TABLE A-2 Industry-Specific Gross Output Multipliers: Buffalo Area[a] *(2)*

Sector No.	Industrial Sector Definitions	Gross Output Multiplier (M_j)
18	General building contractor, heavy construction contractor, special trade contractors	3.027
50	Electrical equipment and supplies	3.111
51	Transportation equipment	2.822
53	Transportation, communication, and utilities	2.52
54	Wholesale and retail trade	2.812
55	Finance, insurance, and real estate	2.12
56	Services	2.939

[a]Genesee County is considered part of the Buffalo economic area.

gross output multipliers (M_j; see Table A-2) and the following method of calculating industry-specific earnings multipliers: given M_j, the industry-specific gross output multiplier for industry j and earnings/gross output ratio (e_j) is calculated as follows:

$$e_j = (1/M_j)\ (E_j) + (1 - 1/M_j)$$

where e_j is the industry j's earnings/gross output ratio and E is the national earnings/gross output ratio (0.3008). Having computed e_j for each of the regional industries, then ($M_j e_j$) represents the industry-specific earnings multiplier for industry j. The industry-specific earnings multipliers reported in Table A-1 were applied to the payroll expenditure categories as well as to the expenditure categories of goods and services.

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Methodology for Forecasting Air Travel and Airport Expansion Needs

WAHEED UDDIN, B. FRANK McCULLOUGH, and MELBA M. CRAWFORD

ABSTRACT

Forecasting to assess future needs for a business or facility has become an indispensable part of the planning process. The air travel market appears to be very sensitive to the prevailing business cycles, and it demands frequent updating of forecasts. A methodology is presented for statistically forecasting airline passenger traffic and for assessing the future needs for expansion of airport facilities. Two basic approaches to develop models based on statistical fit of the historical time series data are described. The total airline passenger data collected at the Robert Mueller Municipal Airport in Austin, Texas, were used in the analyses. Several regression models developed by using annual airline passenger data show sales tax revenue as a strong predictor. The same data collected on a monthly basis are analyzed by using Box-Jenkins univariate time series models. The best fitting Box-Jenkins seasonal ARIMA model is later used to forecast airline passenger traffic for specified lead times. Forecasts for longer lead times are also made by using the selected regression equations, which indicate that around 5.5 million total airline passengers are projected for 1990. Finally, the impact of the projected air travel demand in 1990 on existing aviation and terminal facilities is examined.

Forecasting in aviation and airport planning is needed (a) for airport design, which is based on the projected level and pattern of demand; (b) to evaluate airport performance to determine how well the demand placed on an existing level is handled; (c) to prepare a master plan; and (d) for financial planning. Demand projections include volume and peaking characteristics of airline passengers; mix and number of aircraft needed for air carrier operations; terminal area requirements; ground access system, gate position, taxiway, apron, and runway requirements; and so forth. The most important of all these is total airline passenger demand, as the rest of the airport planning is based on volume and peaking characteristics of airline passengers. In this study forecast models are developed for monthly and yearly volumes of airline passengers.

The airline passenger data in this paper refer to total arriving and departing passengers on an annual or monthly basis at a given location. Such data are vital to the operating agency of a particular airport and to the commercial airlines. A methodology is presented for predicting the air travel demand and its impact on future expansion of related airport facilities by using the Robert Mueller Municipal Airport in Austin, Texas, as an example.

AIRLINE PASSENGER TRAFFIC IN AUSTIN

The airline passenger data at Robert Mueller Municipal Airport, Austin, Texas, are used in this paper as a case study to empirically compare different statistical forecasting models. The region surrounding the airport has experienced tremendous economic and urban growth during recent years, and this trend is expected to continue in the foreseeable future. The aviation and passenger handling facilities at the airport are currently being utilized at near capacity. Figure 1 shows annual airline passenger

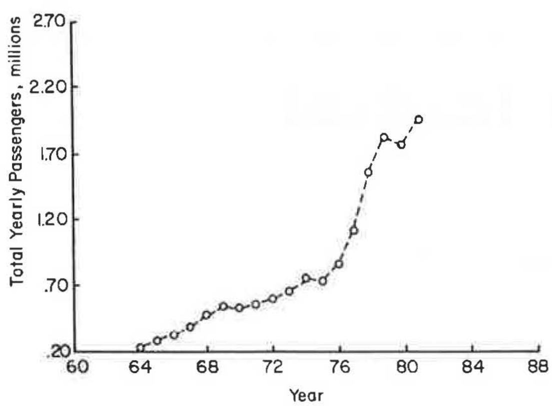

FIGURE 1 Annual airline passenger series at Robert Mueller Municipal Airport, Austin.

data from 1964 to 1982 for the Robert Mueller Municipal Airport in Austin. Exponential growth such as that observed in this figure for Austin is not uncommon in the air travel history of a rapidly growing area.

FORECASTING TECHNIQUES IN AVIATION

Forecasting is not a precise science. Reliable forecasting costs more but better knowledge of the magnitude and fluctuations of the response variable will ultimately result in satisfactory performance of an airport. Most of the approaches used in aviation forecasting fall into one of the three major categories discussed next.

Judgmental Forecasting

This is a subjective approach that relies on a survey of professional judgments, but it lacks any statistical measure. This method is not considered in this study.

Market Analysis Methods

In the market-share model, the forecast is based on a proportion of the regional or national level of activity assigned to the local level, which is assumed to be a regular and predictable quantity. In this method, the existence of a data source minimizes the cost of forecasting but it neglects abnormal growth factors at the local level and will generally underestimate the projection for an area such as Austin.

In the market-definition method, behavioral characteristics of travelers in a region are examined by separating them into distinct groups according to income, occupation, age, and so forth. Travel characteristics of each group are then studied. Forecasting is accomplished by simply projecting into the future the size of groups. It is a time-consuming and relatively expensive method that requires large samples to identify socioeconomic factors underlying travel choice. This method was beyond the scope of this study.

Statistical Techniques

Statistical modeling is widely used for forecasting air travel demands. Simple regression analysis is used to develop a trend or exponential extrapolations. A multiple regression model is the most reliable method; it relates variations in air traffic to variations of different socioeconomic factors. This approach has been used in this study to develop an annual airline passenger model.

Time-series modeling of airline passengers is also done by using the Box-Jenkins approach. The Box-Jenkins ARIMA models are stochastic process models especially useful for modeling a time series with seasonal components, as shown in Figure 2, for

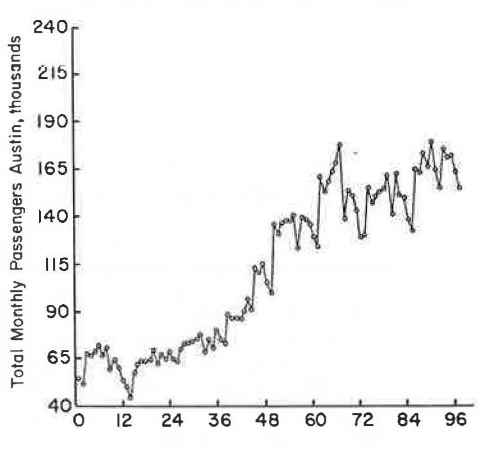

FIGURE 2 Monthly series of total airline passengers at Robert Mueller Municipal Airport, Austin.

the monthly airline passenger data for the Austin airport.

DEVELOPMENT OF STATISTICAL MODELS

Application of Time-Series Models

Time-series analysis is used extensively to model processes that exhibit dynamic characteristics over time. These models typically yield improved forecasts for problems in which the dependent variable is autocorrelated. The application of time-series models for airline passenger data is described by various authors (1-3). Box-Jenkins time-series models in this study are developed for monthly data of total airline passengers at the Robert Mueller Municipal Airport in Austin.

Box-Jenkins ARIMA Models

An observed time series can be considered as the realization of an underlying stochastic process. Box-Jenkins ARIMA models are built empirically from the observed data on three underlying process components:

1. An autoregressive (AR) component: an observed event at time t is regressed on its previous values.
2. An integrated (I) component: represents the trend in the data. Trend can be removed by differencing operation.
3. A moving average (MA) component: an observed event at time t is linearly dependent on a finite number of previous shock terms.

The mathematical theory and detailed treatment of Box-Jenkins models are contained in Time Series Analysis, Forecasting and Control (1). ARIMA model building is an iterative procedure, as shown by the flow diagram in Figure 3.

The first step is to identify the form of Box-Jenkins model that is most suitable to fit the given time series. The basic tools of the model identification are

1. A plot of the data versus time,
2. An autocorrelation function (ACF) graph of the original series, and
3. A graph of the partial autocorrelation function (PACF) of the original series.

If the series is nonstationary (indicated by a linear damping in the ACF graph), then it can frequently be made stationary by a differencing operation of an appropriate order.

At the estimation stage the model parameters are calculated and the model is then subjected to diagnostic checking. Box and Jenkins (1) recommend that in order to accept the model, the residuals must be uncorrelated and normally distributed. The chi-square statistic is used to satisfy this requirement. Graphs of the ACF and PACF of the residuals are then examined to reveal any hidden autoregressive or moving average terms not included in the initial ARIMA model. Appropriate model modifications are made by repeating the identification and estimation procedures until

1. The chi-square statistic is acceptable,
2. All autocorrelations in the ACF graph of the residuals are insignificant,
3. All partial autocorrelations in the PACF graph of the residuals are insignificant, and
4. The estimated parameters meet the required stationarity and invertibility conditions (1).

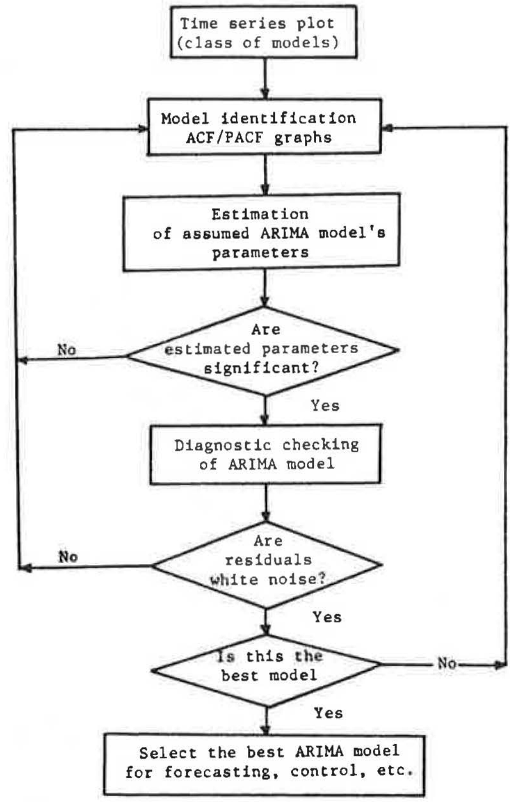

FIGURE 3 Iterative procedure of ARIMA model building.

List of Notations

The general seasonal ARIMA model for a discrete time series $Z_1, Z_2, Z_3, \ldots Z_{t-1}, Z_t, \ldots$ (measured at equal time intervals) can be represented as

$$(1 - \phi_1 B - \phi_2 B^2 \ldots - \phi_p B^p)(1 - \Phi_1 B^s - \Phi_2 B^{2S} \ldots - \Phi_N B^{Ns}) \cdot \nabla^d \cdot \nabla_s^D \cdot Z_t$$
$$= (1 - \theta_1 B - \theta_2 B^2 - \theta_3 B^3 \ldots \theta_q B^q)(1 - \Theta_1 B^{1s} - \Theta_2 B^{2s} \ldots - \Theta_n B^{ns}) \cdot a_t.$$

where

Z_t = discrete time series,
s = seasonal length,
B = backward shift operator ($B \cdot Z_t = Z_{t-1}$),
a_t = random shock term; normally distributed, independent with zero mean and variance equal to σ_a^2,
$(1 - \phi_1 B - \phi_2 B^2 \ldots \phi_p B^p)$ = regular autoregressive process of order p,
$(1 - \phi_1 B^{1S} - \phi_2 B^{2S} \ldots \phi_N B^{NS})$ = seasonal autoregressive process of order N,
∇^d = regular differencing operator of order d,
∇_s^D = seasonal differencing operator of order D,
$(1 - \theta_1 B - \theta_2 B^2 \ldots \theta_q B^q)$ = regular moving average process of order q, and
$(1 - \Theta_1 B^{1S} - \Theta_2 B^{2S} \ldots \Theta_n B^{nS})$ = seasonal moving average process of order n.

Model Identification

Visual examination of the time-series plot (Figure 2) reveals

1. A linear trend component;
2. Seasonality, as indicated by the periodic peaks (repeating every 12 months); for example, there is a peak every August, indicating high travel period, followed by a periodic sharp drop in September. Another periodic peak occurs in March, preceded by a periodic drop in February.

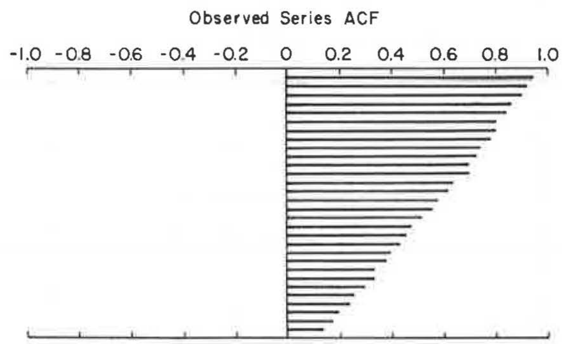

FIGURE 4 The ACF graph of original monthly series, Z_t.

The ACF graph in Figure 4 shows that the autocorrelations decreased linearly, suggesting a nonstationary process. Subsequently, several orders of regular and seasonal differences of the original series were computed and the respective ACF graphs were examined. Figures 5 and 6 show the ACF and PACF graphs of the first order regular and 6-month seasonally differenced series ($\nabla \cdot \nabla_s^6 \cdot Z_t$); this series satisfies the stationarity requirements. The peak at lag 6 in the PACF graph (Figure 6) suggests a seasonal AR term of the order 6 in the initial model. The coefficients of this model were estimated and found to be significant. The graphs of the ACF and PACF of the residuals showed significant peaks at lags 18 and 24. After different models were considered and the required diagnostic checking had been performed, the best ARIMA model was found to be of the following form:

$$\nabla \cdot \nabla_s^6 \cdot (1 - \Phi_6 B^{6s} - \Phi_{18} B^{18S} - \Phi_{24} B^{24S}) \cdot Z_t$$
$$= (1 - \Theta_6 B^{6S} - \Theta_{17} B^{17S}) \cdot a_t.$$

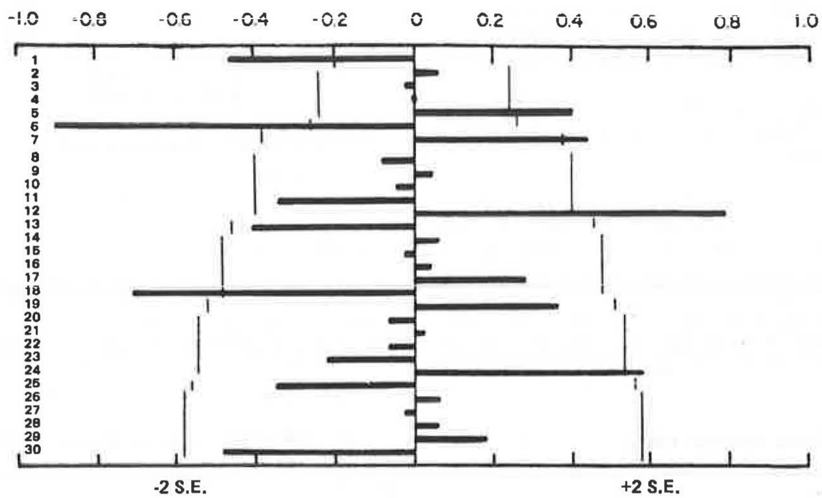

FIGURE 5 ACF graph of the first order regular and 6 month seasonally differenced series.

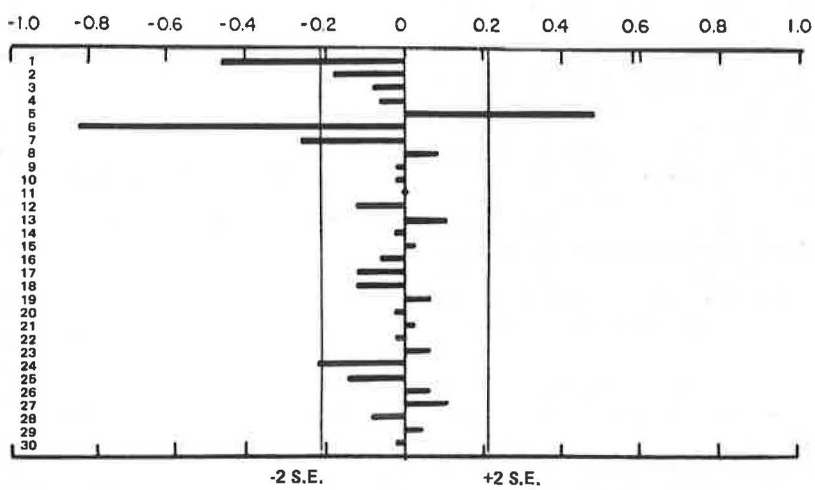

FIGURE 6 PACF graph of the first order regular and 6 month seasonally differenced series.

The ACF graph of residuals is shown in Figure 7 and shows no significant autocorrelation. Similarly,

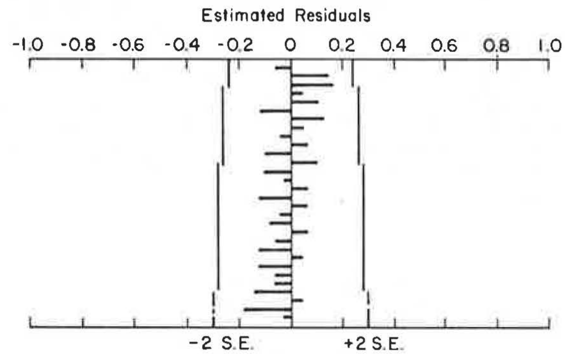

FIGURE 7 ACF graph of residuals.

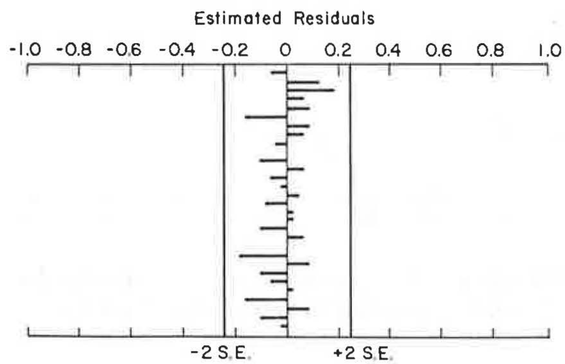

FIGURE 8 PACF graph of residuals.

the PACF graph (Figure 8) of the residuals indicates only white noise. The chi-square statistic (χ^2) is 17.290 with 25 degrees of freedom, which leads to acceptance of the null hypothesis of white noise at the 10 percent significance level.

Model Estimation

The estimated values of the parameters and their 95 percent confidence intervals are given in Table 1. Figure 9 shows the plot of the original series and the corresponding estimated series. The time-series plot (Figure 2) also indicated a possible nonhomogeneity in variance, so a log transformation of the original data was also considered. No appreciable improvement in the fit of the data was obtained. Further transformations were not considered in this study.

Application of Regression Models

It was also desired to develop predictive equations based on annual data. Because of the limited number of observations, the Box-Jenkins approach could not be applied to the annual airline passenger data (Figure 1). Regression techniques were therefore used to develop predictive equations.

Economic and Socioeconomic Factors

To develop regression equations based on past historical data for annual airline passengers, the nature of the variables that have influenced and will continue to influence travel demand must be

TABLE 1 Estimated Parameters of Box-Jenkins ARIMA Model

Parameter No.	Seasonal Parameter Type	Parameter Order	Estimated Value	95 Percent Confidence Interval Lower Limit	Upper Limit
1	Autoregressive	6	-.8002	-1.0009	-.5995
2	Autoregressive	18	-.7889	-1.0471	-.5306
3	Autoregressive	24	-.6947	-.9716	-.4179
4	Moving average	6	.3539	.1060	.6019
5	Moving average	17	-.4604	-.7191	-.2016

Note: Residual sum of squares = 2.270; number of residuals = 67; residual mean square = 3.661; residual standard error = 6050.875.

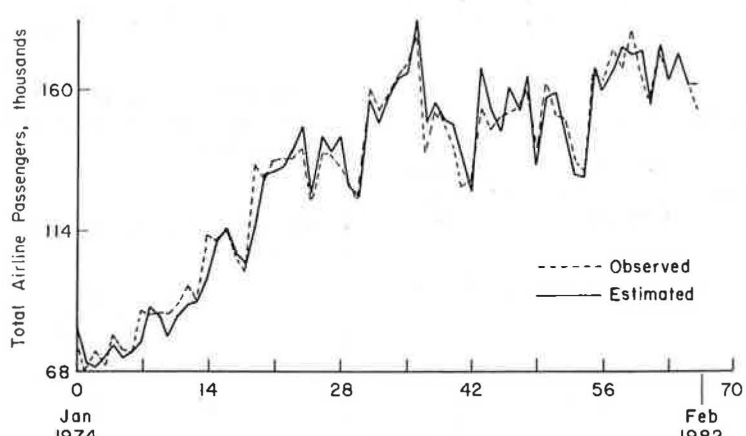

FIGURE 9 Plots of the original series and estimated series of ARIMA model.

considered. Several economic, socioeconomic, and other factors related to industrial and urban growth were considered for investigation:

1. Population (in thousands),
2. Per capita income,
3. Electricity consumption,
4. Water consumption,
5. Bank clearings,
6. Civilian work force, and
7. Sales tax revenue.

Historical annual data for all these variables were collected from the city of Austin. Figure 10 shows an exponential growth in sales tax revenue. Other variables also showed a similar growth pattern.

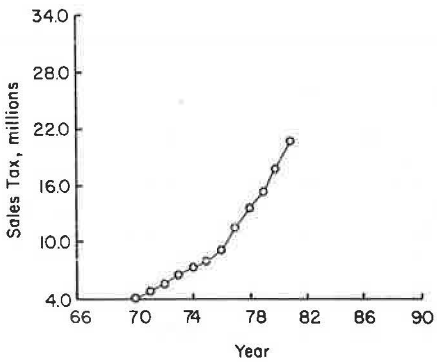

FIGURE 10 Annual sales tax revenue data, Austin.

Summary of Results

Table 2 gives predictive equations that define the relationships between annual airline passengers and some significant predictors. Equation 1 in Table 2 was developed by using the multiple linear regression technique to identify the most significant explanatory variables. This equation contains the nonzero intercept term, which is difficult to justify physically. The value of this term can be made zero by forcing the regression equation through the origin. Equation 2 was developed by using this option. The annual airline passenger plot in Figure 11 is nonlinear, and Equation 3 in Table 2 presents a nonlinear regression model. The estimated series is plotted in Figure 11. As noted in Table 2, all regression equations are associated with high R^2 values. The regression coefficients are statistically significant.

FORECASTING AIRLINE PASSENGER DEMAND

The equations discussed in the preceding section were used to forecast annual airline passenger traffic. The basic assumption underlying the forecasts is that the process and the estimated parameters are time invariant. In the regression models (Equations 1 and 2), forecasts of annual airline passenger totals were made by using the projected values for sales tax revenue and population. The forecasts of airline passengers using all three equations are shown in Figure 12. A summary of future annual airline passenger demand is given in Table 3. The forecast performed with the Box-Jenkins model was based on monthly passenger data taken from January 1976 to May 1982. The methods described by Box and Jenkins (1) for obtaining forecasts were used in this study.

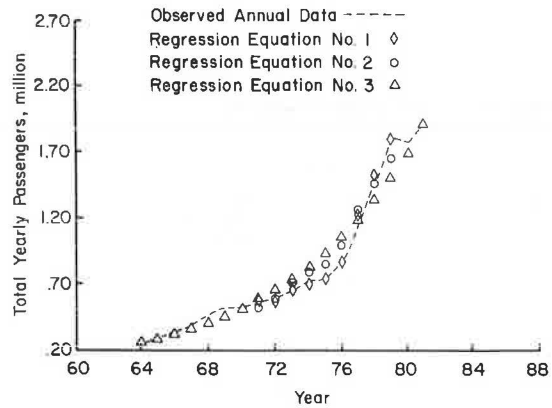

FIGURE 11 Annual airline passengers at Robert Mueller Municipal Airport, Austin—observed and estimated series.

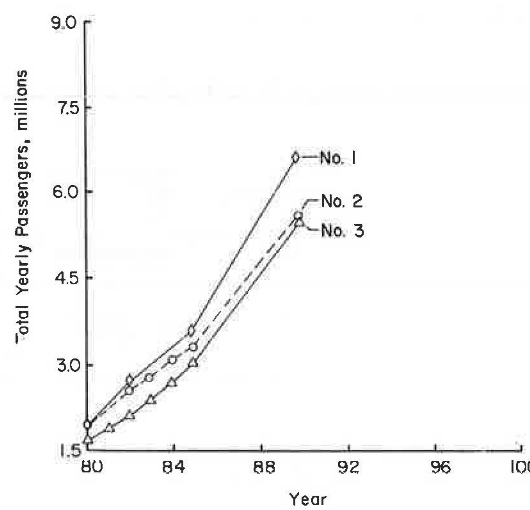

FIGURE 12 Comparison of forecasts—annual airline passenger demand at Robert Mueller Municipal Airport, Austin.

TABLE 2 Estimated Parameters of Regression Models of Annual Airline Passenger Data

No.	Equation	R^2-Value
1	$PAX = 2071959.8 + 0.1809(STR) - 6.2428(POP)$	0.987
2	$PAX = 0.1081(STR)$	0.991
3	$Log_n(PAX) = 249.79123 - 466193.63\ (1/yr)$	0.96

Note: PAX = total yearly airline passengers; STR = sales tax revenue, yearly ($); POP = population (thousands); and R^2 = explanatory power of a regression equation and is desired to be a value between 0.9 and 1.

TABLE 3 Comparison of Forecasts

Year	Equation 1	Equation 2	Equation 3	Box-Jenkins Model
1982[a]	2,701,928	2,552,165	2,142,513	2,208,899
1983[b]	-	2,801,273	2,412,337	2,390,654
1984	-	3,107,252	2,715,813	-
1985	3,590,808	3,312,896	3,057,102	-
1990	6,657,828	5,634,766	5,515,484	-

Source: Directorate of Aviation, Austin, Texas.

[a]Actual number of arriving and departing airline passengers during 1982 at Robert Mueller Municipal Airport is 2,207,519.

[b]Actual 1983 count is 2,500,621.

Figure 13 shows forecasts and their 95 percent confidence intervals for lead times up to 10 months.

Forecasts made for 1982 and 1983 and compared with the actual figures (Table 3) obtained from aviation authorities at the Robert Mueller Municipal Airport in Austin indicate the reasonable predictability of Equations 2 and 3 and the ARIMA model.

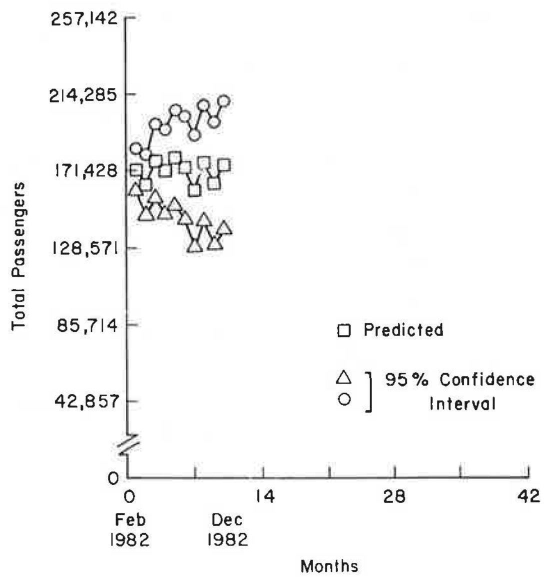

FIGURE 13 Application of ARIMA model to forecast in lead times.

ASSESSMENT OF AIRPORT FACILITIES EXPANSION

A report (4) was published that contained the results of forecasts, assessments of present facilities and future needs at the Robert Mueller Municipal Airport in Austin, and economic consequences of delaying a much needed, long-term planning program. The reaction in the community as well as among local aviation officials was very positive (5). The assessment of expansion needs is not meant to be very precise. The results of this study were reported (4) as a service to the local community.

Generally, air-travel-related facilities are designed to handle the expected number of airline passengers. These facilities include

1. Aviation facilities, such as runways, taxiways, aprons, and navigational aids for aircraft movements;
2. Terminal areas and automobile parking facilities to serve the air travellers and accompanying visitors; and
3. Adequate airspace.

The following sections outline the projected space requirements and the available facilities at the Robert Mueller Municipal Airport in Austin (6,4).

Ground Facilities and Parking Space

The terminal building of the airport and other structures, such as the traffic control tower and the concourse for the six gate positions, cover an area of 135,000 ft^2. A typical peak hour passenger (TPHP) flow of 0.04 percent of the annual flow and 24,200 ft^2 of space per 100 TPHP flow, as recommended by the FAA (7) for a domestic terminal facility, were used for the projection. The requirement projected for the 1990 estimated passengers is 484,000 ft^2. Adequate parking is an important consideration in the design of modern airports. If forecast demand is realized, the parking space required by 1990 will be about three times the present capacity, as shown in Figure 14.

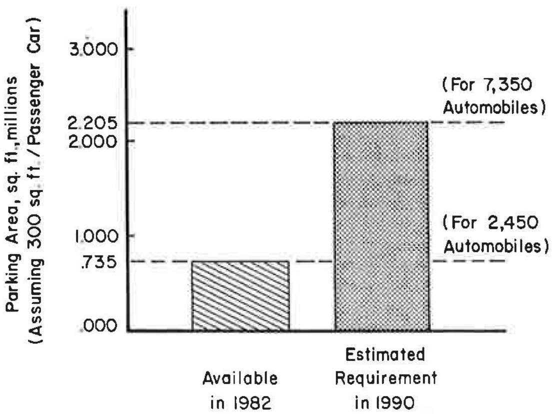

FIGURE 14 Projected automobile parking space needs at airport.

Other Aspects

Consideration must also be given to the future requirements for runway, taxiway, apron, and gate facilities. The level of passenger traffic projected will require an instrumented secondary runway suitable for air carrier operations in order to provide additional capacity and for emergency use. This implies more taxiways and apron space. These expansions will not be possible using the runway configuration at the present site. Thirty gate positions are projected for 1990 based on an approximation of five gate positions per 1 million airline passengers. The airspace requirement is a vital part of any airport planning. The existence of Bergstrom Air Force Base near the municipal airport limits the full utilization of available airspace at the present time. The proximity of Tims Airpark and the proposed plans for its expansion and instrumentation will further complicate the airspace issue.

Noise Impact and Land Requirement

A large part of Austin's urban area is directly under the approach and departure paths of the Robert Mueller Municipal Airport and Bergstrom Air Force Base. The impact of aircraft operations results in an objectionable noise level for the communities near the airport, which is a function of the duration and number of operations and the time of day. The projected increased number of aircraft will bring a larger area within the limit of objectionable noise contours. The land requirement projected for 1990 (1) is 3,000 acres, which is substantially higher than the 700 acres available at the existing site.

CONCLUSIONS AND RECOMMENDATIONS

In this paper the historical data on airline passengers at the Robert Mueller Municipal Airport in Austin, Texas, were examined, and the various economic, socioeconomic, and other factors, such as urban and industrial growth, were investigated to assess their impact on future air travel demand. Statistical models of the total airline passenger series were developed and used to make forecasts. The important findings of the research include the following:

1. The predictive models predict reasonably accurate forecasts. By 1990, the annual airline passenger demand will be around 5.5 million.
2. The present site does not provide sufficient room for long-term expansion. A large expansion in the number of gate positions, terminal facilities, and automobile parking space will be required.
3. A decisive factor in the selection of any future site for the airport should be the availability of extensive areas for land use planning and control.

The Austin City Council has formed a task force that is extensively studying all available options for the future of the Robert Mueller Municipal Airport (8), keeping in view the projections of annual airline passengers.

ACKNOWLEDGMENT

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Determination of the Appropriate Number of Taxicabs to Serve an Airport

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ABSTRACT

Airport managers constantly receive complaints from airline passengers about the suspected overcharging, poor service, and uncleanliness of taxicabs that serve the airport. Unfortunately, many airport officials find it politically and practically difficult to adequately supervise the airport curb services being offered by taxicab companies and individuals. In addition, airport taxicab groundside access has been increasingly aggravated in many U.S. cities by the relatively recent deregulation of taxicab firms and their operations. Many of these problems are directly related to the total number of taxicabs permitted to serve the airport. In the short run the demand for airport taxicab service is relatively fixed, and thus allowing too many cabs encourages overcharging and deteriorating vehicles as operators find it difficult to maintain financial viability. On the other hand, permitting too few vehicles results in excessively attractive taxicab incomes and passenger inconvenience through long delays on busy holidays and peak travel periods. In the analysis that follows, actual operation statistics and data from the Detroit Metropolitan Airport