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A Predictive Method For the Estimation of Material Demand for Aircraft Non-Routine Maintenance

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Abstract A method is developed to forecast material demand caused by aircraft non-routine maintenance. Non-routine material consumption is linked to scheduled maintenance tasks to gain insight in demand patterns. Subsequently, a suitable prediction model can be applied to forecast material demand. To test this approach, a structural part selection of the Boeing 737NG fleet of KLM Royal Dutch Airlines has been sampled to form a test case. Several regression and stochastic models have been applied to the part selection to judge model fit and validity. Resulting from this analysis, the Exponential Moving Average (EMA) was chosen as superior model for its small error values and ability to capture general demand trends. The forecast method incorporating the EMA model has been validated by forecasting and comparison against an independent dataset. Concluding, the non-routine maintenance forecast method, comprising the non-routine material consumption forecasts linked to scheduled maintenance tasks, can be used to produce material predictions expressed in probability and average quantity figures for upcoming maintenance checks.

Nomenclature

t	=	time
n	=	number of periods
ε_a	=	average demand
ε_t	=	actual demand

1. Introduction

Due to economic effects such as rising fuel costs and increasing competition from Maintenance Repair and Overhaul (MRO) organizations in low-wage countries, MRO organizations in Western Europe are continuously striving to minimize costs while delivering maximum service. Cost savings may however in no way comprehend the service level of aircraft. This is an everlasting trade-off between availability and costs which is also reflected in the supply chain management of MRO organizations. From the production point of view it is crucial to have all required parts in stock, while from the financial side it is important not to have too many or too costly parts in stock, as this all represents dead capital. Data of material consumption, aircraft utilization and an airlines' maintenance program can be captured and used to estimate material demand in advance of maintenance checks, allowing for more optimal purchasing of parts and an associated shift from a reactive stock-level oriented planning to a proactive maintenance activity based planning.

The maintenance of aircraft can be divided into routine maintenance and non-routine maintenance. Routine maintenance consists of a standard number of maintenance tasks, performed when aircraft reach a certain amount of flight hours, flight cycles or calendar age. These routine maintenance tasks are bundled together in packages such as FA and FC checks. Routine maintenance is planned well ahead and the availability of required routine parts approaches 100%. Non-routine maintenance is additional maintenance found during routine maintenance tasks, which is not included in the scheduled task requirements [1]. Non-routine maintenance shows unpredictable behavior and the availability of parts is therefore much lower than for routine tasks.

It is a considerable challenge to bring some predictability in the material demand caused by non-routine maintenance tasks due to the large number of factors contributing to material demand, the sporadic nature of non-routine material demand and the large amount of different part numbers present in the aircraft. Currently, MRO organizations such as KLM E&M do give forecasts about non-routine maintenance tasks. However, these forecasts are based only on the amount of required man-hours and are not given on a material specific level. In case a part number required for non-routine maintenance is not available in the stock of the MRO, it thus has to be ordered at a vendor during the maintenance check. Hence there is a risk that the part cannot be delivered and installed within the time of the maintenance check with an Aircraft On Ground (AOG) as result. MRO organizations require method(s) and/or model(s) to accurately predict material demand in advance of the maintenance check, to reduce the risk of expensive AOG orders and to allow for more accurate inventory management.

Consequently, the goal of the present research is to develop a method and tool able to predict material demand for aircraft non-routine maintenance. To be able to sample and test the proposed method and associated models, the research scope is limited to ATA structure chapters 51-57 for the Boeing B737 NG aircraft (encompassing the main fuselage parts), for which a dataset is available from KLM Engineering & Maintenance (E&M).

2. Literature

The spare parts demand for aircraft maintenance can be characterized using time intervals and quantity variation. Typically, demand type can be identified by considering the Coefficient of Variation (CV) and Average Inter Demand (ADI) values [2] – see Equations (1), (2) and (3), where t is time, n is the number of periods, $\mathcal{E}_a$ is the average demand and $\mathcal{E}_i$ is the actual demand.

$$ADI = \frac{\sum_{i=1}^{n} t_i}{n} \tag{1}$$

$$CV = \frac{\sqrt{\frac{\sum_{i=1}^{n} (\varepsilon_i - \varepsilon_a)^2}{n}}}{e_a} \tag{2}$$

$$\varepsilon_a = \frac{\sum_{i=1}^{n} \varepsilon_i}{n} \tag{3}$$

The ADI and CV values can be used to identify demand patterns [2]:

- **Slow moving, or smooth demand**: regular demand with a limited variation in quantity
- **Intermittent demand**: extremely sporadic demand, with no accentuated variability in the quantity of the single demand
- **Erratic demand**: large variation in quantity, but constant distribution over time
- **Lumpy demand**: great number of zero-demand periods and large variation in quantity.

These demand patterns (or types) are shown in Figure 1. Ghobbar *et al.* [3] suggest cut-off values for ADI (1.32) and CV (0.49) to categorize demand as having a constant distribution over time (ADI < 1.32) or a variable distribution over time (ADI > 1.32), with limited variation in quantity (CV < 0.49) or a large variation in quantity (CV > 0.49). The cut-off values are given in Figure 1.

Non-routine maintenance (and associated material demand) is characterized by many instances of zero-demand and significant variation in quantity. As such, the demand classification of non-routine material is typically intermittent or lumpy; this assumption will be checked for the dataset considered in this study. Traditional stochastic forecasting methods give accurate results with smooth, regular demand, but provide inaccurate results with intermittent and lumpy data [4], as the special role of zero values is ignored in analyzing and forecasting demand. Furthermore, traditional forecasting methods assume a normal, classic bell-shaped curve between the likelihood of the value and the demand. However, this normal distribution assumption is not valid for intermittent and lumpy demand [5].

Ghobbar *et al.* [3] consider a range of forecasting models of this demand type. Based on the characteristics of the dataset (see Section 4), a variety of regression and stochastic models have been selected for subsequent analysis of model fit. The

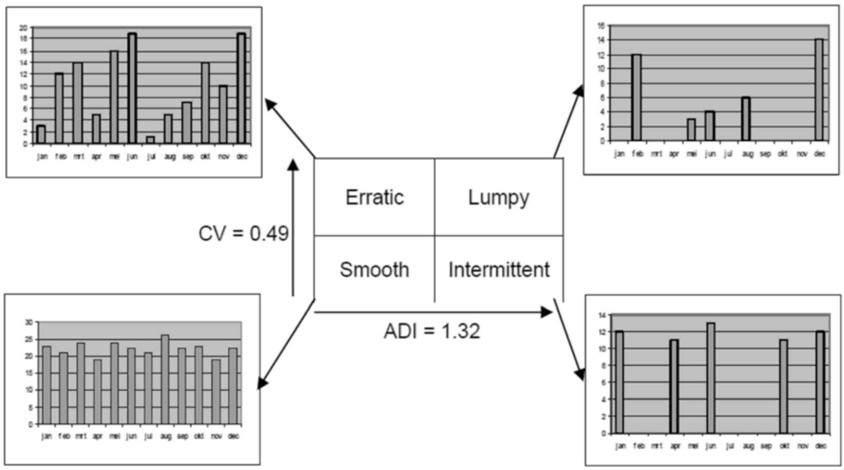

Figure 1: Spare part classification [2]

regression models taken into account for evaluation are a weighted mean and linear, exponential and polynomial models, while the stochastic models consist of Single Exponential Smoothing, Moving Average, Exponential Moving Average, Savitzky-Golay filter, Croston's method and the Syntetos Boylan Approximation [3, 6, 7].

3. Method

The first step in the general method for the prediction of material demand for non-routine maintenance is to link non-routine material demand with scheduled maintenance tasks. An overview of the relation between non-routine material demand and its linked scheduled maintenance task is provided in Figure 2.

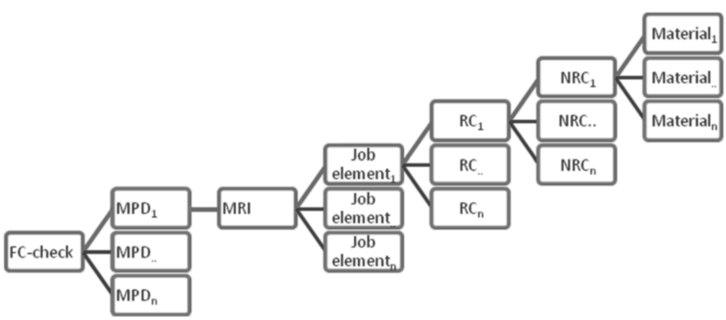

Figure 2: Link between FC-check, MRI maintenance tasks and non-routine material orders

A maintenance check such as the FC-check consists of a set of scheduled maintenance tasks given out by Boeing in the Maintenance Planning Document (MPD) or given out by the MRO organization as Maintenance Required Inspection (MRI) tasks. Each scheduled task contains job elements provided as Routine Jobcards (RC). If during the performance of the maintenance task a part defect is found such as corrosion or cracks it is written down on a Non-Routine Jobcard (NRC). In order to restore the functionality of the part material is required, given as the non-routine material. By linking non-routine material demand to scheduled maintenance tasks an insight is acquired which parts are inspected when, and can hence be demanded. Furthermore datapoints are acquired for inspections with zero demand by looking up how many times the maintenance task is performed. Subsequently the inspection interval of the scheduled maintenance task has been looked up from which the individual tasks can each be assigned to a maintenance check. With this information per maintenance check a list of part numbers can be obtained with accompanied probability and average quantity figures.

As lumpy demand by definition consists of a small number of nonzero data points, a binning strategy has been incorporated into the method to enable reliable forecasting of demand. If too few data points for a specific individual part number are present, the part number is binned into a group of similar part numbers and the demand pattern of the group is analyzed. By comparing the data points of the individual part number with the data points of the part group a prediction can still be made. When too few data points are present for the similar part group, the part number is subsequently binned into a Job Instruction Card (JIC) zone and the demand pattern of all parts in the JIC Zone is analyzed. It has to be emphasized that an individual part is always part of a similar part group and that specific parts can be located in different JIC zones. Different JIC zones never overlap. This grouping strategy is visualized in Figure 3.

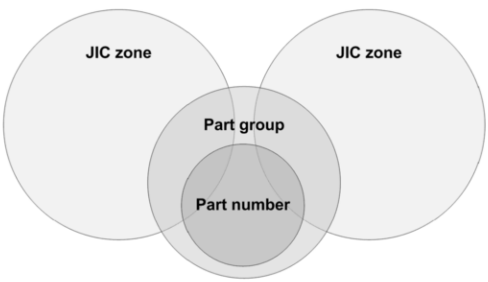

Figure 3: Grouping strategy of individual part numbers into (1) similar part group, or (2) JIC zone part group

4. Case study: Boeing 737NG maintenance data

To analyze the suitability of the developed method, a research sample has been developed using maintenance data related to structural parts (ATA chapters 51-57) of the Boeing 737NG fleet maintained at KLM E&M. The data is first checked for completeness, after which the various regression and stochastic models have been applied to the dataset. Finally, the results were analyzed leading to selection of the most suitable forecasting model to be used in conjunction with the non-routine material demand forecasting method. This selection has been validated using an independent data sample.

4.1. Data analysis

Maintenance data from KLMs fleet of 46 Boeing 737NGs has been collected from the recently implemented system Maintenix as well as from the Aircraft Maintenance Program of KLM and imported in an Microsoft Excel® database. As the Maintenix software was implemented in January 2010 a limited amount of data is available for research as is shown in Figure 4.

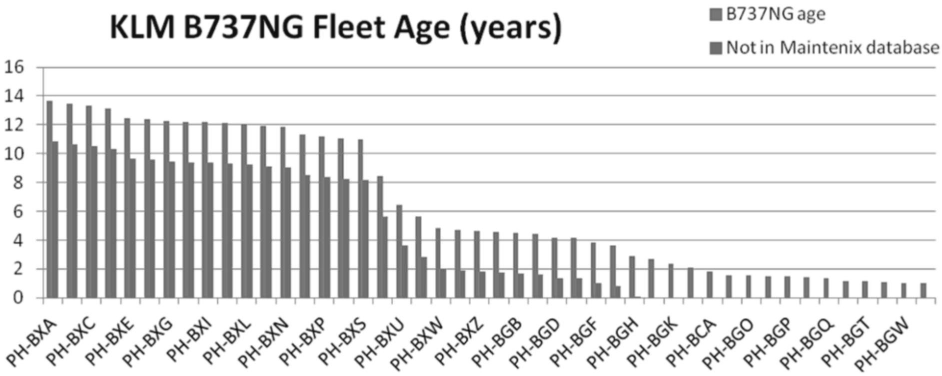

Figure 4: KLM B737NG fleet age including period implemented in Maintenix

A total of 44 FC-checks has been stored in Maintenix up until January 2010, divided over six different checks, as shown in Figure 5. The inspection interval of each FC-check is given by either 24 calendar months, 6000 flight hours, or 4000 flight cycles, whichever boundary condition is reached first.

After cleaning the data, material ordered for non-routine maintenance work has been linked to scheduled maintenance tasks. By looking up the inspection intervals of each maintenance task, it is possible to determine what material demand can be expected in which maintenance checks. This furthermore provides valuable information when specific parts have been inspected but have not been replaced, representing zero demand data points. Using the demand intervals and quantities, it has proven possible to characterize material demand per part number.

To improve anticipated forecasting performance and focus research efforts, a Pareto chart of the structural part numbers has been made based on the cost impact, defined as the installed part quantity times the unit cost[1]. The top 10 cost impact part numbers, representing 60% of the total structural material costs, has been selected to test the prediction models on. The material demand is lumpy (ADI > 1.32, CV > 0.49) for all of these part numbers.

For these part numbers both the probability per FC-check, given as the hit-rate per FC-check, and the average quantity per FC-check have been calculated based on historical consumption data. Subsequently, the various regression and stochastic models have been applied to identify demand patterns for both the probability and average quantity plots. An example is given in the following Section.

4.2. Example of analysis: Forecasting demand for a single part number

As an example, demand for cabin windows is forecasted using the various regression and stochastic methods. Following the proposed forecasting method, the scheduled maintenance task for which cabin windows are replaced is first determined, as well as the interval of the task and the FC-checks in which it is embedded. This information is

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[1] Given the sensitive nature of cost information, this Pareto chart is not represented here.

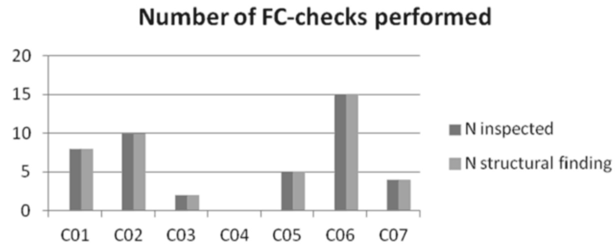

Figure 5: Number of FC-checks performed with a structural finding

provided in Table 1. The scheduled MRI task is performed in all FC-checks and hence demand can be expected in every FC check.

Table 1: Scheduled MRI tasks and intervals for which cabin windows are replaced

MRI task	Qty.	%	MRI threshold	MRI interval	Inspected in check
562000010101/01	340	99.7%	-	24 CMON	All FC
532000011001/01	1	0.3%	36000 CYCLES,12 CYR	24000 CYCLES,8 CYR	FC06,FC10
Total	**341**	**100%**			**All FC**

Hereafter, historical maintenance data is used to calculate both the probability per FC-check and average quantity per FC-check, which the models are subsequently applied to. The stochastic probability plot is given in Figure 6.

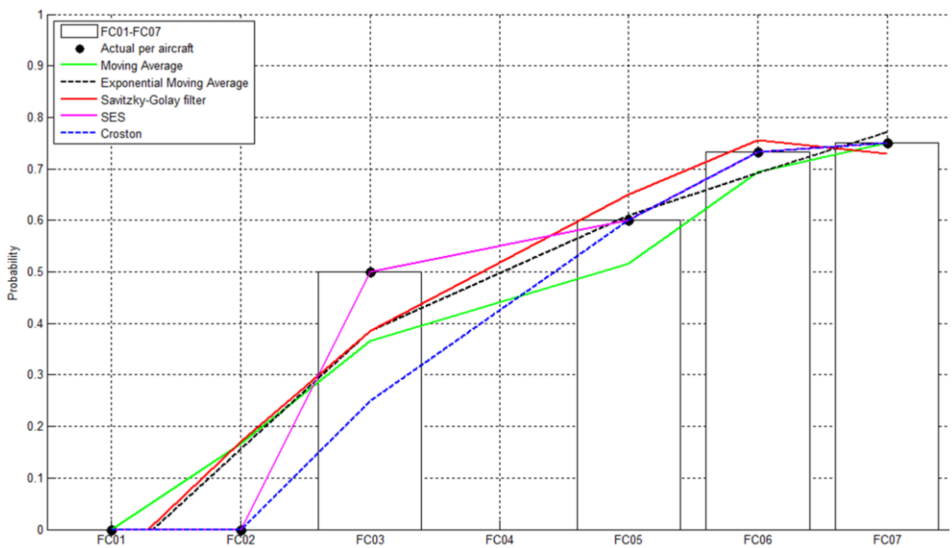

Figure 6: Stochastic probability plot per FC-check for the cabin windows (part number 140N2139-1)

In order to evaluate the accuracy of each model based on the consumption data included in the database, the Sum of Squared Error (SSE) and Root Mean Squared Error (RMSE) are calculated for all FC-checks for both probability and quantity forecasts. Equations (4) and (5) express the SSE and RMSE. The forecast error e_t is given in equation (6), where Y_t is the actual quantity at time t and F_t represents the forecasted value for time t.

$$SSE = \sum_{t=1}^{n} e_t^{\,2} \tag{4}$$

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(e_t)^2}{n}} \tag{5}$$

$$\varepsilon_t = Y_t - F_t \tag{6}$$

The evaluation results for the cabin windows are shown in Table 2.

Table 2: Accuracy of forecasting models for cabin windows

140N2139-1: Cabin Window Assembly	Forecasting model	Probability		Quantity	
		SSE	RMSE	SSE	RMSE
	Weighted Mean	0.60	0.31	571.17	9.75
	Linear	0.07	0.13	158.5	6.29
	Weighted Linear	0.29	0.27	772	13.8
	Weighted Exponential	0.79	0.44	97.52	4.9
	Weighted 2nd Polynomial	0.27	0.30	206.70	8.30
	Weighted 5th Polynomial	0.00	0.00	0.00	0.00
	MA	0.05	0.09	52.80	2.96
	EMA	0.04	0.08	26.65	2.10
	Savitzky Golay Filter	0.04	0.09	15.58	1.61
	SES	0.00	0.00	0.00	0.00
	Croston	0.06	0.10	6.25	1.02
	SBA	0.50	0.29	250.65	6.46

Similar analyses have been performed for the demand probabilities and quantities of the top 10 part numbers by cost impact. As mentioned, various regression and stochastic models have been applied to forecast demand probability and quantity. For each of these models, the forecasting errors have been evaluated.

4.3. Results & Validation

When considering the overall forecasting results and errors, the regression forecasting models have turned out to be unreliable in predicting non-routine material demand per FC-check. This is caused by the fact that not every part is inspected in all FC-checks due to the different inspection intervals of the maintenance tasks. The only regression model that has enough degrees of freedom to capture this reactiveness is the 5th degree polynomial. However, this forecasting model gives unrealistic values when extrapolating.

The stochastic models show significantly better forecasts. Due to the high reactiveness, the irregular demand patterns are captured by these models. For the stochastic forecasting models a clear distinction can be seen between the MA models (MA, EMA, SG) and the SES models (SES, Croston, SBA) in all plots. The MA models are reactive and approximately follow the path of actual observed values. Moreover the MA models are able to capture general trends rather than simply connecting historical values. The SES model as used in this research gives the lowest predictions errors, which can be explained by the used smoothing factor of one. As the calculated average probabilities and quantities per FC-check are based on actual historical data, it makes no sense to scale down the values using a smoothing constant. Therefore, the smoothing factor alpha was chosen as one, with as a consequence that the SES model exactly follows the historical data.

The EMA method has been chosen as the most suitable model for use in the forecasting method, given its low error values for the part number selection and ability to capture general demand trends. The EMA model has subsequently been verified and validated by forecasting material demand for an FC07 check at KLM. This check is independent from the previously introduced dataset. For this specific FC07 check, seven part numbers have been demanded that were included in the part selection of this research. Using the forecasting method and the EMA model, demand for five of seven parts has been forecasted with a probability above 50% and with specific quantities. Moreover, all parts that have been forecasted by the EMA method with a probability above 50% have indeed been demanded at or near the quantities forecasted.

5. Conclusion

In this research a method has been developed to forecast material demand related to non-routine maintenance tasks. To test the methodology, a part selection was made based on the cost impact, defined by the installed part quantity times the unit cost. The top 10 part numbers amounting to 60% of the total structural part costs were selected as test case. Historical maintenance data has been consulted to calculate the probability of demand per maintenance check. Subsequently a variety of forecasting models have been applied to the data. The stochastic models have shown satisfying results. The Exponential Moving Averages (EMA) model has been chosen as the best forecasting model as it produces low error values whilst still being able to capture general demand trends. For validation of the EMA model, an FC07 check which was not included in the original dataset has been used for forecasting material demand, after which the predictions have been compared to the actual demand. Using the forecasting method and the EMA model, demand for five of seven parts has been forecasted with a probability above 50% and with specific quantities. Moreover, all parts that have been forecasted by the EMA method with a probability above 50% have indeed been demanded at or near the quantities forecasted. IN conclusion, it is shown that it is indeed possible to bring a measure of predictability in the demand of parts due to non-routine maintenance by linking to the scheduled maintenance tasks.

A recommendation following from this research is to further research the demand distributions per specific FC-check. In this research the average values per FC-check have been used, which might include data outliers. Furthermore if maintenance data of different operators are used, a different distribution of flight hours, flight cycles and aircraft age might be seen per maintenance check. Moreover the scheduled maintenance tasks embedded in FC-checks might vary per operator. It is therefore recommended to link non-routine material demand solely to scheduled maintenance tasks when comparing different operators.

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