LONG-TERM AND SHORT-TERM FORECASTING TECHNIQUES FOR REGIONAL AIRPORT PLANNING

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ABSTRACT
The aim of this paper is to explore forecast passenger demand techniques in long-term and short-term perspectives at regional airports. The analysis has been applied at Bologna Airport, a large regional airport in Italy with a balanced mix of low cost traffic and conventional airline traffic. In the long-term perspective, a time series model is applied to forecast a significant growth of passenger volumes at the airport in the period 2016-2026. In the short-term perspective, time-of-week passenger demand is estimated using two non-parametric techniques: local regression (LOESS) and a simple method of averaging observations. Adopting cross validation method to estimate the accuracy of the estimates, the simple averaging method and the more complex LOESS method are concluded to perform equally well. Peak hour passenger volumes at the airport are observed in historical data and by use of bootstrapping, these are proved to contain little variability and can be concluded to be stable.

Keywords: airport, passenger demand, forecasting techniques.

INTRODUCTION
The annual number of passengers traveling with commercial air transport has increased substantially in recent years and is expected to continue increasing, with regional airports experiencing extra strong growth. Both the number of flight movements and the average load factor of each flight are increasing. In the Airbus forecast of 2015-2034, the global number of revenue passenger kilometers (RPK) is expected to double between 2014 and 2034, while the intra-Central European market is forecast to experience 4.4% annual growth (Airbus, 2015). The growth in demand for air traffic is partially driven by macroeconomic factors such as increased globalization and the change of travel behavior arising from demographic changes during economic upswings, particularly in Asian and eastern European economies. Another factor is the introduction in the 1990s of Low Cost Carriers (LCC) such as Ryanair and Easyjet, which has stimulated demand by introducing low fare flights. The price pressure has proved challenging to the established airlines, often referred to as Former Flag Carriers (FFC) or Legacy Carriers, and has led to an industry-wide lowering of fares. As airlines search to reduce costs, regional airports have experienced an increase in attractive power; since smaller and less used airports don't experience the congestion found at bigger airports, operating at these often increases productivity for the airlines. For example, in the Frankfurt-London route, Ryanair flying between Stansted-Hahn has 33% better productivity of aircraft and crew than Lufthansa has flying between the bigger airports Heathrow-Frankfurt. This is due to the less time spent being idle in queues, both on ground and in the air (Dennis, 2008). From the perspective of the management of a regional airport, the fast growth in number of passengers puts pressure on an effective planning of the capacity of the airport. Capacity improvements in airport infrastructure represents large and lumpy capital investments and long-term forecasts of passenger volumes and peak hour volumes are therefore of high importance (Jones and Pitfield, 2007; Mantecchini, 2015).

Itinerary scheduling and congestion planning are also essential aspects for the airport management. Traditionally, airports have been separated into hubs and spokes and this has determined much of the scheduling for regional airports, which are generally considered as spokes. In recent development, however, the separation between hubs and spokes has become less distinct. Within the hub and spoke-paradigm, passengers who wish to traverse between two spoke airports that are not directly connected to each other, are directed to a hub to take an interconnecting flight. In effect, hubs collect passenger demand from their connected spokes and redirects it to the desired spoke destinations. To synchronize transfers, hub scheduling is organized such that flights from spokes arrive simultaneously in a small time window and then depart in another small time window. This results in planned waves of arrivals and departures at the hubs with very concentrated passenger flows and risk of congestion. Because flight scheduling in this system is done with prioritization on time of arrival at the hub, the wave dynamics of passenger ow are less pronounced at spoke airports. This hub and spoke system used to be the system maintained by national flag carriers, as they centered their operations on one hub airport. However, LCC airlines tend not to use the paradigm of hub and spoke scheduling for cost reasons (Doganis, 2010). Since LCC is growing its share of the market, the hub and spoke separation is becoming less distinct. In light of this, it is of growing interest for airport management to understand how passenger demand varies during the week and how concentrated the passenger flows are, in order to plan operations.

Another topic of high importance for the aviation industry is its impact on the environment. (Lantieri, Mantecchini and Vignali, 2016; Postorino and Mantecchini, 2014 and 2016; Gualandi and Mantecchini, 2009)
Due to its international nature and dimension, the aviation industry is generally exempt from national CO₂-
targets established in the Kyoto Protocol and other
agreements. In combination with the heavy growth of
the industry, air transport poses a serious threat to the 2°C
target on global warming which has been set by IPCC.
Although several international organizations, for example
International Civil Aviation Organization (ICAO) and EU,
work towards implementing measures such as CO₂
emission trading and carbon neutral growth, the process
is slow. And while a lot is invested in developing more
efficient technology solutions for the industry,
technological progress in itself is unlikely to improve
the situation to a satisfying level. Bows-Larkin et al (2016)
make the conclusion that “the aviation industry’s current
projections of the sector’s growth are incompatible with the
international community’s commitment to avoiding the
2°C characterization of dangerous climate change”. They
further argue that there is a clear role for demand
management in aviation, i.e. attempting to reduce demand
by increasing fares throughout the industry.

This paper provides techniques for forecasting
passenger demand at a regional airport on long-term and
short-term basis. A long-term forecast of passenger
demand on a quarterly level is obtained using a seasonal
ARIMA time series model. A non-parametric predictive
model of passenger demand during the times of the week
is created by local regression technique (LOESS) as well
as by a simpler average value technique. Further, estimates
of the annual peak-hour passenger ow (Standard Hour
Rate and Busy Hour Rate) are obtained, and the variability
in these estimates is analyzed using bootstrapping. The
techniques are applied on data from Bologna Guglielmo
Marconi Airport, a large regional airport in the Emilia-
Romagna region of Italy that handled 6.9 million
passengers in 2015. The airport has a balanced mix of
LCC and former flag carrier traffic.

LITERATURE REVIEW

Because of its high economic relevance, the field
of forecasting air traffic demand is widely explored;
nevertheless, no single technique holds the place as a
standard method for forecasting. For example, executive
judgement, the judgement of a person with some specific
knowledge of the route or market in question, is still one
of the techniques most widely used (Doganis, 2010).
Academic research tends to focus on statistical methods
but also here the approaches differ. For example, Xie,
Wang & Lai (2014) obtained a short-term forecast of
passengers by using hybrid seasonal decomposition and
support vector regression. Profillidis uses traditional and
fuzzy regression models to forecast the passenger demand
(2000).

Previous researches on time-of-day demand have
been made, for example, by Koppelman et al (2008), who
construct a model for the desirability of a flight itinerary
based on qualitative factors including time of departure. In
this model, the time of departure is modeled both as a
dummy-variable for every hour of the day, and as a
continuous combination of sine- and cosine-functions with
estimated parameters. In short, these models indicate that
mid-morning and late-afternoon flights are preferred;
midday flights are moderately preferred while early-
morning and late-evening flights are unpreferred by
passengers. They found that the model based on sine- and
cosine-functions significantly rejects the model with hour
dummies as the true model. The authors also go on to
present a schedule delay model that values the
attractiveness of an itinerary based on how much it differs
from assumed ideal departing times. The model gives
however no insight in how the day of the week impacts the
desirability of a flight.

METHODOLOGY

A time series is a data series \( \{y_t\}_{t=1}^T \) collected
with equal time steps \( t = 1,\ldots,T \). By fitting a model, such as
the ARIMA, to the data, forecasts of future values of \( y_t, t > T \)
can be obtained. Below, important concepts in the
analysis of time series are introduced, closely following
Tsay[14].

In the analysis of time series, stationarity and weak
stationarity are two important properties. A time series
\( \{Y_t\}_{t=1}^T \) is said to be strictly stationary if the joint
distribution of \( y_{i_1},\ldots,y_{i_k} \) is invariant under time shifts, i.e.
that the joint distribution of \( y_{i_1},\ldots,y_{i_k} \) is identical to
\( y_{i_1+\delta},\ldots,y_{i_k+\delta} \) for all \( i \) and \( k > 0 \). Strict stationarity is a strong
condition, which is hard to verify in practice. In
applications, it often suffices to verify that a time series is
weakly stationary. A time series \( \{y_t\}_{t=1}^T \) is said to be
weakly stationary if the mean and autocovariance of \( y_t \)
are time-invariant, i.e. if

\[
E(y_t) = \mu \quad \text{and} \quad \text{Cov}(y_t, y_{t-i}) = \gamma_i
\]

for \( t = 1,\ldots,T \).

The autoregressive integrated moving average model,
ARIMA\((p, d, q)\), is formulated as

\[
(1 - \sum_{i=1}^{p} \phi_i B^i)(1 - B)^d y_t = \left(1 - \sum_{i=1}^{q} \theta_i B^i\right) \epsilon_t
\]

where \( B \) is the lag operator, i.e. an operator that returns
the previous element in the time series \( By_t = y_{t-1} \). The
parameter \( p \) represents the number of lags present in the
autoregressive part of the model, \( D \) represents the order of integration and \( q \) represents the order of the moving
average part of the model. \( \{\epsilon_t\} \) is assumed to be a white
noise series with mean zero and variance \( \sigma^2 \).

Several alternative methods exist to test for
stationarity in an observed time series. Examples include
Augmented Dickey-Fuller (ADF) test, Phillips-Perron
(PP) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS)
test. In this work, we will stick to the ADF test. The model
with lag \( p \) is formulated as:

\[
y_t = \phi y_{t-1} + \beta_1 \delta y_{t-1} + \ldots + \beta_p \delta y_{t-p} + \epsilon_t
\]
The ADF tests the hypothesis $H_0: \phi = 0$ and $H_1: \phi < 0$. In other words, the null hypothesis is that the time series has a unit root while the alternative hypothesis states that it is a stationary process. The test should be performed with various values of $p$ in order to account for different autoregressive lags in the model. The actual test is performed with a calculated test statistic versus tabulated values of a non-standard distribution (Tsay, 2005).

The Akaike Information Criterion (AIC) is an information criterion used to determine the optimal setup of coefficients in a regressive model. Based on the AIC criteria, the model that corresponds to the lowest value of AIC should be selected to represent the data.

AIC is defined as:

$$AIC = -\frac{2}{T} \ln(\text{likelihood}) + \frac{2}{T} \cdot k$$

Here, likelihood is the maximum likelihood for parameters of the model. Based on the AIC criteria, the model that corresponds to the lowest value of AIC should be selected to represent the data.

Time series that are measured on a cyclical basis over the year typically follow a heavy seasonal pattern and the time series model needs to be adjusted to capture this; a common method to handle the serial correlation of the time series model needs to be adjusted to capture this; a further seasonal differencing can be applied as:

$$\Delta_s(\Delta y_t) = (1 - B^s) \Delta y_t = \Delta y_t - \Delta y_{t-s} = y_t - y_{t-1} - y_{t-s} - y_{t-s-1}$$

With seasonal differencing as well as seasonal autoregressive and moving average terms, the seasonal model ARIMA(p,d,q) x (P,D,Q)s is formulated as:

$$\left(1 - \sum_{i=1}^{p} \phi_i B^i\right)\left(1 - \sum_{i=1}^{P} \Phi_i B^i \right)(1 - B)^d y_t = \left(1 - \sum_{i=1}^{q} \theta_i B^i\right)\left(1 - \sum_{i=1}^{Q} \Theta_i B^i \right)a_t$$

The airline model is a special case of seasonal time series ARIMA(0,1,1) x (0,1,1)s, which is used as an example by Box, Jenkins and Reinsel (1994). It is formulated as:

$$(1 - B)(1 - B^s)y_t = (1 - \theta B^s)(1 - \Theta B^s)a_t$$

where $a_t$ is a white noise with variance $\sigma_a^2$, $\theta$ and $\Theta$ are positive constants $< 1$. This is however not necessarily the model that best fits the data in this work. Maximum likelihood is commonly used to estimate time series models (Tsay, 2005).

Local regression models (LOESS) can be used in order to find the relationship between a dependent variable $y$ and independent variables $t$ in a setting where it's not practically possible to find a closed form function to describe the relationship. The following theory follows Cleveland (1979).

We let $y_i$ for $i = 1,...,n$ be observations of a dependent variable and let $(t_i, s_i)$ for $i = 1,...,n$ be corresponding independent variables. We further assume that the data $y_i$ has a relationship to $t_i$ that can be expressed as $y_i = g(t_i) + e_i$ and that the errors $e_i$ are assumed to be independently identically normally distributed with mean 0 and variance $\sigma^2$. The difference from classical regression models, however, is that $g(t)$ does not need to belong to a parametric class of functions such as polynomials, but it succeeds that $g(t)$ is a smooth function of the independent variables $t$.

We let $b(t)$ be a vector of polynomial terms in $t$ of degree $d$. At each query point $t_0 \in \mathbb{R}^d$, we estimate the fit:

$$\hat{f}(t_0) = b(t_0)^T \hat{\beta}(t_0)$$

This is done by solving the minimization problem:

$$\min_{\beta(t_0)} \sum_{i=1}^{n} K_h(t_0, t_i)(y_i - b(t_i)^T \beta(t_0))^2$$

Where $K$ is a weight function, or kernel. It is defined as:

$$K_h(t_0, t) = W\left(\frac{|t_0 - t|}{h}\right)$$

where $h$ is a distance parameter which has to be chosen and $W(t)$ is a weight function, usually the “tricube” function:

$$W_{\text{tricube}}(u) = \begin{cases} (1 - |u|^3)^3 & \text{if } |u| < 1 \\ 0 & \text{otherwise} \end{cases}$$

In effect, this means that all points within the distance of $h$ are given weights $K_h(t_0, t) > 0$ with diminishing weights the farther the point is from the evaluated point $t_0$. Zero weight is given to all points beyond the distance $h$.

The parameter $h$ is called the bandwidth and is a free parameter in the local regression model. A large bandwidth makes the regression average over more observations, which implies lower variance but a higher...
bias, $h$ can either be the distance of the $k$-nearest 
neighbour to $t_0$, or a specified metric distance window 
around $t_0$.

**CASE STUDY**

Two different datasets have been used in this 
paper. The first dataset consists of passenger volumes 
registered at the Airport of Bologna on a quarterly basis 
from 2007 until 2015. The start year 2007 is chosen since 
this was the year that LCC-airlines started operating at 
the airport, which had a major impact on passenger volumes. 
This dataset is an aggregate of arrivals and departures, and 
does not separate LCC-airlines from other airlines. This 
dataset is used to calibrate the time series and form a long 
term forecast.

The second dataset consists of passenger figures 
for every flight at the Airport of Bologna during 2013-
2015. This dataset enables separation between arriving 
and departing flights, separation between LCC and FFC 
airlines, as well as a seasonal separation between summer 
and winter. Following the standard at the Airport of 
Bologna, summer scheduling takes place between 15th of 
April and 15th of October, while the rest of the year has 
winter scheduling.

In order to forecast passenger demand between 
2016 and 2026, an ARIMA($p,d,q$) x (P,D,Q)$_d$ time series 
model is estimated on quarterly passenger data from 2007-
2015.

The ARIMA($p,d,q$) x (P,D,Q)$_d$ model includes 
seasonal lags and the number of lags $p$, $P$, $q$ and $Q$ are 
determined by the Akaike Information Criterion (AIC).

With the objective to find the relative density of 
departing passenger demand during the time of the week, a 
predictive model is trained from intraday data in the 
detailed data set covering all flights from 2013-2015. A 
significant portion of the passengers at Airport of Bologna 
travel with LCC airlines. These depart at fix hours during 
the day (typically close to 6 a.m., 10 a.m. and 8 p.m.). It 
can be assumed that these passengers chose their flights 
because of its ticket fare rather than that it suits their 
preferred embarking time.

Passengers who chose to travel with the FFC 
airlines are generally less price sensitive, and therefore 
their chosen departure time has a closer relation to the 
actual demand of flights. For this reason, LCC airlines 
have been removed from the data set so that it only covers 
FFC airlines.

Some modification has been done to the data set. 
The data set covers 159 weeks, over a period where the 
annual number of passengers has grown by 11%. This 
implies that the weeks will not have identically distributed 
numbers of passengers. To account for this, the passengers 
at each hour are measured as percentage of the number of 
passengers during the week, which will neutralize the 
trend from the data. In order to avoid heteroskedasticity, 
logarithmic values of the observations are used. Due to 
this, observations with zero passengers are removed. To 
account for this, the values at each time point are scaled 
proportionally to how large fraction of the observations 
that are zero in that time.

In order to obtain the predictive model, two 
methods are used and evaluated. One modelestimates the 
mean number of passengers per hour at each fifteen 
minutes interval of the week, and the mean is then used for 
prediction. Another model is obtained with the LOESS 
method to predict new data points for each fifteen minute 
period.

**RESULTS**

The observed and differenced volume of 
passengers at the Airport of Bologna can be seen in 
Figures 1 and 2. There is a clear trend in the non-
differenced data but the differenced data appears to have 
mean zero and constant variance.

![Figure-1](image1.png)  **Figure-1.** Observed passenger volumes on quarterly basis (2007-2015).

![Figure-2](image2.png)  **Figure-2.** Differenced passenger volumes on quarterly basis (2007-2015).

In order to validate this, the ADF test is 
performed for various lags in the autoregressive term $p$ to 
show stationarity. The results are shown in Table-1.

The ADF test concludes that the non-differenced 
data series has a unit root but that the differenced value of 
passengers are stationary. In light of this, a difference 
operator $d = 1$ will be included in the model.
Table-1. ADF test results for AR lags 0-2.

<table>
<thead>
<tr>
<th>Model</th>
<th>Result ADF</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obs. p=0</td>
<td>Unit root</td>
<td>0.52</td>
</tr>
<tr>
<td>Obs. p=1</td>
<td>Unit root</td>
<td>0.50</td>
</tr>
<tr>
<td>Obs. p=2</td>
<td>Unit root</td>
<td>0.97</td>
</tr>
<tr>
<td>Diff. p=0</td>
<td>Trend stationary</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Diff. p=1</td>
<td>Trend stationary</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Diff. p=2</td>
<td>Trend stationary</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

A seasonal ARIMA(p;d;q) x (P;D;Q)s model with degree of seasonal component s = 4 and seasonal and non-seasonal integration d = 1 and D = 1 is formulated. In order to determine the optimal number of lags in the model, an exhaustive comparison between models with all possible combination of lags p, q, P, Q up to 6 steps has been performed. The models are fitted on the data, and corresponding AIC is calculated. The model with the lowest AIC is found to be of the form ARIMA (0;1;1) x (0;1;1)_4:

\[(1 - B) (1 - B^4) y_t = (1 - 0.2048 B) (1 - 0.5119 B^4) u_t.

In order to test the performance of the model ARIMA (0;1;1) x (0;1;1)_4, it is set to forecast 2014 and 2015 after being estimated from the data points 2007-2013. The forecast is shown in Figure 3 along with the actual values for 2014 and 2015.

A forecast between 2016 and 2026 is made from the estimated model, and is shown in Figure-4 (the blue line indicates the sum of the previous 4 quarters on a rolling basis). The model suggests a heavy growth of passenger demand at the airport, reaching above 11 million annual passengers in 2026, corresponding to an annual growth rate of 4.77%.

Figure-4. Forecast of passengers on a quarter basis.

In order to find the density of passenger demand during the week, two non-parametric models have been estimated. The first model is computed by taking the average passenger volume at each hour of the week and the second model is estimated with local regression. The resulting models are shown in Figures 5-8.

Figure-5. Time of the week demand model (average method - winter).

Figure-6. Time of the week demand model (average method - summer).
The test error rate in the models is estimated using 10-fold cross validation. As can be seen in Table-2, the MSE is fairly similar for the two methods, even though very different techniques are used in order to obtain them.

Table-2. Cross validation for time of the week models.

<table>
<thead>
<tr>
<th>Season</th>
<th>Method</th>
<th>Cross validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td>Local regression</td>
<td>2.97212 x 10^{-5}</td>
</tr>
<tr>
<td>Summer</td>
<td>Local regression</td>
<td>1.70344 x 10^{-5}</td>
</tr>
<tr>
<td>Winter</td>
<td>Average method</td>
<td>2.96291 x 10^{-5}</td>
</tr>
<tr>
<td>Summer</td>
<td>Average method</td>
<td>1.70835 x 10^{-5}</td>
</tr>
</tbody>
</table>

CONCLUSIONS

The time series models considered in this paper performs well and forecasts a significant growth of passenger volumes at the case study airport. In 2026, the number of annual passengers is forecast to succeed 11 million, compared to 6.9 million in 2015, after having grown with an average annual rate of 4.77%. Regarding the time-of-week curves, it can be concluded that the LOESS method does not have any advantage in accuracy over the averaging method, even if the two approaches are significantly different. Further, the findings of Koppelman et al can be confirmed since mid-morning and late-afternoon flights are preferred, midday flights are moderately preferred while early-morning and late-evening flights are unpreferred.

REFERENCES


