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# Inventory control models for spare parts in aviation logistics

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**Abstract**

Effective inventory management has a direct influence on monetary savings, high customer service level and product quality and thus plays an essential role in a company's economic and strategic performance. Forecasting and inventory models for aviation logistics are essential in commercial aviation. The objective of this paper is to study the problem of identifying the optimal order quantity of aircraft spare parts and the demand periods using the Order-Up-To (OUT) inventory model in conjunction with the Negative Binomial Distribution (NBD) and the (s, S) inventory model with Revised Power Approximation Method. These models are compared and contrasted via a real-world paradigm. The analysis reveals that the OUT inventory model in conjunction with the Poisson distribution allows ordering the lowest order quantity. However, the (s, S) inventory model with the Revised Power Approximation outperforms it in terms of average total inventory costs.



*Keywords:* Inventory management; Airline industry; Negative Binomial distribution; Order-Up-To (OUT) inventory model; (s, S) inventory model; Revised Power Approximation Method.

## 1. Introduction

In the airline industry, most spare parts cost a significant amount of money and have a direct expenditure impact on company performance. Moreover, the unavailability of the right spare part may cause the company high expenditures such as flight cancellations, shipping arrangements or the aircraft downtown time. Thus, one of the most significant issues in the airline industry is to provide a reliable approach for the spare parts ordering process, particularly in terms of the order quantity and period.

In the airline industry, the customer satisfaction level and the total inventory costs are considered as the most significant elements that company managers should take into consideration. The fundamental goal of an airline is to provide safety and quality services by maintaining the high customer service level at the lowest inventory cost. However, many factors affect the customer satisfaction level in the airline, such as the spare parts' availability and uniqueness, geographic location of the suppliers, different lead times, and bureaucracy.

Aircraft-On-Ground (AOG) cases refer to any failure in providing spare parts for the aircraft which has a result the aircraft to remain on ground and to flight cancellations. From aviation statistics, a medium-size international airline with a fleet of about 50 aircraft of various types faces around 1,000 AOG incidents annually. With the average time needed to order a required item estimated at about 40 hours and the resultant costs for an airline can easily exceed $40-50 million annually [1]. Thus, the development of an appropriate inventory model that could help an airline to forecast and manage its inventory effectively is critical.

The main goal of this paper is to assess inventory models that could help a commercial airline to control effectively its


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inventory level by minimizing total inventory cost and by maintaining a high customer service level (99%).

According to the International Air Transport Association (IATA) [2], the spare parts inventory of an airline can be classified into three inventory types: rotable, repairable and expendable. The three main differences between the inventories are the scrap rate, the financial terms, and the life cycle. Rotable inventory has 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, the inventory is considered to be used once it is consumed.

Airlines further distinguish two more types of inventory: life limited parts and consumable inventory. Life limited spare parts have a predefined cycle time that is carefully monitored by the operator, while the consumable inventory has 100% scrap rate and is removed once consumed. In addition, there are three different types of defective spare parts depending on the part's importance to the firm such as Go items (when they fail the airplane still can fly), No-Go items (when they fail the airplane cannot fly), and Go-if items (when they fail the airplane still can fly, if minor repair is being conducted).

This paper is organized as follows. Section 2 presents a brief literature review on the inventory policies applied to airlines spare parts. Section 3 gives the proposed solution methodology implemented in this study which is based on two models: (i) the Order-Up-To (OUT) inventory model in conjunction with the Negative Binomial Distribution (NBD) and (ii) the (s, S) inventory model in conjunction with the Revised Power Approximation method. Numerical results are presented in Section 4 with a comparison of the performance of the two inventory models implemented in this study, over a real-world paradigm. Finally, Section 5 presents the conclusion of this study and recommends a few areas for further research.

## 2. Literature review

Given the detailed literature review in [3, 4] and in the interest of brevity, only a few key references on the methods tested are provided in the sequence.

The demand of the airlines spare parts is irregular, usually intermittent (there are many periods with zero demand and a few periods with 1 unit or low demand) and lumpy demand (when the non-zero demand is large). Syntetos et al. [5] provide a categorization of the demand patterns. According to their scheme there are four types of demand based on the coefficient of variation of demand sizes and the average demand interval: smooth, intermittent, erratic and lumpy.

Hopp et al. [6] examined inventory control practices for enterprise producing mail tools. A comprehensive literature review on repair processes in the airline industry is given in Garg [7]. Two nonlinear programming formulations, iterative approach, and GAMS methodology are presented in Gu et al. [8]. In Badkook [9], the agreement between the AOG process and routine aircraft maintenance is provided. Segerstedt [10] examines a refined inventory model based on Croston's model that applies gamma distribution and takes into account the lead-time.

Gamberini et al. [11] highlight the geometric distribution function and present a case study with real data in the inventory operation for small and medium-sized businesses with lumpy demand. Many studies demonstrate the effectiveness of the inventory model that is based on the empirical data. Babai et al. [12] concentrate on the study of the OUT inventory model specifically for the components with the cost constraint. They showed that compound Poisson distribution satisfies well the calculation of the OUT.

Nenes et al. [13] also give a model with Poisson distribution for the inventory control of the intermittent and lumpy demand. According to John Boylan, the Negative Binomial Distribution is the most convenient for modelling intermittent demand data. This study presents a comparison between inventory models for different target Customer Service Levels when the Croston's approach is used to forecast the demand and different demand distributions are considered.

Ehrhardt and Mosier [15] present a modification of the power approximation method given by Ehrhardt [16], for computing (s, S) inventory policies. The numerical computations of the s and S parameters are determined with under the Poisson and Negative Binomial distributions. The comparison showed that the modified approach is more accurate than the initial power approximation method in most of the cases.

## 3. Solution methodology

Two inventory models were selected to be implemented to the data of the Airline company:

(1) the Order-Up-To inventory (OUT) model in conjunction with the Negative Binomial Distribution (NBD) that is based on the research by Syntetos and Boylan [14] (and is briefly described in Sub-section 3.1); and
(2) the (s, S) inventory model in conjunction with the Revised Power Approximation that is based on the research by Ehrhardt and Moiser [15] (and is briefly described in Sub-section 3.2).

The real-world data accessed in this study describe the 10-year demand history of over 5,000 Stock Keeping Units (SKUs) of a commercial airline with aircrafts from all three major manufacturers. For the purposes of this paper, eighteen rotable and repairable aircraft SKUs from Embraer, Airbus, and Boeing were chosen. The selected spare parts codified in Table 1 include both repairable and rotable spare part types.

Figure 1 represents the actual 10-year demand history of SKU 3 which illustrates the fact that the demand is intermittent with many periods without demand occurrences. This type of demand is representative of the demand of the other SKUs in Table 1 as well as of the demand of most aircraft spare parts.

For the purposes of this paper, an arbitrary 22-month window was chosen to reflect relatively stable operational conditions while still accounting for seasonal variations. Three smoothing constant values of 0.05, 0.10 and 0.15 were considered for the calculation of the forecasts and of the smoothed mean squared error (MSE). Four values of Customer Service Level were investigated: 90%, 92%, 95%, and 99%.

The main goal of the analysis was twofold: to maintain (i) a high level of customer service and (ii) a low total inventory cost.

Table 1. Selected spare parts.

| Aircraft | Spare Part Type | SKU | Spare Part quantity |
|---|---|---|---|
| *Embraer* | Repairable | SKU1 | 3 |
| | Rotable | SKU6 | 3 |
| *Airbus* | Rotable | SKU4 | 3 |
| | Repairable | SKU5 | 3 |
| *Boeing* | Rotable | SKU2 | 3 |
| | Repairable | SKU3 | 3 |

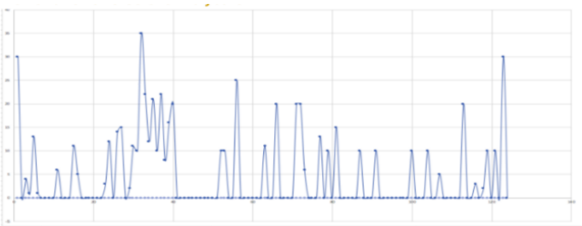

Fig. 1. 10-year demand history for SKU 3

### *3.1. The Order-Up-To (OUT) inventory model in conjunction with the Negative Binomial Distribution (NBD)*

In the OUT inventory model, at the beginning of each review period T, the inventory Position (on hand inventory + on order inventory - backorder) is reviewed. If the (Net stock + Receipts – Demand) is below the Order-Up-To level (S), then the difference between S and the inventory position is ordered.

We adopted the analysis of Syntetos and Boylan [14], according to which the OUT inventory model is the most suitable inventory policy to deal with intermittent demand patterns. The Syntetos and Boylan approach was taken as the basis for the further calculations, with a periodic review system where period T = 1 month. T and S are the output parameters of the model. The inputs are: the demand, the lead time (L=1 period), the customer service level, the spare part unit cost, its holding cost (unit cost X 0.05), its shortage cost (unit cost X 0.50), mean period forecast and variance (taken as smoothed MSE over (T+L)). Moreover, the Negative Binomial Distribution (NBD) is used in further computations for the OUT inventory model.

For obtaining final results of mean and variance of the demand distribution per period, Croston's forecasting method is used. Syntetos and Boylan [14] proposed a modification to Croston's estimator and illustrated the achieved efficiency on the real data. The equations are omitted. According to the literature review, Poisson distribution is one of the frequently used methods for the estimation of the OUT level for intermittent demand. However, Syntetos and Boylan [14] outline that NBD performs well with intermittent and lumpy demand patterns. Maintaining a high level of customer service is one of the main objectives of this work and is used as the constraint in the calculations in order to identify the efficiency of the inventory models. We adopted the following formula for calculating the Customer Service Level (CSL):

$$\mathrm{CSL}=\frac{Total\ Picklist-AOG\ Requisition}{Total\ Picklist}=\frac{Total\ Demand-Backorders}{Total\ Demand} \tag{1}$$

Cutting the costs down is a highly essential task for each enterprise. The average total inventory cost was calculated as the sum of the average positive stock times the holding cost plus the average negative stock times the shortage cost.

### *3.2. The (s, S) inventory model in conjunction with the revised power approximation method*

This method is described in Ehrhardt and Moiser [15]. Details are again omitted. The two parameters, the reorder level or minimum inventory (s) and the OUT level or maximum inventory (S) as well as the average total inventory costs with the different customer service levels and smoothing constant values need to be calculated. Table 2 presents different methods of (s, S) inventory model described and tested by Porteus [17].

Table 2. List of methods in (s,S) model used in Porteus [17].

| | | | | | |
|---|---|---|---|---|---|
| 1 | ONE-SHOT | 7 | NEWSBOY | 13 | NODISC |
| 2 | EXTAIL | 8 | DISCR | 14 | EMPIR |
| 3 | EOQROP | 9 | MCR | 15 | ANALOGY |
| 4 | EOQREV | 10 | ITER | 16 | POWER |
| 5 | EOQMULT | 11 | NONEWS | 17 | DETER |
| 6 | SKEW | 12 | NOEMULT | | |

According to the results of the testing, the Power Approximation method is the nearly optimal (s, S) inventory model with more accurate calculations of parameters among other methods in the list. According to the method, an order of size (S – y) is placed when the inventory position y = on hand inventory + orders - backorders <= reorder point (s). The method requires only the mean and the variance of the actual demand for calculations. Equations are omitted.

#### *3.2.1. The Revised Power Approximation*

In 1984, Ehrhardt and Mosier [15] fixed the Power approximation method of Ehrhardt [16] which had certain drawbacks, with the major drawback being that the order quantity (Q) vanishes when the variance approaches to zero, and introduced the Revised Power Approximation (RPA) method which considers the mean, variance and setup cost for the quantity calculation. Moreover, the RPA method considers unsatisfied demand as a backlogged and lead time as a constant. This method is appropriate for all demand distributions except for normal. The equations are provided below:

$$\mathrm{Q} = 1.30\mu^{0.494}(K/h)^{0.506}(1+\sigma_L{}^2/\mu^2)^{0.116} \tag{2}$$

$$z = [\frac{\mathrm{Q}}{\sigma_L b/h}]^{\frac{1}{2}} \tag{3}$$

$$s_p = 0.973\mu_L + \sigma_L(0.183/z + 1.063 - 2.192z) \tag{4}$$

If Q/ Forecast is more than 1.5, the reorder point and OUT level are calculated as follows:

$$s = s_p \quad (5)$$

$$S = s_p + D_p \quad (6)$$

Otherwise, when Q/ Forecast mean demand is less than 1.5, the $s$ and $S$ values are equal to:

$$s = \min\{s_p, S_0\} \quad (7)$$

$$S = \min\{s_p + Q, S_0\} \quad (8)$$

Where, *So* is an empirical modification of Wagner (1965) and is calculated by:

$$S_0 = (L+1)\mu + \vartheta\sigma\sqrt{L+1} \quad (9)$$

$$\int_{-\infty}^{\vartheta} \frac{\exp\left(-\frac{x^2}{2}\right)}{\sqrt{2\pi}} dx = \frac{b}{(b+h)} \quad (10)$$

In equation (10), *b/(b+h)* defines the customer service level.

To determine the reorder point and the Order-Up-To level, the Setup cost should be calculated from equation (11):

$$K = \left(\frac{Average\ size * h^{0.506}}{1.3 * Average\ demand^{0.494} * \left(1 + \frac{\sigma^2}{Average\ demand}\right)^{0.116}}\right)^{1.97} \quad (11)$$

where, the average size of SKU is the average demand divided by the number of non-zero actual demand throughout the period, and the average demand is the average of the actual demand and σ^2 is the variance of the actual demand.

## 4. Numerical results

In this Section, due to space limitations, only the comparison results (in terms of the average total inventory costs, customer service level and order quantity) of the two inventory models considered in this study, are given for an SKU. It has been numerically proved that the same trend applies to all 18 SKUs experimented in this study.

Table 3 demonstrates the results of the application of the Order-Up-To and RPA inventory models on the empirical data sample of Table 1.

The Order-Up-To inventory model presents the forecasted order quantity and the order periods based on the Negative Binomial and Poisson distributions. The order quantity is calculated over the 22-month period for SKU 1 (repairable part) with the unit cost of 4725 USD.

Moreover, two constraints are applied across all series: customer service level, ranging from 90% to 99%, and smoothing constant values of alpha, ranging from 0.05 to 0.15. As it may be observed from Table 3, the results vary significantly with the alteration of the CSL and smoothing constant parameters.

The values obtained in Table 3 indicate that the CSL is achieved by all the developed methods. The results also indicate that the OUT inventory model with Poisson distribution gives the lowest order quantity compared to all other alternative estimators in all simulated experiments. For example, for smoothing constant alpha 0.05 and customer service level of 99%, total order quantities for SKU 1 equal 78, 62 and 77 for NBD, Poisson and Revised Power Approximation (RPA) inventory models, respectively.

Table 3. Total order quantity for SKU 1.

| | | **NBD** | **Poisson** | **RPA** |
|---|---|---|---|---|
| 90% | 0.05 | 74 | 52 | 69 |
| | 0.1 | 75 | 52 | 70 |
| | 0.15 | 75 | 52 | 70 |
| 92% | 0.05 | 75 | 57 | 74 |
| | 0.1 | 76 | 52 | 74 |
| | 0.15 | 76 | 52 | 72 |
| 95% | 0.05 | 77 | 53 | 75 |
| | 0.1 | 77 | 55 | 76 |
| | 0.15 | 77 | 53 | 76 |
| 99% | 0.05 | 78 | 62 | 77 |
| | 0.1 | 80 | 33 | 73 |
| | 0.15 | 80 | 60 | 73 |

Overall, it may be said that almost any CSL could be achieved by ordering the higher number of spare parts to ensure the required inventory availability. However, this may result in excessive inventory and associated costs. Thus, despite the fact that some methods offer low order quantity and high customer service level does not guarantee the effectiveness of the method, since the total inventory costs should also be taken into account.

As it can be seen from Table 4, the total inventory costs with the three different methods are calculated over the same period and stock out levels. In terms of CSL of 99%, despite the fact that the method using Poisson distribution has the lowest order quantity, the total inventory cost incurred with RPA are the lowest compared to OUT inventory model with NBD and Poisson distributions (approximately 2270.1, 2085.2, and 2073.2 USD respectively for alpha=0.05).

Table 4. Average total inventory costs.

| | | NBD | Poisson | RPA | |
|---|---|---|---|---|---|
| 90% | 0.05 | 2927.5 | 2742.6 | 2734.7 | 7% |
| | 0.1 | 2793.9 | 2804.2 | 2644.0 | 5% |
| | 0.15 | 2722.0 | 2701.5 | 2658.3 | 2% |
| 92% | 0.05 | 2876.1 | 2249.5 | 2819.2 | 2% |
| | 0.1 | 2485.8 | 3338.3 | 2493.5 | 0% |
| | 0.15 | 2455.0 | 2773.4 | 2654.8 | -8% |
| 95% | 0.05 | 2485.8 | 2054.4 | 2012.4 | 19% |
| | 0.1 | 2270.1 | 2382.0 | 2198.9 | 3% |
| | 0.15 | 2270.1 | 2187.9 | 2153.5 | 5% |
| 99% | 0.05 | 2270.1 | 2085.2 | 2073.2 | 9% |
| | 0.1 | 2393.3 | 2547.4 | 2318.9 | 3% |
| | 0.15 | 2629.6 | 1838.6 | 2032.3 | 23% |

In order to test the effectiveness of the developed models the two models were tested for all 18 spare parts and a similar trend was observed. Also, when the unit cost of the spare part was higher, the cost difference between the methods was higher.

Furthermore, the above results were compared against the Simulation model developed by Yesdauletov et al. [4]. Table 5 shows the total inventory costs of SKU 23, SKU 102, and SKU 328 with the same Customer Service Level of 99%. A simulation model was developed in 2018 and the results satisfied the company objective. However, the (s, S) inventory model in conjunction with the RPA method outperforms the Simulation model. The resultant decrease in the total inventory cost is 5.66%, 2.91%, and 8.26% for SKU 23, SKU 102, and SKU 328, respectively.

Table 5. Total inventory costs calculations using different inventory models

| Total Cost | Simulation Model [4] | OUT Model with NBD | (s, S) Model with RPA [3] | % Difference |
|---|---|---|---|---|
| PN1 | 203030.87 | 201020.66 | 191538.56 | 5.66 |
| PN2 | 436737.36 | 445385.62 | 424016.85 | 2.91 |
| PN3 | 3842.02 | 4020.00 | 3524.79 | 8.26 |

(The full range of experiments that were performed can be found in [3].)

## 5. Conclusion and further research

The comparative evaluation in this paper demonstrates one potential approach to the airline inventory management problem aiming at keeping a high customer service level of 99% while minimizing simultaneously total inventory costs.

The proposed approach is based upon the development of two inventory models: (1) the OUT-inventory model with Negative Binomial and Poisson distributions and (2) The (s, S) inventory model with the RPA method. The two models were tested based on real historical data of aviation logistics describing spare parts' demand and orders over an almost 2-year window.

The findings demonstrate that the models may be adopted for any customer service level from 90% to 99% and smoothing constant values of alpha ranging from 0.05 to 0.15.

The costs associated with the ordered inventory rise with the increase of the CSL and thus are subject to decision-making. Overall, the OUT inventory model in conjunction with the Poisson distribution allows ordering the lowest order quantity.

However, the (s, S) inventory model with the RPA outperforms in terms of average total inventory costs. The advantages of the latter model could be explained by the following factors:

(i) The RPA method calculates the reorder point and order up-to level for any value of variance, while the other two methods assume the value of variance as the product of mean and 1.05, when it approaches to zero. This assumption decreases the accuracy of the calculations in the OUT inventory model.

(ii) The RPA method outperforms other models particularly in calculating the costs of the expensive spare parts. The results prove that for the relatively inexpensive spare parts the cost difference is not as high as when it comes to the cost estimation of the expensive spare parts.

The key innovation of the work presented is the development of a practical toolbox for controlling aviation inventory costs that is fairly robust with respect to customer service levels and smoothing constant values of alpha.

Future research should focus upon the continuous refining of the models described in this paper by examining alternative time windows of the demand. The key objective will be to examine various combinations of suitable inventory models and distributions of the demand to reduce further the total inventory costs while maintaining a stricter customer service level (typically exceeding 99%).

## CRediT author statement

Papadopoulos: Conceptualization, Funding acquisition, Project administration, Supervision, Writing - Review & Editing. Tsakalerou: Project administration, Validation, Supervision, Writing - Review & Editing. Babai: Methodology, Data curation, Software. Kenzhevayeva: Investigation, Writing - Original Draft, Visualization, Formal analysis, Software. Katayeva: Investigation, Writing - Original Draft, Visualization, Software, Formal analysis. Kaikenova: Writing - Original Draft, Software, Visualization. Sarsembayeva: Writing - Original Draft, Visualization.

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