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Forecasting Techniques for Sales of Spare Parts

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Abstract*: *Forecasting plays a significant role in planning the future activities of an organization. An effective trade-off is achieved between inventory management and catering demands through an accurate forecast. A detailed study on procurement and planning processes has been conducted in this study. The need for a decision making statistical tool to forecast sales data of spare parts is the main area of focus. Spare part sales pattern remains to be undetermined as it does not follow a specific trend or seasonality. Statistical programming has been performed using 'R Studio' to analyse the monthly sales performance. The process is found to improve when a weekly order inflow is considered. ARIMA model is found to improve the accuracy of forecast by 40 percent. Also, accuracy of forecasting performed considering weekly order inflow was higher than that obtained by considering monthly inflow.

Keywords* : *Time series forecasting, spare part sales, ARIMA forecasting

I. INTRODUCTION

In the present scenario, forecasting has marked its importance in various areas including stock market, finance, geology, etc., [1]. Vital problems such as managing energy consumption have also been addressed efficiently using forecasting [2]. Complexity of systems have led to significant changes in the area of forecasting wherein linear and nonlinear methods are being used with combination of more than one standard model/ machine learning techniques (Hybrid models such as ARIMA-ANN model) [1, 2, 3]. Selection of proper forecasting techniques might help to smoothen the shocks in supply and demand of the market [3]. Study of a particular market would reveal the factors that play a significant role in demand and supply of that market, hence paving way to formulate a nearly accurate forecasting technique to minimize errors [3, 4]. Eventually, accurate forecasting allows industries/ government to maximize the profit. Presently, serious measures are being taken by governments to address issues of national emergency [5]. Presence of large amount of data has mandated the usage of computers in every industry [6]. Several algorithms and tools are available to assist forecasting time series of real time data. Common models upon which the automatic algorithms work include Auto Regressive Integrated Moving Average (ARIMA) and exponential smoothing [7, 8].

Manufacturing and automotive industries hold a significant share in Gross Domestic Product (GDP) of many countries. Major focus areas of these industries include quality management systems, lean systems, environment conservation systems etc. [8]. Mass customization due to alterations in customer demand has shortened the product life cycle, increasing the difficulty to forecast [9]. Spare part segment remains highly erratic as there are no specific trends or seasonality that govern their demand. Various viewpoints to address this issue needs to be balanced i.e., maintaining service levels by maintaining proper inventory management while taking care of the affordability and feasible alternatives [8].

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II. LITERATURE REVIEW

In recent years, time series forecasting have found significant application in real time systems. Complexities of systems may arise due to more than one of these conditions: unpredictable demand as in the case of spare part segment, high capital investment in stock market, dealing with perishable items as in dairy industry/ food industry [1, 10]. Determination of trend and seasonality play a major role in selection of a suitable forecasting method so as to minimize the errors. One of the methods to identify factors affecting the demand is through hypothesis validation [10]. Raw data might require some standardization to improve the usability and interpretability prior to forecasting process. There are also a lot of assumptions made often during any study in order to suffice the conditions specified for the model(s) selected for the study [1]. Many researches use hybrid models by combining the desired factors from each of the chosen models. The efficiency of the hybrid model can also be determined by comparing with each of the existing models [11].

III. RATIONALE BEHIND THE STUDY

The service agreement indicates the quicker response of service team in reducing the down time of compressors. In India, the maximum time to restore air in a compressor is only 48 hours. The spare parts required for servicing the compressor has to be made readily available at any point of time. The revenue generated from spare parts business was found to be the major profit contributor in a manufacturing organization. On receipt of customer order, the service engineer with create a sales order in the dealer portal.

The sales order is processed in the ERP system and then converted into production order considering the current raw material and Work in progress inventory. System generates production order only for the required quantities. We are maintain one Kanban quantity as the demand to service between the lead time. If the materials are in stock then packing and dispatch will happen on the same day. Once materials are dispatched the ERP system will generate Kanban triggers to suppliers. The E-trigger generation will consider the current stock, pending E-triggers and pending production orders. This activity is automated in ERP system and the frequency of E-trigger generation is once in three hours. On receipt of E-triggers suppliers will dispatch the materials to the spares division. Figure 1 gives a high level representation of the system under study.

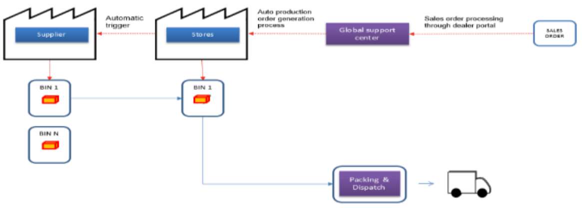

Fig. 1. Process trajectories

The delay in spare parts delivery leads to the over stocking of spare parts at the spares division, dealers and customers. This leads to an excess inventory in the entire supply chain.

The major failures are due to the non-availability of parts from suppliers. Inadequacy of sales forecast found to be the major cause for failure which is identified through a structured problem solving approach.

In his context we need to predict the future business in advance. This will make the suppliers to plan raw materials and other resources in advance. The supplier base also has some considerable amount of bottle neck and strategic suppliers which are imported from countries like China, Italy, Germany. This requires a long lead time to reach the spares division. To overcome this problem, we are in need of an advanced forecasting process. After adopting the new forecasting process then the accuracy of forecasting to be improved.

A. Factors considered for forecasting

Major factors that affect forecasting are listed in figure 2.

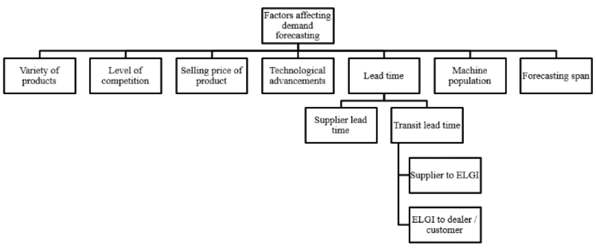

Fig. 2. Factors affecting demand forecasting

1. Variety of products – If the product variety is high then grouping of demand can be done.
2. Level of competition – In a competitive market it is difficult to forecast since customer may opt for other product in case of stock-outs
3. Selling price of product – Multiple price slabs and sales promotions campaigns also to be considered during demand forecasting
4. Technological advancements - Forecasting of new products is difficult when compared to the existing products. Nowadays new products launching frequency is increased to overcome the market competition
5. Supplier lead time – It is time taken by the supplier on receipt of purchase order to the delivery of materials to ELGI stores. It includes both manufacturing and transit time.
6. Transportation time – It is time taken between the transit of spare parts from spares division to dealer / customer locations.
7. Machine population – Spare parts sales is directly proportional to the sales volume of compressors. Based on the usage, spare parts like filters, oils, pistons, piston rings are to the replaced at certain time intervals.
8. Forecasting span – Accuracy of forecasting is depending mainly on the time period of forecasting.

B. Expected outcomes of forecasting

Below mentioned are some of the expected outcomes of forecasting, as shown in figure 3.

1. Covering the gap between the demand and supply of the product.
2. Regulation of raw material supply by estimation
3. Optimization of the utilization of resources by producing in accordance to the requirement

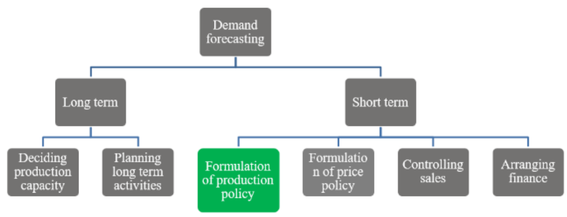

Fig. 3. Outcomes of forecasting

IV. METHODOLOGY

ARIMA is a univariate time series model wherein the forecast is purely based only on the past sales. A minimum of 40 data points would be required to implement this forecasting technique [1, 12]. The liner relationship between two variables and between lagged values in a time series are measured. For instance, r1 would measure the relationships between yt and yt −1 , yt and yt −2 etc.

$$r_k = \frac{\sum_{t=k+1}^{T}(y_t-\bar{y})(y_{t-k}-\bar{y})}{\sum_{t=1}^{T}(y_t-\bar{y})^2} \qquad (1)$$

Differencing (the change between consecutive observations of the original series) can be written as in eqn. (2). This is done to transform the time series to be stationary [1].

$$y_t' = y_t - y_{t-1} \qquad (2)$$

Statistical properties of a stationary time series are all constant over time. Time series is a linear equation with inputs being lags of the dependent variable and forecast error as shown in eqn. (3).

Output: y = constant + weighted sum of single or multiple historical values of 'y' + weighted sum of single or multiple historical values of error 'e' (3)

Error lags are not linear coefficients and hence they are not independent variables. Hence, ARIMA models containing error lags require nonlinear computations. Stationary time series lags and forecasted error are termed as autoregressive and moving average respectively. Model represented as ARIMA (p, d, q) denotes the following, which is represented in eqn. (4) [1]:

- 'p' – order of auto-regression
- 'd' – degree of first differential
- 'q' – order of moving average

$$Y_t = c + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + e_t \qquad (4)$$

The moving average model of order 'q' is represented in Eqn. (5).

$$Y_t = c + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_p e_{t-p} + e_t \qquad (5)$$

Where 'Y' is the output of a time series and 'et' is the error in the series.

Also, the study involves comparison of results using the below widely used error measure techniques:

Root Mean Square Error (RMSE) is the difference between the actual values and forecasted values, and accumulates the difference as predictive ability.

$$RMSE = \sqrt{\frac{\sum_{t=T}^{T+k}(\hat{y}_t - y_t)^2}{n}} \qquad (6)$$

Mean Absolute Deviation (MAD) is the average of absolute value of the actual and forecasted values.

$$MAE = \sum_{t=T+1}^{T+k}\left|\frac{\hat{y}_t - y_t}{n}\right| \qquad (7)$$

V. RESULTS AND DISCUSSION

The ARIMA model forecasting is applied for the sample B004800770001 using R Studio software and the results are given below.

The observed time series below (figure 4) shows peak demand during 2 months. Other than this there are no abnormalities noticed in this time plot. The ACF plot proves that the autocorrelations lie within the threshold limits.

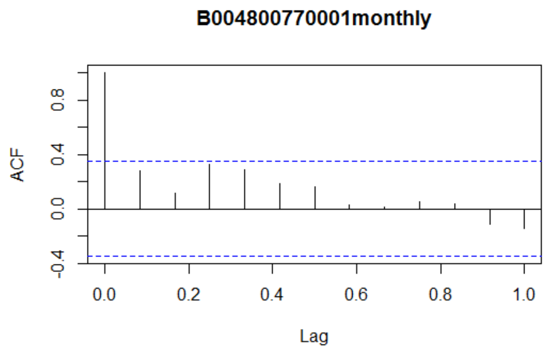

Fig. 4. ACF plot (monthly)

The PACF (figure 5) shows that there is no abnormality noticed in the data set and are within the limits.

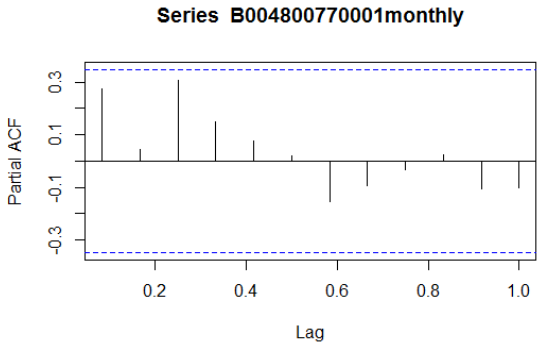

Fig. 5. PACF plot (monthly)

Using the auto ARIMA function the coefficients obtained are (0, 1, 1).

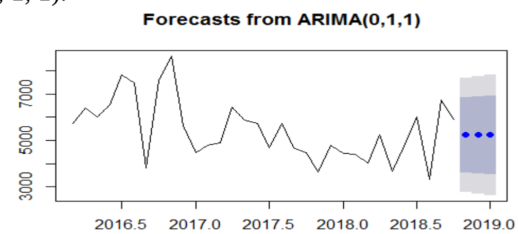

Fig. 6. Forecast (monthly)

The accuracy of the time series data is further improved by increasing the number of data points from monthly data for weekly data. The number of months taken in previous analysis is 32 and now number of weeks taken for analysis is 86. Further the monthly sales data is directly proportional to the availability of materials in stock at warehouse. Hence the accuracy of data has be further improved by using the order in flow data. This overcomes the problem material shortage. The ARIMA model forecasting is then applied for the weekly order inflow data for sample B004800770001 using R Studio software. The results are shown below.

The observed time series below shows peak demand during 3 weeks. Other than this there are no abnormalities noticed in this time plot.

The ACF plot (figure 7) reveals that the autocorrelations are within the threshold limits.

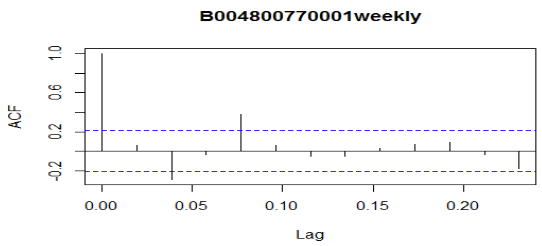

Fig. 7. ACF plot (weekly)

The PACF (figure 8) shows that there is no abnormality noticed in the data set and are within the limits.

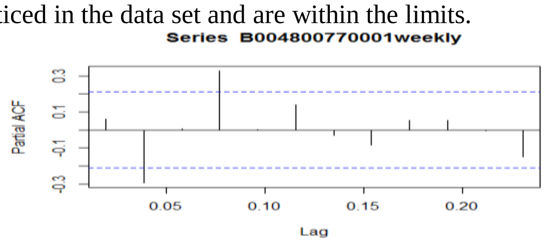

Fig. 8. PACF plot (weekly)

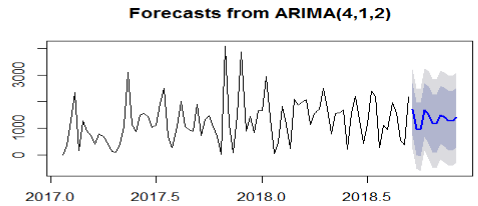

Fig. 9. Forecast (weekly)

VI. CONCLUSIONS AND FUTURE SCOPE

In this study we use two different criteria namely methods, Root Mean Square Error (RMSE) and Mean Absolute Deviation (MAD) to compare the accuracy of the results.

In order to access the accuracy of the forecasting methods, the RMSE and MAD criteria are compared in this study. The table presents the RMSE and MAD criteria for the forecasting models analysed in the study.

As per the results achieved from the below table (table 1) Auto ARIMA model with weekly data using R Studio software has the best value of RMSE and MAD equal to 735 and 569. Hence, the comparison shows that the most efficient model among the listed is Auto ARIMA model with weekly data using R studio software. The results has been deployed to the entire data set and found that the accuracy of the forecasting is improved by 40% from the current level.

Table I: Comparison of methodologies

Methodology	*Frequency*	*Software used*	*RMSE*	*MAD*
Simple moving average	Monthly	Minitab	1,603,23 4	1,027
Singe exponential smoothing	Monthly	Minitab	1,479,31 5	987
ARIMA model with coefficient (1,1,1)	Monthly	Minitab	Not feasible	
Auto ARIMA model	Monthly	R studio	1,217	971
Auto ARIMA model	Weekly	R studio	735	569

The parts for which accuracy is to be improved has been studied and found that the volatility is missing in the prediction. It is necessary to explore the possibility of advanced forecasting algorithms like

i. GARCH Model

ii. Hybrid ARIMA and GARCH model

iii. Hybrid ARIMA and ANN model

The detailed study infers that the order inflow is skewed during third and fourth week of every month. The budgeted future sales growth has also to be incorporated in the planning model. Deriving of new algorithm incorporating the skewness and the sales growth was found to be challenging task in the future work which is to be explored further.

REFERENCES

1. Babu, N.C. and Reddy, E.B. 'A moving-average filter based hybrid ARIMA-ANN model for forecasting time series data', Applied Soft Computing Journal Vol.23, pp.27-38, 2014
2. Deb, C. Zhang, F. Yang, J. Lee, S.W. and Kwok Shah, K.W. 'A review on time series forecasting techniques for building energy consumption', Renewable and sustainable Energy Reviews, No. 74, pp.902-924, 2017
3. Liu, H. and Shi, J. 'Applying ARMA-GARCH approaches to forecasting short-term electricity prices', Energy Economics, pp.152-166,2013
4. Nieto, M.R. and Carmona-Benitez, R.B. 'ARIMA + GARCH + Bootstrap forecasting method', Journal of Air Transport Management, Vol. 71, No.1-8, pp.1-8, 2018
5. Ohyver, M. and Pudjihastuti, H. 'Arima model for forecasting the price of medium quality rice to anticipate price fluctuations', Procedia Computer Science, Vol. 135, pp. 701-711, 2018
6. Villegas, M.A. and Pedregal, D.J. 'Automatic selection of unobserved components models for supply chain forecasting', International Journal of Forecasting, 2018
7. Hyndman, R.J. and Khandakar, Y. 'Automatic time series forecasting: The forecast package for R', Journal of Statistical Software, Vol.27, 2008
8. Vargas, G.C.A. and Cortes, E.M. 'Automobile spare-parts forecasting: A comparative study of time series methods', Journal of Automotive and Mechanical Engineering, Vol.14, pp. 3898-3912, 2017
9. Ramos, P. Santos, N. and Rebelo, R. 'Performance of state space and ARIMA models for consumer retail sales forecasting' Robotics and Computer-Integrated Manufacturing, Vol.34, pp.151-163, 2015
10. Vineesh, D., S. P. Anbuudayasankar, and M. S. Narassima. "Enhancing Dairy Manufacturing through customer feedback: A statistical approach." IOP Conference Series: Materials Science and Engineering. Vol. 310. No. 1. IOP Publishing, 2018.
11. Khandelwal, I. Adhikari, R and Verma, G. 'Time series forecasting using Hybrid ARIMA and ANN models sbased on DWT Decomposition', Procedia Computer Science, Vol.48, pp.173-179, 2015
12. Narassima M S, Anbuudayasankar S P, Vasudevan S K, Abhinavaram J 'Physicians and Users Perceptions Towards Wearable Health Devices'. Indonesian journal of electrical engineering and computer science. Vol. 5, pp 234-242, 2017
13. Autoregressive Integrated Moving Average models (ARIMA) (online), Available: http://www.forecastingsolutions.com/arima.html

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Saravanan A M is a Senior Engineer Materials at ELGI EQUIPMENTS LTD, Coimbatore. He has industrial experience of 12 years and researches extensively in forecasting, production planning, statistical control and supply chain management. His areas of interest include data analytics, statistical processes to control and improve the production activities.

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