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The Use of Demand Forecasting Techniques for the Improvement of Spare Part Management

M. Suyunova

***Abstract*—the study conducted in this paper is made for a company experiencing a lack of safety stock and poor inventory management. The research suggests a suitable forecasting technique in accordance with established measures and provides a feasibility study. This work offers a comprehensive literature review along with detailed analytical and simulation models to illustrate the performance of the technique using real data.**

***Index Terms*—demand forecasting, inventory control, spare parts**

I. Introduction

Spare parts as common inventory stock elements exist to satisfy maintenance needs. Effective spare part management allows businesses to reach high levels of service without additional inventory costs. Absence of the proper control leads to low levels of service as well as excessive amounts of spare parts in the inventory with an unnecessarily high cost. The safety stock is basically the minimum amount of inventory kept in stock as mitigation in case of stock-out situations. Companies struggle to improve their spare parts inventory through high complexity and unnecessary expenditures [1].

Currently, the company encounters losses due to an excessive number of vehicle spare parts in the warehouse as well as shortages of necessary parts in cases of breakdown of the cars. Hence, maintenance in this case requires having some safety stock policy as part of inventory management. Thus, the use of an appropriate forecasting technique in order to not only create safety stock, but also, to reduce the inventories can be a potential solution to the problem [2]. In the company, the implementation of the demand forecasting techniques is still not widely common. Instead of using mathematical approaches in demand-forecasting field, most of the employers still rely on intuition and experience. Thus, the introduction of the simple but time-tested demand forecasting techniques will be helpful for the improvement of the inventory management.

II. Research Background

A. Research objectives and measures

Establishing objectives and measures in the beginning of the research is an important aspect that allows the target of the research to be defined and it also specifies and narrows the research field. Additionally, it allows the evaluation of the research outcomes against initially set objectives and the ability to make relevant decisions during the research. Thus, the objectives of the current research is to propose a demand forecasting approach that potentially promotes spare part management improvement and produce a feasibility study of the proposed approach (as a tool) based on available data in order to evaluate its appropriateness. Additionally, it is rational to establish measures of the proposed tool to avoid misunderstandings and regretful outcomes. These measures are: the proposed tool should be simple in understanding and computing; it should not require large amounts of historical data; adequate accuracy of the proposed technique; minimum financial expenditure during implementation and utilisation of the proposed tool.

B. Research methodology

The purpose of the research is to find out if there are some appropriate techniques for short forecasts that meet the requirements mentioned above. Additionally, the research answers to hypotheses if it is feasible to implement the proposed tool. The literature review chapter of the research focuses on the critical evaluation of various forecasting techniques used in the field of spare parts. This research is based on the appropriate books and academic journals obtained from available resources. Next step presents the description of data collection procedure and analytical model construction that demonstrates data analysis as well as performance of the proposed technique with the selection of the different values of smoothing constants. Then, the hand-based simulation model is constructed on the basis of the analytical model in order to represent the benefits of the proposed tool. The results of the model construction part are critically evaluated in the further step of the research. The feasibility study section provides SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis of the proposed tool in order to illustrate the strengths and weaknesses of the tool along with the opportunities that it can offer in the future and the threats or obstacles that the user may encounter. Further ahead, the evaluation of the research findings against established requirements takes place. The last step of the research is drawing conclusions including determination of the contributions to the company as well as recommendations for future work.

III. Literature Review

A. Critical comparison and selection of demand forecasting technique

Ghobbar and Friend examined several forecasting techniques using real data of aircraft maintenance [3]. The data had an intermittent pattern and their experiment showed that moving average, Holt's technique and Croston's approach, are performing better than other techniques such as exponential smoothing. Willemain, Smart, Shockor and DeSautels conducted another comparison between various forecasting techniques by using enormous amounts of industrial data [4]. They found that the bootstrapping

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M. Suyunova was with University of Sunderland, Sunderland, UK (e-mail: bg69bl@student.sunderland.ac.uk).

approach provides them with more accurate results in comparison with exponential smoothing and Croston's approach. Also, Eaves and Kingsman compared many forecasting techniques [5]. For this reason, they used data from Royal Air Force UK. The results showed that the Syntetos-Boylan Approximation is one of the most accurate forecasting approaches to use in spare parts inventory control. Also, Teunter and Duncan carried out another comparative study using data from the same source as Eaves and Kingsman [6]. The execution measure that they used was focused on an accomplished administration level. The outcomes of their study denote that Croston's approach performs better than moving average and exponential smoothing. In order to approve the successful performance of their Syntetos-Boylan Approximation technique, Boylan and Syntetos conducted a comparison between forecasting techniques including their approach, the original Croston's approach and simple moving average [7]. A simulation practice used 3000 products from the automotive manufacturing where the demand is ''fast intermittent". The outputs proved that their technique is a superior estimator.

It is clearly seen that Syntetos-Boylan Approximation technique is mostly recommended by authors due to its better performance in comparison with other techniques. However, this research is orientated on the measures that cannot be ignored during selecting the right technique. Also, there are some other factors such as the availability of data and limited experience of the company in forecasting field should be taken into account while choosing an appropriate forecasting method for further analysis due to avoiding the regretful situation. Thus, considering the measures and factors along with the literature outcomes, two techniques such as simple moving average and simple exponential smoothing roughly match the established parameters. Thus, the final result of the selection process will be suggested in analytical model that show the performance of these two techniques. The technique with better performance using sets of real data will be recommended for utilisation.

Simple Moving average (SMA) is one of the simplest methods used for modelling and forecasting [8]. Basically, this method is the mean of the previous *n* observations. Equation (1) for simple moving average presents "one step ahead" short forecast:

$$F_t = SMA_n = \frac{\sum_{i=t-n}^{t-1} D_i}{n} = \frac{D_{t-1}+D_{t-2}+\cdots+D_{t-n}}{n} \qquad (1)$$

where,
Ft - the forecast for period *t* in period *t*-1
D_t –demand during periods of time *t* (D_t, t ≥ 1)
n – number of past observations
D_t – value of all past demand.

The performance of the simple moving average technique depends on the span or the number of periods to be averaged. The greater span is appropriate in more stable data because of a larger smoothing effect. In the contrary, smaller span has the ability to react quickly when there are high fluctuations in the data.

Brown created *single (simple) exponential smoothing* (or SES in short) during his operational investigation for the US Navy [9]. There are some reasons that make his approach especially attractive. Namely, it takes into account business constraints and is quite easy to implement. It is a good method for constantly revising a forecast when more recent experiences are taken into account. In other words, latest observations are given more weight than earlier observations. The weights that SES uses are [α] for the most recent observations, [α(1- α)] for the next most recent, [α(1-α)^2] for further, and so on. This weighting equation is written as:

$$F_{t+1} = \alpha D_t + (1-\alpha)F_t \qquad (2)$$

where,
F_{t+1} – forecast for next period
D_t – current observation of demand for present period t
F_t – forecast for present period t
α – the smoothing constant (0 ≤ α ≤ 1).

The smoothing constant α in the exponential smoothing technique functions as the weighted factor and α determines the extent of influence of the current demand on the forecasted value. If α is closer to 0, the new forecast will be similar to the old data, but α closer to 1 significantly adjusts an error that happens in the foregoing forecast.

B. *Forecasting error measures*

Measures of accuracy are used in order to test the performance of the forecasting technique and the presence of errors. Basically, forecasting error of period *t* is simply the subtraction of the actual demand from forecasted value for that period. Thus, the equation for the forecasting error is as follows:

$$e_t = F_t - D_t \qquad (3)$$

where,
e_t – forecasting error of period *t,*
F_t – forecasted value for period *t,*
D_t – actual demand for period *t.*

The most often used techniques to measure forecasting accuracy are Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE). MAD determines average absolute deviation of forecasted values from actuals. It calculates the average of all forecast inaccuracies and divides by *n* number of periods as it is shown in equation (4). Also, it uses only the absolute value of errors.

$$MAD = \frac{\sum|D_t - F_t|}{n} = \frac{\sum|e_t|}{n} \qquad (4)$$

Wright et al. found out that MAD is less affected by outliers that frequently occur in practical situations in comparison with other measures [10]. It is regularly tested in the researches and from a forecasting viewpoint it is claimed to keep a balance between its advantages and disadvantages [11]. Also, according to past experience, the moving average and exponential smoothing techniques show the best MAD results for all demand combinations that indicate their compatibility in measures.

$$MAPE = \frac{\sum 100\times\left|\frac{D_t - F_t}{D_t}\right|}{n} \qquad (5)$$

The benefit of MAPE is that this measurement does not depend on the demand size [12]. It is known as a widely used technique and is independent of scale. However, MAPE is unable to provide reliable results in periods of zero demand which happens regularly in the spare parts

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environment, but during other periods this issue significantly reduces. MAPE is the percentage of errors found in the forecasting [13].

IV. DATA COLLECTION AND MODEL CONSTRUCTION

A. Data collection

In accordance with the type of research to be undertaken, only a quantitative approach of data collection is used. The type of data required for the proposed demand forecasting techniques are records of previous years of the demand for spare parts. The source of necessary information depends on the availability of previous records. In order to improve the quality of data, it was sorted and selected with certain criteria to illustrate the performance of the proposed tool. During sorting, it was important not to have data with an intermittent demand, since it requires more complex forecasting approaches that contradict the established measures.

B. Analytical model construction

Model construction is fitting the collected data into an appropriate forecasting model for further analysis. It allows the investigation of the behaviour of past demand in order to minimise the forecasting error. These investigations are fundamental for a further simulation model. Forecasts of future demand are made with the assumption that the past data is the best predictor. Even though, orders for spare parts and their actual demand has a slight different meaning, this analytical model assumes that the past order amount was an actual demand.

Table I. Demand forecast for the period 17 using simple moving average with three-period and six-period SMA and forecast error

Period (t)	Actual demand	Three-period SMA	Three-period SMA error	Six-period SMA	Six-period SMA error
1	50	-	-	-	-
2	35	-	-	-	-
3	25	-	-	-	-
4	40	36.6	3.4	-	-
5	45	33.3	11.7	-	-
6	35	36.6	-1.6	-	-
7	20	40	-20	38.3	-18.3
8	30	33.3	-3.3	33.3	-3.3
9	35	28.3	6.7	32.5	2.5
10	20	28.3	-8.3	34.17	-14.17
11	15	28.3	-13.3	30.8	-15.8
12	40	23.3	16.7	25.8	14.7
13	55	25	30	26.7	28.3
14	35	36.6	-1.6	32.5	2.5
15	25	43.3	-18.3	33.3	-8.3
16	55	38.3	16.7	31.7	23.3
17		**38.3**		**37.5**	

As it was suggested in the previous section, simple moving average and simple exponential smoothing techniques are used for constructing an analytical model. For illustrative purposes these techniques were applied on the past data to forecast the demand for period 17. Both analytical and simulation models are deterministic processes.

Table I shows the results of the simple moving average technique using equation 1. As it was noticed, the span of 3 performs better when there are fluctuations in the data in comparison with the span of 6. Fig 1 clearly demonstrates that six-period moving average is more smooth and stable in comparison with the three-period moving average.

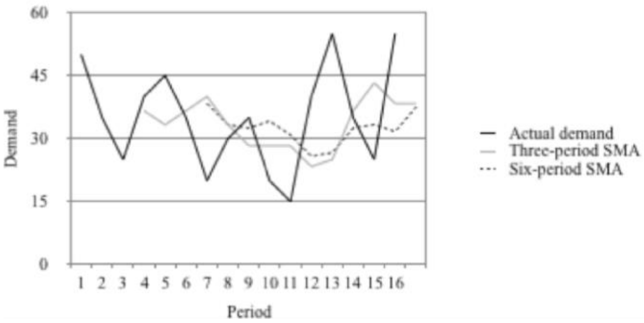

Fig 1. The behaviour of moving average with three-period and six-period SMA

The forecast error was determined using MAD and MAPE forecasting accuracy measures. The smaller the error the more accurate the forecast. In this case:

N=3 MAD = 11.66 MAPE = 39%

N=6 MAD = 13.08 MAPE = 46%

Table II. Demand forecast for the period 17 using the exponential smoothing technique with α =0.3 and α =0.7 and forecast error

Period (t)	Actual demand	α = 0.3	Forecast error e_t (α = 0.3)	α = 0.7	Forecast error e_t (α = 0.7)
1	50	50	0	50	0
2	35	45.5	-10.5	39.5	-4.5
3	25	39.3	-14.3	29.3	-4.3
4	40	39.6	0.4	36.8	3.2
5	45	41.2	3.8	42.5	2.5
6	35	39.3	-4.3	37.3	-2.3
7	20	33.5	-13.5	25.2	-5.2
8	30	32.47	-2.47	28.5	1.5
9	35	33.2	1.8	33	2
10	20	29.3	-9.3	23.9	-3.9
11	15	24.9	-9.9	17.7	-2.7
12	40	29.5	10.5	33.3	6.7
13	55	37.1	17.9	48.5	6.5
14	35	36.5	-1.5	39	-4
15	25	33	-8	29.2	-4.2
16	55	39.6	15.4	47.3	7.7
17	-	**44.22**	-	**52.7**	-

Table II demonstrates the exponential smoothing technique for smoothing constants 0.3 and 0.7 using equation 2. Different values of smoothing constant α were used in order to illustrate the difference in behaviour of the demand. The value chosen for α is critical in the analysis. Small α is required in cases when stable and smoothed

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random variations are desired. Larger α is more appropriate when there is a need in quick response to real fluctuations in the pattern. The forecast error in this case is:

$\alpha = 0.3$ MAD = 7.72 MAPE = 27%

$\alpha = 0.7$ MAD = 3.83 MAPE = 12%

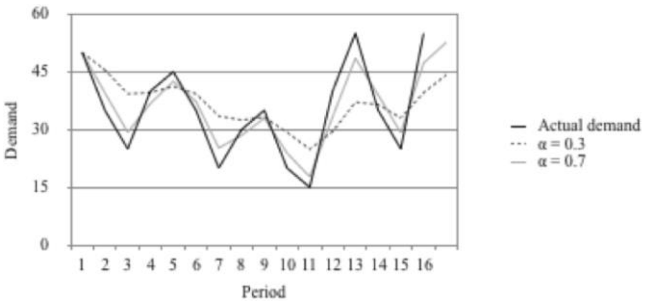

Fig 2. The behaviour of exponential smoothing with different smoothing constants

According to Fig 2 that illustrates the behaviour of demand with different smoothing constants, it is noticeable how stable and smooth the values for α = 0.3 in comparison with α = 0.7 where the values fluctuate wildly. The smoothing constant α = 0.7 is better on the basis of minimising the percentage of error. However, it is important to note that in the analytical model the trend and seasonal variations of the observations have not been taken into account. Thus, SES is recommended for further investigation in the simulation model.

C. Hand-based simulation model construction

Since the necessary data have been collected and a suitable forecasting technique has been chosen and analysed, the hand based simulation model needs to take place. Simulation model is based on real historical data presented in the analytical model, however extends it by considering trend and seasonality components. Basically, the purpose of the simulation model is to estimate the real life behaviour of demand for spare parts. The further evaluations of the results of the simulation model allow the user to determine the appropriateness of the proposed tool. From analytical model, it can be concluded that simple exponential smoothing with smoothing constant value of 0.7 is the most appropriate tool in the current situation. The simple exponential smoothing technique lags behind gradually growing and dropping trend. Since the simulation model observes the trend and seasonal variations in order to model the real life situation, these components are tracked by a regression line and seasonal adjustment methods, respectively. One of the simple ways to estimate trend is using regression line. The equation is as follows:

$$y - y'' = b\,(x - x'') \qquad (6)$$

where
y – the value of the item to be forecast
x – time period
b – the trend
y" – the mean of y
x" – the mean of x

$$b = \frac{\sum xy - \frac{\sum x \sum y}{n}}{\sum x^2 - \frac{(\sum x)^2}{n}} \qquad (7)$$

Equation (6, 7) defines the trend line of the actual demand for spare parts. Fig 3 illustrates that the trend of the actual demand is absent or exists with very slight positive pattern.

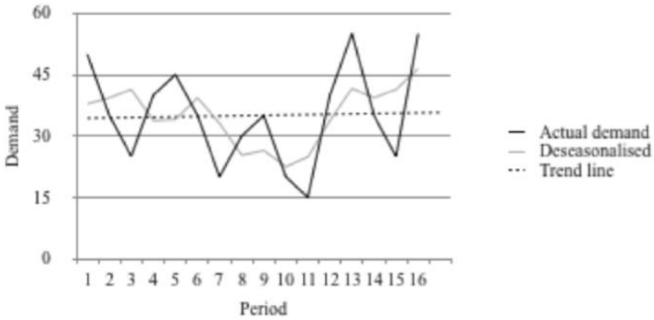

Fig 3. Seasonally adjusted actual demand with trend line

According to Fig 3, it can be seen that every third period shows a noticeably higher demand. It indicates the presence of a seasonal pattern within the data. Understanding the seasonal behaviour of data allows the user to know what to expect in the future and be prepared for peak and low demand periods. However, removal of seasonal fluctuations allows users to recognise strengths and weaknesses of the data. Thus, in order to see the pattern that is independent from seasonality, data is seasonally adjusted (or deseasonalised). Seasonal adjustment is a process that improves the characteristics of the 'parameter estimates' for the regression of time series. For this practice, previous observations are utilised for the calculation of a trend factor in addition to 'seasonal index' as an estimate of the trend-cycle and seasonal components. These trend factors and seasonal indexes are then used to subtract the relevant factors from the time series, permitting analysis of data without the components and subsequent modification of the forecast [14].

Simulation model allows users not only to predict the behaviour of the future demand, but, also, take into account important components such as trend and seasonality that can affect future variables in order to make forecast more accurate and reliable.

E. Critical evaluation of models

The presented analytical and simulation models can be considered as a very simple example that illustrates how the process of forecasting works in real life. Even though, there are plenty of complex ways for predicting the future demand with better performance and accuracy, the choice of the current one depends on initially set measures. Although, the discussions of models and logical flow of the forecasting steps are kept as simple as possible, the interpretation of models to the extent of its possibility includes considerations of the important components such as trend and seasonality patterns.

As a simple example, provided analytical and simulation models cannot fully capture all the aspects and uncertainties that can occur in the real life situations. However, those models show the basics of short demand forecasting and, despite of their simplicity, illustrate the benefits and potential contribution to inventory control. Thus, the introduced forecasting models can be considered as a better tool to control inventory within the company that has the capability to predict the future demand and keep safety stock.

From the models, it is clear, that the exponential smoothing technique with α = 0.7 performed very well with the provided data in comparison with the other techniques that showed a significantly higher rate of errors. However, it is important to note that same technique can perform differently with different input data, for example, intermittent demand, which is common in the spare parts field. Thus, it requires other approaches to deal with zero demand periods.

V. Feasibility study

Feasibility study aims to define whether the proposed tool is feasible to be implemented. This study focuses on analysis of the proposed tool, in this case, Simple Exponential Smoothing; in order to highlight the most significant features of the tool and potential consequences of its implementation. SWOT analysis was chosen as a powerful technique that helps to clearly illustrate the strengths and weaknesses of the tool as well as identify the possible opportunities it can open for the user and the threats that the user can face as it is shown in Fig 4.

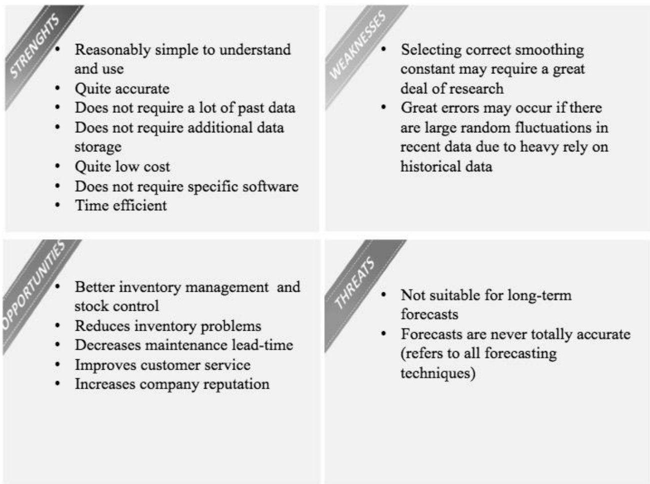

Fig 4. SWOT analysis outcomes

Strengths and weaknesses in SWOT analysis are considered as internal factors within the company, whereas opportunities and threats mostly relate to external factors. From Fig 4 it can be determined that Simple Exponential Smoothing technique meets all the established measures. Thus, it can be concluded that the implementation of the proposed forecasting technique is quite feasible in terms of the features introduced. However, the user should keep in mind that this technique is suitable only for short forecasts and it is not applicable for long-term forecasts. Also, any forecasting techniques can have a certain amount of error and almost never provide with hundred per cent correct future values.

VI. Conclusion

As it was discussed earlier, the successful implementation of the proposed forecasting tool potentially can enable the company to improve inventory management and safety stock control as well as diminish some inventory problems. Extended maintenance lead-time caused by inventory problems can potentially be reduced since the inventory management is improved and safety stock is made. These improvements add value to business through quick responses to customer requests, which enhances overall customer satisfaction and company reputation.

There is no conclusion that the proposed tool is the “best” in terms of forecasting methods. In accordance with comparative studies, there are better forecasting techniques with better accuracy metrics for spare parts management. The selection and proposition of the tool to forecast future demand is mostly based on the established measures. Thus the tool is quite simple and accurate, when it deals with data without significant trends along with seasonality patterns. Otherwise, it is recommended as a task for future work to implement more complex forecasting techniques that can deal with the described type of data such as Double and Triple exponential smoothing techniques, The Croston’s methodology and The Syntetos-Boylan Approximation technique. However, these techniques require a good level of expertise.

Also, the financial aspect of tool implementation and possible financial profits from its application is not included. However, the research time and available data limitations are a reason behind this gap in the feasibility study. Thus, this part is considered as a recommendation for future work activities.

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