Dynamic Forecasting of Demand and Supply in Nonstop Air Routes

VIJAYA KUMAR AND YORGOS STEPHANEDES

Passenger air-travel forecasting is receiving renewed emphasis as a result of increasing congestion and delays at airports across the country. Addressing the forecasting problem, a set of dynamic demand and supply models were developed for a given airline on a nonstop air travel route (Twin Cities to Chicago). The dynamic specifications were developed using time-series analysis and the causal relationships between cause and effect were confirmed with Granger causality tests. The models were developed based on a modest amount of monthly data from sales receipts and schedule information over the 1979 to 1983 period. In general, the models forecast demand and supply with reasonable accuracy, with an average forecasting error of less than 4 percent. Application of the forecasting equations to policy analysis indicates that, although the effect of improved service (more seats available) on demand lasts for approximately three months, the major impact is strongest during the first month, concurrent with service changes, implying little loyalty by passengers to their airline. The policy results also indicate that the airline's reaction to a sudden surge in demand is more sluggish and lags demand change by a month, probably as a result of the costs involved in crew and aircraft allocations.

Passenger air-travel forecasting is receiving a renewed emphasis after several years of neglect. The emphasis in this rather specialized field is due largely to increasing concerns about the levels of congestion and delay at airports as well as the more general effects of deregulation on intercity intermodal travel. Over the past four decades, intercity travel has changed dramatically in terms of cost, speed, and comfort. Yet today, only one-third of the population makes regular trips by air (*1*), indicating that air travel is probably at just a fraction of its potential. At the same time, existing air travel is overloading many air corridors and air terminals. To be sure, the present overcrowding has been precipitated by the deregulation of the airline industry.

The deregulation of discount fares in 1978 provided a means for the airlines to attract more passenger traffic. More than two dozen new airlines have been created to meet the growing demand, which has surged to unprecedented peaks. However, because the government is no longer protecting inefficient carriers, high-cost operators have been especially hard hit by ferocious competitive pressures. Prior to deregulation, obtaining new-route authority was usually the most serious barrier to an airline's internal expansion, because the Civil Aeronautics Board (CAB) took a restrictive view toward awarding new routes. With deregulation, new-route authority became available with only minimal delay. As a result, airlines wanting to expand quickly found a merger useful in obtaining aircraft ground facilities and other scarce factors of production. Smaller airlines experienced increased incentives to consider merging with one another or with larger airlines for economic survival.

Deregulation has further created strong incentives for the commercial airlines to extract the greatest possible output from the existing fleet. Besides increased hours of use, aircraft are now scheduled so as to better fit particular markets or city-pairs, an improvement made possible by enhanced freedom in route selection and abandonment. Planes are also now flown on somewhat longer hops on average, as well as later at night and earlier in the morning (which makes the increase in load factors all the more remarkable). In addition, aircraft seem better positioned relative to their markets by time of day and geographic location, thereby filling previously missing gaps in the hub-and-spoke networks created by regulatory restrictions.

These changing conditions are forcing air carriers to make critical decisions about fare pricing, fleet expansion, route structure, and flight scheduling. Of all the available alternatives, service changes and fare pricing, applied selectively to individual intercity routes, appear to be two of the most feasible solutions. However, selection of appropriate fare policies and operating requirements calls for employment of rigorous methods for estimating air passenger demand on different routes and evaluating performance of the new service under consideration. If the evaluation process is to be effective in the long term, it must be dynamic in nature and address and overcome specific problems characterizing the unstable equilibrium between demand and supply and the short- and long-term effects of demand and travel patterns resulting from the new service.

The methodology and findings presented in this paper are part of a larger project in intercity travel. The objectives of that project included the development of simple and realistic yet rigorous models that can be used to forecast intercity travel demand and supply. Primary considerations were the availability of data for development and use of the models and the effectiveness of the models for intercity route policy analysis. The work presented here is only a modest attempt in developing a tool for estimating the impacts of air travel supply on demand and vice versa, through time. While the initial application is in nonstop, route-level service by one airline, the method is being extended to situations involving stops and multiple routes as a part of a larger hub-and-spoke network.

V. Kumar, Metropolitan Council of the Twin Cities Area, 300 Metro Square Building, St. Paul, Minn. 55101. Y. Stephanedes, Department of Civil and Mineral Engineering, University of Minnesota, 500 Pillsbury Dr., S.E., Minneapolis, Minn. 55455.

In the mid and late 1960s, several research efforts were directed toward the development of intercity travel demand forecasting tools. Among them, direct demand models began to dominate. However, because of their aggregate nature, these models proved inaccurate and grossly overestimated future growth. Further, the models were not policy-oriented since most of their variables were related to the socioeconomic characteristics of the cities and were not under the control of the transportation planner.

In 1969, the National Cooperative Highway Research Program (NCHRP) designed and financed a detailed research study (*2*) to define the social and economic factors affecting intercity travel and to use resulting relationships with existing traffic prediction tools to forecast intercity travel. The models developed in the NCHRP were based on a vast amount of aggregate data obtained from various counties across the nation having different socioeconomic characteristics. For this reason, the models performed reasonably well when applied at the regional level but proved useless at the route or corridor level. In addition, since these models did not include variables representing the service levels, their usefulness in evaluating transportation-related policies was very limited.

In the 1970s, economists, transportation planners, and system analysts began to contribute to the development and empirical estimation of a class of demand functions based on the logit and related models of discrete choice. Disaggregate approaches to analyze travel demand showed very promising results and a wide variety of advances have been achieved to date.

Despite the preponderance of logit models as tools of demand analysis in urban travel (*3, 4*), not much attention was paid to extending the disaggregate approach to intercity travel until 1974. In 1974, Watson (*5*) attempted to compare model structure and predictive power of aggregate and disaggregate models of intercity mode choice. The results of his study indicated that disaggregate models provide better statistical explanation of mode choice behavior. Several tests showed that the errors associated with the aggregate models were several times as large as those associated with the disaggregate models.

Following Watson, Stopher and Prashker (*6*) and Grayson (*7*) explored the feasibility of using an existing data base, namely, the National Travel Survey (NTS) for the development of intercity passenger forecasting procedures. The results of their study indicated that NTS data are not suitable for a disaggregate modeling approach. A large number of assumptions were necessary to cope with multiple airports, schedule and fare changes during the year, access and egress characteristics, and so on. For this reason, the reliability of the model coefficients was questionable. In particular, the model by Stopher and Prashker (*6*) included intuitively incorrect signs and, therefore, the estimates of modal shares were not meaningful. Grayson's model was found to perform better on the national and regional levels than on the route-by-route level.

For the first time, in 1978, a time-series analysis of intercity air travel volume was carried out by Oberhausen and Koppelman (*8*) to produce short-term forecasts. These authors used the Box and Jenkins approach (*9–11*) to develop univariate models, which account for monthly as well as seasonal patterns in a time-series of historical data. Results showed that univariate models produced reasonably accurate forecasts. The study also included the estimation of a bivariate time series model incorporating air fare as an explanatory variable. Though this model did not produce a significantly better fit of the data, it was found to be potentially useful from a management standpoint because it facilitated the comparison of elasticities and the evaluation of alternative strategies.

Finally, in a recent study, Abkowitz and Tozzi (*12*) developed regional air demand models using air traffic, demographic, and economic data, and the Ordinary Least Squares technique. A comparison of these models with those derived with prederegulation data indicated that the basic factors which influence regional travel have not changed since deregulation. The results of the study also showed that the regional air travel market is distinctly different from longer haul and other specialized markets.

Although most of the work to date has addressed specific intercity travel demand issues, no study has effectively addressed the dynamic interactions between demand and supply and the ways in which such interactions may affect the implementation of specific policies through time.

DATA

The data used for this analysis were obtained from a Twin Cities-based commercial airline and covered the time period from October 1979 through April 1986, a total of 79 months (data points). The air route considered is Minneapolis/St. Paul to Chicago. A summary of available data follows:

- Total number of available seats (ASEATS),
- Total number of revenue passengers (RPASS),
- Passenger Load Factor (PLF),
- Number of departures per week day (NDEPWD),
- Number of DC10 departures per week (DC10PWK),
- Number of Boeing 727 departures per week (S727PWK),
- Number of Boeing 747 departures per week (S747PWK),
- Round trip economy fare (EFARE), and
- Round trip full fare (FFARE).

The total number of available seats (indicating supply) was obtained by multiplying the average seating capacity for each aircraft type (including DC10s and Boeing 727s and 737s) by the number of departures per week that aircraft type made. Where the monthly data on revenue passengers were not available (second and third quarters of 1984), the system-wide load factors were used at the route level to estimate the unavailable data points.

METHODOLOGY

While many methods exist for analyzing the data and developing demand-supply specifications, there are two major methods that are distinguished by the way time is treated in the analysis:

- Cross-sectional analysis employs data from different areas but at the same point in time. The analysis assumes that all variables are in equilibrium during the planning period. Any delayed interactions (e.g., between passenger demand and air travel seats) are overlooked. Results are applicable to long-term assessment.

- Time-series analysis employs data from one area but at different points in time. The analysis makes no assumption about long-term equilibrium. Results can point to relations among variables as they occur through prespecified time increments. Therefore, this method is applicable to short-term analysis.

Most studies in this area of research have relied on cross-sectional methods that can determine correlations but cannot break those correlations into causal links. However, it is important that the demand and supply specifications developed be causal rather than descriptive, that is, be able to formulate and test hypotheses on the relation between causes for change and their estimated impacts. Time-series techniques address the issue of causality more directly than do cross-sectional techniques and this is the major reason they form the basis for this analysis.

VARIABLES

Air travel demand between any two cities depends on the travel characteristics along the route as well as the demographic and socioeconomic characteristics of the cities. The travel characteristics include travel cost, schedule delays, discount benefits, safety record of the airline, service frequency, and courteous inflight service. Similarly, the service supplied by an airline is primarily influenced by passenger demand, energy prices, and resource availability. Concurrent work by this research team and related work in the literature indicate that demand for business and nonbusiness (mostly pleasure) travel directly depends on the full fare and economy fare. Further, passenger load factor affects the availability of tickets, thus influencing demand. It is also believed that the service supplied on a particular route by an airline depends mostly on demand.

Ideally, when forecasting air travel demand and supply, it would be desirable to enhance the transferability potential of the specifications by including such variables as population, business employment, tourist activity, and characteristics of all airlines competing in the route. However, this research deals with only one airline and the principal objective is to first identify the important causal links between demand and supply characteristics of that airline ceteris paribus. For this reason, it was hypothesized that changes in air passenger demand and supply could be explained by changes in certain relevant policy variables such as service frequency, travel costs, and load factors. While this does not constitute an exhaustive list of all possible variables, it does appeal to two important points, that is, the variables make sense as likely contributors to changes in demand and supply, and, importantly, data were readily available for this airline to measure these variables over time.

To be sure, price and schedule changes made by the competition can significantly influence the demand characteristics of an airline. Therefore, including service characteristics of competing airlines, should, it is believed, improve the explanatory power of our model specifications. However, at the time this study was initiated, data on competing airline characteristics were not readily available. For this reason, variables referring to airline competitors have not been included in the analysis. However, in continuing work on this topic, the characteristics of airline competition are being incorporated in the model specifications.

Having identified the possible causal variables, historical data were collected on demand, supply, fares, and load factors and a series of Granger causality tests (*13*) was conducted to test the initial hypotheses and identify the direction and magnitude of causality among the variables. The appropriate lag structure for each independent variable was then determined and the final models developed using the vector autoregression method.

Determination of Causality

To determine the existence and direction of causality between demand and supply and other variables, a series of causality tests was performed. The effect of seasonality could be incorporated in these tests by employing a seasonal dummy variable. However, in order to keep the demand and supply models relatively simple, the seasonal parameters were not included. Instead, time-series data were deseasonalized every 6 months to remove the major seasonal effects.

The first step in determining whether a variable X (e.g., available seats) "causes" a variable Y (e.g., revenue passengers) consists of formulating the null hypothesis that X does not "cause" Y. Next, X is regressed on past, present, and future values of Y, i.e.,

$$\begin{aligned} X_t = {} & a_1 X_{t-1} + a_2 X_{t-2} + \ldots + a_q X_{t-q} \\ & + b_0 Y_t + b_1 Y_{t-1} + \ldots + b_q Y_{t-q} \\ & + c_1 Y_{t+1} + c_2 Y_{t+2} + \ldots + c_k Y_{t+k} + e_t \end{aligned}$$

for some integers q and k where X_t, Y_t = variables X and Y at time t and e_t is the residual. Under this hypothesis, all future coefficients of Y should be zero, i.e., $c_h = 0$ for $h = 1, 2, 3, \ldots k$. If they are all zero by an F-test, no causality is likely. On the other hand, if even one future coefficient is not zero, then X is said to cause Y. To be sure, even this test cannot replace the experimental demonstration of a causal relationship. The test only implies that changes in one variable precede, in a statistical sense, changes in another variable; such precedence is necessary but not sufficient for true causality.

From several conversations with airline officials, it was concluded that the effect of demand on supply and vice versa could last up to roughly 3 months. For this reason, the regression equation for the causality test was developed using three leads for the independent variable. The results of the causality tests are summarized in Table 1. Based on a 10 percent level of risk that the test statistic could lead to false rejection of the null hypothesis, the results of causality tests indicate that the following variables cause RPASS: ASEATS, EFARE, FFARE, and PLF (Passenger Load Factor), thus confirming initial beliefs. However, the Passenger Load Factor was not available for several time periods and, therefore, system-wide average values would have to be used in the analysis thus decreasing model validity. Further, Load Factor is not a useful policy variable. NDEPWD (Number of DEPartures per Week Day) does not cause RPASS. A possible explanation for this is that the airline increased the seating capacity on this route by adding bigger aircraft (such as DC10s) and not by changing departures significantly. Consequently, the models did not capture any impacts on demand due to service frequency. As expected, the causality tests indicate that RPASS causes ASEATS.

TABLE 1 RESULTS OF CAUSALITY TESTS

Test Hypothesis	Probability of Correct Hypothesis (%)	F-Value
FFARE does nót affect RPASS	0.033	7.60
PLF does not cause RPASS	0.018	7.55
EFARE does not affect RPASS	0.018	5.03
ASEATS does not affect RPASS	0.048	3.14
NEPWD does not affect RPASS	0.910	0.17
RPASS does not affect ASEATS	0.090	3.58
EFARE does not affect ASEATS	0.310	1.89
FFARE does not affect ASEATS	0.340	1.67

Estimation of Lag Lengths

The Oberhausen and Koppelman study (*8*) indicates that the lag structures associated with air passenger demand are a relatively short 3 to 4 months. To confirm this hypothesis, a series of tests was conducted in which two systems of regression models with differing lag lengths were compared against each other through a chi-square test. A null hypothesis was formed in which the unrestricted equation (with up to six lags) was assumed to have better predictive capability than the restricted one (with fewer than six lags). The results of the chi-square tests indicate that the system with two lags can adequately represent the demand and supply pattern. The estimated chi-square value was significant at the 8 percent level (chi-square = 45.1 at 64 degrees of freedom).

Based on the results from the causality tests and lag length analysis, two specifications for demand and supply were developed using the vector regression method. A summary is provided in Table 2. At 90 percent confidence level, the t-statistics presented in that table indicate that most model parameters were statistically significant.

TABLE 2 DEMAND AND SUPPLY MODELS

Independent Variable	Lags	Dependent Variable: RPASS[a] Coefficient	RPASS[a] t-Value	ASEATS[b] Coefficient	ASEATS[b] t-Value
RPASS	0	–	–	–	–
	1	0.2605	2.3	−0.2995	−1.82
	2	−0.1502	−1.3	−0.0025	0.15
ASEATS	0	0.5011	8.6	–	–
	1	−0.2208	−2.3	0.6277	5.23
	2	0.1042	1.2	−0.0988	−0.86
FFARE	0	92.172	1.8	–	–
EFARE	0	−221.28	−2.3	–	–

NOTE: Dashes indicate not applicable.
[a] $R^2 = 0.73$.
[b] $R^2 = 0.80$.

APPLICATIONS

Test of Model Performance

The above demand-supply models were developed with the data from the Twin Cities to Chicago route for the period October 1979 through January 1983. The models were first tested by simulating their own data for the same period (Figures 1 and 2). To determine their forecasting capabilities, the models were then used to forecast demand and supply from February 1983 through January 1985 (Figures 1 and 2) and the results were compared with observed data.

The comparisons indicate that the absolute percentage error associated with each individual monthly forecast is within 20 percent. The average percentage error in demand forecasting indicates an underestimation of 3.5 percent; in supply forecasting, it indicates an overestimation of 1.8 percent. As the two figures illustrate, the general trend of the estimated demand and supply follows that of the observed values.

Note that the model underestimates demand during the first 4 years and overestimates during the fifth year. However, data for certain time intervals were not available directly from the airline company and, therefore, system-wide average load factors and constant capacity for different plane sizes were used in deducing these data. This may not have resulted in some underprediction in demand and slight overprediction in supply.

The residuals or error terms for a true model are expected to be distributed as white noise, that is, identically normally distributed with zero mean and constant variance. The Q-statistic, used to test this hypothesis for the residuals of the demand and supply models, is chi-squared distributed within the 10 percent confidence limit for 59 degrees of freedom, indicating that the specified models adequately represent the demand and supply.

Policy Example

The models developed here can be used to assess the forecast impact of contemplated changes in airline policy prior to their implementation. For example, let the number of seats supplied by the airline on a given route change by a one-time 10 percent increase this month (i.e., at $t - 0$). Most airlines are faced with situations where they may have to provide more (or fewer) seats as a result of an unusual event (such as changes in energy prices, important national events, holidays, etc.). Sometimes, airlines offer very low prices for a limited period as an introductory offer. Other times, they intentionally increase their service level or capacity in order to dominate the market and capture more passengers. In such cases, the demand equation can be used to forecast the resulting changes in demand this month, next month, and in the months beyond.

The forecast impacts of the seat-supply policy on demand are illustrated in Figure 3. As the figure indicates, demand increases by a maximum of 2.4 percent practically at the same time with the supply increase, but decreases steadily thereafter until it falls back to its original value before it finally returns to it in the long term.

The impact analysis indicates that the effect of service change lasts 3 to 6 months but the major impact is strongest during the first month. This is typical of airline travel. In particular, conversations with airline officials reveal that most tickets are sold within the first few weeks following the service improvements. This indicates that air travelers tend to take immediate advantage of the best offer, leading to the conclusion that they may not be loyal to their airlines.

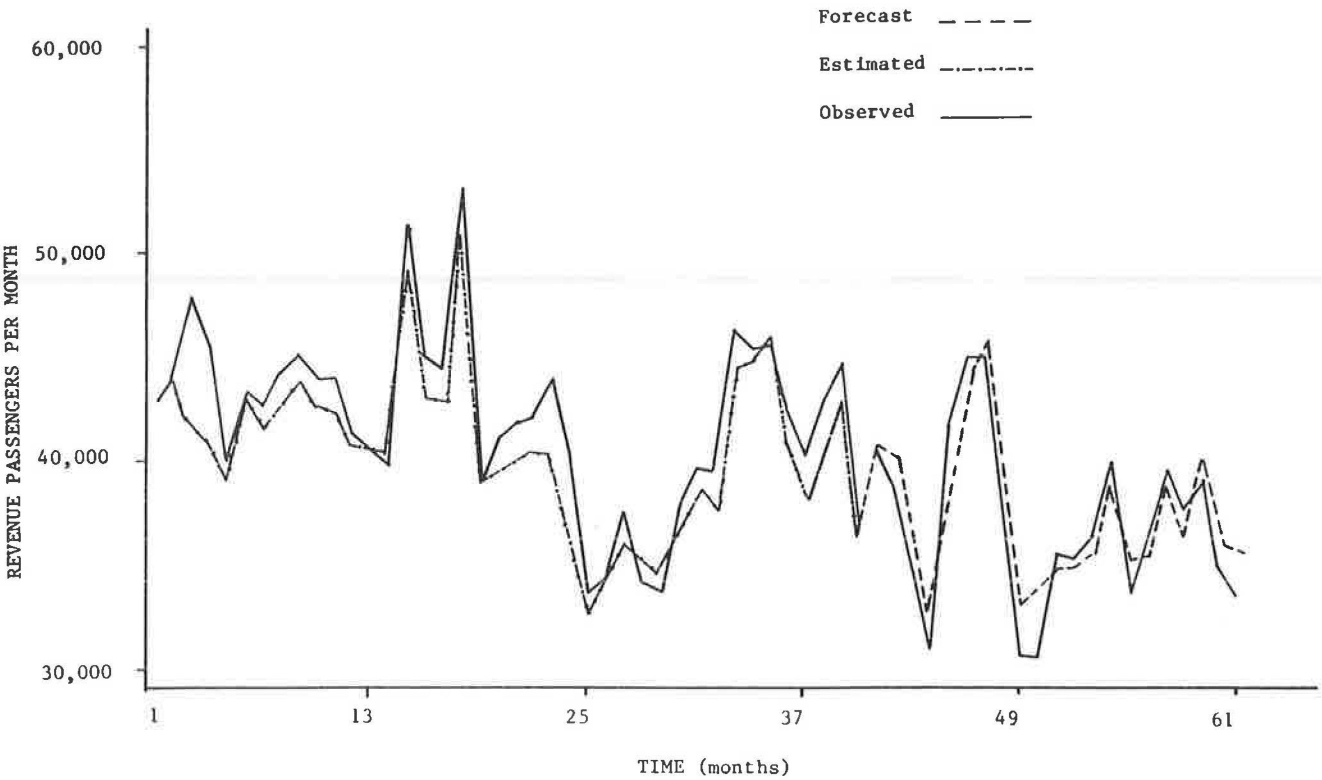

FIGURE 1 Observed and estimated values of demand.

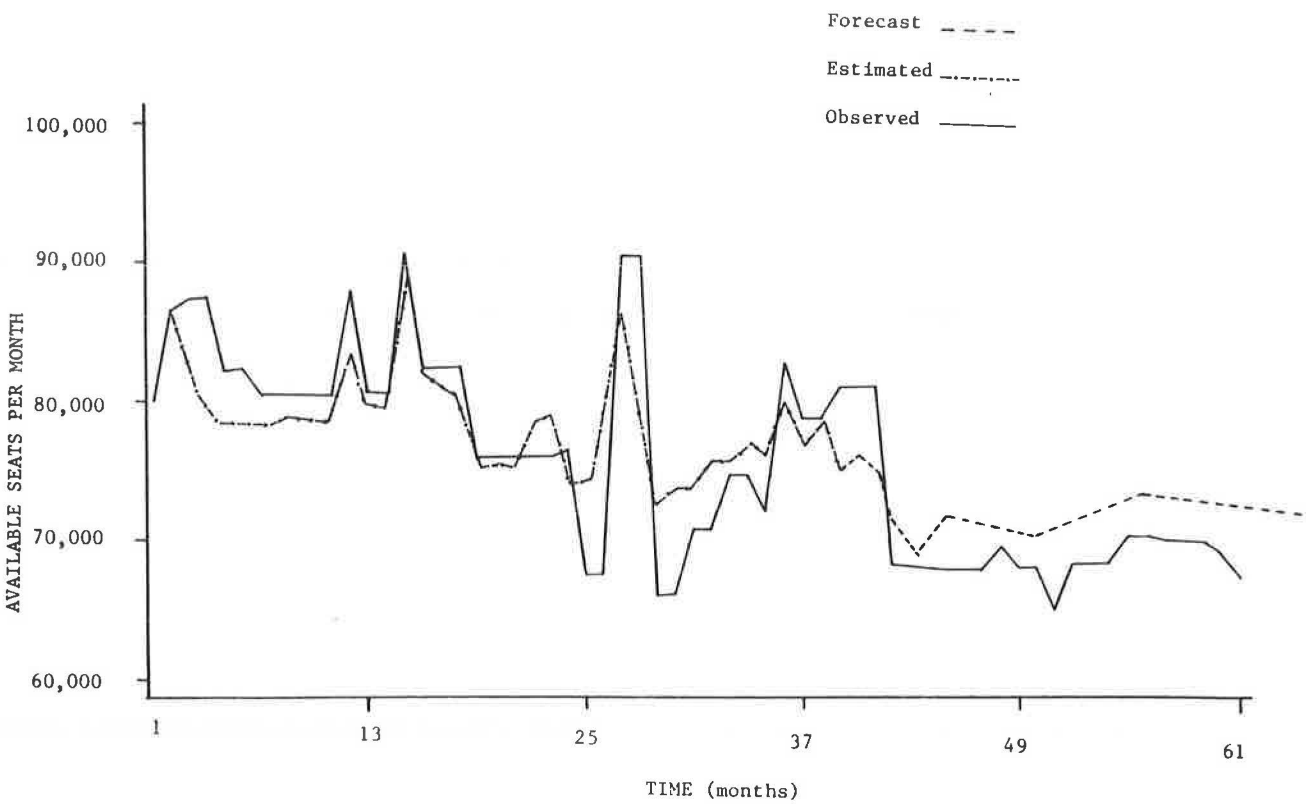

FIGURE 2 Observed and estimated values of supply.

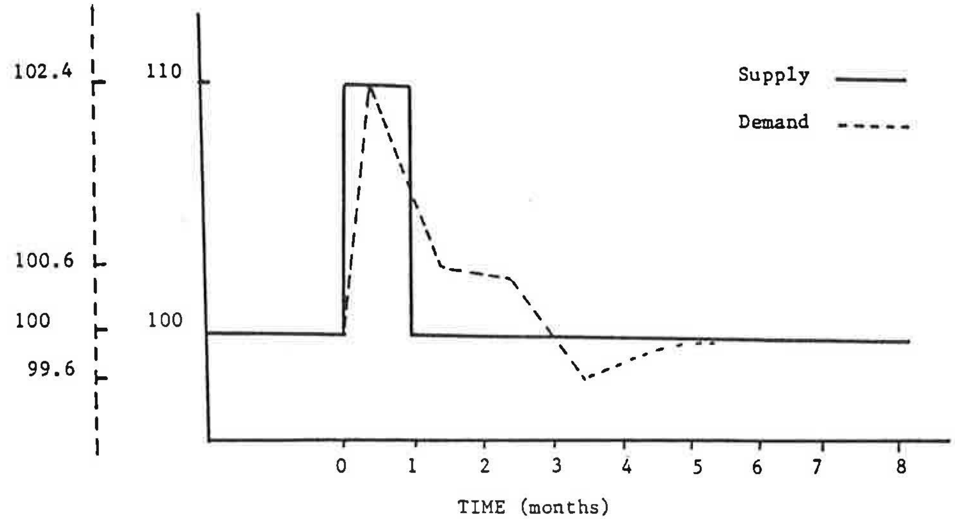

FIGURE 3 Influence of supply on demand.

The estimated impacts of air travel demand on supply are illustrated in Figure 4. As the figure indicates, a 10 percent surge in demand causes supply to increase by 1.3 percent in the second month; it then gradually decreases and finally reaches its original level by the seventh month. From Figures 3 and 4, it is also evident that the airline's reaction to a sudden surge in demand is more sluggish (the significant effect lasts longer) and slower (lags by a month) than the passengers' response to a corresponding sudden improvement in the service supplied. This impact behavior appears to be consistent with the current practices adopted by most airlines with regard to service changes. More specifically, the higher costs involved in changing the flight schedule information and reallocating the flight crew discourage most airlines from making frequent sudden changes in the service supplied.

The models developed in this research could also be used to test the impacts of different pricing policies through time. In particular, full fare and economy fare could be increased or decreased, at the same time or at different times, and their resulting impact on demand and supply studied. For instance, it was determined that fare elasticity of demand is −1.1 in the first 4 months but zero in the long term. Further, by combining these models with a ticket choice decision model, it would be possible to determine the optimum values for full fare and economy fare in order to maximize the overall profit on this route. Work along these directions is currently in progress.

CONCLUSIONS

Time-series models were developed that can be used to identify the time-dependent impacts of demand on supply, and vice versa, in nonstop air routes. Developing the models, which are based on causal relationships, required a modest amount of data that can be easily obtained from sales receipts and schedule information. The model performance is satisfactory, with average forecasting errors below 4 percent. By including seasonal data, the models could be further improved in terms of their forecasting abilities.

Application of the forecasting equations to policy analysis indicates that, although the effects of improved service (more

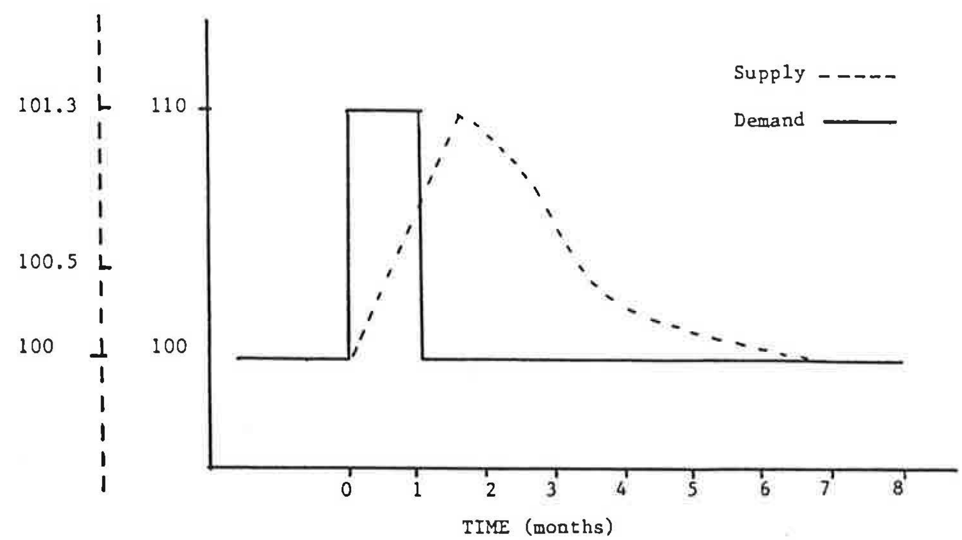

FIGURE 4 Influence of supply on demand.

seats available) on demand last for approximately 3 months, the major impact is strongest during the first month, concurrent with the service change, implying little loyalty by passengers to their airline. The policy results also indicate that the airline's reaction to a sudden surge in demand is more sluggish and lags the demand change by a month, probably as a result of the costs involved in crew and aircraft reallocations.

Current approaches adopted by most airlines in setting their pricing strategy, schedule changes, and so on, are classified. For this reason, we were unable to meaningfully compare the forecast method with the current practices followed by the airline industry.

The work presented here is only a modest attempt in developing a tool for estimating the impacts of air travel supply on demand and vice versa, through time. While the initial application is in nonstop, route-level service by one airline, the method is being extended to situations involving stops and multiple routes in intercity multimodal travel.

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