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Demand Forecasting in an Automobile Supply Chain Using Time Series Model

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ABSTRACT

In today's uncertain environment forecasting of demand is one of the vigorous tasks for enlightening actions of the supply chain. Inappropriate demand forecasting increases the total cost of the supply chain. Some of the issues can be resolved with the proper demand forecasting mechanism. In this paper, authors have attempted to forecast the sales data of automobile manufacturing firm using use moving average method (MA) and Autoregressive-moving-average method (ARMA) of time series models.

Key words : Supply Chain, Forecasting, Time Series Analysis, Automobile, Model.

1. INTRODUCTION

A large number of time series is collected during various industrial operations with the enormous use of information technology. This data can be investigated by several techniques and tools of time series analysis [3,6]. A Forecast is an expectation of occurrence some events in future. Forecasting is very vital for many fields like industry, government organizations, medicine, economics, social sciences etc. Forecasting problem may be addressed for short medium or long term. Time series model explained in the given paper is a chronological sequence of activities or observations; it is a time-oriented model. It requires data to develop the model, this data may be the total inventories over a period of a month, this may be the sales over a period of time etc. The importance of forecasting is experienced when it is realized that how important is forecasting a planning stage. These days forecasting has become an inherent part of the decision-making. Recently, [1,5] have given a measure to find the value of the bullwhip effect with unrelated forecasting methods. Although several kinds of forecasting techniques are there but the domain of the use of different techniques are different. No single method is suitable in all the situations. Therefore, it becomes very important to choose right kind of technique at the right time by taking all the factors available into the consideration. Although many factors are available but the most important factors are accuracy and the cost involved. How much money will be involved in making the forecast? What are the benefits that will be occurred after making the accurate forecasts or otherwise what are the consequences or losses incurred by erroneous forecast? It has been experienced in past that best forecasts are not the most precise or least cost forecast rather it is the unification of both the factors as experienced by management.

2.FORECAST DEMAND IN A SUPPLY CHAIN

In the supply chain, an accurate forecast is very significant. An erroneous forecast may lead to an excess of finished goods piling up in the storage causing extra maintenance and storage cost or otherwise way end up in shortages of material, finished goods, or services resulting in poor customer services. Organizations can reduce the probability of occurrence of these events; one of the ways is by providing the better forecasting methods. Other ways include the better collaborative planning among all the players of the supply chain from manufacturer to the customer[2,4].

The literature about the forecasting approaches is mainly classified into two types: qualitative and quantitative. Qualitative forecasting is subjective in nature, meaning the decision depend upon the knowledge of the concerned expert. They are mostly used where there is no data or very fewer data available to forecast. Whereas, Quantitative forecasting techniques are used when the historical data is available. They are comparatively better in terms of accuracy of results.

3.TIME-SERIES METHODOLOGIES

The time-series approach endeavor to project the previous knowledge into the future. These approaches use historical data and are considered as the most suitable and the most precise approach to forecasts a judiciously short time perspective. Various time series forecasting models have been proposed in the literature, these include simple models based on Moving Average (MA) and somewhat complex like Autoregressive Moving Average (ARMA) as shown in figure 1. These models are comprehensively used by various logistic systems. When the demand does not display any pattern or a trend, Moving averages are best used. Whereas ARMA models are used in simulation and prediction of industrial and economic time series. Therefore, a moving average process of order q, MA(q)is given by expression (figure 2 and figure 3).

$$y_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots . -\theta_q \varepsilon_{t-q}$$

Where ε is white noise.
Irrespective of values of the weights, an MA (q) method is persistently static. In terms of the backward shift operator, the MA (q) process is

Predictable significance of MA (q) process is determined by expression

$$E(y_t) = E(\mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots . -\theta_q \varepsilon_{t-q})$$
$$= \mu$$

The variance is given by expression,

$$(Var(y_t = \gamma_s(0) = Var(\mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots . -\theta_q \varepsilon_{t-q})$$
$$= \sigma^2(1 + \theta_1^2 + \cdots + \theta_q^2)$$

The auto covariance at lag k can be calculated from

$$\gamma_y(k) = Cov(y_t, y_{t+k}$$
$$= E[(\varepsilon_t - \theta_1\varepsilon_{t-1} - \cdots \theta_q\varepsilon_{t-q})(\varepsilon_{t+k} - \theta_1\varepsilon_{t+k-1} - \cdots - \theta_q\varepsilon_{t+k-q})]$$

$$= \begin{cases} \sigma^2 \left(-\theta_K + \theta_1 \theta_{K+1} + \cdots .. + \theta_{q-k}\theta_q\right) . k = 1, 2 \ldots q \\ 0, k > q \end{cases}$$

Autocorrelation function at lag k,

$$\rho_y(k) = \frac{\gamma_y(k)}{\gamma_y(0)}$$
$$= \begin{cases} \dfrac{\theta_K + \theta_1 \theta_{K+1} + \cdots .. + \theta_{q-k}\theta_q}{1 + \theta_1^2 + \cdots + \theta_q^2} \; k = 1, 2 \ldots q \\ 0, k > q \end{cases}$$

The autocorrelation function is helpful in finding the MA model. However, when it comes to real life problems, autocorrelation function behavior changes. Its value will be very small after the lag. The easiest determinate order MA model is obtained when q = 1

$$y_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1}$$

In MA (1) process, auto covariance function is-

$$\gamma_s(0) = \sigma^2(1 + \theta_1^2)$$
$$\gamma_s(1) = -\theta_1\sigma^2$$
$$\gamma_s(k) = 0, k > 1$$

Autocorrelation function for MA (1) process:

$$\rho_y(1) = \frac{-\theta_1}{1 + \theta_1^2}$$
$$\rho_y(k) = 0, k > 1$$

This precise auto covariance only depends on the time separation or lag and not on the complete location of the points of the series. Random shocks at every point are likely to be self-determining and come from the same distribution through the location at zero and constant scale. Moving average forecasting method is used to estimate the demand for any future period based on the demand observations from the previous periods. The order quantity q_t placed by the manufacture to the supplier can be expressed. The lagged error terms are not observable in moving the average model, therefore, the Fitting of the moving average estimates is more complicated than with autoregressive models.

Table 1: Forecasting Through Moving Average Time Series

S No.	Month	Indent Data 2014-2015	Forecasted Data 2014-2015	Actual Sales Data 2014-2015
1	April	46280	40625	46280
2	May	41040	46400	41040
3	June	45000	34452	43200
4	July	47520	40802	47520
5	August	43740	45327	43740
6	September	49820	44702	49820
7	October	40500	46350	40500
8	November	21060	45287	21060
9	December	20500	39162	20500
10	January	15800	25803	15000
11	February	20500	25803	20320
12	March	31840	21888	31840

MA forecasting method is used to estimate the demand for any future period based on the demand observations from the previous periods. Table 1 shows the sales data of an automobile company and the forecasted data using MA forecasting method. In a time series, ARMA models are quantitative models in nature and are widely used in many fields (figure 4). The behavior of a time series from past values can also be predicting using ARMA models.
The depiction of the autoregressive moving average model, ARMA (p, q) represents that autoregressive terms denoted by p and moving-average terms are denoted by q (table 2).

This model encompasses the AR (p) and MA (q) models.

Broad equation for ARMA (p, q) is given by

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \Theta_i X_{t-i} + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i}$$

Whre c: mean of the process

ε_t: white noise (error term)

Θi: coefficients of MA process

ₒi: coefficients of AR process.

When a given method is represented by function of sequences of unseen shocks, ARMA models are used.

Table: 2 Forecasting Through Auto Regressive Moving Average Time Series

S No.	Month	Indent Data 2014-2015	Forecasted Data 2014-2015	Actual Sales Data 2014-2015
1	April	46280	44746	46280
2	May	41040	44548	41040
3	June	45000	41199	43200
4	July	47520	44780	47520
5	August	43740	45886	43740
6	September	15000	41004	49820
7	October	20320	50762	40500
8	November	31840	35613	21060
9	December	20500	19540	20500
10	January	15800	21786	15000
11	February	20500	16569	20320
12	March	31840	23945	31840

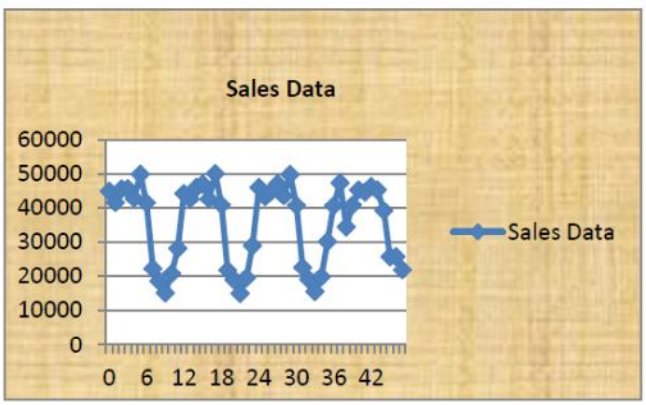

Figure 1: Data using Moving Average method

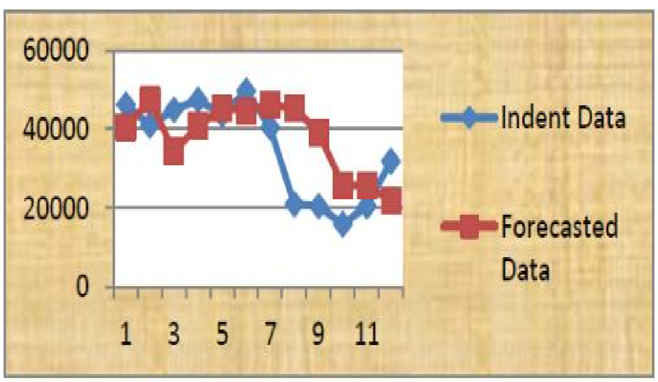

Figure 2: Plot Using Moving Average

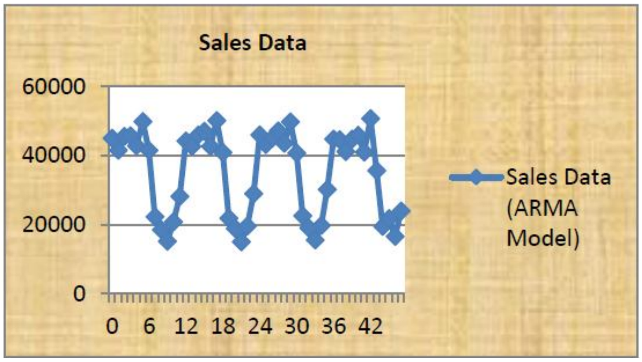

Figure 3: Data using ARMA model

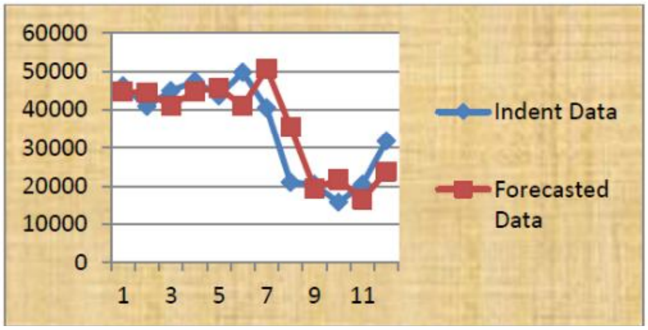

Figure 4: Plot using ARMA model

4.CONCLUSION AND FUTURE SCOPE

Thus, it can be concluded that when the data series is inactive in nature and a linear pattern is depicted then the time series models are useful means for forecasting. In order to validate the MA, ARMA models, a data set of an automobile firm has been taken into consideration. The Company is one of the largest suppliers of mechanical and electronic security system to original equipment manufacturers and about 20% of its products are being exported to other countries. Using this collected data, the future demand is predicted. The observations in the training set are used for building the. So the indent sales data from the year 2011 to 2014 is being used as training set and the data pertaining to 2014-2015 is made the validation set. Fuzzy time series models may be used to remove the limitations of the given time series models.

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