DEMAND FORECASTING FOR FERTILIZERS— A TACTICAL PLANNING FRAMEWORK FOR INDUSTRIAL USE

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ABSTRACT

Demand planning and distribution are the most important aspects of tactical decision support in manufacturing organizations. Tactical demand forecasting with emphasis on consumption of fertilizers helps to determine appropriate manufacturing polices to meet the needs of how, when and where to produce in how much quantity by an organization. In this paper we introduce a framework for forecasting processes that support tactical and operational planning in production processes. We present a monthly forecasting model using Autoregressive Integrated Moving Average (ARIMA) methods to estimate the consumption of fertilizers using historical monthly fertilizer consumption data, and rainfall. An analysis is presented on variants of ARIMA models considering seasonality, trend, using three types of rainfall data. We use forecasted, smoothened and normal rainfall to study the impact of the performance of the various ARIMA models as well as to demonstrate the effectiveness in forecasting along with historical monthly consumption data of fertilizers. The analysis shows the demand consumption is not only dependent on seasonal behavior but also the consumption pattern of over the previous months. The forecasting accuracy improves significantly by using monthly consumption data as well as rainfall information rather than obtaining annual forecasts using seasonal factors.

The proposed framework/models can be used by manufacturing companies producing either seasonal or non-seasonal products to effectively understand the monthly and seasonal behavior of the market demand and thus plan their production needs effectively. Larger production capacities motivate manufacturers to produce fertilizers well ahead of demand but storage expenses are quite expensive. We study the consumption pattern against the varying production capacities and identify policies to define appropriate levels of stocks to be kept at different points of time by the organizations to facilitate the ease in supply of produce considering the uncertainties faced during agriculture production including change in the rainfall pattern.

Keywords: *Demand Forecasting, Fertilizers, ARIMA, Tactical Planning, Inventory Management.*

1. INTRODUCTION

The process of climate change and the agriculture produce are interrelated processes, which take place on a global scale. The effect of climate on agriculture is related to variabilities in local climate conditions rather than in global climate patterns. In last few years, the impact of climatic change is quite highly felt on the plan of agriculture production as well as need to use fertilizers at different points of time. It has been observed that some places face shortages on fertilizer needs where agriculture produce are of high volume and other places have seen pile of fertilizers but not in use. This uncertainty of agricultural produce and distribution could be felt globally through inflation on food and vegetable prices. Moreover, the global population increase necessitates higher demand of foods driving the need to increase the crop yield and emphasizing the need to plan the production of fertilizers which are in a way essential for achieving increased agricultural production.

The top five countries control more than 50 per cent of the world's production capacity for the main nitrogen, phosphate, and potash fertilizers. The global consumption of fertilizers is increasing at the rate of 3–4% over the last decade with the aggregate consumption of nitrogen more than double the consumption of phosphate and almost four times the consumption of potash. The consumption of fertilizers in India has exceeded domestic production in the last decade in both nitrogenous and phosphatic fertilizers. The requirements of potassic fertilizers are met through imports as India does not have commercially viable sources of potash.

The consumption of fertilizers is dependent on various factors including agricultural related factors such as geographical aspects, calamities, rainfall and irrigation patterns, soil quality, farming methods, availability of technology and information, varieties and qualities of seeds as well as access to capital and other inputs. Additionally, the fertilizer consumption depends on more macro oriented factors such as market forces and policies regarding demand and supply. The availability of fertile land impacted by increasing population and urbanization is also another major factor. It is necessary to understand the use of fertilizers in different parts of the country over time as well as role of factors influencing the consumption of fertilizers at state/regional level as the application of essential plant nutrients in right quantity and right proportion, through correct method and time of application, is the key to increased and sustained crop production [Sharma and Thaker, 2011].

Many of the stated factors cannot be explicitly defined and measured in the short run, and hence it is worthwhile to use the metrics which are easily available and measurable to study the behavior of demand for fertilizers in the market at different levels such as national, state, regional, and even at company level with short planning horizons such as monthly and quarterly terms to understand the need for effective planning for production and distribution as well as if necessary plan for importing the same in case of capacity shortages.

The earlier available publications in fertilizer demand planning is predominantly based on annual demand data rather than placing more emphasis on monthly consumption data. In this paper, an attempt has been made to use two factors viz., historical fertilizer consumption data and rainfall to understand the seasonal behavior of use of fertilizers and thus present forecast models to enable planners to use them for tactical planning requirements.

2. SHORT TERM FORECASTING AND TACTICAL DEMAND PLANNING

Fertilizer manufacturing is an energy and capital intensive process and the Indian domestic industry is highly regulated with a view to ensure availability of fertilizers to all the regions at affordable prices. Demand for fertilizers stems directly from agriculture. The type of crops grown, the extent of irrigation, use of high-yielding variety of seeds, etc. determine the demand for fertilizers. Last few years, however, have not seen any significant capacity additions and our country being forced to depend on imports to meet the growing demand.

The domestic industry may be classified into three main categories on the basis of the nutrients—nitrogenous, phosphatic and potassic fertilizers. Urea is the main nitrogenous fertilizer produced in India, while Di-ammonium Phosphate (DAP) and Single Super Phosphate (SSP) are the important phosphatic fertilizers produced in the country. Urea and DAP are produced by large players, while SSP in view of the relatively simple technology involved, is produced by small and medium sized players while potassic ones are only imported.

Keeping the above factors in mind, it is necessary that fertilizer companies effectively plan their monthly and seasonal requirements for fertilizer demand and effectively utilize the capacities to produce appropriate quantities saving costs both on inventory as well as capacity loss in the form of less utilized capacity. Fertilizer forecasting can be categorized into three stages complimentary to each other, *i.e.*, (i) assessment of potential, (ii) forecast of demand and (iii) forecast of sales [Parthasarathy, 1994]. First two are important for policy makers while the second and third stage is important for organization that produce and distribute the produce.

The forecasting methods used in planning fall into one of the four types:

- *Agronomic methods:* Measurement of potential through need-oriented and long term plans.
- *Time Series Methods:* Relies on historical data to analyze the demand patterns to forecast the future.
- *Causal Models:* Seeks to establish a cause-effect relationship between the fertilizer demand and other independent variables in the marketing environment such as amount of credit, fertilizer-produce price ratio, rainfall, etc.
- *Qualitative Methods:* Human judgment combined with rating systems are used when information is scarce or is unreliable, as in the elementary stage of the product life cycle.

The second and third methods are the methods to be used when we wish to forecast the near term future of a product with the availability of past historical data to assess the effect of these factors on demand.

The focus of this paper is in aiding the managers of fertilizer manufacturing and distribution organization to study the historical data and forecast the monthly and seasonal demand for their products for next few months based on past consumption of fertilizers, and actual rainfall in the region. An attempt is made to use ARIMA Models to effectively forecast the fertilizers' needs for the identified market under discussion. We also study the consumption pattern of fertilizers against the production capacities and present policies and strategies to carry appropriate levels of stocks at different points of time by the organizations to facilitate the ease in supply of fertilizers considering the uncertainties faced during agriculture production including change in the rainfall pattern.

3. TACTICAL DEMAND PLANNING FRAMEWORK

The forecasting process framework is presented in the Figure 1 basically begins with definition of fertilizers sold in the market, collection of consumption data of fertilizers, identification of outliers (*i.e.*, any inconsistent values against the trend such as promotions, events, etc.), correction of outliers, use of forecast models (such as exponential smoothing, ARIMA, etc.) to generate forecasts for future *N* months, overriding the forecasts by the sales or business managers considering the market factors (events, promotions, rainfall, etc.) to enable the production managers to appropriately manage the produce, and finally calibrating the accuracy of forecasts against actual periodically. The framework is dynamic in the sense that the forecast models are continuously reviewed against their performance using the accuracy factors such as Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE), R Square statistic, etc. The forecasts are generated every month (or period) for next *N* months and review consists of analyzing the outliers and factors to understand whether the forecast methods used are in line with the business expectation. Inconsistency in demand plots against the production indicates that either the model parameters need to be tuned or methods need to be changed.

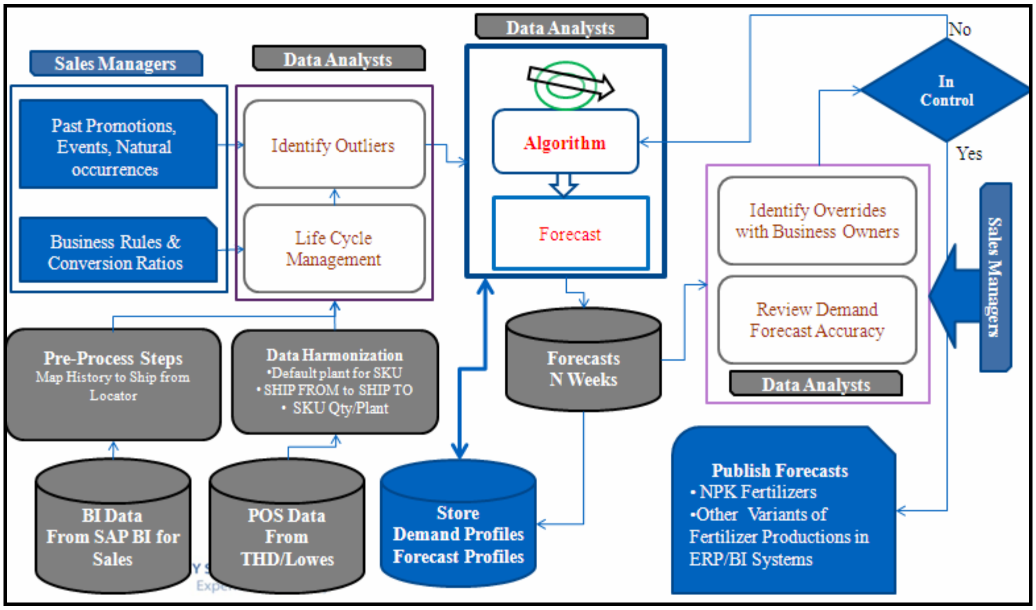


Fig. 1: Tactical Demand Planning Framework

4. ARIMA MODELS

Time series methods use historical data as the basis of estimating future outcomes. Linear/trend estimation, moving average, exponential smoothing, and ARIMA (The acronym ARIMA stands for "Auto-Regressive Integrated Moving Average") models are some of time series estimation methods. Most time series patterns can be described in terms of two basic classes of components: trend and seasonality. The former represents a general systematic linear or non-linear component that changes over time and does not repeat within the time range captured by our data. The latter may have a formally similar nature, however, it repeats itself in systematic intervals over time. Those two general classes of time series components may coexist in real-life data. Though there are no proven methods to identify trend components, determining the trend may not be difficult if trend is consistently increasing (or decreasing).

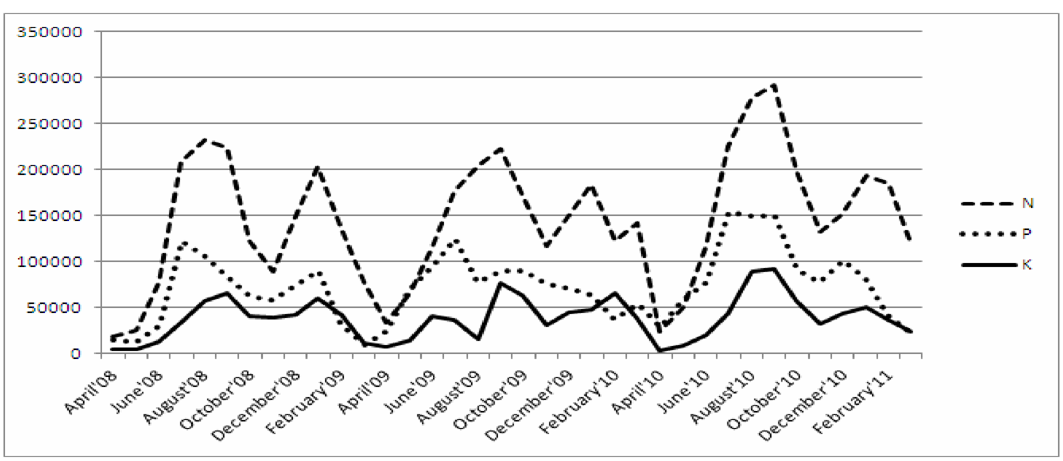


Fig. 2: Sample Demand Profile on Consumption of Fertilizers

Smoothing which is a type of an averaging [Jain, 2000] can be used as a first step in trend identification. The most common technique is moving average smoothing which replaces each element of the series by either the simple or weighted average of *n* surrounding elements, where *n* is the width of the smoothing "window". Seasonal patterns of time series can be examined via correlograms. Correlogram displays graphically and numerically the autocorrelation function (ACF), *i.e.*, serial correlation coefficients (and their standard errors) for consecutive lags in a specified range of lags (e.g., 1 through 30). Strong autocorrelations between successive data points indicates serial dependence on the data. One another useful method to examine serial dependencies is to examine the partial autocorrelation function (PACF)—an extension of autocorrelation, where the dependence on the intermediate elements (those within the lag) is removed. In other words the partial autocorrelation is similar to autocorrelation, except that when calculating it, the (auto) correlations with all the elements within the lag are partialled out. Another aspect to be understood in time series is stationary aspect in the data. It involves determining whether data has a constant mean, variance, and autocorrelation through time. If not, data needs to be differenced to obtain stationary characteristic.

Monthly volume data of fertilizer consumption typically exhibit few or all of the above characteristics of demand profile depicted in Figure 2 and ARIMA models can be used to predict future monthly or quarterly volumes thus aiding in planning and distribution. A non-seasonal ARIMA model is classified as an "ARIMA(p, d, q)" model, where:

- p is the number of autoregressive terms,
- d is the number of non-seasonal differences, and
- q is the number of lagged forecast errors in the prediction equation.

p, d and q would take values 0, 1 or 2 depending on the nature of data for typical practical requirements. If the data exhibit seasonal trends as well, one can use seasonal ARIMA (SARIMA). R statistical software, an open source tool (Verzani, 2005) could be used to fit ARIMA models. Though they are also easy to implement directly on spreadsheets (Heiberger and Neuwirth, 2009) with little knowledge of mathematics, R has an Excel interface for invoking R functions from EXCEL. Selection of the right model depends on estimating ACF, PACF and few other coefficients as well as determining the deviation of forecasts from the actual data using average(or squared) errors and standard deviations of errors.

5. CASE STUDY OF CONSUMPTION DATA

In this section we use the consumption data of a selected geography to demonstrate the ARIMA Models used in the suggested framework for detailed analysis. We used five years of monthly consumption data for our analysis. The corresponding monthly rainfall data for the same period is used an indicator variable to analyze its impact on improving forecast accuracy.

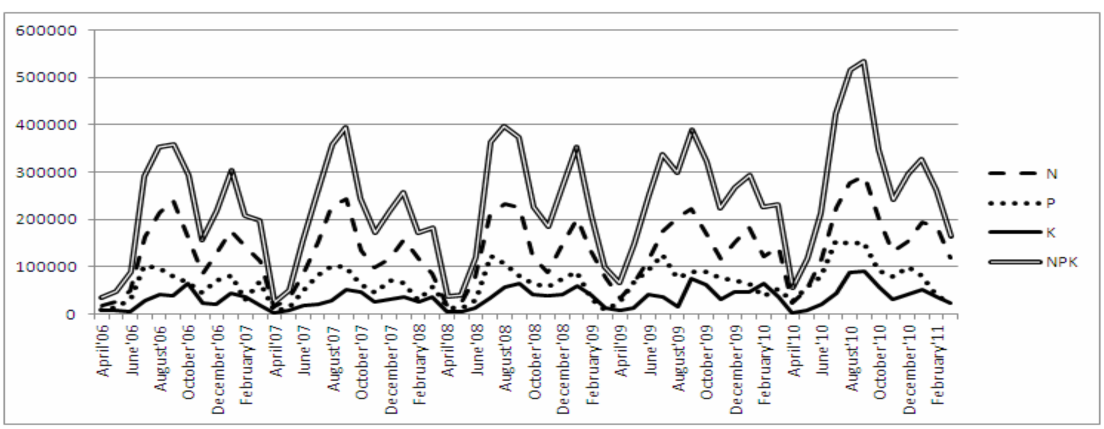


Fig. 3: Demand Plot for Consumption

5.1 Data Analysis

The data exhibit seasonal trend with demand for fertilizers peaking around July–August and December–January every year indicating the Khaif and Rabi cycles respectively. December–January demand peak values are about 20–30% less than the July–August peak values of demand for the fertilizers. The data thus exhibits both seasonal and annual trend in its behavior. The rainfall plot presents the expected and actual for five years time period. We do see that there exists a positive correlation (at monthly level granularity) of 0.55 between quantum of rainfall received and consumption of fertilizers used in the five year time period.

5.2 Forecast Analysis

We compare the performance of two variants of ARIMA models. We have considered three variants of ARIMA Models, viz., pure seasonal model [PS] – SARIMA (0, 0, 0) × (1, 1, 2); ARIMA with seasonal and historical trend [AS] – SARIMA (1, 1, 2) × (1, 1, 2); and ARIMA with rainfall as regression or indicator variable [AS(R)] – SARIMA (1, 1, 2) × (1, 1, 2)R. The models are studied for three planning horizons: annual, half yearly and quarterly. Two variants of rainfall data are considered. Normal rainfall monthly data is taken from metrological department and forecasted monthly rainfall data is obtained from historical rainfall figures using 3 month moving averages.

Three years of historical data is required to forecast for future *N* months in seasonal ARIMA models. We compare the two models by forecasting the consumptions for the year the Apr'10–Mar'11. The Mean Absolute Percentage Error (MAPE) and R Square metric are used in the performance comparison of the variants of ARIMA methods.

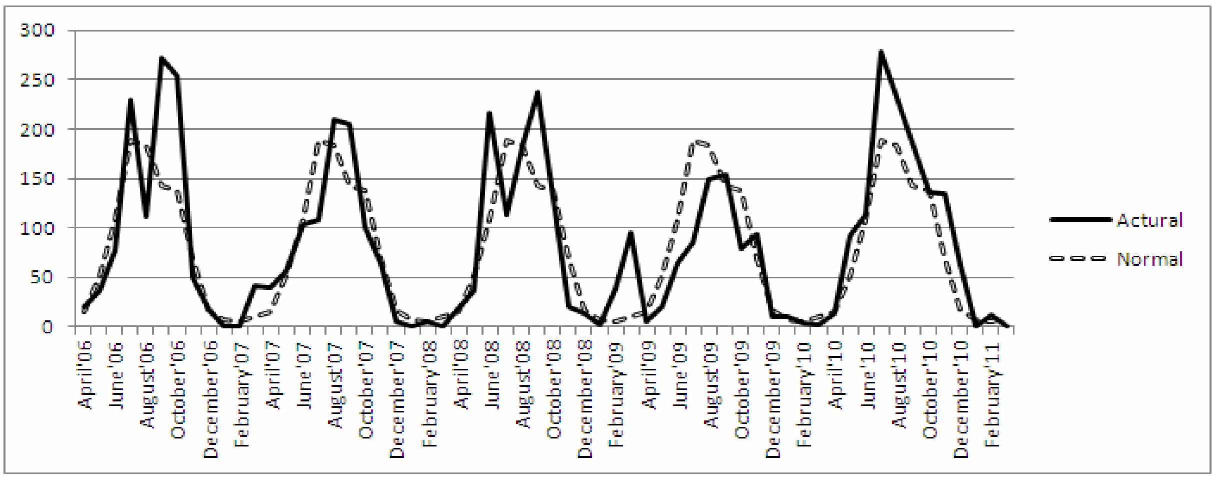
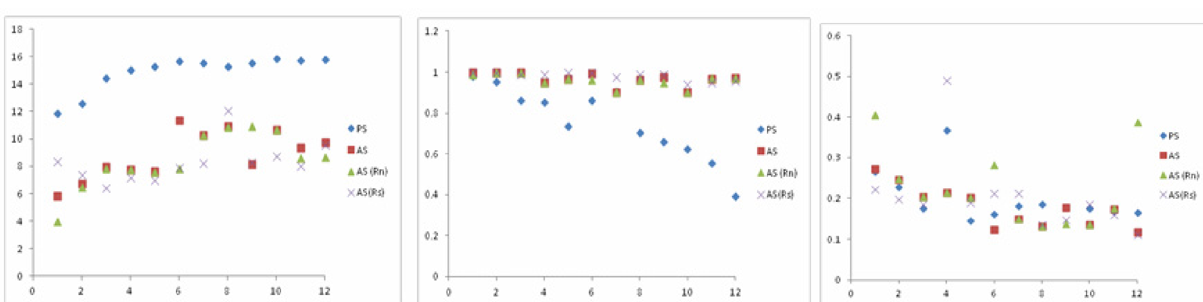


Fig. 4: Rainfall Plot (Actual and Normally Expected)

We also compare the performance of the SARIMA (1, 1, 2) × (1, 1, 2)R_n (uses the normal expected rainfall) against SARIMA (1, 1, 2) × (1, 1, 2)R_s (actual rainfall smoothened over previous 3 periods) across the four categories of fertilizer consumption data. SARIMA (1, 1, 2) × (1, 1, 2)R_s provides better MAPE values in case of N and NPK consumption pattern while the use of normal rainfall provides better MAPE values in case of P and K consumption pattern as shown in Table 1.

The base model SARIMA (0, 0, 0) × (1, 1, 2) is the typical annual forecasting approach typically used by practitioners in industry that uses annual consumption data with seasonality for fertilizer production planning and distribution. Our analysis shows that the demand consumption is not only dependent on seasonal behavior but also on the consumption pattern of over the last 36 months. The forecasting accuracy as shown from our experiments improves not only by using monthly consumption data but also using normal or forecasted rainfall data.



(a) Plot of MAPE for 12 data sets (b) Plot of R Square against 12 data sets (c) Plot of forecast MAPE against 12 data sets (12 Period Model)

Fig. 5: Plot of NPK Results

Figure 5 presents the plot of MAPE (in %) [5a], plot of R Squares [5b], and plot of forecast MAPE (in fraction) [5c] against the consumption data sets generated on rolling basis from Apr'10–Mar'11 for 12 months forecasts.

Table 1: MAPE (in %) and Average Absolute R^2 Values Against the Consumption Patterns of N, P, K, and NPK Fertilizers on 36 Months Historical Data

	N		*P*		*K*		*NPK*	
	MAPE	R^2	*MAPE*	R^2	*MAPE*	R^2	*MAPE*	R^2
SARIMA (0, 0, 0) × (1, 1, 2)	11.34	0.941	29.32	0.653	29.58	0.510	14.98	0.755
SARIMA (1, 1, 2) × (1, 1, 2)	8.02	0.967	20.67	0.929	14.17	0.921	8.88	0.965
SARIMA (1, 1, 2) × (1, 1, 2) R_n	7.91	0.970	18.46	0.960	15.59	0.903	8.465	0.959
SARIMA (1, 1, 2) × (1, 1, 2) R_s	6.42	0.979	20.13	0.959	18.25	0.945	8.26	0.980

5.3 Stock Planning under Varying Production Capacity Constraints/Demand Uncertainty

Three possible demand scenarios against capacity are generally exhibited in seasonal fertilizer consumption data:

- *Scenario 1:* Demand peaks during one or more points of time in a year and is much more than the capacity
- *Scenario 2:* Demand is more than the capacity for a wider span of time (2 to 3 months) and remains less than the capacity in the rest of the year.
- *Scenario 3:* Demand fluctuates above and below the capacity over a wider planning horizon.

In case of Scenarios 1 and 2, the demand necessitates the manufacturer to plan the fertilizer produce during the lean periods ahead of the peak periods thus leveraging the additional capacity available in the earlier time periods. However the early produce time is decided by the cost required to store the fertilizers in inventory or warehouses and how long the produce can be stored before the start of the peak season. In case of shortages, when the total demand for the peak or higher periods greater than the capacity, plans need to prepared for procuring or importing the fertilizers from other sources. The production plan can be formulated as a mathematical model solvable in reasonable time using either open source or commercial solvers in case the decisional outcomes of planning are directly dependent on demand consumption data, capacity data, and inventory holding costs (Stadtler and Kilger, 2009).

Safety stocks using fill rate is suggested in this work to address the demand scenarios where demand peaks one or more points of time in year. A fill rate is the percentage of demand that is met on time. Higher the fill rate, lower the safety stocks need to be kept. While in case of cycle service rate, based on pure safety stock policy, is the probability that we do not run out of inventory while waiting for the produce to come in. The fill rate can be arrived using the following formula (Silver *et al.*, 1998):

$$\text{Shortage} = Q(1\text{–}FR)/\sigma_L$$

where Q is the market demand in period t, FR is fill rate and σ_L is the standard deviation of demand over lead time L.

In Scenario 3, safety stock plans either based on fill rate or cyclic service levels may used depending on the variations in demand which is fluctuating above and below the capacity in a continual basis for relatively longer time horizon.

6. SUMMARY AND CONCLUSIONS

A forecasting framework is presented in paper for tactical planning in manufacturing organizations. The consumption data of a specific region is used as the case data to understand the behavior of the data with reference to trend and seasonality as well as impact of rainfall on consumption. Variants of ARIMA models are tested against with and without the use of rainfall data. Normal rainfall data obtained from metrological department and smoothened rainfall obtained using 3 month moving averages is used to understand the behavior of the variants of ARIMA models. The use of rainfall data exhibits improvements in forecast accuracy on the identified ARIMA Models. Finally, we present three scenarios of demand behavior observed using the case data and present tactical planning options for the managers to effectively plan the produce against the annual market demand.

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