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Demand forecasting methods for spare parts logistics for aviation: a real-world implementation of the Bootstrap method

Baisariyev, M.[a], Bakytzhanuly, A.[a], Serik, Y.[a], Mukhanova, B.[a], Babai MZ.[b], Tsakalerou M.[a,*], Papadopoulos CT.[c]

[a]*School of Engineering and Digital Sciences, Nazarbayev University, Nur-Sultan, Kazakhstan*
[b]*Kedge Business School, Bordeaux, France*
[c]*Aristotle University, Thessaloniki, Greece*

* Corresponding author. *E-mail address:* mariza.tsakalerou@nu.edu.kz

Abstract

One of the critical issues that an airline faces in its day-to-day operations is a correct prognosis of the necessary quantity of spare parts that are continuously fed into unexpected maintenance operations. Indeed, there is a critical need for accurate forecasting methods to predict the demand of these spare parts in order to minimize the so-called Aircraft-On-Ground situations. This paper describes the real-world implementation of the Bootstrap method and the assessment of its performance with actual data from aviation logistics. The analysis reveals that the Bootstrap method, while not the most accurate in every case, should be preferred over other popular methods in spare parts forecasting for aviation, because is more agile and can address adequately all categories of demand. A simple decision support system is then presented to assist airline materials managers in using the bootstrap method. The system is expandable and can potentially incorporate other forecasting method as well.

Keywords: Airline spare parts; Forecasting; Single Exponential Smoothing (SES); Syntetos and Boylan approximation (SBA); Multiple Regression; Croston's method; Modified Croston's; Bootstrap method.

1. Introduction

Aircraft on Ground (AOG) is a special designation used in the airline industry to define cases when a flight cannot be accomplished due to technical problems of the aircraft. According to International Air Transport Association (IATA) [13], the airline spare parts could be classified into three inventory types: rotable, repairable and expendable.

The three main differences between these spare parts are the scrap rate, the financial terms, and the life cycle. Rotable spare parts have relatively low scrap rate, whereas the scrap rate of the repairable parts should be taken into account when it comes to planning. As for the expendable spare parts, these are considered to be used once they are consumed. Two more types of spare parts are the life limited parts and the consumable parts. Life limited spare parts have a predefined cycle time, while the consumable parts have a 100% scrap rate and are removed once consumed. Technical problems include situations when it requires to change critical spare parts and other components that might make aircraft impossible or difficult to fly and aircraft stay on the ground. Continuous occurrence of this problem leads to huge financial expenses and affects the brand image of a carrier. Moreover, AOG situations may also involve expensive purchase of critical spare parts from external suppliers, which puts extra strain on the budget of the company and delays that impact customer satisfaction.

The demand of the airlines spare parts is irregular; usually it is intermittent (viz., there are many periods with no demand

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and a few periods with low non-zero demand) and often lumpy (viz., when the non-zero demand is large).

While numerous methods have emerged to address the issue of forecasting spare part demand for aviation, their performance is highly variable depending upon the type of the parts and the demand pattern. The Bootstrap method, while not the most accurate in every case, has emerged as a possible candidate for broad-based forecasting of airline spare parts [1, 2].

The objective of this paper is to test the Bootstrap forecasting method on real-world data of aviation logistics from a medium-size international airline and to develop a simple Decision Support System (DSS) to assist in its implementation [3].

The airline operates several aircraft types from three different aircraft manufacturers in its fleet, which creates additional inventory control and forecasting challenges for the company. The huge expenses incurred from stockout cases necessitates the quest for highly accurate forecasting methods to assist the materials management of the airline in their ordering process.

The paper is organized as follows. Section 2 presents a brief literature review on the forecasting methods applied to airline spare parts. This is followed, in Section 3, by an articulation of Bootstrap, the specific solution methodology that is implemented in this study, and its performance with real-world airline data. Section 4 outlines the DSS that was designed to assist airline materials managers in using the bootstrap method. Finally, Section 5 summarizes the conclusions of this study and discusses a set of future research directions.

2. Literature review

Figure 1 presents a detailed taxonomy of available forecasting methods, both qualitative and quantitative. Qualitative forecasting methods come in four flavors and quantitative methods are parsed into four subgroups with a total of thirteen distinct approaches.

The highlighted boxes in Figure 1 represent the forecasting methods that figure most prominently in aviation logistics. In the sequence, a brief discussion is presented on each of these methods with the explicit intent simply to introduce them and to summarize their performance and the conditions under which they perform best. Given the detailed literature review in [1, 2] and in the interest of brevity only a few key references on the methods tested are provided in the sequence.

Syntetos et al. [4] provided a categorization of the demand patterns. According to their scheme there are four types of demand based on its coefficient of variation and the average demand interval (ADI): smooth, intermittent, erratic and lumpy.

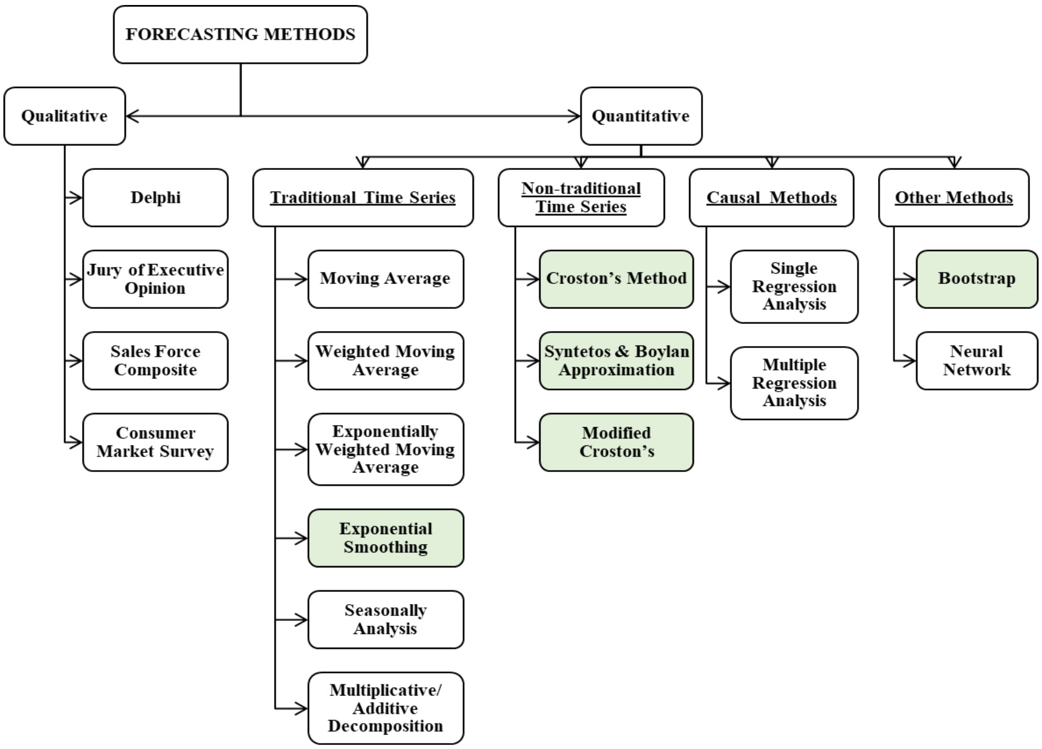

Fig. 1. Forecasting methods categorization.

Regattieri et al. [5] analyzed the forecasting tools for spare parts with lumpy demands. Based on the historical data of Alitalia, the performance of twenty forecasting techniques was compared with each other by the mean absolute deviation (MAD) accuracy method. The results showed that the most accurate forecasts are obtained by a weighted moving average, exponentially weighted moving average, and Croston's methods.

Ghobbar [6] experimented with 13 different forecasting methods on one of the largest UK flight carriers and compared them in terms of the mean absolute percentage error. The aim of the research was to simplify the results obtained by forecasting method performance by demand categorization. The research proved experimentally that Croston's, Holt's, and weighted moving average methods performed better than others on intermittent demand pattern.

Single exponential smoothing was a commonly used forecasting technique for predicting the intermittent and lumpy demand of spare parts in aviation until the new method, Croston's was introduced. Croston [7] proved that forecasts of simple exponential smoothing lead to an increase of stock levels and introduces his own method. Croston's method is based on exponential smoothing, however, the method estimates separately demand sizes and demand intervals. It helps to surplus the stock level and prevents errors at the same time. Since its introduction, Croston's model has been widely used as strong forecasting method for intermittent demands.

Nevertheless, many modifications by various researchers were applied to Croston's method to improve its accuracy [1]. Eventually, Syntetos and Boylan [8] significantly altered Croston's method by adding a new estimator. The improved method, named the Syntetos and Boylan Approximation (SBA), allows for obtaining unbiased forecasts. Head-on comparison with the original Croston's method reveals that SBA offers more accurate forecasts when the demand intervals are greater than 1.25 time periods.

Babai et al. [9] agree that Croston's method and SBA show promising results for intermittent demand patterns but not when there is a risk of obsolescence in the demand. Thus, they introduced a new method, the Teunter-Syntetos-Babai (TSB) to address the problem by updating the demand probability rather than the demand interval. The modification is based on the usage of moving average of three non-zero demands instead of exponential smoothing. Testing the TSB forecasting method on real data coming from the military sector and from the automotive industry revealed that the method is particularly effective when dealing with obsolescence. In this paper, the term Modified Croston's refers to the TSB flavor.

Willemain et al. [10] dealt with irregular demand patterns and estimated the cumulative distribution of demand over a certain lead-time. The main idea was to base the forecast of the future events on the sample of historical data that are self-resampled many times. Their method named Bootstrap was tested over nine industrial datasets and proved to be more accurate than time-series methods, namely, Croston's and exponential smoothing techniques. In the sequence, the term Bootstrap refers to the Willemain et al. flavor.

The following section deals with the application of the Bootstrap method to a set of real-world aviation logistics data.

3. Solution methodology

The main idea behind the Bootstrap method is to base the forecast of future events on a sample of historical data that has been self-resampled repeatedly.

The exact steps involved in the Bootstrap algorithm are described concisely in Figure 2. Initially, after listing all the periods in terms of time buckets (i.e., months for the purposes of this paper) the corresponding zero or non-zero demand values are allocated to each time bucket. (The total length of the time series employed in practice depends on the aircraft operational patterns of each airline.) In the first step, based on two demand states, zero and non-zero, the probability of transitions is calculated via a first-order Markov process as proposed by Mosteller and Tukey [11]

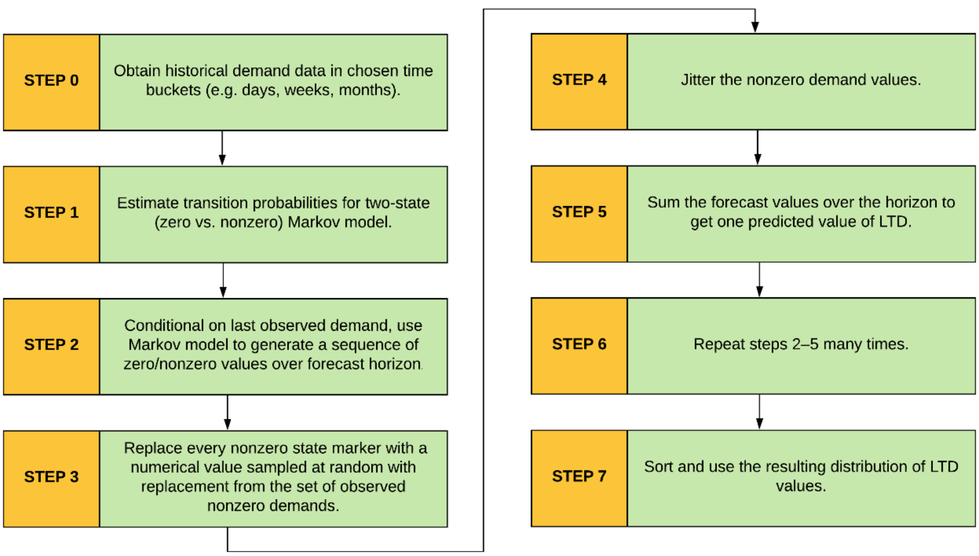

Fig. 2. The steps of the Bootstrap method that comprises the core algorithm of Bootstrap forecasting method as outlined in Willemain et al. [10].

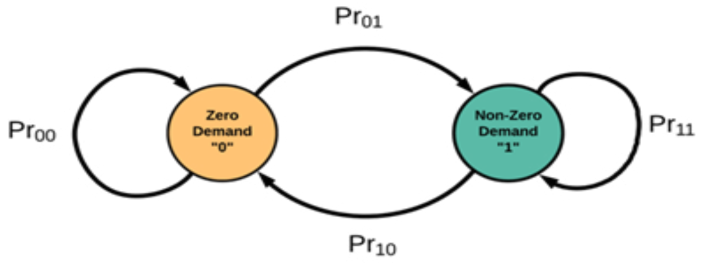

Fig. 3. Applying First Order Markov Model in order to model the pattern of stochastic changes between zero and non-zero demands.

and depicted in Figure 3. The second step involves marking by “0” or “1” the time buckets in the forecasting horizon (i.e., lead-time) by taking into account the condition of the last demand value. The third step comprises of assigning numerical demand values to the “1”-s from the previous step by consulting historical demand values. The fourth step proceeds with jittering to generate life-like values around the observed demand values. The fifth step involves summing the demand values over the forecasting horizon. The sixth step involves repeating steps 3 to 6 several times so that a distribution can be generated in the seventh and final step.

Having constructed the model, the first objective was to test and verify whether the probabilistic prediction computed by the Bootstrap method matches the real demand values for chosen lead time periods. The Bootstrap model was implemented in Excel by programming in Visual Basic Applications. Three main Excel files were combined in order to retrieve the list of spare parts according to selected constraints: (i) Recommended Spare Parts List file, (ii) Rotable spare parts, (iii) Rotable-repairable spare parts.

This approach makes it possible to create a table of spare parts that contains a spare part number, aircraft local number, type of spare part, quantity per aircraft and demand. The main function that was implemented is the VLOOKUP Excel function that makes it possible to take a spare part name from one list, to find through the whole set of data from another list, allocate the corresponding row and retrieve data from the required column. The ability to filter the list provides the additional capability of identifying the specific aircraft model, spare part and Quantity per Aircraft (QPA) value.

The Bootstrap model was further enhanced by basing the forecasting on extending period length. (That is, as the scanning progresses through all historical demand values, the oldest values will be still included in the calculations.).

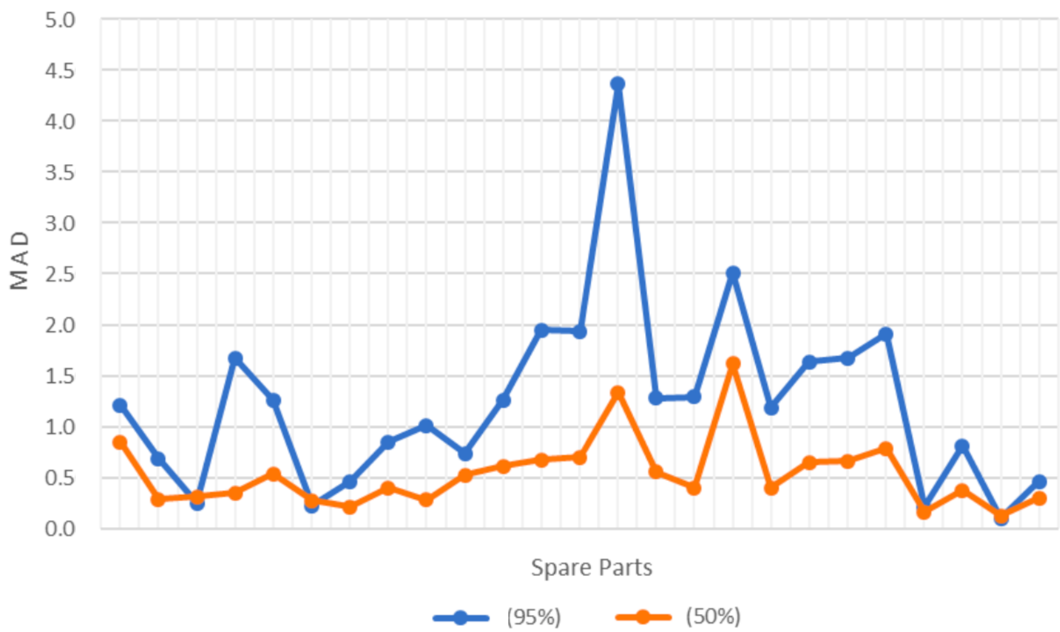

Fig. 4. Mean Absolute Deviation (MAD) values for 26 distinct spare parts (dots) with intermittent demand patterns.

There are three different input parameters in the extending period length mode that a user must define: (i) the number of periods (months) for which the model will forecast; (ii) the number of period (months) that the algorithm will scan for historical data; and (iii) the mean average deviation desired

In the implementation of this paper, two levels of confidence were examined, 95% and 50%. (The 50% value as an alternative choice was based on the average lead-time demand value demanded in the aviation industry to replenish the stock of spare parts.) In both cases, the Mean Average Deviation (MAD) criterion, that is the mean absolute (non-negative) error, was used to compare the accuracy of the forecasted values. Finally, the demand classification procedure was performed according to the guidelines set forth by Syntetos et al. [4].

In the interest of brevity, the results of Bootstrap forecasting for 25 distinct parts with intermittent demand patterns and 3 parts with lumpy demand patterns are reported here. The forecasting for the 25 intermittent demand parts is depicted in Figures 4. From Figure 4 it becomes apparent that using the 50^{th} percentile value for the empirical distribution generates better forecasting accuracy than using the 95^{th} percentile value, since the respective MAD values are almost always lower. Indeed, the average MAD value for all 25 spare parts with intermittent demand pattern was 1.238 (at 95%) and 0.535 (at 50%).

The situation however was reversed when the Bootstrap method was employed for three spare parts with lumpy demand patterns. The average MAD value for all 3 spare parts with intermittent demand pattern was 8.032 (at 95%) and 2.882 (at 50%). In both cases, the Bootstrap approach was less accurate than in the case of parts with intermittent demand patterns.

A regression analysis was then conducted to assess the dependency between mean absolute deviation and average demand interval values. The analysis showed that there is such a dependency, with an the R^2 value of 0.54 (at 95%) and 0.69 (at 50%). This implies that knowing the average demand interval for a spare part, one can roughly anticipate the mean absolute deviation and the level of the accuracy of the prediction will be higher for forecasts based on the 50^{th} percentile due to the higher R^2 value.

A second regression analysis was conducted in order to assess whether a relationship exists between the observed service level and the average demand interval. The results of the analysis showed that there is a significant relationship between the average demand interval and the observed service level for the forecasts conducted with the 50^{th} percentile value, where R^2 value is 0.73.

The plots showed that the higher the average demand interval or the greater the amount of zero demand values in the historical data, the higher the observed service level. On the other hand, when the average demand interval is lower the observed service level approaches the value of claimed service level or the 50^{th} percentile of the empirical distribution.

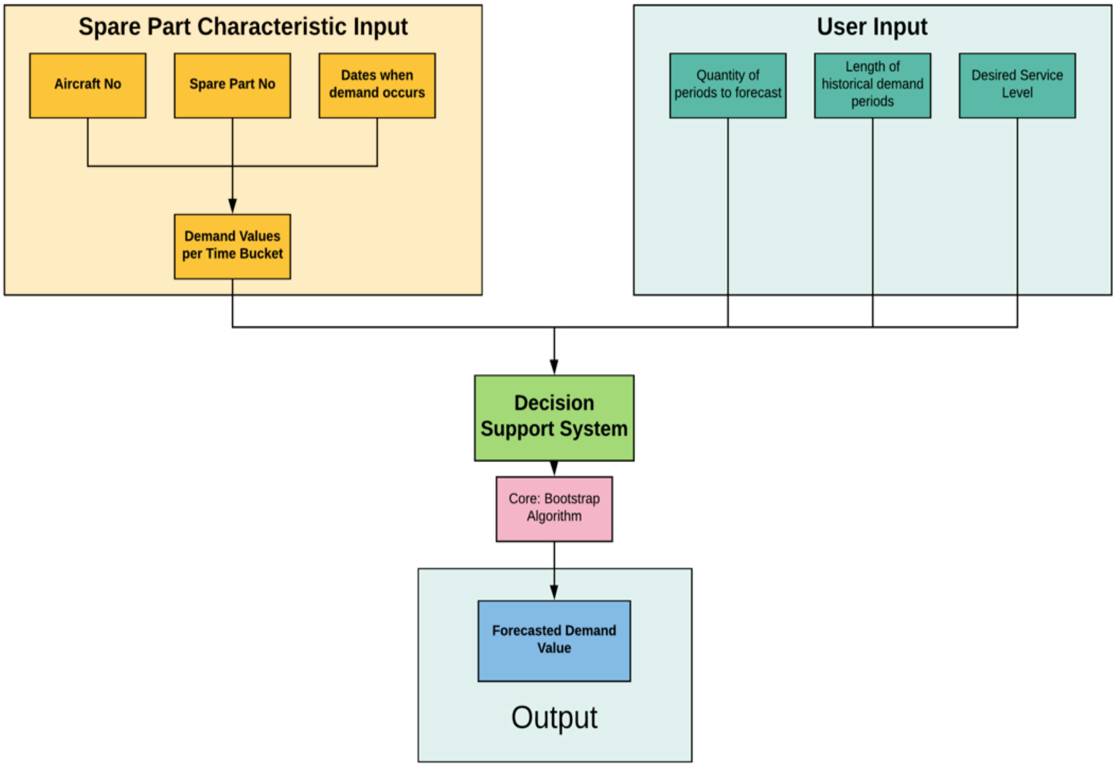

Fig. 5. The architecture of the proposed DSS for spare parts forecasting.

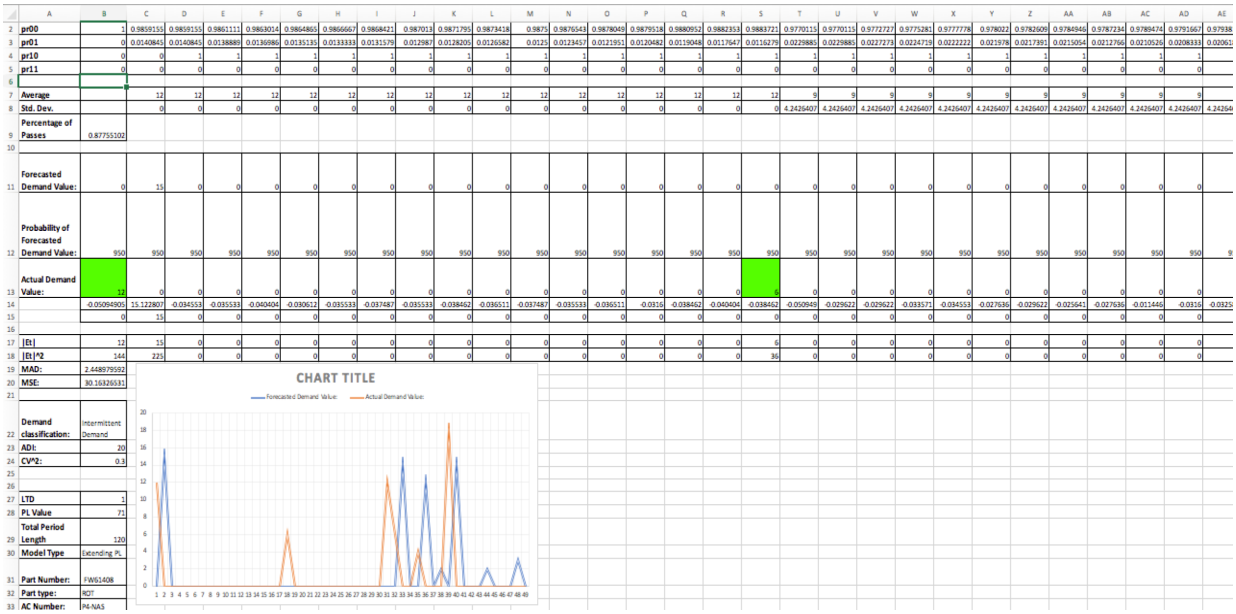

Fig. 6. Screenshot of the "Main Results" page that summarizes the information necessary for the user.

The results of regression analysis for forecasts based on the 95th percentile showed that there is little relationship between the average demand interval and the observed service level with an R^2 value 0.06. To put it differently, Bootstrap forecasts with the 95th percentile regardless of the value of average demand interval generates observed service level close to the claimed one. The average observed service level for the stated 95% service level was 91% (with a standard deviation of 6%). The 4% average difference between the claimed and observed service level was deemed a very good result for the Bootstrap forecasting method, exceeding the expectations of the airline.

Considering that the majority of the airline's spare parts exhibited intermittent demand patterns, it was decided to proceed with the design of a DSS for the implementation of the Bootstrap method in day-to-day operations [12].

4. A simple decision support system

In the aviation industry, there are many commercial DSS software that were developed to assist with crew and flight scheduling. The logic behind these systems is to allow the final users to bypass advanced mathematics computations and the interpretation of their results.

In this context, the objective was to design a DSS that would allow maintenance personnel to derive useful information without having to be proficient in forecasting methodologies. The basic functions and features of the proposed DSS are shown in the schematic of Figure 5. This DSS receives two general types of input data in order to generate the output, which is the forecasted demand value up to 12 months in advance.

The first type of input data is related to spare part in terms of its historical demand values, spare part identification number and aircraft family the spare part belongs to. The second type of input data is depended upon the user and involves the quantity of future periods to forecast, the length of historical demand periods to scan for and lastly the desired service level.

The combination of the two data types is then processed in the decision support system's main Bootstrap algorithm that is written in Visual Basic Application programming language. Finally, the DSS outputs the forecast demand value for the chosen level of service level or confidence level and the number of periods to forecast for in an aggregate form.

Apart from the main architecture, the DSS has the additional add-on feature where the demand data can be classified into four different demand categories.

A snapshot of the "main results" of the proposed DSS based on Bootstrap forecast method is shown in Figure 6. The screenshot provides a succinct view of the type and wealth of information provided to the end-user. The Bootstrap algorithm generates the lead time distribution that is obtained as a result of 1000 runs. Subsequently, based on the

Furthermore, the automated information processing generates period by period the following data for the user: the change dynamics of the transitions, the average and standard deviation values of observed non-zero demand, forecasted values with corresponding graph, error analysis and concise information box about the spare part and the user-inputted parameters.

Finally, the demand classification, which is one of the add-ons for the decision support system, can be activated by pressing the "Demand Classification" button on the "Main Page" worksheet. Not shown in here due to space restrictions.

5. Conclusions and further research

This paper presented a case study of the implementation of the Bootstrap method with real demand data for the spare parts of an airline. The analysis revealed that the Bootstrap method provides very accurate results for the parts of the airline that exhibit intermittent demand patterns but less so for parts with lumpy demand patterns.

Evaluating the method for 25 distinct spare parts with intermittent demand patterns demonstrated that the 50^{th} percentile choice exhibited on the average better MAD values than using the 95^{th} percentile one.

On the basis of this analysis, a simple decision support system (DSS) was developed to assist the materials managers of the airline in using the Bootstrap method.

Future research should focus on modifications of the Bootstrap method that will be able to address equally well spare parts with lumpy demand patterns. In addition, future efforts should focus on migrating the DSS from its Excel implementation to a form that could be integrated as a module in the airline's Enterprise Resource Planning (ERP) system.

CRediT author statement

Papadopoulos: Conceptualization, Funding acquisition, Project administration, Software, Supervision, Writing - Review & Editing. Tsakalerou: Project administration, Validation, Supervision, Writing - Review & Editing. Babai: Methodology, Data curation, Software. Baisariyev: Investigation, Writing - Original Draft, Visualization, Formal analysis, Decision Support System Development, Software. Bakytzhanuly: Investigation, Writing - Original Draft, Visualization, Software. Serik: Writing - Original Draft, Visualization, Formal analysis. Mukhanova: Writing - Original Draft, Visualization.

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