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PERFORMANCE EVALUATION OF MILITARY AIRCRAFT INVENTORY FORECASTING SYSTEMS

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ABSTRACT
In this article, the outcome of a study conducted to evaluate the effectiveness of a system utilized for military aircraft inventory forecasting and management is presented. The research objective was on the precision of the current system being used for inventory management. To conduct the study, both existing and proposed systems were compared by simulating stock level targets. The study finds that generic inventory forecasting systems do not deliver the level of precision required for specialist inventory forecasting.
Keywords: Inventory, forecasting

1. INTRODUCTION

The MK/MKa Chinook helicopter is one of the most durable and versatile utility military aircrafts in operation by the United Kingdom Royal Air Force (RAF). The helicopter's haul capacity is over 10t. Maintenance and support of the RAF MK/MKa Chinook helicopter fleet is currently provided by Boeing's United Kingdom through Life Customer Support programme (UKTLCS).

The major challenge faced by UKTLCS is on ensuring that it is able to deliver in real time, spare component parts to the four major Boeing sites used for the Chinook maintenance. To facilitate this process, UKTLCS uses an advanced inventory forecasting system called Service Planning and Optimization System (SPO), which has been developed by the Philadelphia, based software developing firm MCA solutions.

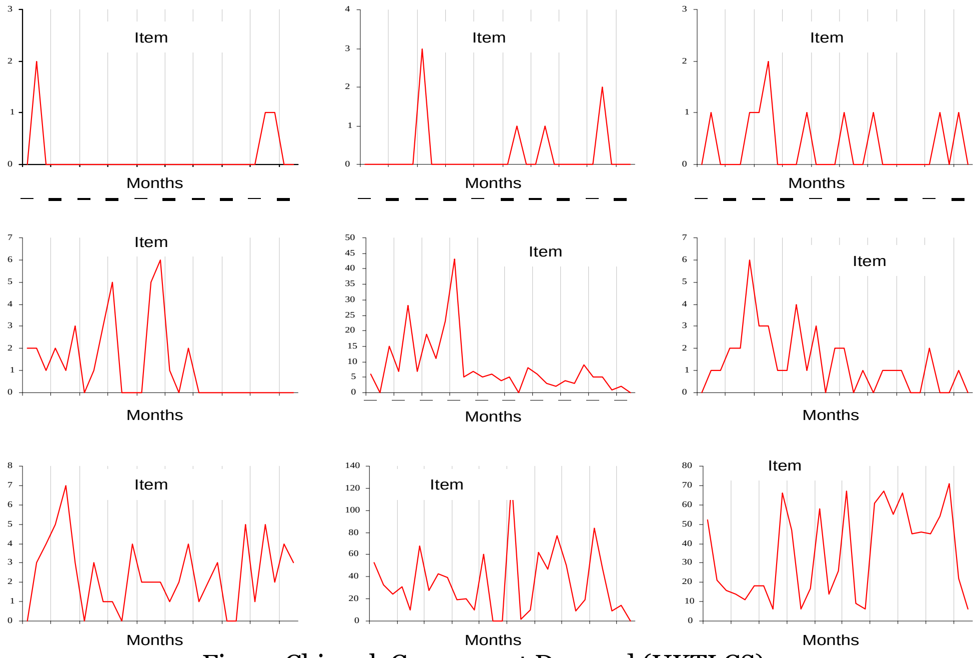

Fig. 1. Chinook Component Demand (UKTLCS)

UKTLCS faces two major challenges in its support of the MK/MKa Chinook helicopter support programme. The first is to ensure that it ensures that spare components are delivered on time at the right maintenance site. Secondly, the programme team faces a challenge of ensuring that its supply chain is optimized. Both objectives have to be met within the context of irregular demand patterns demonstrated by the spare components [1, 2]. There are however advantages of optimizing its supply chain. In the first place, Boeing will be able to rationalize floor space, and in the process reduce inventory and unnecessary storage cost (which will eventually be converted into savings for the Air force). Secondly, optimization of its supply chain is likely to reduce overall maintenance duration. In fig. 1, we show the irregular nature of the typical demand pattern of spare components of the MK/MKa Chinook helicopter. In Table 1, on the other hand, we show for example the shows the monthly demand for the first 10 spare components we identified. The data is representative of component demand over a period of 29 months.

Table 1. Monthly demand for the first 10 spare components

Item	Year 1											Year 2												Year 3						Total Spare Demand
Item 1	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	2	0	0	0	**7**
Item 2	0	1	0	0	0	1	1	2	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	1	0	**10**
Item 3	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	7	0	2	0	0	**0**	0	0	0	0	0	**13**
Item 4	1	1	1	1	3	1	1	0	4	1	1	0	2	0	0	1	1	1	1	1	0	1	0	0	1	0	0	1	0	**25**
Item 5	1	7	2	0	4	0	0	0	2	2	1	5	4	3	1	3	6	0	0	1	1	3	2	2	0	3	0	0	0	**53**
Item 6	0	1	1	0	2	1	0	1	1	3	0	0	0	0	1	0	1	0	1	1	1	1	0	0	0	0	0	0	0	**16**
Item 7	1	0	0	0	0	0	0	1	0	0	0	0	1	0	3	2	1	0	1	1	1	2	**0**	0	0	1	0	1	0	**16**
Item 8	2	2	0	3	2	2	1	3	5	0	0	2	0	0	1	0	1	2	0	0	1	1	0	1	2	1	0	0	0	**32**
Item 9	1	0	2	1	1	2	1	3	3	0	0	1	0	1	3	0	3	0	4	2	7	1	2	2	1	2	**0**	8	0	**51**
Item 10	2	1	1	0	3	2	3	0	0	0	3	3	0	1	2	1	0	1	0	1	0	0	0	1	1	1	1	1	0	**29**
Item 11	1	6	1	0	9	1	1	2	1	1	0	5	1	1	1	2	5	2	1	0	5	1	1	0	1	0	5	2	3	**59**
Item 12	0	3	4	5	7	3	0	3	1	1	0	4	2	2	2	1	2	4	1	2	3	0	0	5	1	5	2	4	3	**70**
Item 13	2	0	0	2	0	0	0	0	0	0	2	0	0	0	1	1	0	0	0	1	0	3	1	0	0	0	0	0	0	**13**
Item 14	0	2	0	0	0	0	0	0	2	1	0	0	0	0	**0**	0	1	0	0	0	0	0	0	**0**	0	0	0	0	0	**6**
Item 15	2	0	0	0	4	2	4	**0**	0	0	0	0	0	3	1	0	2	1	0	**0**	1	0	0	0	0	2	1	**0**	0	**23**
Item 16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1	1	0	0	2	**6**
Item 17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	2	1	1	**6**
Item 18	1	1	1	1	1	0	1	0	3	3	6	0	0	0	1	3	2	0	6	0	1	1	2	3	0	5	1	1	0	**44**
Item 19	1	0	0	1	0	0	0	0	0	0	1	2	0	4	0	0	1	0	6	4	0	0	1	0	1	1	3	3	2	**31**
Item 20	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	**7**

2. METHODOLOGY

Our study was conducted with real data obtained from Boeing (approval granted by the UK Ministry of Defense). The MK/MKa Chinook helicopter is a very advanced aircraft. It consists of over 13,000 spare components, thus presenting a major challenge to maintain.

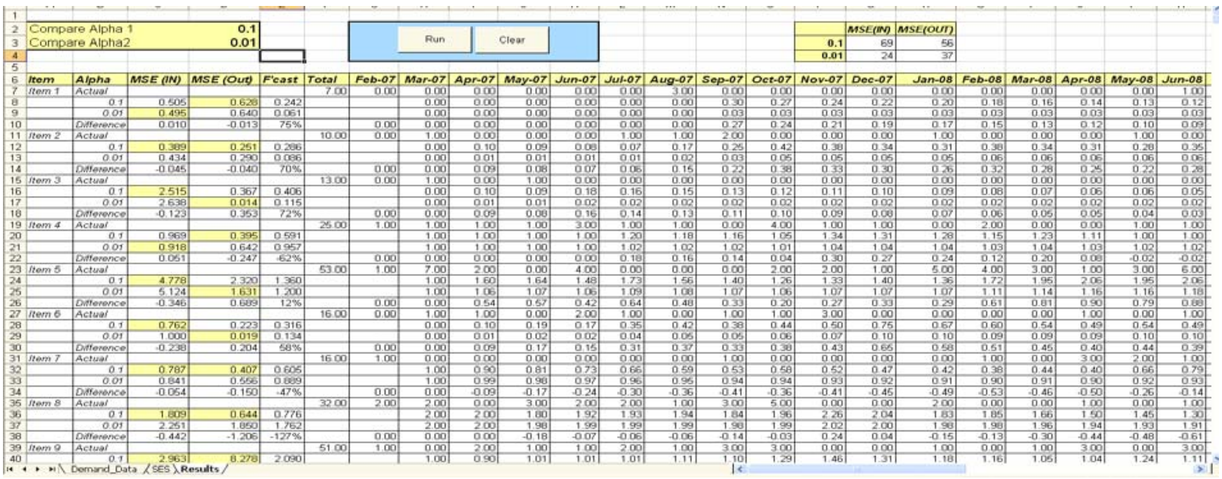

Fig. 2 Screen shot of model parameter forecast

In line with earlier studies [3, 4, 5], the study commenced with the collation of all spare component demand data (of the 13,000 components) into an excel spreadsheet. In order to obtain historical data, which was not made available by Boeing, we created and ran a VBA macro [6] against the spare component dataset which we had obtained from Boeing. We then began the process of identifying what constituted 'critical' components of the aircraft. We subsequently identified a total of 92 spare components as critical based on three criteria. In the first place, that once damaged, would negatively impact on the ability of the aircraft to perform its primary military role, and secondly that once this component was removed from the aircraft, it was un-repairable and therefore would need to be replaced. The final criteria related to cost. These were components that were the most expensive to repair. From the list of spare components, we identified a total of 40 components that represented more than $200 million in terms of expenditure. Using VBA and excel an automated method was created to model parameter forecasts on a large scale using a very small hold out period. A screen shot is shown in fig. 2

Once the spare components were identified, we now commenced with the allocation of unique part numbers to each component. We used networks to achieve this. The process meant that each component that could be replaced was allocated with an LR (Line Replaceable) number, while spare components which were designated as only service replaceable, we designated with an SR (Service Replaceable) number.

3. PRELIMINARY RESULTS

This stage of our study involved the performance of a diagnostic test on the SPO system which is currently being used by Boeing's UKTLCS's team for inventory planning and forecasting. We created a modeling macro using VBA to facilitate key parameter processing of SPO's performance in inventory planning and forecasting. This was conducted against live results which are shown in Table 2. We acknowledge the limitation of this approach as MCA's formula for smoothing forecast remains proprietary and therefore is not in the public domain. As a result, based on our interpretation of the SPO user guide which claims that MCA smoothing is a variation of SES, we have made assumptions on SPO's configuration. We especially note that periods of zero (0) demand appear not to update the value of forecast. Our interpretation is that it is likely that MCA Smoothing utilizes [2] method for forecasting intermittent. This methodology assumes that demand sizes are primarily distributed identically while at the same time being independent. According to scholars [7, 8], biases with this model may occur on occasions when demand size estimators (Z_t) and interval of demand (p_t) are independent then:

$$E\left(\frac{z_t'}{p_t'}\right) = E(z_t')E\left(\frac{1}{p_t'}\right) \quad (0)$$

But,

$$E\left(\frac{1}{p_t'}\right) \neq \frac{1}{E(p_t')} \quad (0)$$

Overall, we observed conflicting outcomes with the demand patterns. For example, while spare components such as Item 88 (Table 2) appeared inaccuracies in demand with a series of zero (0) demands being followed by a demand of 157 components, which again is followed by a subsequent zero (0) demand, Items 29 and 33 (Table 2) both indicated similar demand patterns. On the other hand, good performing items appeared to show extremely low values which were under 1.5. In our opinion, such values is indicative of the positive aspects of Croston [2] which provides for more superior in conditions that do not achieve and intermittence of 1.25.

Table. 2 Performance of Existing Forecast System

ITEM	OBS	DEMAN	F'CAST DEMAND	TOTAL ERROR	PCT ERROR	ME	MSE	MAE	USTAT
Item 13	13	11	27.72	-16.72	-152.00%	-1.29	4.11	1.83	0.75
Item 29	6	1	3.75	-2.75	-274.50%	-0.46	0.35	0.58	1.14
Item 33	6	3	8.47	-5.47	-182.42%	-0.91	1.41	1.11	0.71
Item 53	6	1	4.94	-3.94	-394.35%	-0.66	0.57	0.72	1.44
Item 88	6	12	73.75	-61.75	-514.58%	-10.29	125.92	10.29	2.05

Table. 3 Range of worst performing items

Item	Location	Mean	High	Standard. Deviation	Zero Freq	Skew	Demand Interval
88	Site A	11.41	157	29.70	17	4.52	2.42
29	Site B	0.72	3	1.03	17	1.23	2.42
45		1.07	7	1.60	14	2.29	1.93
57		1.79	11	2.30	10	2.47	1.53
63		1.14	4	1.13	10	0.84	1.53
13	Site C	0.45	3	0.83	21	1.80	3.63
54		3.76	16	3.99	7	1.33	1.32
62		6.93	22	5.22	2	0.91	1.07
66		0.45	2	0.69	19	1.27	2.90

It is perhaps important that we do highlight that in order to explore how well or poor performing the SPO forecast was, a selection of the poorest performing (Table 3), and exceeding (Tab. 4) items was conducted.

Table 4. Range of exceeding performing items

Item	Location	Mean	High	Standard Deviation	Zero Frequency	Skew	Demand Interval
10	Site A	1.00	3	1.04	11	0.83	1.61
49		0.35	2	0.65	17	1.73	3.83
72		1.79	6	1.72	9	0.93	1.45
89		18.03	40	12.79	2	0.34	1.07
24	Site C	0.59	3	0.95	19	1.50	2.90
44		0.31	3	0.66	22	2.77	4.14
67		7.93	27	7.22	1	1.35	1.04

Based on an intermittence of 1.25.(see Croston [2]), we observe that the worst performing items show similarities while the items with exceeding performance appeared to exhibit no deficiencies (in comparison with the worst performing items). We infer that this implies that the scale of the average demand interval does have an influence on the forecast performance of SPO. The final aspect of the test involved comparing two separate α values of the 92 components using SES. It will be recalled that we had earlier made assumptions based on our understanding of the SPO user guide that MCA smoothing represented a variation of SES. Our adoption of this approach was also heavily influenced by previous work [5], which in particular highlights critical reasons why demand and inventory forecast of combat spare components for helicopters are best undertaken with exponential smoothing models. In this case, we found that when the parameter values were reduced from 0.1 to 0.01, there was an associated precision decrease in MSE (In) values from 69 to 23 and MSE(Out) values from 56 to 36. Overall, the our evaluation appears to suggest that much lower MCA smoothing values of 0.01 have negatively impacted on the precision of UKTLC's inventory forecasting

4. FINAL RESULTS

Having completed the evaluation of the SPO system, the next stage of our study now commenced with the development of an improved forecasting model. The objective was to develop a model which will improve on the SPO model with a view to enhance applicability to the by UKTLCS programme. Based on requirements presented by UKTLCS, we sought to develop a model that (i) allowed for choice in forecast periods, (ii), was able to support forecasting over any time series that exceeded a year and at the same time delivered forecast capability over a single time series and (iii) allowed for Forecast assessment against a selection of statistics of fit.

Development of the model in normal circumstances would be primarily undertaken using SAS High Performance Forecasting (SAS/HPF) which provides an automatic means of generating substantial quantities of forecast which are reliable. However we were unable to utilise this software because of licensing and UK importation problems. As a result, we instead utilised VBA and excel to create an appropriate model which is shown in fig. 3.

```
'Places Monthly Demand into SES Model

For Month_Demand = 1 To 29

        Sheets("SES").Range("C" & Month_Demand + 6).Value = Sheets("Demand_Data").Range("H" & Item_Num +
        1).Offset(0, Month_Demand).Value

  Next Month_Demand

'Increments Results into Data Table

      .Range("A" & Result_Cell).Value = Sheets("Demand_Data").Range("A" & Item_Num + 1).Value
      .Range("B" & Result_Cell + 3).Value = "Difference"
      .Range("B" & Result_Cell).Value = "Actual"
      .Range("B" & Result_Cell + 1).Value = .Range("Compare1").Value
      .Range("B" & Result_Cell + 2).Value = .Range("Compare2").Value

      Sheets("SES").Range("AlphaSES").Value = .Range("Compare1").Value
      .Range("C" & Result_Cell + 1).Value = Sheets("SES").Range("MSE_IN").Value
      .Range("D" & Result_Cell + 1).Value = Sheets("SES").Range("MSE_OUT").Value
      .Range("E" & Result_Cell + 1).Value = Sheets("SES").Range("Forecast").Value
      .Range("AL" & Item_Num + 7).Value = Sheets("SES").Range("Forecast").Value

  For Result_Demand = 1 To 29

        .Range("F" & Result_Cell).Offset(0, Result_Demand) = Sheets("SES").Range("C" & Result_Demand +
        6).Value
        .Range("F" & Result_Cell + 1).Offset(0, Result_Demand) = Sheets("SES").Range("D" & Result_Demand +
        6).Value

  Next Result_Demand

    Sheets("SES").Range("AlphaSES").Value = .Range("Compare2").Value
    .Range("C" & Result_Cell + 2).Value = Sheets("SES").Range("MSE_IN").Value
    .Range("D" & Result_Cell + 2).Value = Sheets("SES").Range("MSE_OUT").Value
    .Range("E" & Result_Cell + 2).Value = Sheets("SES").Range("Forecast").Value
    .Range("AM" & Item_Num + 7).Value = Sheets("SES").Range("Forecast").Value
```

Fig. 3 Selected codes from the VBA model

The model was run with parameters which were both non optimized and optimized. We note however that studies [9] are yet to support the notion that adaptive models are likely to deliver more accurate forecast. We ran the optimized and non optimized parameter levels at a level of default of 0.1 which in most cases is recommended. In tab. 6, we show the optimized result, while in tab. 7, we show the non- optimized results which show the most appropriate model based on a parameter value of 0.1. This is based on generic values of forecasting value. We must however note that due to the criticality of the MK/MKa Chinook helicopter role in the RAF, Boeing's management maintains the position that spare components forecasting may be exceeded rather than underestimated.

Table 6. Optimised parameter estimations

Forecast Type	Observe	Av. Demand	Av. Theil	Av. MAPE	Av. Zero
Naïve	5	7.20	-	3.49%	24.80
SES	4	22.25	0.858	3.63%	15.50
LES	1	12.00	0.791	2.98%	19.00
MA(3)	1	29.00	0.661	3.86%	14.00
MA(6)	2	11.00	0.887	5.94%	20.50
MA(9)	3	154.33	0.849	3.95%	4.33
MA(12)	29	30.24	0.950	7.33%	13.55
Croston's	8	144.88	0.650	3.41%	10.25
SBA Croston's	35	126.23	0.815	4.43%	15.06
Modified Croston's	4	39.50	0.815	3.88%	12.00
HW Additive	0	-	-	-	-
HW Multiplicative	0	-	-	-	-

Table 7. Non-optimised parameter estimations

Forecast Type	Observe	Av. Demand	Av. Theil	Av. MAPE	Av. Zero
Naïve	0	-	-	-	-
SES	1	12.00	0.831	3.45%	19.00
LES	12	238.50	0.855	3.57%	11.08
MA(3)	2	123.00	0.763	2.91%	6.50
MA(6)	6	12.00	0.861	5.04%	20.17
MA(9)	4	117.50	0.866	4.49%	8.75
MA(12)	42	26.78	1.008	8.84%	14.17
Croston's	0	-	-	-	-
SBA Croston's	0	-	-	-	-
Modified Croston's	3	119.33	0.660	3.40%	8.00
HW Additive	14	113.64	0.751	4.25%	14.07
HW Multiplicative	8	67.88	0.841	4.97%	15.13

5. CONCLUSIONS

We find on graphical examination of both the optimized (fig. 4) and non-optimized (fig. 5) forecast appear more precise in their forecasting of the current system being used for inventory management. When compared for one of the specified items which is shown in tab. 8, we observe that due to differences in forecast projections, the tools should best be optimized. Once the optimization is conducted, we immediately observe that the SBA model provides the most precise forecast.

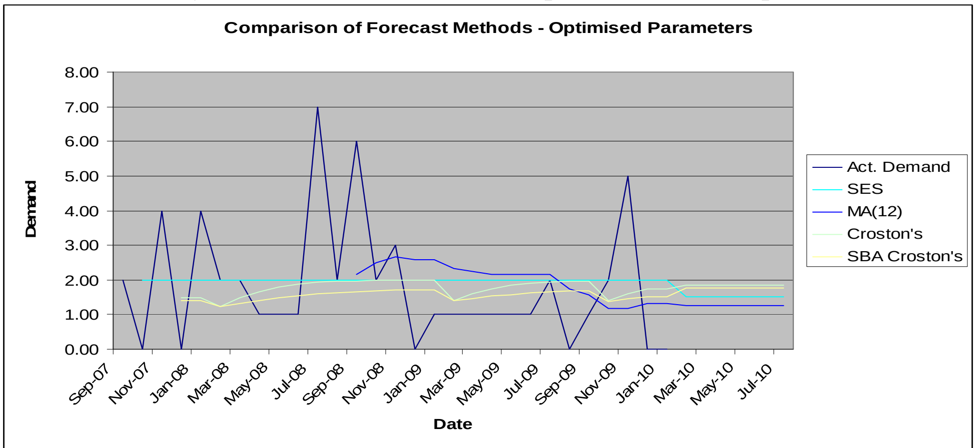

Fig. 4 Optimised Forecast

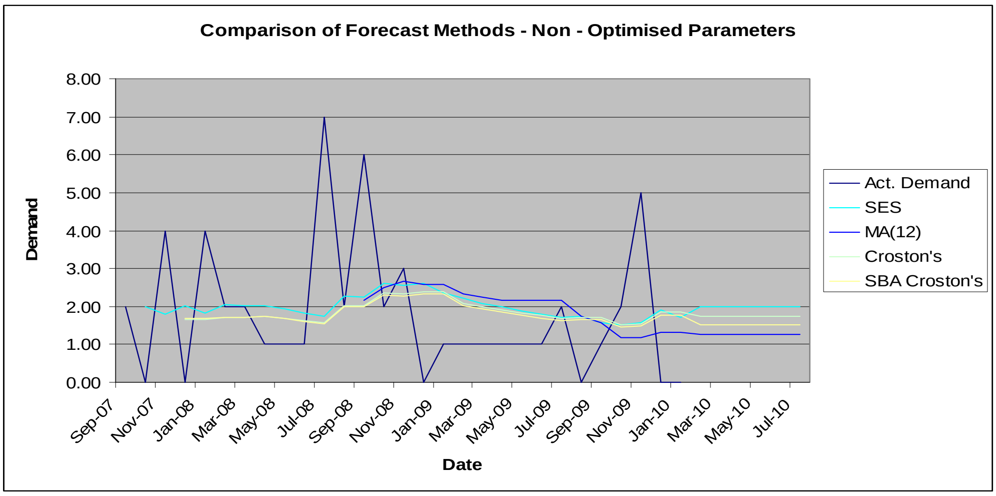

Fig. 4 Non-optimized Forecast

The findings suggest that in its present state, the SPO system may need to be enhanced in order to help the UKTLCS effectively conduct its operations. To effectively enhance SPO will require among others, incorporating more dynamic functionalities into its repertoire.

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