

A MULTIVARIATE ARIMA MODEL TO FORECAST AIR TRANSPORT DEMAND

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1. INTRODUCTION

Forecast of air transport demand has a great influence on the development of airport master plans with respect both to airside (runways, taxiways, aprons, technological devices) and landside (boarding/landing area, waiting rooms, etc.), given that it depends on the amount of passengers during the reference time period, usually the year or more years for such aim.

As a result of deregulation and increases in travel opportunity, the air demand is continuously increasing, despite some negative peaks due to political and/or market driven events that reduce the user willingness to travel.

Furthermore, the offered services have quickly changed in the last years both in terms of trip organization and monetary costs, also because various alliances and mergers have occurred, together with the emergence of new air carriers on the market (Janic, 2000).

As airport managers, carriers have also a great interest in the demand modelling and simulation, particularly when there is a competitive market and users can choose among different services. The task is not easy to accomplish, given the complexity of the current situation where more air carriers can compete by offering different fares, different origin/destination airports serving the same areas, different on board services and so on.

Usually, the estimation of the air transport demand can be obtained by different models/methods, among which national(multi-mode) models, time series models and market surveys (RP – SP methods) are the most used.

Multi-mode models proposed in the literature to forecast travel demand at a national level can be used to obtain an estimate of the air travel demand, by using random utility behavioural models to simulate mode choices (see for example Cascetta *et al.*, 1995). However, they do not analyse the temporal evolution of demand nor the specificity of regional airports subject to increases in specific demand segments.

Time series models have been widely used, among the others Melville (1998), Karlaftis and Papastavrou (1998), Abed *et al.* (2001), Postorino and Russo (2001), Hensher (2002), Postorino (2003), Inglada and Rey (2004), Lim and McAleer, 2002; Ling Lai and Li Lu (2005). However, mainly simple autoregressive time series models have been used, even if with explanatory variables, while there are very few examples of ARIMA models and no one on the calibration of univariate and multivariate ARIMA models in the specific topic of the air transport demand simulation for a regional airport.

Finally, market surveys are a good sources of information, and airports as well as air carriers can collect data about passengers when they are waiting for travelling or on-board. However, only few airports regularly collect data about passengers, while data of air carriers are mainly based on customer satisfaction surveys or ticket sales information for financial purposes rather than demand

simulation.

Other techniques that could be used are Neural Networks (NN) models, a well known and widely treated tool inspired to human brain they try to simulate. Recently, fuzzy-NNs approaches have been used to forecast mode choice (Pribyl and Goulias, 2003; Sadek, *et al.*, 2003; Postorino and Versaci, 2006). However, NNs do not allow the explicit values of the parameters to be obtained, so the interpretation of the model in terms of elasticity values, parameters ratios and so on cannot be achieved.

In this work, both univariate and multivariate time series models are proposed to estimate the demand levels about Reggio Calabria regional airport (located in the South of Italy) to capture both the trend of demand and the effects induced by the different policies started at the airport. Furthermore, the hedonic pricing theory has been applied to estimate the trip fare, which despite its importance usually cannot be used because fare data are not available.

The application is particularly interesting because due to the fare policy adopted by the flag carrier operating at the airport since many years and some variations in the number and schedule of flights, particularly during the previous two years, passenger demand at the airport changed in the last ten years against expectations (a promising positive trend has been followed by a very strong demand reduction). Recent modifications started by the local airport authority in the supply (more air carriers, new destinations and lower fares) are expected to produce an increase in the air transport demand, also due to induced trips generated by the new supply.

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2. OVERVIEW OF ARIMA TIME SERIES MODELS

Time series demand models have as main aim the simulation of the demand trend for a given time period, on the basis of a known data base concerning the modeled variables.

From a theoretical point of view, a time series is a stochastic process, i.e. an ordered sequence of random variables, where the time index t takes on a finite or countable infinite set of value. Mean and variance of the stochastic process are used to describe it together with two functions: the AutoCorrelation Function (ACF) ρ_k , k being the lag, and the Partial AutoCorrelation Function (PACF) π_k , k being the lag.

The ACF is a measure of the correlation between two variables composing the stochastic process, which are k temporal lags far away; the PACF measures the net correlation between two variables, which are k temporal lags far away.

ARMA (AutoRegressive Moving Average) models are a class of stochastic processes expressed as (Box and Jenkins, 1970):

$$X_t - \sum_{i=1}^p \phi_i X_{t-i} = a_t - \sum_{j=1}^q \theta_j a_{t-j}$$

where ϕ and θ are model parameters; p and q are the orders of the AutoRegressive (AR) and Moving Average (MA) processes respectively. If the B operator such as $X_{t-1} = BX_t$ is introduced, the general form of an ARMA model can be written as:

$$\phi(B) \cdot X_t = \theta(B) \cdot a_t$$

Estimation of these models requires some conditions to be verified: the series must be stationary and ACF and PACF must be time-independent. Variance non-stationarity can be removed if the series is transformed with the logarithmic function. Mean non-stationarity can be removed by using the operator $\nabla = 1-B$ applied d times in order to make the series stationary. Such transformations lead to an ARIMA (AR Integrated MA) model:

$$\nabla^d \phi(B) \cdot X_t = \theta(B) \cdot a_t$$

The above model is also called univariate because only one variable, depending on its past values, is inserted.

For a given set of data, the Box-Jenkins approach (Box and Jenkins, 1970) is the most known method to find an ARIMA model that effectively can reproduce the data generating the process. The method requires a preliminary data analysis to verify the presence of outliers and then the identification, estimation and diagnostic checking steps.

The identification stage provides an initial ARIMA model specified on the basis of the estimated ACF and PACF, starting from the original data; particularly, the characteristics of ACF and PACF allow the identification of the model order:

1. if the autocorrelations decrease slowly or do not vanish, there is non stationarity and the series should be differenced until stationarity is obtained; then, an ARIMA model can be identified for the differenced series;
2. if ACF ρ_k is zero for $k > q$ and PACF is decreasing, then the process underlying the series is an MA(q);
3. if PACF π_k is zero for $k > p$ and ACF is decreasing, then the process underlying the series is an AR(p);
4. if there is no evidence for an MA or an AR then an ARMA model may be adequate.

Several statistical tests have been developed in the literature to verify if a series is stationary; among these, the most widely used is the Dickey-Fuller test (Makridakis *et al.*, 1998), which requires the estimation of the following model:

$$X'_t = \phi X_{t-1} + b_1 X'_{t-1} + \dots + b_p X'_{t-p}$$

where X'_t denotes the differenced series $X_t - X_{t-1}$. The number of lagged terms in the regression, p , is usually set to be 3. Then, if the original series X_t has to be differentiated, the estimated value of ϕ will be close to zero, while if X_t is already stationary, the estimated value of ϕ will be negative (Makridakis *et al.*,

1998).

The model estimation is carried out after an initial model has been identified; generally, model parameters are estimated by using least squares or maximum likelihood methods.

Finally, different diagnostic tests can be performed.

For large sample size, if the order of the AR component is p , the estimate of the partial autocorrelations π_k are approximately normally distributed with mean zero and variance $1/N$ for $k > p$, where N is the sample size. Then, it should be verified if the residuals of the calibrated model belong to a white noise process. To this aim, the significance of the residual autocorrelations is often checked by verifying if they are within two standard error bounds, $\pm 2/\sqrt{N}$, where N is the sample size (Judge *et al.*, 1988). If the residual autocorrelations at the first $N/4$ lags are close to the critical bounds, the reliability of the model should be verified.

Another test is that of Ljung and Box (1978), defined as:

$$Q = N \cdot (N + 2) \cdot \sum_{k=1}^m (N - k)^{-1} \cdot [\rho_{\hat{a}}(k)]^2$$

where $\rho_{\hat{a}}(k)$ are the autocorrelations of estimation residuals and k is a prefixed number of lags. For an ARMA (p, q) process this statistic is approximately χ^2 distributed with $(k-p-q)$ degrees of freedom if the orders p and q are specified correctly.

To check the normality of the residuals, the Jarque-Bera (JB) test (Jarque and Bera, 1982) can be used:

$$JB = \frac{N - n_p}{6} \cdot \left(S^2 + \frac{(K - 3)^2}{4} \right)$$

where S is the skewness, K the Kurtosis, n_p the number of parameters and N the sample size. This test verifies if the skewness and kurtosis of the time series are different from those expected for a normal distribution. Under the null hypothesis of normal distribution, the JB test is approximately χ^2 distributed with two degrees of freedom.

Starting from a univariate ARIMA model, some explanatory (or independent) variables can be inserted. In this case, the dependent variable X_t depends on lagged values of the independent variables. The lag length may sometimes be known a priori, but usually it is unknown and in some cases it is assumed to be infinite.

Generally, for one dependent variable and one explanatory variable the model has the form:

$$X_t = \alpha + \beta_0 y_t + \beta_1 y_{t-1} + \dots + \beta_P y_{t-P} + e_t$$

where P is the lag length. Such model is called finite distributed lag model, because the lagged effect of a change in the independent variable is distributed into a finite number of time periods. To compute P , these sequential hypotheses can be set up:

$$H_0^i : P = M - i \Rightarrow \beta_{M-i+1} = 0$$

versus

$$H_a^i : P = M - i + 1 \Rightarrow \beta_{M-i+1} \neq 0 | H_0^1, H_0^2, \dots, H_0^{i-1}$$

where M is an upper bound. The null hypotheses are tested sequentially beginning from the first one. The testing sequence ends when one of the null hypotheses of the sequence is rejected for the first time. To assess the i -th null hypothesis the test can be written as:

$$\lambda_i = \frac{SSE_{M-i} - SSE_{M-i+1}}{\hat{\sigma}_{M-i+1}^2}$$

where $SSE_{(.)}$ is the sum of the square errors for a tested lag length. λ_i is F-distributed with 1 and $(N-M+i-3)$ degrees of freedom if $H_0^1, H_0^2, \dots, H_0^i$ are true, N being the sample size of the dependent variable.

The lag length being computed, the explanatory variable can be inserted in the univariate model to derive the so-called multivariate ARIMAX model.

In the general case of more than one explanatory variable, the model is written as:

$$\nabla^d \Phi(B) \cdot X_t = \mathcal{G}(B)_t \cdot a_t + \sum_{i=0}^{P_1} \beta_{t-i}^{(1)} y_{t-i}^{(1)} + \sum_{i=0}^{P_2} \beta_{t-i}^{(2)} y_{t-i}^{(2)} + \dots$$

where: $y_{t-i}^{(j)}$ is the j -th independent variable at time $(t-i)$ and $\beta_{t-i}^{(j)}$ is the corresponding parameter.

3. THE DATA BASE

The application refers to Reggio Calabria airport, in the South of Italy, a small airport that mainly attracts people located around the city of Reggio Calabria (about 52% of the demand is resident in the municipality area) and its province (about 30%), while a little part comes from the city of Messina (Sicily island). Finally, a negligible percentage comes from the nearest provinces of the Calabria administrative region (Fig. 1).

Both univariate and multivariate models have been estimated by using the same data (Table 1), which refer to planed /enplaned passengers at Reggio Calabria airport (sources: Italian Official Statistic Institute ISTAT; Ministry of Infrastructure and Transport; Association of Italian Airports: Assaeroporti).

Table 1 - Planed/enplaned passengers at Reggio Calabria airport

Year	Pax	Year	Pax	Year	Pax	Year	Pax
1989	157225	1993	266782	1997	464161	2001	480287
1990	245711	1994	260539	1998	461091	2002	457862
1991	222571	1995	252294	1999	543041	2003	441099
1992	246306	1996	364036	2000	535264	2004	273758

Note that data referring to 2004 should be considered as outlier, because the airport was closed during the months of March, April and May 2004 for some

adjustment work on the runway.

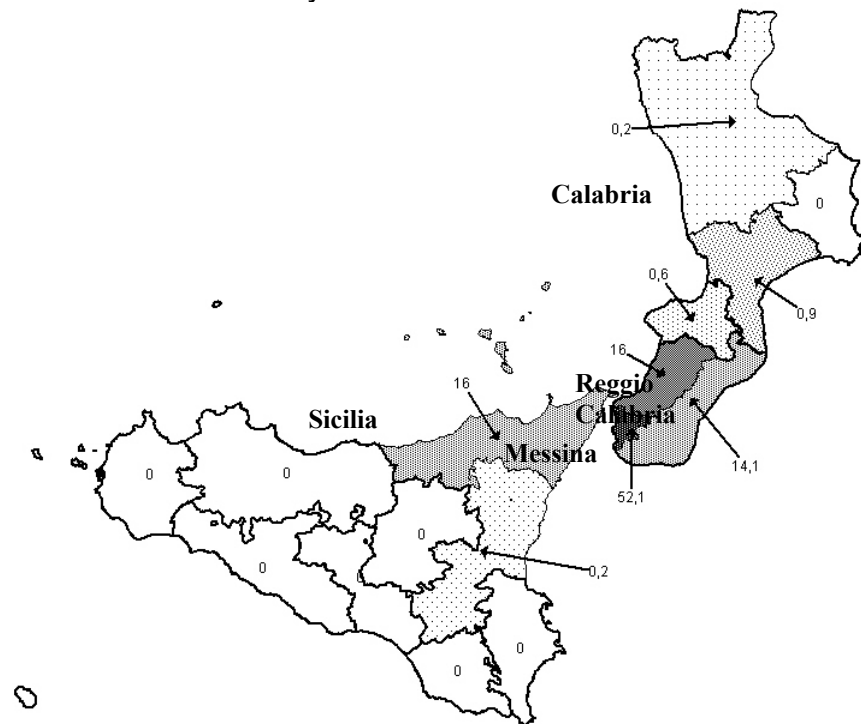


Figure 1 – Reggio Calabria airport and its catchment area (South of Italy)

Furthermore, RP surveys have been realized during the months of December 2005 and March 2006 to collect data about the main characteristics of departing passengers. Such data have been used to estimate a fare model (section 5). Some characteristics of the sample are reported in Figures 2-5. They refer to income distribution, cost refund, trip purpose, flight type.

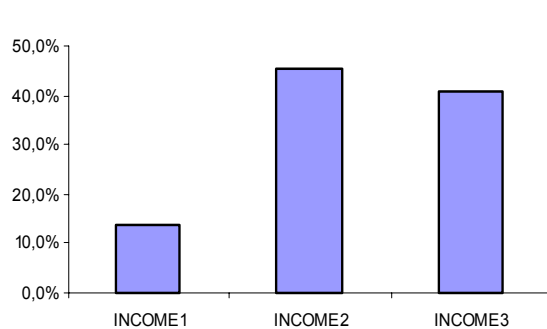


Figure 2 - Income distribution

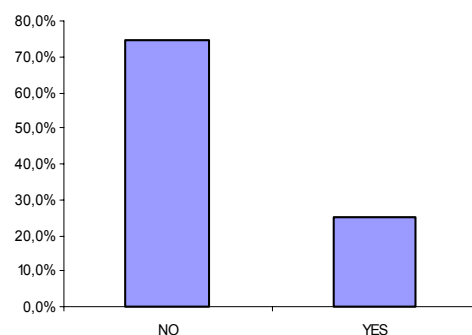


Figure 3 – Cost refund

Income has been divided into three main classes: zero (income 1), low-middle (income 2), high (income 3). Cost refund refers to the possibility that some business passengers are reimbursed, so they are less sensitive to ticket prices. However, as shown in Fig. 3 only about 25% of passengers have cost refund, even if the most part travels for business (Fig. 4). Flight characteristics refer to indirect versus non-stop flights, that are the majority (about 90%); actually, the airport is directly linked to the two main hubs of Rome Fiumicino and Milan Malpensa, from where more domestic and international destinations can be reached, and more recently to some national airports (Venice, Turin,

Bologna, Bergamo, Pisa and Genova) and one international airport (Malta).

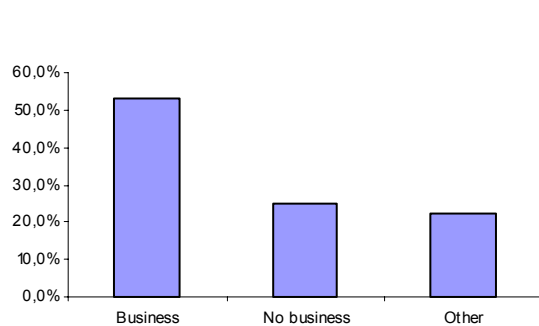


Figure 4 - Trip purpose

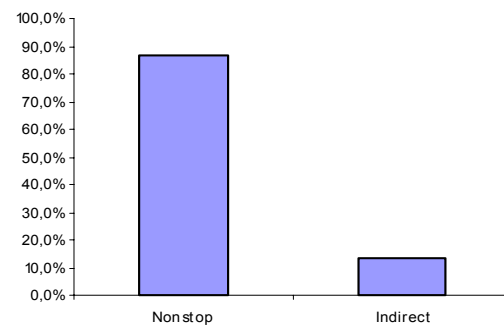


Figure 5 – Flight type

4. CALIBRATION OF TIME SERIES MODELS

Following the Box-Jenkins approach, the ACF and PACF have been estimated for the planned/enplaned passengers time series (Fig. 6). Correlograms analyses show that the ACF decreases linearly and the value of the PACF at lag 1 is close to 1, i.e. there is mean non-stationarity that has been removed by differencing once the series. The Dickey-Fuller test applied to the differenced series confirms its stationarity. To remove the variance non-stationarity the series has been transformed by using the logarithmic function.

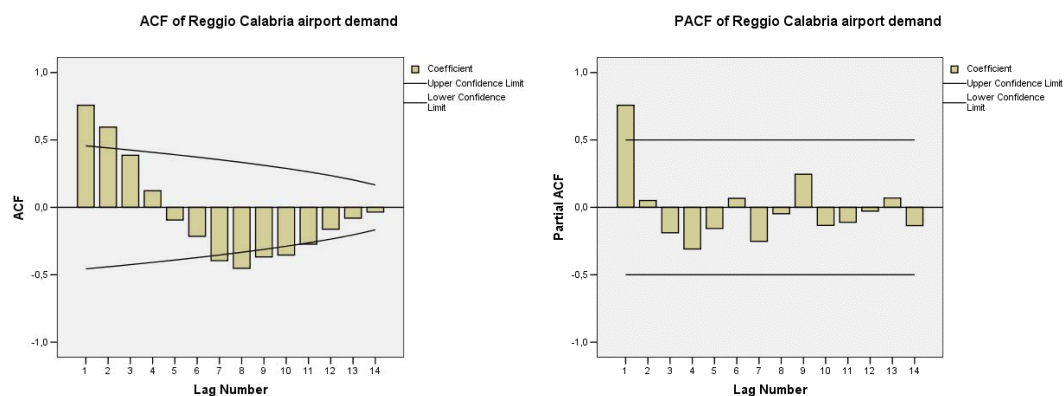


Figure 6 - ACF and PACF correlograms

The estimate of the partial autocorrelation coefficients shows that only π_1 does not fall within the two standard error bounds $\pm 2/\sqrt{N}$ (Fig. 6), so the order 1 can be established for the AR component.

The same procedure is applied to choose the MA component order by using the correlogram of the ACF, that suggests a MA(2) component. Then, from data analysis the identified general model is ARIMA(1,1,2).

4.1 Univariate models

The outlier at year 2004 suggests to estimate two univariate ARIMA (1,1,2) models: the first one without outlier (ARIMA_{SO}); the second one with the outlier suitably modified (ARIMA_{CO}).

ARIMA_{SO} estimates are reported in Table 2, and the estimated trend until year 2006 is depicted in Fig.7. Tests confirm the reliability of the model; particularly the Ljung-Box test can be considered satisfied for $k=12$ and the JB test provides a value of 0.31, i.e. the null hypothesis of residual normality can be accepted.

Table 2 - ARIMA_{SO} model parameters

	Parameter	Value
AR1	Φ	0.91
MA1	θ_1	0.86
MA2	θ_2	-0.05

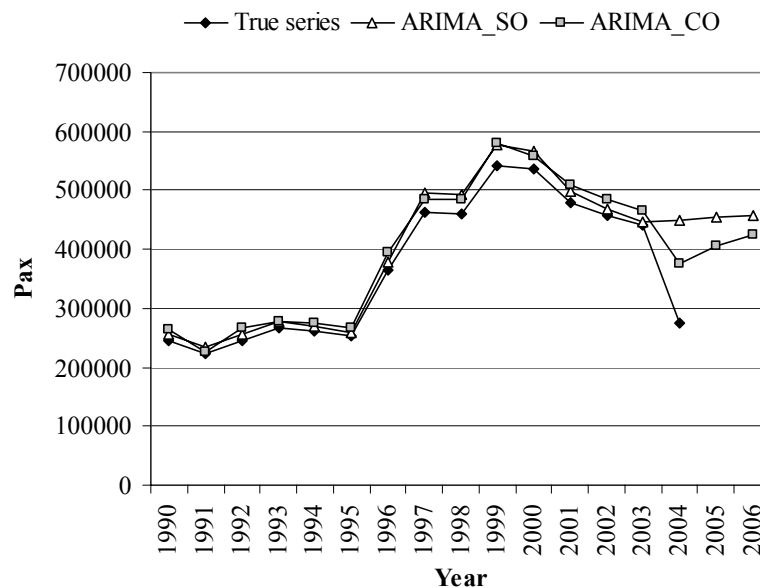


Figure 7 - True and ARIMA series

The ARIMA_{CO} requires a suitable estimate of the outlier that has been performed with a monthly AR(1) model by using the time series monthly data of the latest years. Data referred to 2004 have been estimated by the model and then the ARIMA_{CO} model has been calibrated (Table 3, Fig. 7). Again, the Ljung-Box test can be considered satisfied for $k=12$, and the JB test provides a value of 0.11, i.e. acceptance of the null hypothesis.

Table 3 - ARIMA_{CO} model parameters

	Parameter	Value
AR1	Φ	0.41
MA1	θ_1	-0.47
MA2	θ_2	-0.85
Constant	c	0.06

Comparison between the univariate models shows that both models fit well the true series and are statistically satisfactory. It is important to notice that the estimated value 2006 is practically the same for both models, so they validate mutually (Fig. 7). Moreover, the Reggio Calabria airport official passengers data for year 2005, not used to estimate the models and then considered a hold-out sample data, is 398089 (source: Assaeroporti,

www.assaeroporti.it), very close to the model estimated values.

4.2 Multivariate model

Starting from the univariate models, a multivariate model with two explanatory variables (per capita income, l_t , and yearly number of movements from/to Reggio Calabria airport, m_t) has been considered.

The sequential testing procedure described in section 2 allows the P values for both variables to be identified; particularly, the demand at year t depends on movements in the same year t and on income from year t to year $t-6$:

$$\begin{aligned} (1 - \Phi B) \nabla \ln d_t = & (1 - \vartheta_1 B - \vartheta_2 B^2) \cdot a_t + \\ & + \delta \cdot \ln m_t + \alpha_1 \ln l_t + \alpha_2 \ln l_{t-1} + \\ & + \alpha_3 \ln l_{t-2} + \alpha_4 \ln l_{t-3} + \alpha_5 \ln l_{t-4} + \\ & + \alpha_6 \ln l_{t-5} + \alpha_7 \ln l_{t-6} + \kappa \end{aligned}$$

The results of the model estimation are reported in Table 4 and Fig. 8. The time period considered for the model calibration is referred to 1990-2003, thus avoiding the outlier and allowing the capability of the model to capture the effects of supply changes to be tested, as shown in the next section.

Table 4 - Parameters of the ARIMAX model

Parameter			Value		
AR1	Φ	0.44	$\ln l_{t-2}$	α_3	0.21
MA1	θ_1	1.08	$\ln l_{t-3}$	α_4	-1.33
MA2	θ_2	-0.09	$\ln l_{t-4}$	α_5	1.22
$\ln m_t$	δ	1.22	$\ln l_{t-5}$	α_6	0.26
$\ln l_t$	α_1	-0.004	$\ln l_{t-6}$	α_7	0.002
$\ln l_{t-1}$	α_2	3.45	Constant	κ	-0.08

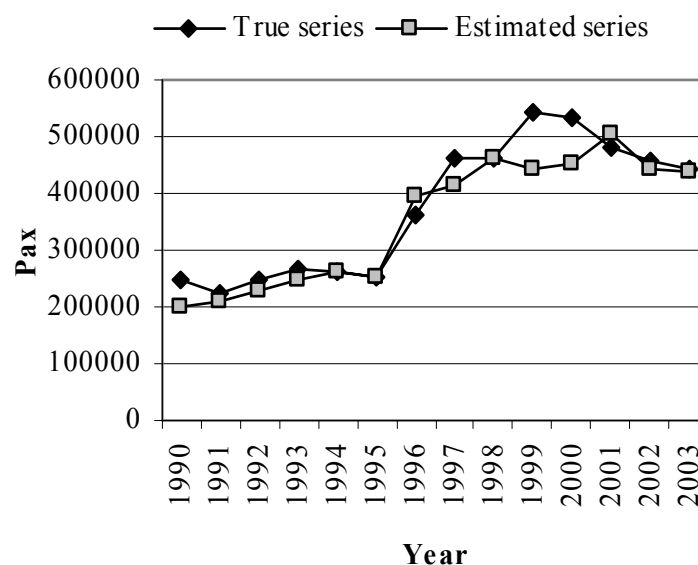


Figure 8 - True and ARIMAX estimated series

4.3 ARIMAX application tests

Some tests have been carried out in order to forecast the demand level both for the current and next year, and to verify if the potential demand increase due to the new offered services meets the capacity in terms of offered seats. Particularly, at the end of 2005 and beginning of 2006, the local airport authority has promoted the introduction of new links with low-cost carriers from/to the airport of Reggio Calabria, specifically to Venice, Turin, Bologna, Bergamo, Genova and Pisa, which add to those already existing to Rome and Milan.

Estimation of the demand level for the current year 2006 and for the next year 2007 by using the multivariate model requires the knowledge of the income and movements explanatory variables for the same years.

The income for the years 2006 and 2007 has been obtained by means of a univariate ARIMA model specifically calibrated by using the available data and the Box-Jenkins methodology, starting from the hypothesis that the boundary conditions are stable.

The number of movements for years 2004 and 2005 has been obtained by official data (source: Assaeroporti, www.assaeroporti.it), while the number of movements for the current year 2006 has been computed by assuming the available data for the first forth months, and assuming that the remaining months have the same number of movements as April. This can be considered realistic, because at the moment there is not any developing plan about new links (more destinations) or flights (increase in the frequency). The same value of movements has been considered for the year 2007, starting from the previous considerations.

The ARIMAX model applied to forecast the demand level provides respectively 709468 passengers (year 2006) and 741248 passengers (year 2007). As the estimated values show, there is a growth of 78% w.r.t. 2005, whereas for the year 2007 there is an increase of 4.5% w.r.t. 2006. These results can be considered reliable, because the first months of the year 2006 have registered a considerable increase in the number of planed/enplaned passengers at Reggio Calabria airport, due to the significant increase of the air transport offer, particularly if compared with the offered service in the previous ten years. After this encouraging answer of the demand to the new supply system for the current year, the successive more moderate increase of 4.5% agrees with the forecast demand rate provided by Eurocontrol (www.eurocontrol.int) and IATA (www.iata.org) for the European market.

Finally, in order to verify the ratio between the forecast demand level and the capacity in terms of offered seats, an estimate of the seat number for the year 2006 has been done; such value has been obtained by assuming the same hypotheses as before, i.e. the number of flights on April 2006 remains the same until December 2006. Then, 1164522 seats have been estimated; given that the estimated demand level for the same year is 709468, the average load factor is 0,61. The actual supply can be considered sufficient to satisfy the forecast demand.

Furthermore, the number of movements for the current year is completely beneath the runway capacity, and generally the landside capacity, thus suggesting a potential for the airport growing both in terms of supply and demand.

5. ESTIMATION OF THE TRIP FARE

Travel times and costs are the most used level-of-service relevant variables considered in a demand function. For air transport systems, travel times refer to flight duration; possible waiting time for connecting flights; boarding/disembarkation, baggage claim and access/egress times. Costs mainly refer to monetary costs and generally to fare.

Air fare is the most difficult variable to quantify for at least two main reasons: 1) because useful data are not always available, and 2) because there are a very large set of fare proposed by different air carriers and also inside the same air carrier. For example, many companies consider different fares depending on the day on which the ticket is bought, the time period (week-end, particular days or months in the year), the number of booked people, the age, the participation to flight programs (as frequent flyers programs) and so on. Then the problem of identifying the more suitable fare to calibrate a demand model is not a trivial one. When international trips are considered the problem is still more complex because origins and/or destinations are in different countries with different currencies while the fare has to be expressed in one reference monetary value, e.g., by using the exchange rate that, in turn, is variable during the year.

Sometimes, the yield, i.e. the mean revenue per passenger per miles, or a weighted mean of the official fares have been considered as an estimate of the fare variable. However, in the first case an increase in a particular demand market (e.g. the low income demand) has as a consequence a decrease in the yield and then the fare defined in such a way is weakly representative of the actual fare. In the second case, the mean fare could result poorly representative for some links and/or demand market requiring a great simulation effort particularly in the forecast stage.

The identification of the more suitable representative fare, particularly when the simulation period is quite large, is then really important in the whole process of demand modeling.

To overcome the problem by considering the quality of the offered service (and then, implicitly, the willingness to pay to use it), the hedonic pricing theory could be used. Its basic foundations are that users evaluate the characteristics of goods or the services it offers rather than the good itself. Following this approach, the observed fare can be considered as a function of the offered service and/or user characteristics; users are willing to pay according to the satisfaction they receive.

The trip fare can then be expressed as:

$$F = f(a, b, \dots, d)$$

where:

- F is the trip fare to move between two airports;
- f is a function to be specified;
- a, b, \dots, d are user and/or trip characteristics as comfort, timetables, accessibility, delays, frequency, and so on, which can be obtained by suitable surveys at airports.

The fare model has been specified in linear form, by using as relevant independent variables: user mean income; flight duration time; kind of air

carrier; waiting time for transfer (Table 5); the dependent variable is the declared fare. All data have been collected during the RP interview (see section 3).

Income has been specified as a three-level variables (zero, low and high income), as reported in section 3, depending on the job activity stated by interviewees. Kind of air carrier refers to flag or alternative (included low-cost) air carriers; it assumes value 1 if users choose the flag carrier and 0 otherwise. Time variables depend on the scheduled flights for the various legs and are expressed in hours. Finally, fares have been transformed by using the logarithmic function and refer to one-way trip (for return tickets the value has been divided by two).

Table 5 – Results of the fare model

Variable	Coefficients	t-Student
Income	0.88	23.93
Flight duration	1.45	26.88
Kind of airline	0.47	6.43
Waiting time	-0.82	-13.39
Statistical tests		
R ²	Adjusted R ²	
0.958	0.9579	

As Table 5 shows, all the parameters have correct signs and are statistically significant as well as the overall model (see R² and adjusted R²). Users are willingness to pay more for longer trip, but prefer direct flights or good connections, as the negative value of the waiting time variable suggests. Furthermore, despite a greater monetary cost they prefer flag carriers, probably due to the image of reliability and safety they inspire.

6. CONCLUSIONS

The comparison between univariate and ARIMAX models shows that both models provide satisfactory results, even if the univariate models fit better than the ARIMAX model when there are some peaks (Fig. 9).

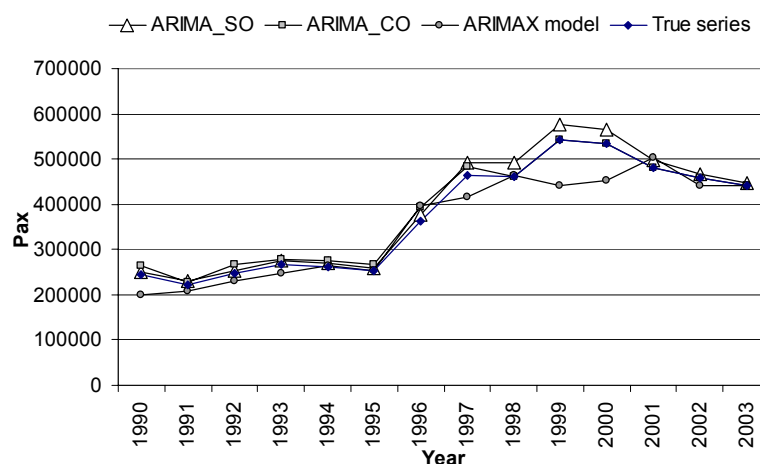


Figure 9 - Trends of the true and estimated series

However, it is not possible to assert that univariate models are better than multivariate models and vice versa. As obtained in this study, the better forecasting power of univariate models is offset by its limits of validity, which depends on the stability of the boundary conditions. Multivariate models solve this problem by using explanatory variables, whose time series, however, are often difficult to find. For this reason no more independent variables have been introduced in the ARIMAX model, given that data are not always available for the examined period. In any case, the estimated ARIMAX model shows a reasonable explanation power and it can be used to test policies about the development of the Reggio Calabria airport. Particularly, the tests carried out following the current development plan of the airport authorities are completely satisfactory and are consistent with forecasts provided by other sources (as IATA and Eurocontrol).

In terms of explanatory variables, fare is one of the most interesting but data are difficult to find. In this work a fare model based on the hedonic pricing theory has been calibrated with satisfactory results, on the basis of a RP survey conducted at Reggio Calabria airport. At this stage, the fare variable could not be inserted in the ARIMAX model, because time series of the explanatory fare model variables are not available. To obtain them, regular surveys should be conducted at the airport, but unfortunately this is a common practice only in some major U.S.A. and European airports.

Further developments concern the use of more explanatory variables, such as the number of served destinations, as well as the implementation of specific Decision Support Systems to test and evaluate the effects of different developing policies, particularly in terms of both landside capacity (due to the predicted demand increase) and airside capacity (due to infrastructure characteristics and ATC systems that set a limit to the maximum number of movements at the airports).

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