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Inventory Cost Minimization of Spare Parts in Aviation Industry

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Abstract

Due to high competition in the aviation industry, cost reduction comes into prominence and becomes more critical each day. An efficient maintenance and spare part inventory management system that operates based on a reliable demand forecasting mechanism can significantly reduce operation costs. However, the conventional forecasting methods in the literature are insufficient to estimate the quantity and occurrence times of the non-smooth demand. When cost minimization is directly targeted, these traditional forecasting methods often give misleading results. This study aims to provide an inventory cost management framework for irregular demand in the aviation industry. It compares recent non-smooth demand forecasting techniques with conventional ones by employing cost-based performance measures to minimize cost. The research with 100 different stock keeping units from the inventory of a commercial airline revealed that non-traditional methods are still in their development phases and need further improvements.

Keywords: Aviation industry; Intermittent demand forecasting; Inventory cost minimization; Spare parts management

1. Introduction

Forecasting has great importance and is widely used in every stage of supply chains from suppliers to customers. Good forecasts lead to the right decisions such as determining how many items should be produced and how we can

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set target inventory levels to minimize stockout and inventory holding costs. Prediction of future spare parts demands to sustain continuous maintenance operations comes into prominence.

The only way to reduce the unfavorable effect of demand fluctuations is by keeping the inventory at some safe level. However, there is a trade-off between make-to-stock and make-to-order decisions as orders arrive. Make-to-stock decisions contain inventory costs such as carrying and holding.

However, make-to-order decisions may cause customers to wait so long as lead times get longer. Some customers are reluctant to wait the lead time long because of the supply chain structure wherein the chain the next step wholly depends on previous steps. Therefore, any waiting time affects all forthcoming processes directly. As a result, stockout costs can be seen in make-to-order decisions while holding costs can be seen in the make-to-stock decisions. Inventory planners aim to reduce the costs of inventory with high customer service levels using appropriate forecasting methods. It is needed to keep the inventory at a certain level by providing the balance between holding and stockout costs. The inventory cost performance of a product will depend on the accuracy of the employed forecasting method.

Managing service parts inventory is complicated in modern businesses, especially in the aviation industry, where the parts holding costs and the stock out costs are extremely high. One wants to simultaneously keep inventory costs low (therefore fewer stocks) but wants to ensure the availability of service parts (therefore high stocks). Service parts demand forecasting is challenging as demand draws a non-smooth pattern with mostly zero values and random non-zero demands. Classical time series forecasting methods usually cannot meet the expectations when applied to non-smooth demand (Şahin and Eldemir, 2018; Kaya and Türkyılmaz, 2018). The problems that arise while handling non-smooth demand data are to be solved to achieve better performance in inventory handling.

There are many benefits of accurate demand forecasting in planning, let alone the fact that effective management of uncertain demand may be a source of competitive advantage. Therefore, this study aspires to take forward the current state of knowledge on forecasting intermittent demand. This study aims to provide a framework that considers inventory costs for practitioners in the aviation industry for the best inventory strategy regarding irregular demand. The remaining of the paper goes as follows. A brief literature review and background information are given in the next section. After that, the forecasting and inventory control models have been put forward in the third section. The details of the test data are given in the third section as well. The findings are discussed at the end of the third section. In the last section, the conclusion is provided with a summary and discussion of future implications.

2. Literature

The inventory policy is the dilemma to determine how much order will be placed regularly or how much order will be constant. In the literature, different scenarios are employed to find optimal solutions (Bakker et al., 2012). Demand forecasting is fundamental in the framework of the spare part to focus on since its relation to developing a prediction of spare parts demand (Driessen et al., 2014). It is essential to identify which forecasting method is superior for each demand type, especially in cases where non-smooth demand data is employed. Croston (1972)'s approach to intermittent demand is the pioneering work for forecasting sporadic demand. The procedure independently estimates the demand interval between two non-zero demand values and the demand size. The forecast for the demand per period is then calculated as the ratio of the forecasts for demand size and demand interval (Croston, 1972). Based on this preliminary study, various cost-based methods are developed for intermittent demand forecasting and compared with traditional performance measures such as mean absolute percentage error (MAPE) and root mean square error (RMSE).

Teunter and Duncan (2009) tested six methods to forecast demand by evaluating a new performance measure that compares the target to the achieved service level (Teunter and Duncan, 2009). From the perspective of achieved service level measure, the original Croston's method, the Syntetos and Boylan (2005), and the Levén and Segerstedt variants (2004) showed better performance than the moving average and exponential smoothing. Altay and Litteral (2011) provides an enhanced overview of the number of SKUs by the categorization schemes. It is stated that, due to excessive stocks and low customer service levels, the biggest challenge is revealed by the demand that is categorized as lumpy demand. The details of demand categorization are provided in section 2.1.

2.1. Demand Categorization

Although different categorizations are available in the literature for non-smooth demand data, the major categorization has three types: intermittent, erratic, and lumpy. The intermittent demand data have a large portion with zero demand, where non-zero demands have random values with small variations.

On the contrary erratic demand with random quantities has significant variation but fewer zero values. In the lumpy demand case, the variation among the non-zero demands is high, and also the interval between two successive non-zero demands is long. The remaining case is called smooth demand data, where the variations among non-zero demands and the frequency of zero demands are low. Syntetos and Boylan's (2005) categorization scheme utilizes two demand parameters; Average Demand Interval (ADI) and Coefficient of Variation square (CV2).

ADI is the average number of periods between two successive demands, which indicates the intermittence of demand,

$$\mathrm{ADI} = \frac{\sum_{i=1}^{N-1} t_i}{N-1} \tag{1}$$

where N indicates the number of periods with non-zero demand and t_i is the interval between two consecutive demands.

CV^2 is squared of the ratio of the standard deviation of the demand data divided by the average demand, which indicates demand variability.

$$CV^2 = \frac{\sum_{i=1}^{n}(D_i-\bar{D})^2}{(n-1)\bar{D}^2} \tag{2}$$

where n is the number of periods, and D_i and $\bar{D}$ are the actual demand in period i and average demand, respectively. Syntetos and Boylan's categorization scheme is given in Figure 1 (Syntetos and Boylan, 2005).

For a smooth demand data, cutoff values are ADI = 1.32 and CV^2 = 0.49.

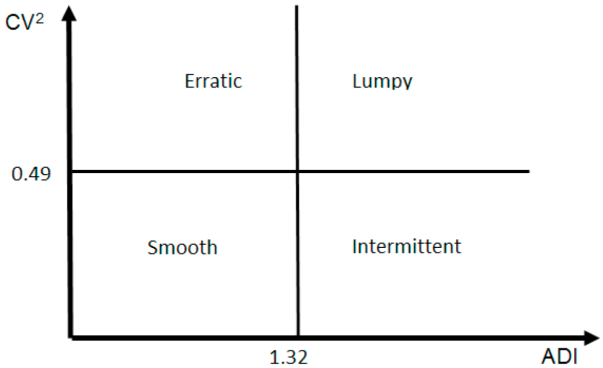

Fig. 1. Syntetos and Boylan Data Categorization Scheme (Syntetos and Boylan, 2005)

2.2. Implications to Inventory Management Systems

In academic literature, authors have studied accurate demand forecasting to provide efficient supply chain management for different industries. For example, Gupta and Maranas (2003) presented that demand uncertainty can be dealt with using demand forecasting and supply network planning model to minimize costs in the chemical industry. Suppose an organization cannot apply an accurate demand forecasting method for future demand. In that case, every department in the firm, such as production planning, inventory management, workforce scheduling, and financial planning, can be affected. Inaccurate forecasts prevent efficient control on the system and cause high costs and low customer service levels. However, by applying accurate demand forecasting, the cash flow in the firm can be controlled better because unnecessary costs are eliminated to generate the possibility of allocating this cash to any other areas in the firm. Demand forecasting with minimum error ensures costs related to inventory are low as possible while customer satisfaction stays high. Therefore, achieving demand forecasting accuracy is the first step to minimize inventory costs in supply chain management.

In Maintenance and Repair Operations (MRO), especially in aviation, forecasting and stock control difficulties arise from the intermittent nature of the underlying demand patterns. If spare parts are managed efficiently, cost savings may be achieved due to high prices and extreme stockout penalties. Management of spare parts entails the categorization of the relevant SKUs and forecasting accurately to facilitate decision-making. In this regard, an appropriate forecasting and stock control method will most probably increase spare parts availability and reduce inventory costs. Since the seminal work of Croston (1972) in the area of forecasting for intermittent demand, a few studies have addressed the implications of non-traditional forecasting methods to inventory management systems even though spare parts in the aviation industry comprise a significant percentage of the inventory, Porras and Dekker (2008). In their studies, Eaves and Kingsman (2004) and Strijbosch et al. (2000) differentiated forecast accuracy and utilized estimators' stock control performances. In the later stages, Willemain et al. (2004) and Syntetos and Boylan (2005) conducted empirical researches on the performance of various intermittent demand forecasting approaches. Boylan and Syntetos (2006) argues that "*no matter what inventory system is in use, the accuracy-implication metrics of stock-holding costs and service level should always be used since this is of prime importance to the organization. These measures should be used when it is difficult to assess forecast error directly. By keeping an inventory method fixed, accuracy-implication metrics offer a direct comparison of the effects of using different forecasting methods*." Thus, stock-holding cost and service level measures are of the highest significance in assessing the performance of a spare part management system.

2.3. Non-smooth Demand Forecasting

The Croston method for sporadic demand forecasting is a widely used technique that performs forecasting by dividing historical demand data into two series, nonzero demand and inter-demand intervals. Inter-demand intervals refer to the time between two consecutive non-zero requests. The method uses exponential smoothing separately for non-zero demand size and intervals between demands (Şahin and Eldemir, 2018; Kaya and Türkyılmaz, 2018). In this study, the following notation is used as suggested by Şahin and Eldemir (2018):

Y(t) is the estimate of nonzero demand size at time t,
P(t) is the estimate of the mean interval between nonzero demands at time t,
X(t) is the actual demand at time t,
Q is the time interval since the last nonzero demand,
α is the smoothing constant,
F(t) is the estimate of demand per period at time t.
Croston forecasting method updates values of Y(t) and P(t) according to the procedure shown in Figure 2.

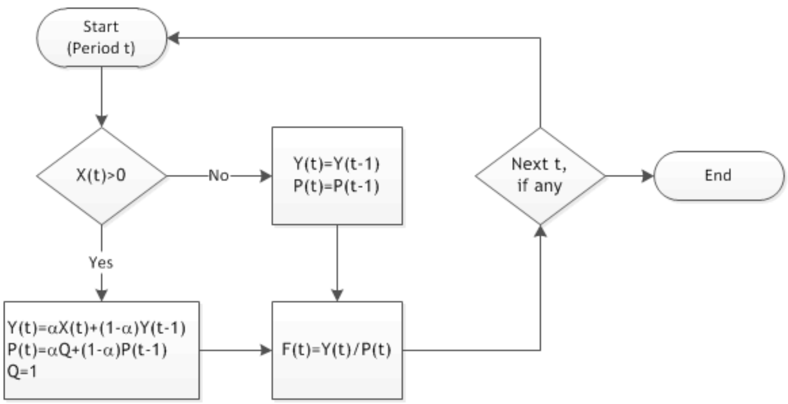

Fig. 2. Croston Method's Algorithm

Croston method calculates the demand forecast for the period t as follows:

$$F(t) = \frac{Y(t)}{P(t)} \tag{3}$$

Later on, researchers have modified the Croston method claiming that the initial technique was biased (Syntetos and Boylan, 2001). The biasness has been eluded by multiplying the forecast for the demand per period with a correction factor of $(1 - \alpha/2)$. Similar to Croston's approach, the estimates are updated for the periods with non-zero demands. Else, estimates are kept unchanged. The period *t* demand forecast is:

$$F(t) = \left(1 - \frac{\alpha}{2}\right)\frac{Y(t)}{P(t)} \tag{4}$$

3. The Methodology and Model

In this study, the following procedures have been performed while founding an efficient spare parts management model;

The historical data set provided by the aviation industry is analyzed and each part's historical data is categorized based on the categorization scheme. Inventory costs are minimized by applying different forecasting methods by searching the best parameters.

The following steps are applied while determining the best strategy to minimize inventory costs:
- Categorize spare parts demand data.
- Split some data for initialization.
- Reserve some of the recent data for validation.
- Choose intermittent demand forecasting methods (Naïve, Exponential Smoothing, Croston, and Syntetos).
- Use constant smoothing factor α as 0.2. Here 0.2 is the default initial smoothing factor.
- Forecast the future demand.
- Calculate order up to levels.
- Determine ordering times and order amounts.
- Calculate inventory holding costs, ordering costs, and stock outs.
- Compare results with a naïve approach.
- If the results are not satisfactory then optimize the smoothing factor "α".
- Then calculate the costs with an optimized smoothing factor.
- Compare different α results, to choose the optimal "α"l parameter.

The optimum smoothing factor that gives minimum inventory cost is exhaustively searched by using spreadsheets. "α" is searched from 0 to 1 range with 0.01 increments.

3.1. Data Set

In this section, the real demand data set of spare parts in Turkish Airlines inventory is employed. These spare parts were selected from among non-smooth demand which has ADIs that are greater than 1.32 or which have CV^2 s that are higher than 0.49. The data covers 106 monthly periods. Descriptive statistics of the non-smooth demand data set is given in Table 1 as the following;

Table 1. Descriptive Statistics of Spare Parts Demand Data

	Num of Occur.	Average Demand	ADI	Demand Per Period	Std. Dev. of Sets	CV^2
Mean	43,9	14,39	3,06	11,04	16,69	0,84
Minimum	16	1,04	1,01	0,18	0,20	0,04
1st Quart	26	2,09	1,83	0,61	1,40	0,33
Median	39	3,07	2,72	1,23	2,40	0,58
3rd Quart	26	2,09	1,83	0,61	1,40	0,33
Maximum	105	543,2	6,6	527,8	645,1	5,2
Count	100	100	100	100	100	100

Examples from each data category are represented in Figure 3.

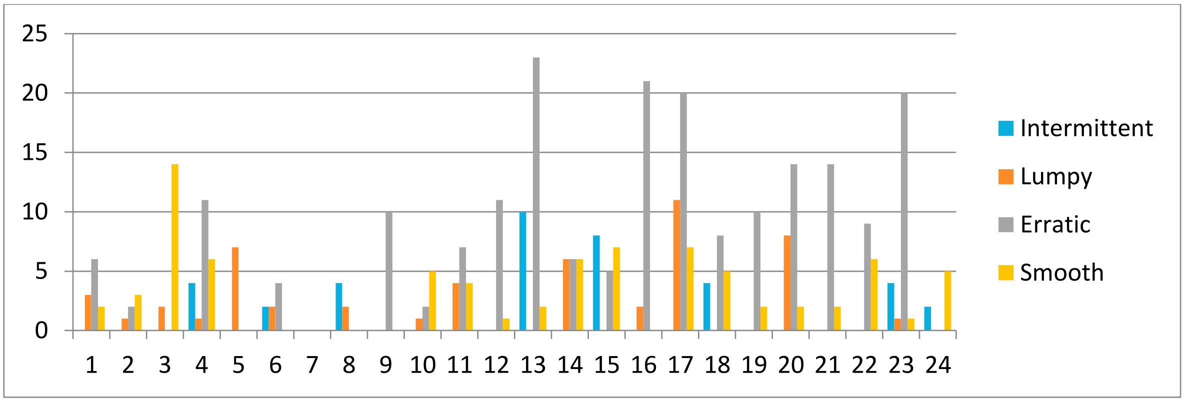

Fig. 3. Different types of non-smooth demand data (monthly)

The number of data types in our data set is given in Table 2.

Table 2. Number of spare parts demand data in each category

Demand Pattern Condition	Demand Type	Number of Data Series
ADI≤1.32; CV^2>0.49	Erratic	8
ADI>1.32; CV^2>0.49	Lumpy	56
ADI≤1.32; CV^2≤0.49	Smooth	1
ADI>1,32; CV^2≤0.49	Intermittent	35

Our data set (each spare part has 106 months of demand data) is divided into three parts with overlapping as follows;

- Initialization: The first 36 months of data is used to initialize the model.
- Optimization: Between the 24th month and 108th month of data is used to minimize total inventory costs by setting all associated parameters.
- Validation / Performance Measure: The last 36 months' data is used to find the performance of the forecasting methods by applying base stock policies.

3.2. Results and Discussion

The tables below represent the comparison of estimation methods with data types after minimizing inventory costs. In Table 3, the results are given when the alpha parameter is fixed and 0.2. Each number shows how many demand dataset of the relevant demand-type gives the minimum inventory cost with which estimation method. For example, the naive method is the method that gives the best results for seven demand dataset out of eight erratic demand data types.

Table 3. Forecasting methods versus data types

Method	Erratic	Intermittent	Lumpy	Grand Total
Croston		1	4	5
Exp.Smoothing	1	5	6	12
Naive	7	29	46	82
Syntetos			1	1
Grand Total	8	35	57	100

The performance of forecasting methods for each demand data type is shown in Figure 4.

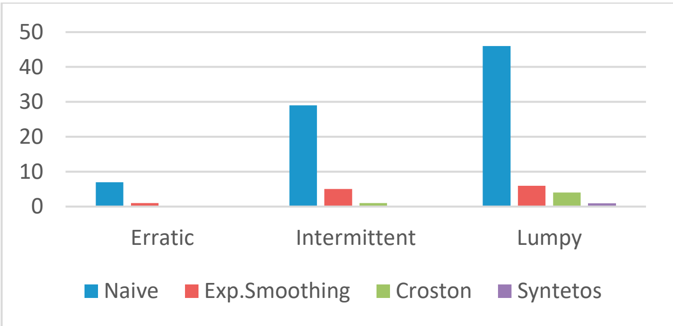

Fig. 4. Forecasting methods vs Data Types

The following results (Table 4) are given when the alpha parameter is optimized for Exponential Smoothing, Croston, and Syntetos.

Table 4. Optimum cost results of forecasting methods versus data types

Method	Erratic	Intermittent	Lumpy	All Data
Croston	2	6	25	33
Exp.Smoothing	2	18	19	39
Naive	4	11	11	26
Syntetos			2	2
Grand Total	8	35	57	100

The performance of estimation methods for each demand data type when the optimum alpha parameter is applied is shown in Figure 5.

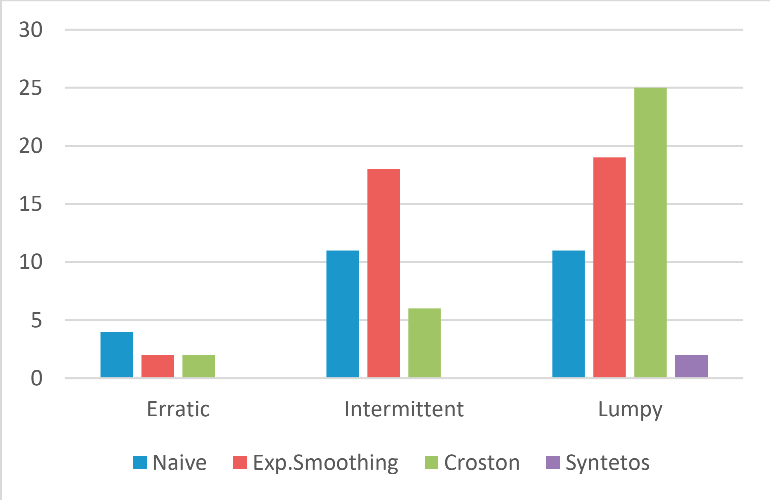

Fig. 5. Optimum cost results of forecasting methods versus data types

The best forecasting methods according to data types are given in Table 5 when the alpha parameter is optimized accordingly.

Table 5. Best Method based on data types

Data Type	Forecasting Method
Intermittent	Exp.Smoothing
Erratic	Naive
Lumpy	Croston

This study focuses on comparisons of estimation methods that take stock cost results into account, instead of traditional forecasting accuracy measures that can be found more practical. Theoretically, the accuracy results of forecasting methods may differ from the results we obtained in this study, even when forecasting accuracy measures generated for non-smooth demand data types are applied, as comparisons are made from a different perspective. This may cause a conflict in the calculations of the results, but practitioners should consider what perspective they should take, whether cost-based or accuracy-based. Although these measures seem parallel in the end, there may be an inconsistency between them when considering the cost parameters.

It may be more meaningful to classify the demand data according to certain values and to share a method that is an alternative to the data type or gives the minimum cost result, rather than suggesting that only one method will be good for this.

4. Conclusion

Traditional per-period forecasting errors may not be suitable for measuring the performance of forecasting methods for items with non-smooth demand, especially where managers often focus on costs. Reducing inventory levels is often an important goal of inventory planners. Precise forecasting can help increase customer satisfaction and help increase better control of the work. Therefore, companies need to have appropriate predictive accuracy measures in place. Further improvements may be possible by considering performance measures related to inventory cost.

The study showed that the best strategy would be the integration of inventory decision-making with non-smooth demand forecasting. The supply-side effect of uncertainty should also be considered. One can show that the choice of forecasting method has a great effect on decisions, such as ordering frequencies and stock level. The methodology presented in this study also provides better means to measure performance of the forecasting systems.

Inventory planners should watch two main objectives while trying to reduce spare parts inventory costs: 1) to show that inventory cost has been reduced through improved forecasts for demand classes, and 2) to determine supply quantity and order time of the products to keep a satisfactory customer service level.

This study will shed light on comparing forecasting methods with optimizing inventory costs considering different demand data types. As a result, after the demand data categorization, companies can decide on the most appropriate forecasting method that will provide minimum inventory costs. This information will help practitioners make their ordering decisions with minimum inventory costs, accurate stock policy, and high service levels for each demand type.

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