Unit Load Devices (ULD) Demand Forecasting in the Air Cargo for Optimal Cost Management

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Abstract:
In recent decades, the airline industry has become very competitive. With the advent of large aircraft in service, unit load devices (ULD) have become an essential element for efficient air transport. They can load a large amount of baggage, cargo or mail using only one unit. Since this results in fewer units to load, saving time and efforts of ground crews and helping to avoid delayed flights. However, a deficient loading of the units causes operating irregularities, costing the company and contributing to the dissatisfaction of the customers. In contrast, an excess load of containers is at the expense of cargo. In this paper we propose an approach to predict the demand for baggage in order to optimize the management of its ULD flow. Specifically, we build prediction models: ARIMA following the BOX-JENKINS approach and exponential smoothing methods, in order to obtain more accurate forecasts. The approach is tested using the operational data of flight processing and the results are compared with four benchmark method (SES, DES, Holt-Winters and Naive prediction) using different performance indicators: MAE, MSE, MAPE , WAPE, RMSE, SMPE. The results obtained with the exponential smoothing methods surpass the benchmarks by providing more accurate forecasts.

Keywords: *Air Transport, ULD, Machine Learning, ARIMA, Exponential Smoothing*

1. Introduction

With the increasing importance of air cargo [1], many traditional airlines have shifted from simple passenger carriers to ”combined” carriers (cargo and passengers). Although passenger traffic remains the main source of revenue for mixed carriers, air cargo transport has become an increasingly important source of revenue for these companies.

Usually, airlines use the bunkers of their passenger plane to transport goods. Thus, the delivery of freight for these carriers is strongly influenced by several factors, as the number of the passengers, the flight schedule, the routing and the amount of baggage each passenger can bring.

For these companies, it is very common to only load freight into the space remaining in the bunkers after the total loading of all the passenger baggage. Therefore, there is no guarantee that a shipment will be sent in a specific flight. For large aircraft, the transport of cargo and baggage is carried out by means of load units (ULD): pallets or containers, which allows rapid loading and unloading of freight and baggage and a gain in terms of time and effort.

Luggage demand forecasting is required to determine the number of ULDs that are required to load baggage on planes and leave enough space to load cargo. Thereby, optimal use of ULDs for passenger baggage will improve passenger service and freight for maximum profit and service.

Currently, ULD allocation to a flight is very empirical. It is therefore necessary to estimate the demand for flight baggage, to provide a scientific basis for this allocation of ULDs for the passenger baggage to be embarked and to improve the efficiency of the service.

In this context, our research aims to use supervised learning methods to predict short-term (7 days) demand for baggage. The objective of this study is to build a prediction based on the ARIMA model and to compare its accuracy with the exponential smoothing models.

The remainder of this paper is organized as follow: in Section II we present the background of forcastings models, section III presents relevant related works, section IV introduces our work and its motivation, V presents the application of the forcasting models, and finally, section VI gives a summary and recommendations.

2. Motivation: ULD Management

2.1. ULD and Baggage Typology

Cargo units are pallets or containers used to load baggage, cargo and mail on containerized planes. They can load a large amount of baggage or freight or mail in one unit. Each ULD has its own packing list (or manifest) so that its content can be tracked.

In our case, there is 4 types of containers that can be loaded according to the types of machines:

- AKE: These types of containers are used on machines B747-400, B787-800 and B767-300;
- DQF: These types of containers are only used on B767-300 machines;
- AAK: These types of containers are used on machines B747-400, B787-800 and B767-300;
- DPE: These types of containers are only used on B767-300 machines, they are rarely used;

Below (Fig. 1) is an illustrating example of an AKE ULD.

ULDs are identified by these types of baggage, which facilitates their management. However, the lack of a sufficient number of ULDs at the level of stopovers

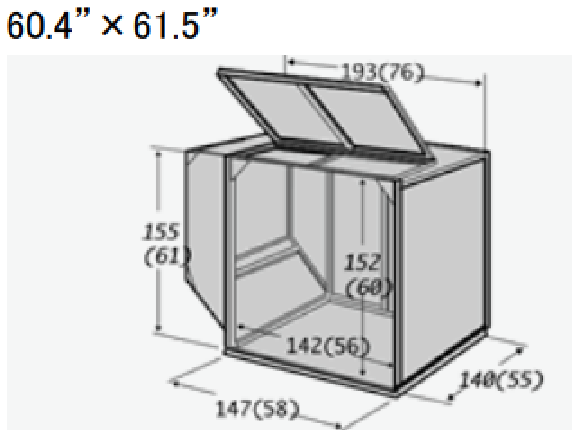

Fig. 1. Example of ULD specification [2]

generates a mixed load of baggage making their treatment heavier, which can lead to delayed baggage and passenger complaints.

2.2. Provision of Stopovers and One-Off Events

A minimum number of ULDs is allocated at the level of each stopover based on the types of machines used during the season for flights to the stopover concerned, the filling of flights (number of passengers departing from the stopover concerned), as well as the operational constraint of the stopover (example: Non-use of AAK type ULDs for flights to Montreal).

During periods of high traffic (such as weekends, holiday periods ..), the stopover time allocated to flight processing does not allow the repatriation of all ULDs unloaded at the stopover making stock rebuilding at the local HUB difficult. It is necessary to wait for the next flights to these stopovers to repatriate the ULD, which is not always the case as it happens times that no jumbo jet is programmed at the level of this stopover.

To ensure that all baggage at a destination will be transported and delivered to their owners in the same flight, the planner checks each morning the movement of the ULDs, the stock status of each destination and the passenger forecasts of the flights of the day. To then send instructions to the station managers on the number of ULDs containing the baggage, and empty (if necessary) to be loaded on board the aircraft for operational flights of the day.

2.3. Motivation

The existing system allows for effective management and planning of ULDs on the company's network, with real-time visibility of the location and status of the ULD, and inventory control at the stations to ensure availability.

However, the anomalies present at the level of sending and processing of messages, the management of stopover stock as well as the irregularities related to the management of occasional events (with high traffic), make the dynamic management of ULDs difficult, which leads sometimes to overstock or under-stock at stopovers and generates delayed baggage.

This makes predictive planning to send the right number of ULDs even more difficult and delicate.

The purpose of this paper is:

- Analyze baggage behavior during different periods for a transatlantic air route.
- Construct a predictive method for forecasting baggage demand.
- Develop a short-term baggage forecast, delivering reliable and credible results for decision-making regarding the number of ULDs to be loaded for each flight.

Baggage demand forecasting was required to determine the fair number of ULDs required to load aircraft baggage for each flight and leave enough space to load cargo.

3. Context and Background: Econometrics and Forecasting Model

3.1. Time Series

A time series is a succession of observations over time. A time series usually consists of several elements:

- Trend: represents the long-term evolution of the series.
- Seasonality: evolution repeated regularly every year.
- Stationary (or residual) component: what remains when the other components are removed and describes the short-term evolution of the series.

A time series comes from the realization of a family of random variables $\{X_t, t \in I\}$, where the set I is a time interval that can be discrete or continuous. For our study, we note the set $I = \{0, 1, \ldots, T\}$, where T is the total number of observations.

3.2. Forecast Models

In this work, we are interested in time series analysis in order to understand the behavior of a variable and its dynamics, to discover the regularities and then to establish a short term forecast.

Prediction methods are often subdivided into categories. We focus on forecasts based on the ARIMA model and the exponential smoothing models.

3.3. BOX JENKINS Method

The Box-Jenkins method [6] refers to a set of procedures for identifying and estimating time series models in the class of autoregressive integrated moving average (ARIMA) models.

Box-Jenkins' approach to building the ARIMA model includes the following steps:

- 1. Identify the parameters p, d and q of the model
- 2. Select the appropriate model
- 3. Diagnose the chosen model
- 4. Use the model for forecasting

3.4. Smoothing Method

The methods of exponential smoothing were introduced by Holt in 1957 [13] and by Winters in 1960 [22] and popularized by Brown in 1962 [7]. They constitute the set of empirical techniques that assign exponentially decreasing weights as the observation is more older. Thus, recent observations have more weight in the forecast than older observations.

Simple exponential smoothing Simple exponential smoothing is used for short-term forecasts. It assumes that the data fluctuates around a reasonably stable average without seasonality and a locally consistent trend. The specific formula for simple exponential smoothing is:

$$\tilde{X}(h) = S_t$$
$$S_t = \alpha \times X_t + (1-\alpha) \times S_{t-1}$$

With α is a real $0 < \alpha < 1$

The predicted value is the weighted average of previous observations. If $\alpha = 0$, then the current value is ignored, the new value depends entirely on the smoothed value that precedes it. The smaller the value of α, the greater the selection of the initial value of S. Thus the choice of the initial value affects the calculation of the values which follow it; it can be initialized by the average of 4 or 5 first observations.

Double exponential smoothing Double exponential smoothing is used when the data show a trend. It is a generalization of simple exponential smoothing that assumes that the series approaches locally through an affine transformation of time. It is an exponential smoothing with a trend [15].

Its specific formula for is:

$$\tilde{X}(h) = S_t + hT_t$$
$$S_t = \alpha \times X_t + (1-\alpha)(S_{t-1} + T_{t-1})$$
$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}$$

Where $0 < \gamma < 1$ and $0 < \alpha < 1$ And h represents the horizon of the forecast made at time T.

Triple exponential smoothing (Holt-Winters) This type of exponential smoothing makes it possible to add to the autoregressive component of the model, a trend and a seasonality. But that can be adapted to the series without seasonality by adjusting them by a line in the vicinity of T [15].

The formula of the additive seasonal HW model is:

$$\tilde{X}(h) = S_t + hT_t + I_{t-p+h}$$
$$S_t = \alpha(X_t + I_{t-p}) + (1-\alpha)(S_{t-1} + T_{t-1})$$
$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}$$
$$I_t = \delta(X_t - S_t) + (1-\delta)I_{t-p}$$

Where $0 < \gamma < 1$ and $0 < \alpha < 1$ and $0 < \delta < 1$ And I_t is the seasonality index smoothed at the end of period t and p is the seasonality cycle.

3.5. Performance and Model Comparison

To assess the credibility of a given model, validation is an essential activity when faced with the need to make critical decisions based on modeling results. It allows us to decide whether the model responds correctly and efficiently to our problem.

Several methods are used in the benchmarking approach for time series data to study the accuracy of a given model:

Partitioning data for time series The partitioning of the data will divide the series to study in 2 periods:

- Train is the set of data used for the analysis and construction of the model.
- Test is the dataset used to verify and validate model performance. We assume that we do not have these data and we want to predict them.
- Future is the period of which we do not really know and we want to predict.

Generally, more data is allocated for training and less for testing. One can choose a fixed data partition or by advancing the learning period (the partitioning is done several times). The latter has several advantages; it allows us to compare the performance of roll-forward deployment scenarios.

Performance Indicators (KPIs) To evaluate the accuracy of the forecast, the validation period must be examined by comparing the actual values Xt and the Ft values generated by the model, by comparing their performance indicators.

Several KPIs are possible for our study:

Mean Absolute Error

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|X_t - F_t|$$

The weaker it is, the smaller the gap between observation and prediction. MAE is not used when the series is intermittent.

Mean Squared Error

$$MSE = \frac{1}{T}\sum_{t=1}^{T}|X_t - F_t|^2$$

It is preferred to MAE because it is more sensitive to errors with small deviations.

Mean absolute percentage error

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\frac{|X_t - F_t|}{|X_t|}$$

It can only apply to strictly positive values.

Weighted Absolute Percentage Error

$$WAPE = \frac{\sum_{t=1}^{T}|X_t - F_t|}{\sum_{t=1}^{T}X_t}$$

Root mean squared error

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(X_t - F_t)^2}$$

Symmetric Mean Percentage Error

$$SMPE = \frac{\sum_{t=1}^{T} F_t - X_t}{\sum_{t=1}^{T} F_t + X_t}$$

The best performing model is the one that minimizes the most these key performance indicators.

Time series are widely used in various fields, such as finance [8] [21], energy consumption [20] [10], cloud performance [16]. We are interested in this paper in predicting the demand for ULDs to optimize the cost of travel.

4. Related Works

The quality of an airline's service depends on its timeliness, accuracy, functionality, quality, and price. For these purposes, airlines need optimization-based decision support systems Optimization [25]. There are several works in the literature that address different aspects of air transport optimization, as airline crew scheduling [4] [12], crew pairing [3] and flight planning among others [17]. However, the study and optimisation of the management of ULDs is still rare, and for the most part does not exploit the techniques of artificial intelligence and machine learning.

Thus, Lu et al. [14] estimate safety stock levels of ULDs for international airline operations which is as the minimum quantity that can support the utilization during the entire trip. Limbourg et al. [19] deal with the problem of an optimal loading of ULDs in an aircraft. Wong et al. [23] has studied the issue of loading passengers' luggage in the cargo hold in an optimal way. Yan et al. [24] proposed a mixed integer non linear model to address the problem of how to load the containers into an aircraft in a stochastic environment.

Deploying machine learning in the business process by using data from logistic information systems offers the company several advantages: anticipating the evolution of its stocks, optimizing flow management by reducing costs, thus enabling the steering committee to focus on decision-making with better control and visibility.

The positive impact of the machine Learning for the supply chain lies in the management of demand forecasting, and the anticipation of product needs, which eliminates operating irregularities (baggage not routed ..) and consequently allows a better service delivery for customers.

In the field of passenger air transport, several studies have been conducted to study the performance of the flight based on historical data (number of passengers, number of baggage lost, number of delays ...) but there are very few works on the estimated demand in terms of baggage (especially ULD).

Among them is Cheng's comparative study on baggage demand forecasting methods [9]. This work compares prediction models: neural networks and multiple regression to predict baggage demand. The models were built based on the historical data of the flight baggage claim. In order to provide a scientific basis for the allocation of resources for checked baggage and to improve the efficiency of the passenger service, forecasts were made by analyzing three types of data (data for all flights, data of a single flight, and data of flights with the same destination). The authors suggest to optimize the neural network model or to choose a more adequate predictive model and address this issue more accurately.

Also, Li conducted an analytical study on the departure baggage check at the airport based on passenger behavior [18]. This study was based on operational data from the airport to establish an analysis of the behavior of the baggage claim process and baggage claim characteristics such as weight and quantity, which can provide support for scientific decision-making for the demand forecast of baggage. The results of this analysis showed that baggage weight follows a widespread distribution of extreme value and demand varies according to the type of flight, which has led to improvements in the baggage registration process.

Bokern [5], who was inspired by D'Engelbronner [11], conducted research on creating a forecast based on two data sources: historical flight data and reservation data. He showed in his thesis that a forecast can be made over a 10-day horizon with an error of 2-3%. We are interested in the prediction made on the basis of the flight data obtained from the ALTEA information system. To create this forecast, Bokern used two types of models: Autoregressive Moving Average Models (ARMA) and Exponential Smoothing (ES) models. A comparison between the models was made on the basis of error measurements to determine which forecasting model is the best in terms of forecasting.

5. Forecasting

5.1. Data Source

The source of the data is the AMADEUS ALTEA Departure Control System - Costumer Management. Two data files will be extracted from the DCS and saved in Excel files:

- Statistics Baggage by period: this file contains statistics on checked baggage in each flight per period (flight number, type of machine, date of departure, departure, destination, number of pieces, total weight of coins ..).
- Filling of flights: provides information on the number of passengers boarded for a flight (flight number, type of machine, departure date, departure, destination, type of cabin, number of PAX recorded, number of PAX on board).

After preprocessing these two files, a table of two columns will be created which will include the date of the flight and the corresponding baggage / passenger ratio and which will represent our series to be analyzed.

date		Bag/Pax
16/04	20:30	1,70952381
17/04	20:30	1,6745283
19/04	20:30	1,76326531
20/04	20:30	1,5990566
21/04	20:30	1,54273504

Fig. 2. Structure of the final file to exploit

5.2. Data Analysis

Before the implementation of the prediction model, it is essential to visualize our series, analyze it and study its behavior over time to check if it contains null values (if yes, use the interpolation), and check if the observed values represent insignificant outliers to remove them. A first analysis of the series makes it possible to analyze the behavior of the data (Fig. 3):

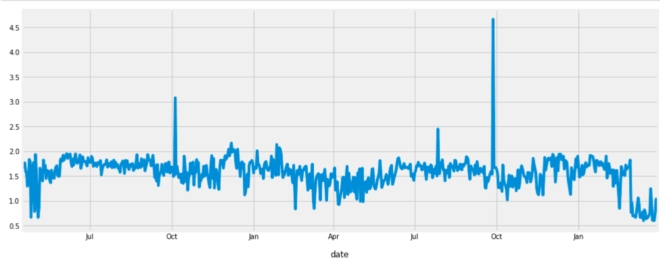

Fig. 3. The series

5.3. ARIMA Model

Recall that the ARIMA model assumes that the series is stationary. Thus, to identify the parameters of the model, a first step will be the study of stationarity.

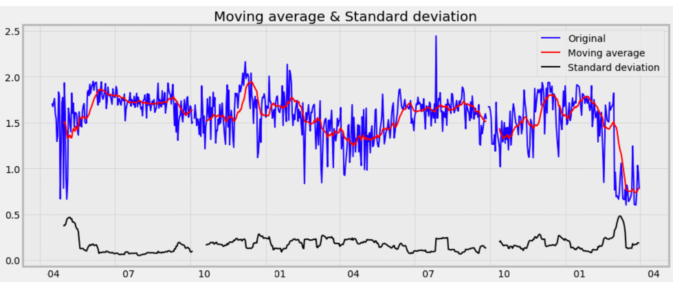

Fig. 4. Mobile Average and Standard Deviation of the series

The Dickey-Fuller test allows us to check if the series is stationary:

From the results, we note that the statistical test is not less than the critical values of 10%, 5% and 1% (Fig. 5) . Thus, We can not reject the null hypothesis H0: "the series is not stationary". So, according to the Dickey-Fuller test we conclude that the series is not stationary and needs to be differentiated.

Let's analyze the correlogram of the original series (Fig. 6):

```
Results of Dickey-Fuller Test:
Test Statistic                  -1.678447
p-value                          0.442250
#Lags Used                      13.000000
Number of Observations Used    701.000000
Critical Value (5%)             -2.865672
Critical Value (1%)             -3.439713
Critical Value (10%)            -2.568970
dtype: float64
```

Fig. 5. Dickey-Fuller test results

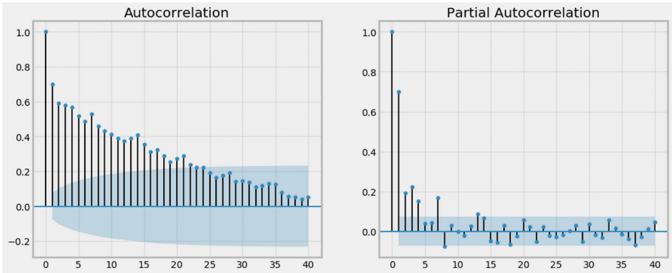

Fig. 6. Correlogram of the original series (FAC, FACP)

Note that the autocorrelation is positive and nonzero for a large number of lags. This confirms that differentiation is necessary.

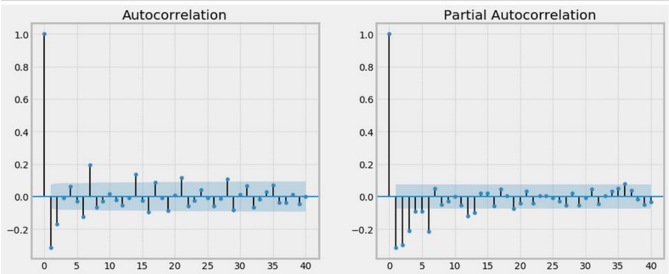

Fig. 7. Correlogram of the series after differentiation (FAC, FACP)

This graph represents FAC and FACP of the series after a first differentiation. Note that offset autocorrelation 1 is negative and greater than -0.5. This indicates that our series does not need to be differentiated and therefore we estimate d = 1. Negative offsets justify differentiation.

On the FAC graph as well as the FACP, we notice that there is a peak at offset 1. This allows us to estimate the parameters p and q, with p = 1 and q = 1.

Model Selection From the foregoing, the model of ARIMA (1, 1, 1) is a suitable model. To make sure of the validity of our choice, we compare the different possible models with the information criteria AIC and BIC (Fig. 1):

We note that the ARIMA model (1, 1, 1) minimizes the two criteria the most. Thus, the model to be implemented will be ARIMA (1, 1, 1).

Diagnosis of residual According to the diagnosis of the residual (Fig. 8), it is found that the autocorrela-

Tab. 1. Comparison of the AIC and BIC of the different models

ARIMA Model	AIC	BIC
ARIMA (0, 0,1)	1830,63593742	1839,78050251
ARIMA (0, 1, 1)	-345,135984579	-335,991419493
ARIMA (1, 0,0)	-177,874517485	-168,729952399
ARIMA (1, 0,1)	-345,0467419	-331,329894272
ARIMA (1, 1,0)	-247,992863849	-238,848298764
ARIMA (1, 1,1)	-372,325641125	-358,608793497

tion is significantly zero for almost all offsets, with the exception of shift 7. Again, the distribution of the residues follows the linear trend of the samples taken from a normal distribution and therefore can also consider that they follow a normal distribution.

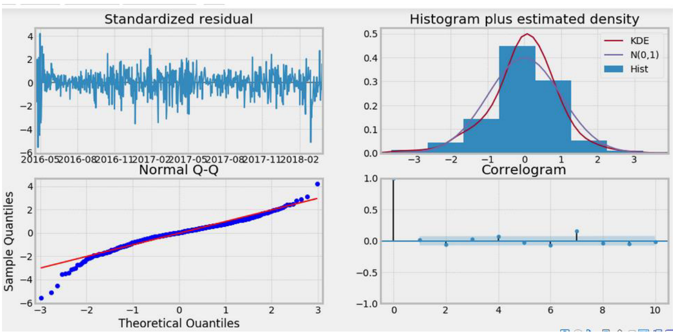

Fig. 8. Diagnosis of residues

The short-term forecast (7 days) gives the following results:

Tab. 2. ARIMA(1, 1, 1) Prediction Results

Datel	Real Value	ARIMA (1,1,1)
04-01	0,551838	0,798146
04-02	0,559496	0,804509
04-03	0,576744	0,806367
04-04	0,610526	0,806910
04-05	0,761290	0,807069
04-06	0,750789	0,807115
04-07	0,633952	0,807128

According to these results, it is noted that the predicted values are higher than the real values. To know to what extent the forecast of this model is accurate, we calculate in the next part the different indicators mentioned above.

5.4. Construction of Smoothing Models

Simple exponential smoothing (SES) Recall that the simple exponential smoothing makes it possible to calculate the prediction from the weighted average, by assigning to each value a weight and where the weight decreases according to an exponential function.

By partitioning the data into training data (Train) and test data (Test), we obtain the following graph :

The table below summarizes the 7-day results of our prediction:

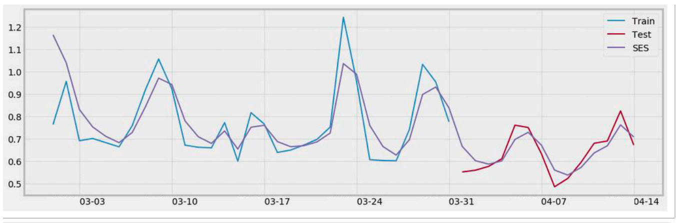

Fig. 9. Simple exponential smoothing

Tab. 3. Simple exponential smoothing Prediction Results

Date	Real Value	SES
04-01	0,551838	0,666563
04-02	0,559496	0,602323
04-03	0,576744	0,586976
04-04	0,610526	0,601106
04-05	0,761290	0,697217
04-06	0,750789	0,729360
04-07	0,633952	0,672115

It can be seen that the predicted values with simple exponential smoothing are higher but very close to the real values.

Double exponential smoothing (DES) Double exponential smoothing, as already seen, is an exponential smoothing suitable for series with a tendency T_t and a level S_t.

The graph below shows the behavior of the series over the three periods: the Learning Train series in blue, the validation test series in red and modeling with the DES in purple:

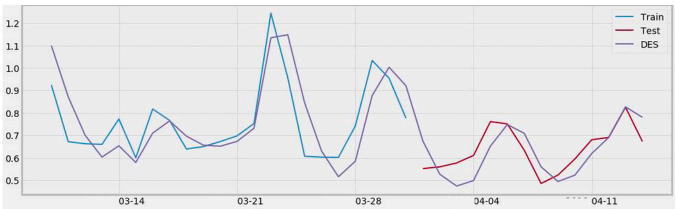

Fig. 10. Double exponential smoothing

And the results of the forecast are presented in the following table:

Tab. 4. Simple exponential smoothing Prediction Results

Datel	Real Value	DES
04-01	0,551838	0,674789
04-02	0,559496	0,526861
04-03	0,576744	0,473992
04-04	0,610526	0,498582
04-05	0,761290	0,651936
04-06	0,750789	0,748076
04-07	0,633952	0,709196

Holt-Winters exponential smoothing (HW) Holt-Winters Smoothing or Triple Smoothing involves applying exponential smoothing to the seasonal component, trend, and level. Thus, to implement it, we must formulate the equation of these last three.

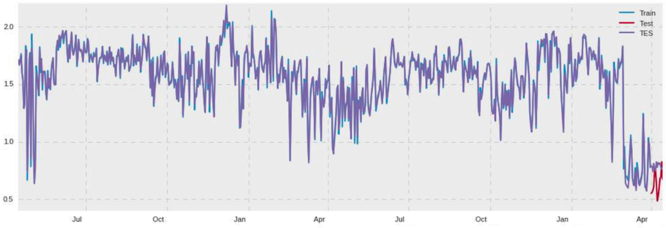

Fig. 11. Triple Exponential Smoothing (HW)

On the graph, we notice that modeling closely mimics our learning series. But by zooming in on the trial period, we observe that the modeling does not adapt well to the real values.

By closely analyzing the graph, it can be seen that the exponential smoothing of HW does not correctly imitate the behavior of the test series:

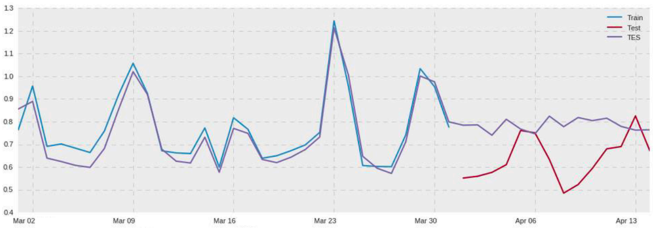

Fig. 12. HW zoomed on the test period

The table below presents the results of this forecast:

Tab. 5. Holt-Winters Prediction Results

Date	Real Value	HW
04-01	0,551838	0,784246
04-02	0,559496	0.779285
04-03	0,576744	0,727776
04-04	0,610526	0,794183
04-05	0,761290	0,765640
04-06	0,750789	0,732398
04-07	0,633952	0,875425

In the next section, we will perform a benchmark between the models as well as calculate the performance indicators of each one.

6. Performances, Discussion and Recommendations

This section presents the synthesis of this work. We summarize the results of each of the models studied and compare them to conclude which model will be the most appropriate for our problem.

6.1. Model Performance

Naive forecast In order to measure the performance of the models used, a first comparison with the naive forecast will be made. We have considered two types of naive forecast: a dynamic and a step by step:

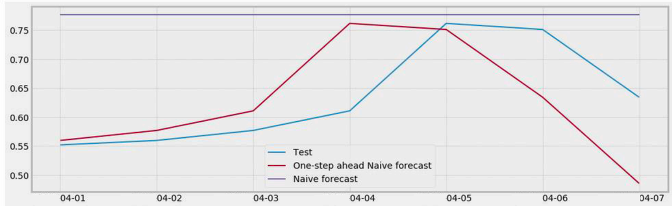

Fig. 13. Naive prediction

To compare between the two types of naive prediction, several KPIs were used:

Tab. 6. KPIs of both types of naive prediction

KPI	OS naive forecast	Naive forecast
MSE	0,008579	0,013474
MAE	0,069330	0,083110
RMSE	0,092617	0,116077
MAPE	10,77%	11,7520%
WAPE	0,1092	0,1309
SMPE	0,55005	0,07003

We note that all the performance indicators calculated for the step-by-step forecast are minimal compared to the dynamic naive forecast. This allows us to conclude that stepwise forecasting is better than dynamic forecasting. But our goal is a 7-day forecast (that is, estimate the next 7 days at one time). This forces us to choose Dynamic Forecasting as a benchmark for our benchmark.

Model Comparison To examine the performance of each forecast model, a forecast analysis was performed.

In this analysis, a 7-day forecast was made for transatlantic route flights after 31 March (taken into account 2 years of history). From these predictions, a comparison can be made between different forecasting methods.

Below is a graph of all the forecasting techniques used:

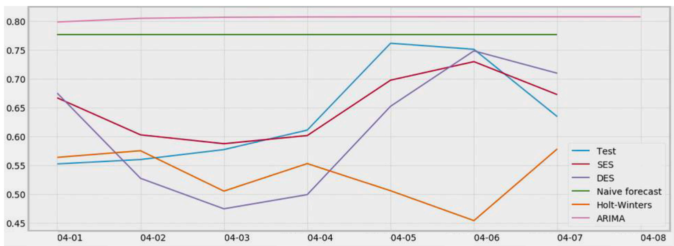

Fig. 14. The different forecasting models

On this graph, the blue line represents the test series containing the actual values while the other lines represent the predicted values according to a model. By visualizing the graph, it is assumed that the simple exponential smoothing gives results closer to the reality compared to the other models.

Let's recap the results of each model:

Tab. 7. Comparison of the results of the forecasting models

Date	Real Value	ARIMA	SES	DES	HW	naïve
01/04	0,551838	0,798146	**0,666563**	0,674789	0,784246	0,776358
02/04	0,559496	0,804509	0,602323	**0,526861**	0.779285	0,776358
03/04	0,576744	0,806367	**0,586976**	0,473992	0,727776	0,776358
04/04	0,610526	0,806910	**0,601106**	0,498582	0,794183	0,776358
05/04	0,761290	0,807069	0,697217	0,651936	**0,765640**	0,776358
06/04	0,750789	0,807115	0,729360	**0,748076**	0,732398	0,776358
07/04	0,633952	0,807128	**0,672115**	0,709196	0,875425	0,776358

By analyzing the table, we notice that under no circumstances does the ARIMA model (1,1,1) correctly mimic the real behavior of our series, with values that are very out of step with reality, followed by the smoothing of Holt- Winters. The values closest to the actual values are shown in bold, followed by the values represented in blue, which are mainly derived from single and double exponential smoothing.

Thus, to decide the choice between the different models and choose the most adequate to our problem, we compare in the following part the performance indicators of the models used.

Interpreting KPIs KPIs or performance indicators allow us to measure the accuracy of our estimators by comparing them with actual values. Several KPIs have been calculated to evaluate the models and to check if the use of different KPIs will result in different results:

This table indicates that all indicators are minimal for simple exponential smoothing. It also confirms that ARIMA (1,1,1) represents the model with the highest error value compared to the smoothing models.

6.2. Summary and Recommendations

The purpose of this study is to evaluate the ARIMA univariate time series prediction method and compare it to the exponential smoothing models (the three types of smoothing) to predict the baggage ratio. The goal is to find a model that fits the data correctly and could predict the behavior of our data.

This is done by first differentiating to remove both the seasonal and trend components and to make the series stationary, then estimate the ARIMA models and adapt them to our data set.

The ARIMA models as well as the exponential models were used in time series analysis and the best performing models were selected according to the information criteria and comparing the error measurements. The best performing models were used for data forecasting.

The data flow is represented by a non-stationary time series. There is a trend and a seasonality. The prediction can be simplified by studying the original differentiated series.

- Taking into account the different models of ARIMA, the ARIMA model (1,1,1) seems the most suitable for the data flow studied based on the information criteria AIC and BIC.
- After identifying and estimating the parameters of ARIMA (1,1,1), a diagnosis of the model was made. Having satisfied all the assumptions of the validity of the model, this model is considered to be the most appropriate ARIMA model for forecasting.
- In addition to ARIMA, in order to determine which method achieves the best results, an exponential smoothing prediction has been made.
- The three types of exponential smoothing (Simple, Double and Holt-Winters) have been implemented by defining functions according to the algorithm corresponding to each type.
- To choose the model that mimics our data as accurately as possible, several performance indicators have been calculated. The most accurate model will be the model minimizing the value of the different calculated KPIs.
- Compared with all the models studied, the simple exponential smoothing allowed us to obtain a better result with an error rate (MAPE) of 6.32%.

7. Conclusion

Baggage demand forecasting becomes a very important task for optimizing the management of ULDs. In this field, little research has been done and others are still improving.

In this paper we applied the methods of predictive analysis taking into account the recommendations of

Tab. 8. KPIs of different forecast models

KPI	Naïve	ARIMA	SES	DES	HW
MSE	0,013474	0,03532	**0,003030**	0,008128	0,023707
MAE	0,083110	0,17037	**0,042298**	0,042981	0,109434
RMSE	0,116077	0,18794	**0,055045**	0,090157	0,153971
MAPE	11,75%	28,75%	**7,00%**	12,98%	15,55%
WAPE	0,1309	0,2683	**0,06769**	0,12545	0,1723
SMPE	0,07003	0,1183	**0,0334**	0,0638	0,0936

the research already done.

The results obtained throughout our study and the steps carried out, showed that the ARIMA model remains far from reality even if it correctly imitated our dataset during the learning, and the simple exponential smoothing model is the a model that minimizes KPIs and therefore is considered the best performing model for our forecast.

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