VOL. 12, NO. 3, FEBRUARY 2017 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

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 CO_2-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 CO_2 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,..,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 $y_{t1},...,y_{tk}$ is invariant under time shifts, i.e. that the joint distribution of $y_{t1},...,y_{tk}$ is identical to $y_{t1+t},...,y_{tk+t}$ for all t 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 $E(y_t)=\mu$ and $Cov(y_t; y_{t-l})=\gamma_l$ for $t = 1,...,T$.

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

$$\left(1-\sum_{i=1}^{p}\phi_i B^i\right)(1-B)^D y_t = \left(1-\sum_{i=1}^{q}\theta_i B^i\right)a_t$$

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. $\{a_t\}$ is assumed to be a white noise series with mean zero and variance σ_a^2.

Several alternative methods exist to test for stationarity in an observed time series. Examples include Augmented Dickey-Fuller (ADF) test, Phillips-Pernon (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:

$$y_t = \phi y_{t-1} + \beta_1 \delta y_{t-1} + ... + \beta_p \delta y_{t-p} + a_t$$

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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. For a model with *k* estimated parameters, used on a sample of *T* observations, AIC is defined as:

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

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 y_t is to use differentiation. However, when the time series has a seasonal pattern of *s* steps, it will also have a high autocorrelation at lags *ks* for *k* = 1, 2,… To adjust the time series for this behavior, 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:

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

The airline model is a special case of seasonal time series ARIMA(0,1,1) x $(0,1,1)_4$, which is used as an example by Box, Jenkins and Reinsel (1994). It is formulated as:

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

where a_t is a white noise with variance σ_a^2, θ and Θ 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 $(t_i,…,t_p)$ 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 $y_i = g(t_i) + \varepsilon_i$ and that the errors ε_i are assumed to be independently identically normally distributed with mean 0 and variance σ^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 su_ces 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 $t_0 \in R^d$,
we estimate the fit:

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

This is done by solving the minimization problem:

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

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

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

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

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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 $(P;D;Q)_4$ time series model is estimated on quarterly passenger data from 2007-2015.

The ARIMA(p;d;q) x $(P;D;Q)_4$ 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 (typicallyclose 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.

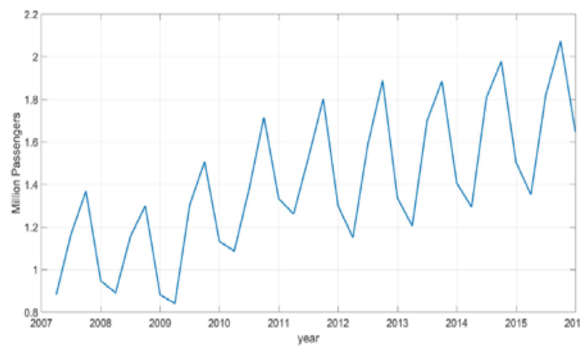

Figure-1. Observed passenger volumes on quarterly basis (2007-2015).

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.

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Table-1. ADF test results for AR lags 0-2.

Model	Result ADF	p-value
Obs. p=0	Unit root	0.52
Obs. p=1	Unit root	0.50
Obs. p=2	Unit root	0.97
Diff. p=0	Trend stationary	< 0.001
Diff. p=1	Trend stationary	< 0.001
Diff. p=2	Trend stationary	< 0.001

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 $(0;1;1)_4$:

$$(1-B)^1\left(1-B^4\right)y_t=(1-0.2048B)\left(1-0.5119B^4\right)a_t$$

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.

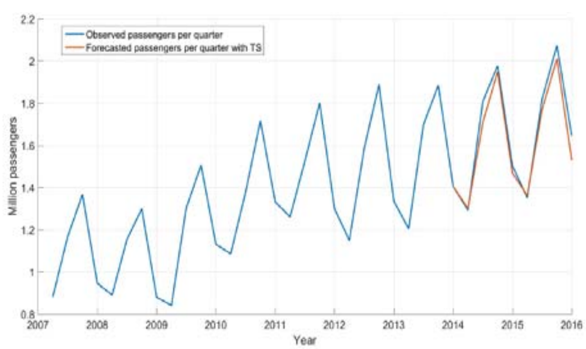

Figure-3. Performance of time series model.

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%.

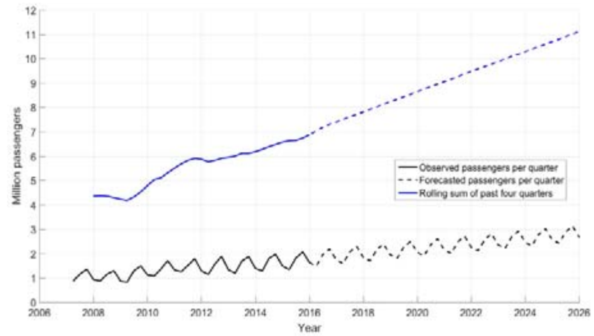

Figure-4. Forecast of passengers on a quarter basis.

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.

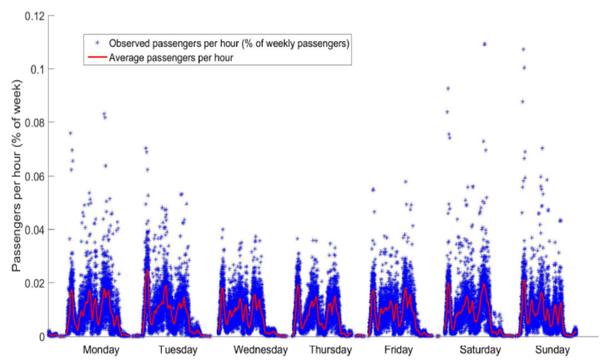

Figure-5. Time of the week demand model (average method - winter).

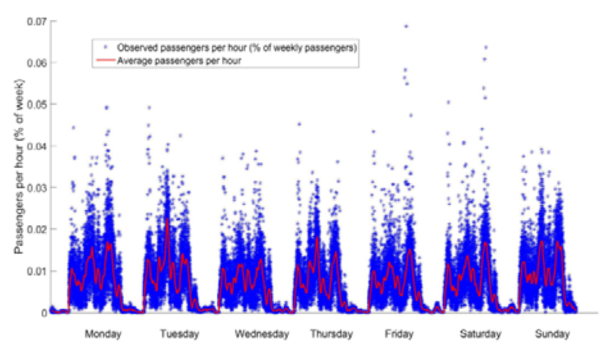

Figure-6. Time of the week demand model (average method - summer).

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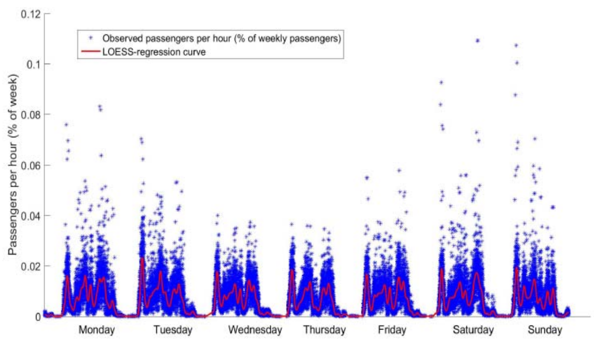

Figure-7. Time of the week demand model (LOESS method - winter).

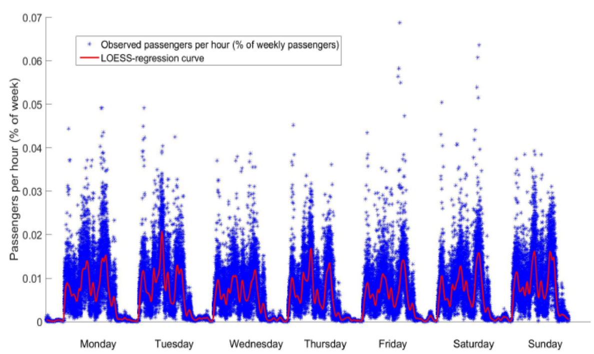

Figure-8. Time of the week demand model (LOESS method - summer).

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.

Season	Method	Cross validation
Winter	Local regression	2.97212×10^{-5}
Summer	Local regression	1.70344×10^{-5}
Winter	Average method	2.96291×10^{-5}
Summer	Average method	1.70835×10^{-5}

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.

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