Demand Forecasting for Irregular Demands in Business Aircraft Spare Parts Supply Chains by using Artificial Intelligence (AI)

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Abstract: Demand forecast accuracy in the service supply chains e.g. spare parts is critical for customer satisfaction and its financial performance. This is a typical logistic network which is affected by irregular demand resulting from contract and non-contract business strategies. Hence, existing forecasting methods that work excellent with smooth and linear demand patterns become less accurate with increasing erratic, lumpy and intermittent demands. Moreover, increasing number of stock keeping units (SKUs) in service supply chains have computational limitations. This is because of the fact that demand keep on fluctuating their demand classes that result in uncertainty and consequently, leads to higher target stock levels (TSL) and lower reorder point (ROP) to ensure higher customer satisfaction. This raises interest in using AI for service supply chains to improve demand forecast accuracy. In this paper, we present a survey of existing forecasting methods used in service and non-service supply chains to select best performing AI methods and performance measures, using ABC classification. Neural network (NN) and Mean Square Error (MSE), are subsequently modelled and used in aircraft spare parts supply chain using data collected from Dassault Aviation, as a function of most commonly used aggregated demand features. The results are compared with frequently and best performing forecast methods for intermittent demand as Croston, Croston SBJ and Croston TSB; and classical methods as moving average (MA) and single exponential smoothening (SES). The analysis and results suggest that NN with higher number of features improve demand forecast accuracy significantly for intermittent demands along with reduction in associated financial implications.

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Keywords: Spare Parts Service Supply Chains, Demand Forecasting, AI Methods, Business Jets

1. INTRODUCTION

The biggest challenge faced by today’s service supply chains is increasing inventory management cost while ensuring high customer satisfaction. This is because of the fact that demand patterns changes as a function of business strategy adapted by supply chain partners. For example, spare parts supply chain is a typical logistic network with contract and non-contract type business strategies. In presence of multiple suppliers and strict quality standards, the customer orders are not limited to OEM (original equipment manufacturer). This is because one can get the required part, compliant to quality standards, form multiple suppliers at varying costs and lead times. This often results in more and more spare parts getting into non-contract business strategy, resulting in competition over costs and lead times. Consequently, emerging demand patterns are highly uncertain and unpredictable.

In this complex and competitive situation, spare parts supply chains can reduce inventory cost, target stock level (TSL) and improve reorder point (ROP) while ensuring minimum lead times to the customers if and only if they can predict demand forecast more accurately. This becomes more challenging for business aircraft manufacturers supply chains of spare parts because aircraft’s travel pattern and usage is unpredictable in comparison to passenger airline carriers. This results in more fluctuating demand patterns where forecasts are more likely to be inaccurate with severe consequences on the financial performance of respective supply chains.

The spare parts in these supply chains ranges from 300,000 to 500,000 SKUs which adds higher computational complexity and dire need to group spare parts, exhibiting similar demand characteristic. Moreover, the cost and lead time of these parts can range from few USD to hundreds and thousands of USD with lead times up to 2 years. The inventory costs associated to these logistic networks are in the billions of USD which is majorly met by capital investment. Hence, this give huge rise of interest in the forecasting methods for spare parts service supply chains of business aircraft industry. This is because of the fact that even partial improvement in the demand forecast accuracy can result in the savings of millions of USD which is beneficial for both business aircraft manufacturer and the shareholders of the company as it reduces capital investment while ensuring higher customer satisfaction levels.

In this paper, we focus on spare parts service supply chain of business aircraft manufacturers to find best forecast methods for either each or group of parts exhibiting similar demand characteristics for competitive advantage. We present survey of existing most frequent forecasting methods for service and
non-service supply chains to identify the best AI methods and performance measures using ABC classification. The NN and MSE are found as the best AI method and accuracy measure. These are used in a case study based on spare parts demand data, collected from Dassault Aviation, as a function of commonly and frequently used aggregated demand features. Moreover, forecast accuracy is compared with most frequently and best performing forecast methods for uncertain and unpredictable demand as: Croston, Croston SNB (Syntetos-Boylan approximation), Croston TSB (Teunter -Syntetos-Babai) and Croston SBJ (Shale-Boylan-Johnston); and classical methods as Moving Average (MA) and Single Exponential Smoothing (SES). The analysis and results suggest that NN with higher number of features do improve demand forecast accuracy of uncertain and unpredictable demands along with reduction in associated financial implications, significantly.

2. LITERATURE REVIEW

This section presents a brief review on demand classification techniques; and most frequently and best performing forecast methods, measures of accuracy and input features from non-spare and spare parts service supply chain studies. Moreover, we also present ABC classification technique used to retain best performing and likely most adaptable forecast methods and performance measures. These are then modelled and used with other forecast methods as a function of number of input features for their best adaption in business aircraft spare parts supply chain. The case study and results are presented in next section.

2.1 Spare parts and demand classification

In this section, spare parts demand characteristics of business aircraft and airline careers are compared to distinguish the challenges faced by respective spare parts logistic networks. Moreover, due to high number of spare parts in these supply chains, it is highly important to analyze and choose existing methods to classify the demand patterns. Hence, we present and choose demand classification method for grouping of the spare parts in the case study.

The spare parts demand of airline carrier is more regular and predictable than business jets because their usages and travel patterns are available to estimate the need of respective spare parts. Whereas, it is not the case with business aircrafts due to their unpredictable usages and flight patterns, primarily based on their leisure usage and confidentiality. Hence, this is not easy to predict which business aircraft might need which part at which location. Another big difference between these two aircrafts’ spare parts is interchangeability. The airliners have higher number of interchangeable parts than business aircraft because later are designed for special and specific functions. Besides, there are significant variations in price and demand volume. However, both types of aircrafts share varying prices and lead times.

The computational cost and complexity associated with the forecast of each part in the service supply chain is practically not feasible. Therefore, classification is used to group these parts based on similar demand characteristics to have better and more accurate demand forecasts for subsequent optimal inventory related decisions. Eaves and Kingsman (2004) proposed loose classification of demands as the function of demand and quantity variations (Table 1). (Syntetos, Boylan, and Croston, 2004) quantified this conceptual classification and proposed experimental cutoff values for coefficient of variation ($CV^2=0.49$) as representative of quantity variation and average demand interval ($ADF=1.32$) as representative of demand variations. In the next section, we focus on irregular demand forecasting methods due to space restrictions.

### Table 1. Four considered demand type and variability representation

<table>
<thead>
<tr>
<th>Demand Type</th>
<th>Variability</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smooth</td>
<td>LOW</td>
<td>LOW</td>
</tr>
<tr>
<td>Erratic</td>
<td>HIGH</td>
<td>LOW</td>
</tr>
<tr>
<td>Intermitent</td>
<td>HIGH</td>
<td>HIGH</td>
</tr>
<tr>
<td>Lumpy</td>
<td>HIGH</td>
<td>HIGH</td>
</tr>
</tbody>
</table>

2.2 Frequently used Forecasting Methods, Accuracy Measures and Demand Features

The traditional forecasting methods have focused on regular demand patterns; however, Croston (1972) was the first who presented an exponential smoothing method for the irregular demand forecast in inventory control system. He concluded that intermittent demand could lead to improper stock levels and suggested to use separate estimates of demand size and interval between consecutive demand occurrences. Syntetos (2001) reassessed Croston’s method with focus on its forecast performance and presented modification with approximately unbiased demand/period estimates and showed superiority of the revised method. Syntetos, Babai, and Gardner (2015) investigated that simple parametric or bootstrapping method is more appropriate to forecast demand mean and variance for intermittent demand class. The results confirmed the suitable performance of the former and questioned the benefit of latter relative to its complexity. These extensions are referred as Croston SNB, Croston TSB and Croston SBJ methods (Kourentzes, 2014).

Amin-Naseri and Tabar (2008) have employed recurrent NN, multi-layered perceiver NN and generalized regression NN for forecasting spare parts from lumpy demand class. They used real data gathered to examine the forecasting performance of proposed approaches by comparing it to Croston’s and Syntetos and Boylan approximation methods. The results confirmed the superiority of the AI based NN methods.

Forecasting demand for spare parts and aircraft spare parts in particular have been widely investigated in the literature (Ghobbar and Friend, 2003; Hua and Zhang, 2006; Chen and Chen, 2009; Muñoz and Muñoz, 2011). Ghobbar and Friend (2002) focused on sporadic nature of demand for aircraft
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