) = -3.94 + .180\ \ln(TRAFL_{t-1}) + .383\ \ln(F_t) + .174\ \ln(COMP_t)$$

the application of fleet assignment models. Many fleet assignment models have been developed in recent years, both within academic institutions and by aircraft manufacturers. One such model is FA-4, developed in the Flight Transportation Laboratory at M.I.T.

FA-4 is a linear programming model which determines the optimal number of daily flights scheduled over each segment of a route structure network. The objective function to be maximized is the difference between total revenue and the sum of direct and indirect operating costs. The optimization process is constrained by a number of economic factors including, among others, prescribed load factor conditions, fleet availability, minimum number of departures in the various markets, and maximum number of departures from the various stations.

Among the necessary input information is a set of demand vs. frequency relationships for the various markets. The frequency variable, n, in the demand vs. frequency relationship for a given market is the number of daily departures, assuming that each departure is nonstop, that the demand distribution is uniform over time of day, and that the departure scheduling is such that the average displacement time is minimized. It can be shown that for n daily departures, this optimal scheduling places the departure of each flight i, D_i, at the following times:

$$D_i = \frac{2i - 1}{2n} \qquad i = 1, 2, \ldots, n$$

where the [0, 1] time scale is defined from the start to the end of the traveling day.

Given the flight schedule implied by the equation above, it can be shown that the average displacement time is as follows:

$$\overline{DT} = \frac{D}{4n}$$

where D = length of the traveling day.

Since the level of service variable LOS is defined as the ratio of non-stop jet block time, t_o, to the average of the flight and displacement times, then level of service can be defined as a function of n as follows:

$$LOS = \frac{t_o}{t_o + \frac{D}{4n}} = \frac{n}{n + \frac{D}{4t_o}}$$

The standard value of the length of traveling day used by FA-4 researchers in the development of demand vs. frequency relationships for long and medium haul markets is D = 16 hours. The nonstop jet time for a flight from Boston to San Francisco is roughly t_o = 6.0 hours. Substituting these values into the above equation yields the relationship between level of service and number of flights (assuming optimal scheduling) for the Boston to San Francisco segment.

$$LOS\ (BOS\text{-}SFO) = \frac{n}{n + \frac{16}{4(6.0)}} = \frac{n}{n + 0.667}$$

Substituting this LOS function into the estimated demand equation for large long haul markets (Figure 14) yields the demand vs. frequency relationship for Boston to San Francisco.

$$Q_D(BOS\text{-}SFO) = \log^{-1}(-0.0859)\left(\frac{n}{n + 0.0667}\right)^{0.429} \cdot F^{-1.26} \cdot SE^{1.73}$$

The volume of passenger demand, given a fixed fare F and level of socio-economic activity SE, is defined as Q_{D_F}. By employing this notation, the equation above can be non-dimensionalized as follows:

$$\frac{Q_D}{Q_{D_F}} \text{(BOS-SFO)} = \left(\frac{n}{n + 0.667}\right)^{0.429}$$

The numerical results are presented in Table 1. The demand vs. frequency relationship summarized within this table indicates that 30% of the total potential demand will be satisfied with only one daily departure. The 95% saturation frequency is five daily departures for the Boston-San Francisco market.

Chicago-New York is a large medium haul market with a jet block time of roughly t_o = 2.5 hours. The following results are obtained for the Chicago-New York market using the equations for large medium haul markets given in Figure 15.

$$\text{LOS(CHI-NYC)} = \frac{n}{n + \frac{16}{4(2.5)}} = \frac{n}{n + 1.60}$$

$$\frac{Q_D}{Q_{D_F}} \text{(CHI-NYC)} = \left(\frac{n}{n + 1.60}\right)^{0.534}$$

The resulting demand vs. frequency relationship for the Chicago-New York market is tabulated in Table 2. If a single flight were scheduled, 60% of the potential demand would be satisfied. The 95% saturation frequency for the Chicago-New York market is sixteen flights.

The results imply, as expected, that the long haul Boston-San Francisco

Table 1 Demand vs. Frequency Relationship for Boston to San Francisco

Number of Flights n	Level of Service LOS	Percentage of Total Demand Q_D/Q_{D_F}
0	0.000	0.000
1	0.750	0.803
2	0.818	0.884
3	0.857	0.918
4	0.882	0.936
5	0.900	0.948
6	0.913	0.956
7	0.923	0.962

Table 2 Demand vs. Frequency Relationship for Chicago to New York

Number of Flights n	Level of Service LOS	Percentage of Total Demand Q_D/Q_{D_F}
0	0.000	0.000
1	0.385	0.600
2	0.556	0.731
3	0.652	0.796
4	0.714	0.836
5	0.758	0.862
6	0.789	0.881
7	0.814	0.896
8	0.833	0.907
9	0.849	0.916
10	0.862	0.924
11	0.873	0.930
12	0.882	0.935
13	0.890	0.940
14	0.897	0.944
15	0.904	0.947
16	0.909	0.950
17	0.914	0.953
18	0.918	0.956

market will saturate with fewer scheduled departures than will the medium haul Chicago-New York market. The demand vs. frequency curves for these two markets are superimposed in Figure 16.

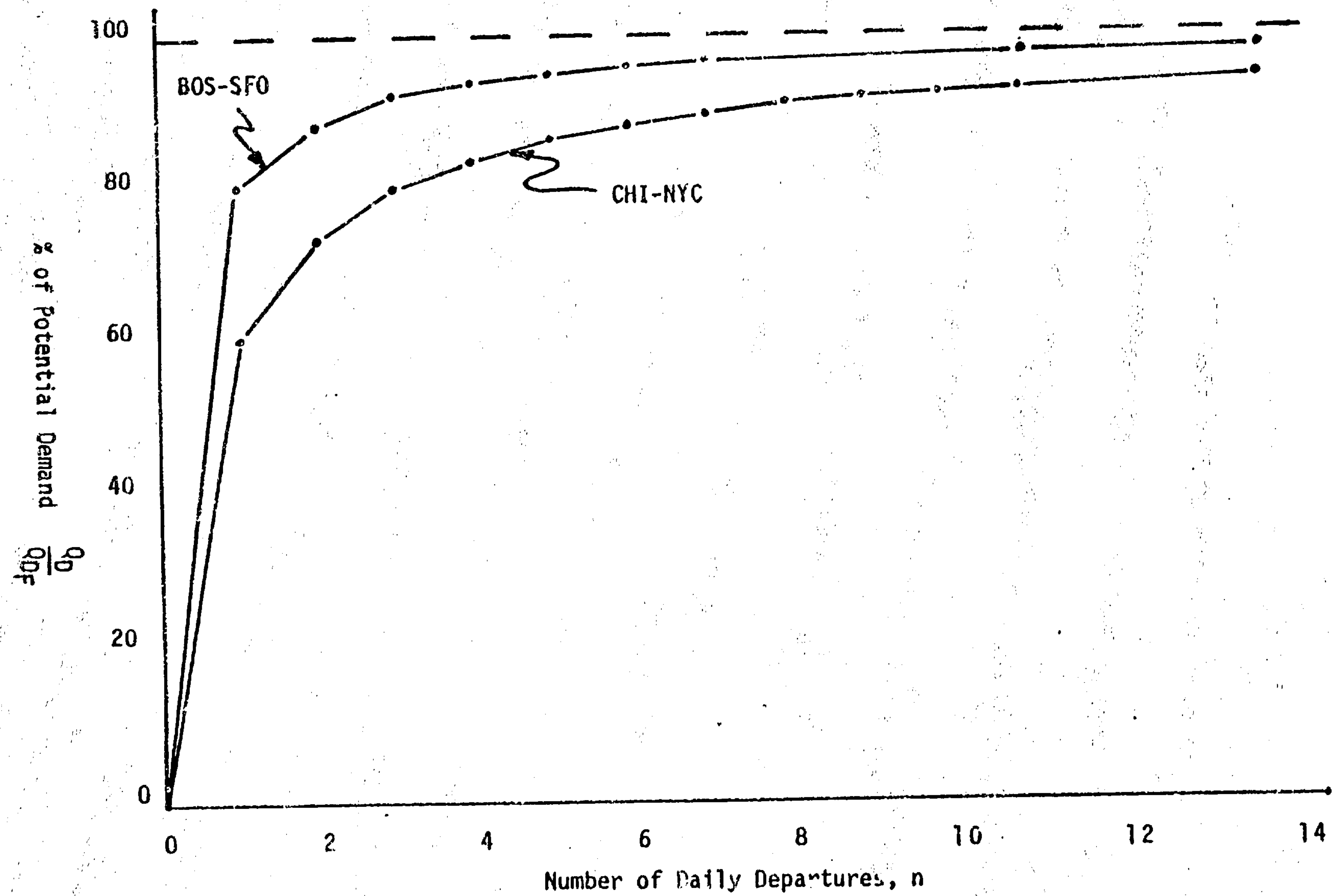
3.1.5.2 The Impact Upon Demand of New Technologically Advanced Aircraft

The introduction of a new technologically advanced aircraft will affect the consumers of air passenger transportation in one or two ways. Either the quality of service in a given market will be altered, or the fare structure will change, or both. For example, the introduction of a supersonic transport in long haul markets will improve the level of service by substantially reducing trip time. It may as well result in a price change if a fare premium is charged for the privilege of enjoying this high speed service.[5] If a new fuel-efficient subsonic aircraft were introduced, the savings cost to the airlines would hopefully be passed along to the consumer in the form of either fare reductions or less frequent and/or smaller fare increases. These two hypothetical cases are investigated here.

The Introduction of a Supersonic Transport on Long Haul Domestic Routes.- It is recognized that the introduction of a supersonic transport on domestic routes creates the obvious problem of sonic boom over land. However, for illustration purposes, this problem is ignored in considering SST service between Boston and San Francisco.

In 1974, there were two daily nonstop flights each way between Boston and San Francisco. The value of the level of service variable LOS was 0.792, and approximately 199,000 one-way trips were purchased in this market. In this section, the equipment used for these flights (United's 747 and TWA's

Figure 16 Demand vs. Frequency Curves, Boston-San Francisco and Chicago-New York



L-1011) will be "replaced" by a Boeing SST and the resulting impacts upon demand will be estimated.

Assuming a total of one half hour for taxiway occupancy and acceleration to and deceleration from cruise speed, a cruise speed of 1800 miles per hour, the block time of an SST flight between Boston and San Francisco, approximately 2700 miles, is estimated as

$$t_0 = 0.5 \text{ hours} + \frac{2700 \text{ miles}}{1800 \text{ mph}} = 2.0 \text{ hours}$$

This figure is invariant of direction since, at the cruising altitude of the SST, jet stream effects are negligible.

The resulting level of service figures are 1.468 from Boston to San Francisco and 1.321 from San Francisco to Boston. The value of the market level of service is the geometric mean of the two directional values which equals 1.393. This represents a 75.9% increase in LOS.

The coefficient of level of service for large long haul markets is estimated to be 0.429 (Figure 14). Assuming no increase in fare, the 75.9% increase in level of service due to the introduction of supersonic service results in a 0.429 x 75.9% or 32.6% increase in traffic, to 264,000 passengers.

The price elasticity for fare on large long haul markets was estimated in Figure 14 to be -1.26. Supposing that a 30% surcharge were placed upon SST service, the model implies a 1.26 x 30% or 41.1% decrease from the 264,000 passenger figure, to 155,000 passengers. This figure assumes, however, that passengers are offered only the SST as an alternative. If both subsonic and supersonic services were offered (at different prices), the flight selection behavioral process would involve both trip time and price considerations (as opposed to merely trip time). This is a very complex situation, involving the time value of money, and it should be considered for future research.

<u>The Introduction of a Fuel Efficient Subsonic Aircraft on Medium Haul Routes</u>. The next generation subsonic aircraft is likely to be a medium-range two or three engine plane with a capacity of about 200 people. It will bridge the gap between the shorter range and smaller capacity narrow-bodies (DC-9, 727, 737) and the longer range and greater capacity wide-bodies (DC-10, L-1011, 747). It will hopefully be substantially cheaper to operate in terms of direct operating cost per available seat-mile) than the existing four-engine narrow-bodied planes (DC-8, 707).

If the new generation aircraft were introduced, it is reasonable to believe that the cost savings felt by the airlines would be passed on to the consumer over time, in terms of lower fare levels than would be charged if the technology were not introduced. Furthermore, it is possible that level of service could be affected, but this is uncertain and a function of many factors, such as number of planes purchased by the airlines, expected utilization, etc.

It is beyond the scope of this summary to evaluate the degree to which the introduction of the new equipment will affect fares and quality of service in a given market, particularly since the design parameters of the new aircraft have not as yet been finalized. However, the level of service coefficient and the fare elasticities of the demand analysis equations can provide a clue as to how the service and fare changes caused by the introduction of the new aircraft affect demand.

For example, suppose the new technology aircraft were introduced, resulting in no appreciable change in level of service but, over time, a decrease (in constant dollars) of between 5% and 30% in fares in 700 mile markets, roughly the length of the Chicago-New York market. Since, from Figure 15, the estimate of price elasticity for large medium haul markets is 0.583, the model would predict the traffic volume increases in that market shown in Table 3.

3.1.5.3 Aggregate Forecasting

The project of applying the models developed in this thesis to aggregate demand forecasting is nearly as complex a task as the development of the models themselves has been. Four major steps are involved in this operation:

Step 1. Determination of Market Sample

Step 2. Gathering of Data

Step 3. Prediction

Step 4. Sensitivity Analysis

The purpose of this section is to outline each of these four steps.

It is not necessary, nor perhaps is it even reasonable, to employ the same sample of markets that was used to calibrate the models for the forecasting process. For the purpose of forecasting aggregate traffic (in, say, RPM's) by length of haul, it is suggested that the samples contain the historically largest (in terms of density) markets in each length of haul grouping, for the following three reasons:

Table 3 Effect Upon Demand in Chicago-New York Market of Fuel Efficient Aircraft, Assuming a Resulting 5% - 30% Decrease in Fare (Constant Dollars)

Percentage Decrease in Fare	Percentage Increase in Demand
5	2.92
10	5.83
15	8.75
20	11.7
25	14.6
30	17.5

(1) For a fixed sample size, this sampling procedure will provide the maximum ratio of sample RPM's to population RPM's.

(2) The forecasting accuracy of the demand equations (in terms of lower standard errors) appears to be greater for larger markets.

(3) Using a sample for forecasting that is different than the sample used for calibration provides a means for verifying the performance of the model by "forecasting" past aggregate demand and comparing this to actual figures.

The size of the sample is a function of the amount of resources available. The most time and cost sensitive task, with respect to sample size, will be data gathering.

The necessary socio-economic data are currently being processed by the Bureau of Economic Analysis of the Department of Commerce. The data will include projections of the socio-economic variables (total personal income and income of service industries) through the year 2000.

Scenarios of technological variables can be provided by the aircraft manufacturers and by NASA. Service levels and fares will have to be estimated based upon these technical inputs, by industry predictions of the changes in the various components of direct and indirect operating costs, and by economic forecasts of the appropriate price deflators.

Once the sample has been selected and the data gathered and processed, the estimates of the demand levels for each of the markets for each of the economic and technological scenarios may be obtained by direct substitution into the demand equations. The traffic forecasts may then be summed to obtain aggregate demand forecasts.

Sensitivity analysis is a necessary component to determine how responsive the demand forecasts are to perturbations in each of the factors specified in the technological and economic scenarios. Careful attention must be paid to ensure that the model will not produce bad results if any of the input information is slightly in error.

Section 4. Conclusions and Recommendations for Future Research

A series of models have been developed which may be used to forecast future passenger traffic in U.S. domestic air passenger markets. These models are sufficiently policy-sensitive so as to measure the impacts upon market demand due to changes in quality of service, fares, and technological factors. On the surface, the general structure of the models is sufficiently simple so as to be easily communicable to an audience that is unfamiliar with economic theory and econometric modeling. However, the underlying derivations of the components of the model are sufficiently sophisticated so as to capture the important characteristics of this complex industry.

The models are adaptive, in that they may be updated without considerable difficulty as additional data becomes available, although it is not clear that such activity will be necessary. Furthermore, the models are statistically robust in that deletion of any single data points from the samples over which they were calibrated would not substantially alter the estimates.

A common conclusion of other research efforts in this field is that data may not be pooled over lengths of haul to obtain one general demand model. The results of a Chow test in this summary concurred with this proposition.

Furthermore, the results of Chow tests within length of haul classifications revealed that data may not be pooled by market size (as measured demographically). Therefore, the data were segmented into three lengths of haul and three market size strata. Models were then calibrated over subsets of the data extracted from the markets in each of the nine cross-classifications.

In most of the nine cross-classifications, the equations estimated by ordinary least squares provided a good fit, but did not yield intuitively reasonable estimates of the coefficients. Furthermore, the coefficient estimates were imprecise. The suspected cause of the problem was multi-collinearity, and when this suspicion was confirmed, principal components regression was employed to combat the situation. The resulting equations produced reasonable and precise coefficient estimates, but not as good a fit. Since the purpose of this research was to produce a set of models that may be used for policy analysis, it is imperative that the resulting equations bear reasonable and precise coefficient estimates. Consequently, the equations calibrated using ordinary least squares were, in spite of their superior fit, rejected in favor of the equations estimated using principal components deletion.

As was expected, the results of the estimation of the demand equations for short haul markets were unsatisfactory. This is due to the positive relationship between air traffic volume and distance in the short haul because of the supremacy of competing modes for very short distances. Consequently, the fare elasticity was frequently estimated to be a positive number, as fare is a function only of distance. This reaffirms the need for specialized short haul air traffic demand forecasting models which account for the attributes of surface modes.

For medium and long haul markets, the model seems to perform better for larger markets. This is due to a specification problem regarding the route structure variable. In larger markets a greater percentage of the non-local passengers are accounted for by this variable. Therefore, the service equation estimate produced a poorer fit in the medium size and small long haul markets and the small medium haul markets, than it did in the large long haul and large and medium size medium haul markets. The only apparent remedy for this situation is to define a more complex route structure variable, which would require service segment flow data. However, since these data are very costly to process, and since the majority of the long haul traffic is in large markets and of medium haul traffic is in medium and small size markets (for which the route structure variable as defined herein seems to perform well), it is doubtful whether the benefit of this activity would be worth the resource investment.

Comparing the estimated fare elasticities of long (-1.26 ± 0.067) and medium (0.583 ± 0.104) haul markets, where the error terms are $\pm$ two standard errors, it appears that air transportation demand is more price elastic in longer haul markets. The results of the generation of demand vs. frequency relationships in Section 3.1.5.1 leads to the conclusion that in long haul markets demand will saturate with a fewer number of departures than will demand in medium haul markets. The estimates of the coefficients of the socio-economic variable in all demand equations for long and medium haul markets imply that air travel demand is very elastic with respect to personal income and the income of service related industries.

The performance of the models in aggregate demand forecasting models remains to be seen. The application of this research to medium and long-term forecasting is a process nearly as complex as the development of the models themselves. The accuracy of the forecasts that this research will produce can be only as good as the information received regarding future technological and economic scenarios, and only as good as the methods by which these data are processed to generate predictions of the values of the carrier variables. These applications comprise an obviously ripe area for future research.

The determination of accurate estimates of the relative consequences of displacement time vs. flight time, and of the time/cost tradeoff for air travelers, are other pressing topics of interest related to the research of this summary. The former can be used to validate the behavioral assumptions adopted herein for the assignment of passengers to flights, and perhaps improve upon the definition of the level of service variable. The latter would provide valuable information for the analysis of markets in which two types of service, one faster and more expensive and one slower and cheaper, exist. This problem was encountered in the analysis of the introduction of domestic supersonic transport service.

The models developed in this summary are, as previously mentioned, not effective in the analysis of short haul markets. A complement to this research would be a set of short haul air transportation demand models that are sensitive to the relative levels of the attributes of competing modes. The thesis by Blumer, surveyed in the following Section (3.2), does an excellent job of laying the groundwork for such models.

As described in the Introduction, the objective in developing these passenger market models is to develop the means to project passenger demand to feed directly into the NASA ABC-ART model. Although the structure of these models differ, their results should be similar in a common range, roughly between 300 and 500 miles stage lengths. Identical results from each model is not required, but consistent trends and approximate demand levels are necessary to establish confidence in the formulation and calibration of both models.

As a final recommendation, the inclusion of a third stratification, that of market type (business vs. pleasure), would be very useful to gain greater insight since, as Marfisi indicated in his thesis, the demand equation coefficients are sensitive to the type of traveler predominant in the market. This is a very difficult problem to attack since, while a few markets are obviously highly business-oriented (e.g., Boston-New York, Chicago-Detroit), and some obviously highly pleasure-oriented (e.g., Miami-New York, Las Vegas-Los Angeles), most markets are somewhere on a continuum between the two extremes. Unfortunately, no current data are publicly available that can be used to identify the business/pleasure mix of given markets. The production and dissemination of this data, perhaps by onboard surveys conducted by airlines, would constitute a significant breakthrough for researchers interested in this type of analysis.

APPENDIX A

LIST OF REGION PAIRS BY DEMOGRAPHIC STRATIFICATIONS

1-1

Short

Bismarck-Minot (106 miles)
Knoxville-Lexington (157 miles)
Bismarck-Fargo (187 miles)
Las Vegas-Reno (345 miles)

Medium

Jackson-Jacksonville (511 miles)
Reno-Tucson (709 miles)
Las Vegas-Lubbock (775 miles)
Lincoln-Tucson (991 miles)

Long

Fargo-Las Vegas (1205 miles)
Las Vegas-Lexington (1686 miles)
Portland, Maine-Tucson (1825 miles)
Erie-Reno (2065 miles)

1-2

Short

Lincoln-Omaha (55 miles)
Reno-Sacramento (113 miles)
Lubbock-Oklahoma City (269 miles)
Dayton-Knoxville (282 miles)

Medium

Jacksonville-Norfolk (543 miles)
Dayton-Lincoln (665 miles)
Minot-Salt Lake City (737 miles)
San Antonio-Tucson (762 miles)

Long

Las Vegas-Omaha (1099 miles)
Jacksonville-Salt Lake City (1834 miles)
Dayton-Reno (1883 miles)
Norfolk-Tucson (1999 miles)

1-3

Short

Cincinnati-Lexington (70 miles)
Jackson-New Orleans (160 miles)
Knoxville-Memphis (342 miles)
San Diego-Tucson (367 miles)

Medium

Jacksonville-New Orleans (513 miles)
Fargo-Milwaukee (516 miles)
Denver-Tucson (627 miles)
Cincinnati-Portland, Maine (810 miles)

Long

Memphis-Tucson (1224 miles)
Las Vegas-New Orleans (1500 miles)
Jacksonville-Portland, Oregon (2428 miles)
Portland, Maine-San Diego (2623 miles)

1-4

Short

Fargo-Minneapolis (223 miles)
Lexington-Pittsburgh (289 miles)
Dallas-Lubbock (293 miles)
Dallas-Jackson (397 miles)

Medium

Minneapolis-Minot (449 miles)
Reno-Seattle (566 miles)
Dallas-Tucson (839 miles)
Atlanta-Lincoln (841 miles)

Long

Bismarck-Seattle (1014 miles)
Miami-Portland, Maine (1353 miles)
Lubbock-Miami (1400 miles)
Atlanta-Las Vegas (1747 miles)

1-5

Short
Boston-Portland, Maine (95 miles)
Detroit-Erie (155 miles)
Las Vegas-Los Angeles (227 miles)
Cleveland-Lexington (280 miles)

Medium
Las Vegas-San Francisco (419 miles)
Chicago-Lincoln (473 miles)
Portland, Maine-Washington (487 miles)
Boston-Knoxville (830 miles)

Long
Lincoln-Los Angeles (1267 miles)
Chicago-Tucson (1441 miles)
Jacksonville-San Francisco (2369 miles)
New York-Reno (2399 miles)

2-2

Short
Norfolk-Richmond (75 miles)
Oklahoma City-Wichita (156 miles)
Omaha-Wichita (265 miles)
Richmond-Rochester (388 miles)

Medium
Norfolk-Rochester (437 miles)
Sacramento-Salt Lake City (533 miles)
Dayton-Omaha (622 miles)
Oklahoma City-Salt Lake City (865 miles)

Long
Dayton-San Antonio (1079 miles)
Dayton-Salt Lake City (1461 miles)
Sacramento-San Antonio (1463 miles)
Norfolk-Salt Lake City (1935 miles)

2-3

Short

Raleigh-Richmond (138 miles)
Cincinnati-Dayton (63 miles)
Dayton-Milwaukee (285 miles)
Denver-Salt Lake City (381 miles)

Medium

Denver-Wichita (428 miles)
Albany-Dayton (576 miles)
Memphis-San Antonio (626 miles)
Salt Lake City-San Diego (626 miles)

Long

Portland, Oregon-San Antonio (1714 miles)
New Orleans-Sacramento (1879 miles)
Albany-Salt Lake City (1960 miles)
Rochester-San Diego (2251 miles)

2-4

Short

Kansas City-Oklahoma (165 miles)
Dallas-Oklahoma City (185 miles)
Dayton-Pittsburgh (215 miles)
Dayton-St. Louis (339 miles)

Medium

Oklahoma City-St. Louis (462 miles)
Sacramento-Seattle (608 miles)
Rochester-St. Louis (729 miles)
Miami-Richmond (825 miles)

Long

Miami-Rochester (1204 miles)
Houston-Salt Lake City (1204 miles)
San Antonio-Seattle (1775 miles)
Atlanta-Sacramento (2093 miles)

2-5

Short

Dayton-Detroit (175 miles)
Norfolk-Philadelphia (215 miles)
Boston-Rochester (343 miles)
Cleveland-Richmond (362 miles)

Medium

Chicago-Omaha (423 miles)
Chicago-Rochester (522 miles)
Los Angeles-Salt Lake City (590 miles)
Detroit-Omaha (660 miles)

Long

Omaha-San Francisco (1432 miles)
San Antonio-San Francisco (1487 miles)
Boston-Salt Lake City (2105 miles)
New York-Sacramento (2510 miles)

3-3

Short

Memphis-Nashville (200 miles)
Cincinnati-Nashville (230 miles)
Cincinnati-Milwaukee (318 miles)
Memphis-New Orleans (349 miles)

Medium

Milwaukee-Nashville (475 miles)
Albany-Cincinnati (623 miles)
Denver-San Diego (840 miles)
Denver-Milwaukee (908 miles)

Long

Denver-New Orleans (1067 miles)
Albany-Denver (1622 miles)
Cincinnati-San Diego (1865 miles)
New Orleans-Portland, Oregon (2050 miles)

3-4

Short

Cincinnati-Pittsburgh (256 miles)
Houston-New Orleans (303 miles)
Albany-Pittsburgh (367 miles)
Atlanta-Cincinnati (373 miles)

Medium

Atlanta-New Orleans (425 miles)
Milwaukee-Pittsburgh (431 miles)
Miami-Nashville (807 miles)
Cincinnati-Miami (948 miles)

Long

Denver-Seattle (1020 miles)
San Diego-Seattle (1052 miles)
Dallas-Portland, Oregon (1626 miles)
Denver-Miami (1716 miles)

3-5

Short

Chicago-Milwaukee (74 miles)
Raleigh-Washington (225 miles)
Albany-New York (139 miles)
Albany-Boston (145 miles)

Medium

Albany-Detroit (479 miles)
Raleigh-Detroit (503 miles)
Los Angeles-Portland, Oregon (834 miles)
Denver-San Francisco (956 miles)

Long

Cleveland-Denver (1217 miles)
Denver-New York (1624 miles)
Portland, Oregon-Washington (2339 miles)
New York-San Diego (2435 miles)

4-4

Short

Kansas City-St. Louis (229 miles)
Memphis-St. Louis (255 miles)
Milwaukee-Minneapolis (297 miles)
Atlanta-Memphis (332 miles)

Medium

Atlanta-St. Louis (484 miles)
Houston-Kansas City (643 miles)
Atlanta-Dallas (721 miles)
Minneapolis-Pittsburgh (726 miles)

Long

Houston-Pittsburgh (1124 miles)
Miami-Minneapolis (1501 miles)
Dallas-Seattle (1671 miles)
Miami-Seattle (2725 miles)

4-5

Short

Pittsburgh-Washington (193 miles)
Detroit-Pittsburgh (198 miles)
Chicago-St. Louis (256 miles)
New York-Pittsburgh (329 miles)

Medium

Boston-Pittsburgh (496 miles)
Atlanta-Detroit (602 miles)
San Francisco-Seattle (671 miles)
Miami-Washington (920 miles)

Long

Detroit-Houston (1095 miles)
Kansas City-New York (1098 miles)
Houston-Washington (1204 miles)
St. Louis-San Francisco (1736 miles)

5-5

Short

Cleveland-Detroit (94 miles)
New York-Washington (215 miles)
Chicago-Detroit (238 miles)
Boston-Philadelphia (274 miles)

Medium

Boston-Washington (406 miles)
Boston-Detroit (623 miles)
Chicago-Philadelphia (675 miles)
Chicago-New York (721 miles)

Long

Chicago-Los Angeles (1740 miles)
Los Angeles-Philadelphia (2396 miles)
New York-San Francisco (2574 miles)
Boston-San Francisco (2703 miles)

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