Analysis of Time Series Forecasting Techniques for Indian Automotive Industry

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Abstract: Automotive sector is one of the most crucial sectors for any developed or developing Economy. Unknown Demand for vehicles is a significant problem that decreases the productivity of the production environment. Thus, forecasting plays a vital role in planning the production and inventory of an industry. Time series forecasting is a type of forecasting in which last period data is used to determine the industry's trends and sales in the future. In this paper, the authors have deployed nine time series forecasting models for the Demand for vehicles in the Indian Automotive Sector. Authors have deployed Naïve Method, Simple Moving Average, Weighted Moving Average, Simple Linear Regression, Exponential Smoothening, Holt Winter linear Trend, Autoregression, Autoregression Moving Average, and Autoregression Integrated Moving Average models to compare the forecasted Demand and find the best model based on MAPE (Mean Absolute Percentage Error) value. This paper aims to scrutinize these nine models' ability to be implemented while performing market analysis or production planning of automobiles. The result of models helps analyze which model has greater accuracy and less percentage error, which will help production units.

Keywords: Demand Forecasting, Forecasting, ARIMA, Auto Regression, Moving Average, ARMA, Holt Winter

1. INTRODUCTION

The automotive sector is one of the developing sectors, where the most massive investments are made. It has an extensive business volume. Indian automobile production increased at 2.63% CAGR between FY16-FY20, with 26.36 million vehicles being manufactured in the country in FY20. Overall, domestic automobile sales increased at 1.29% CAGR between FY16-FY20, with 21.55 million vehicles being sold in FY20. It contributes significantly to the economic development of countries in the world. Today India's automotive industry is expected to reach Rs 16 to 18 trillion by 2026. Therefore, it is crucial for companies in this sector to correctly manage their resources. To do that, companies should predict the future in the best possible way and anticipate possible issues. Automotive sectors are the critical sector of the Indian economy. There is a dire need for demand forecasting for production planning and predicting future trends in the industry. Demand forecasting plays a significant role in decision making for the upliftment of business. For the past several years, there has been immense development in techniques used for demand forecasting, and new and improved methods are being developed for more accurate results.

Forecasting is a method that uses past data and estimates the future growths. It is a very critical tool for informed decision making and planning. The goal of forecasting is to reduce the effect of random factors on the resulting situation as adequately as possible, as well as help the decision-maker choose the right strategy while making the decision. External factors such as taxes, incomes, etc. and internal factors such as quality, price, popularity of product play a vital role in determining the possible Demand in future. The basic steps in forecasting are determination of objectives of forecasting, selection of item to be forecasted, selection of suitable forecasting model, collection of data, validation of forecasting model and implementation of results.

Usually, when analyzing demand data that are considered time series and represent the historical market demand for the product in a given period of time, there is a necessity for forecasting – to determine the possible product demand in the future. Decision risks such as the minimum number of orders to be placed in the next sales cycle can be minimized using accurate forecasting. Traditionally, the process of the time series analysis is based on searching for patterns in a long period of time by analyzing the changes of values in moments of time; as a result, the future values of the analyzed object are extrapolated.

1.1. What is a Time Series?

Every sequential set of data-points constitutes a Time Series. Each Time Series has two main components: time and value assigned to the corresponding time step. Most common examples of time series are daily changes in stock prices of the company, heights of ocean tides, counts of sunspots, etc.

A time series that records the measurements of a single phenomenon/variable is called univariate, whereas the measurements of multiple phenomena/variables is called multivariate. Our paper focuses on forecasting and analyzing univariate time series of customer demand or number of registered vehicles every year in India, with the third largest road network in the world, the total number of vehicles in the fiscal year 2017 stood at 25.3 million

1.2 Types of Time Series

There exist many classification criteria for time series; in this part we will focus on time dependency and stationarity. Time dependency refers to the influence of past values on the newly observed values of the recorded variable/phenomenon, we can divide time series into two categories: long memory time series and short memory time series. Long memory time series have an auto-correlation function that decreases slowly, these time series describe a process that has slowly changed behavior. Long memory time series can usually be found in meteorological, geological data; an example of long memory time series is the evolution of the mean temperature on planets. Short term time series describe a process with a fast turnover and have an auto-correlation function that decreases rapidly as the longer we are from the present the less useful to the future the measure is. A typical example of these time series are financial data, like stock prices. For the second classification criteria: stationarity, we have stationary and non-stationary time series. Stationary time series are processes that have statistical properties (mean, variance) that do not depend on time. Time series that do not fit the aforementioned description are called non-stationary, these time series are ubiquitous in finance and the retail sector. These types of time series can be tough to predict without any type of pre-processing, that is why we use multiple techniques to stationaries these processes to be able to get better forecasts

1.3 Components of Time Series

There are different patterns of demand variation depending on the time series. These include linear variation (Fig 1), seasonal variation (Fig 2), cyclic variation (Fig 3), random variations (Fig 4).

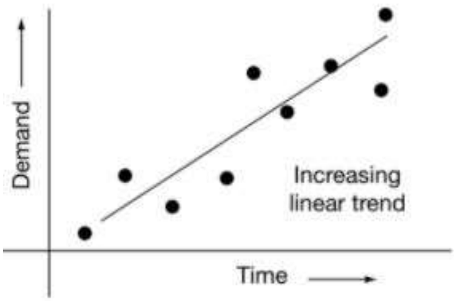
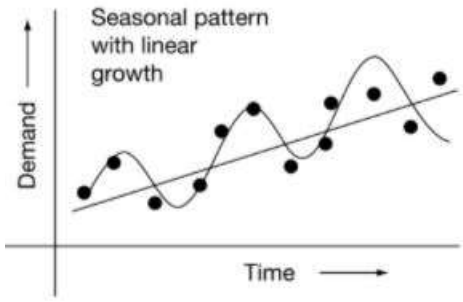


Figure 1



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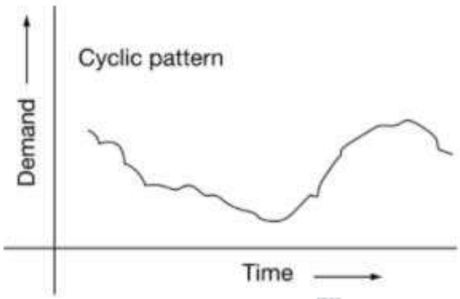

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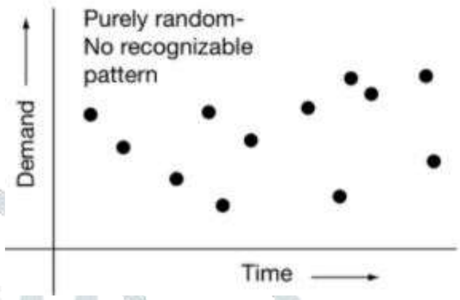

Figure 1

The components of the time series are as follows: -

- *Trends* are noted by an upward or downward sloping line.
- *Seasonality* is a data pattern that repeats itself over a period of certain duration. It leads to a rise or fall in Demand among the seasons. In a particular season demand may increase while in another season demand may decrease.
- *Cycle* is a data pattern that may cover several years before it repeats itself. Cyclic Nature in demand variations shows the same style in increasing or decreasing Demand in future.
- *Random* fluctuations result from random variations or unexplained causes. There are several reasons for random fluctuations in Demand, for example, anticipation of increasing the price or shortage of product in the near future increases the Demand.

2. LITERATURE REVIEW

Seher Arslankya in his research paper implemented time series analysis and artificial neural network methods to estimate sales for future months for the leading company in the automotive industry in Turkey. He examined the monthly data between January 2011 and July 2016 using multiple regression, moving average and artificial neural network model. Furthermore, he compared MAPE values for all models, which resulted in the ANN model giving the best result.

Arnis Kirshners did a comparative analysis of short time series processing methods intending to scrutinize these methods' ability to be used when analyzing short time series. The author has analyzed the moving average Method, exponential smoothening, and exponential smoothening with development trends resulting from moving average having the smallest squared error value but with large forecast smoothening for initial data.

Shamsul Masum elucidates on time series forecasting and its classification and approaches and strategies of time series forecasting. Furthermore, the author has demonstrated how an inappropriate point to point rolling forecast strategy leads to unrealistic outcomes and supports his argument with a comparative analysis of two strategies using the ARIMA model. The author has concluded with the result of rolling single point outcome being deceptive for Euro Dollar Exchange Rates case considered.

Tamal Datta Chaudhuri proposed six different forecasting methods for predicting the time series index of the healthcare sector. The author has demonstrated a decomposition approach of time series for data from January 2010 to December 2016 and illustrated how the decomposition results provide us with useful insights into the behavior and properties exhibited by time series. The author observed that results from the ARIMA model with a horizon of 12 months came out to be the best model with the lowest RSME value, while the Holt Winters method with a horizon of 12 months has the highest RSME value.

Jaydip Sen, in his research paper, uses the Time series - decomposition based Method to analyze the past of the Indian realty sector and predict its future. He uses time series forecasting methods in R programming language to determine future results. He uses time series index value data of the Indian realty sector for six years from 2010-2016 month wise. The methods used for accurate predictions are: Holt Winters exponential smoothening and Autoregressive Integrated Moving Average. He analyses the results from the above-mentioned broad concepts and observes, which is the best one. With the result obtained, he argues that these can be immensely useful for portfolio managers and stock traders to buy or sell stocks at the correct time.

Samita sood elaborates how time series forecasting can be deployed in determining the future development of the Indian tourism industry from past secondary data. The author uses the data for the number of tourists in India from 1980 to 2020 and uses models such as ARIMA and Holt Winter to forecast foreign tourist travel and compare the two models' accuracy. On the basis of MAPE and RMSE, the authors conclude that Holt Winter is a more accurate model than ARIMA in this particular situation.

William R Huss implements univariate estimation techniques such as Holt winter exponential smoothing, Multiple regression, Linear regression to study the load on 49 largest electric utilities in the United States and forecast the load for future planning. The author uses electric utility data from 1972 to 1982, and the results indicate that for shorter periods, Holt Winters Exponential smoothing method is highly accurate, and for more extended periods, extrapolation of Linear regression horizons proves to be efficient.

Deepa, in this paper, reviews, and forecasts the Indian Motorcycle market using Time series forecasting. The author uses SARIMA (Seasonal autoregressive Integrated Moving Method) and Holt Winters Method for prediction. The author compares several years' data and uses MAE and MAPE method to determine which model is more accurate and concludes that both the models are pretty significant but Holt Winters method is numerically more precise than the SARIMA model. According to the author the studies can be further enhanced by using more such models.

3. METHODOLOGY

This paper aims to analyze various time series forecasting methods using a comprehensive data set of registered vehicles or vehicles purchased every year in India. Data for the past 15 years (2001-2017) was collected from the Ministry of Statistics and Programme Implementation, Government of India. Various time series forecasting such as naive Method, simple moving average, autoregression, autoregression integrated moving average, holt winter linear trend is deployed using Microsoft Excel to draw an analysis between the results obtained from forecast and actual values.

Abbreviations used in paper are as follows: -

D_t = Demand in time period t

F_t = Forecast for time period t

t = Time Period / Duration of 1 Cycle

n = number of the averaging period

W_t = weight applied to period t's demand

α = smoothing factor

$\bar{x}$ = mean value of x

Calculation of Mean Absolute Percentage Error (MAPE) :-

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{D_t - F_t}{D_t}\right|$$

4. DIFFERENT TIME SERIES FORECASTING METHODS

4.1 Naive

Naive Method is the most basic forecasting method used in time series forecasting. In this Method the actual value of the last period is considered as a forecast of the current period without changing or implementing any statistical model. It is a special case of the moving average forecasting model where the number of periods used for smoothening is 1.

$$F_t = D_{t-1}$$

The forecast for the T^{th} period is equal to the Demand of the $T\text{-}1^{th}$ period.

4.2 Simple Moving Average

The simple moving average Method calculates the average value of actual Demand for some previous periods and forecast the Demand for the next period. This Method does not take into account the seasonality of data and it can only be used for forecasting the Demand of next period.

$$F_{t+1} = \frac{1}{n}\left(D_t + D_{t-1} + D_{t-2} + \ldots + D_{t+1-n}\right)$$

$$\Rightarrow F_{t+1} = \frac{1}{n}\sum_{i=t+1-n}^{i=t} D_i$$

Assumptions :

1. Observations older than *n* are not included at all.
2. All *n* past observations are treated equally.
3. It requires that *n* past observations be retained.

4.3 Weighted Moving Average

This Method is very similar to that of the simple moving average Method. The only main difference is that weights are allocated to different periods and the largest weight is provided to the most recent period and weights keep on decreasing as we move on to later periods.

$$F_{t+1} = W_1 D_t + W_2 D_{t-1} + W_3 D_{t-2} + \ldots\ldots + W_n D_{t+1-n}$$

Here $W_1 > W_2 > W_3 \ldots\ldots > W_n$ and the sum of all weights is 1 i.e. $W_1+W_2+W_3+\ldots W_n=1$.

Following assumptions are taken in WMA method:

1. Adjustments in the moving average to more closely reflect fluctuations in the data.
2. Weights are assigned to the most recent data.
3. Requires some trial and error to determine precise weights.

4.4 Exponential Smoothing

This is the most popular and efficient statistical Method. It is based on the principle that latest data should be weighed more heavily and 'smoothers' out cylindrical variations to forecast the trend. It assumes that as the data gets older it becomes less relevant. It is a more sophisticated WMA method that calculates the average of a time series by giving more weight to recent data. In this Method both the actual Demand and the forecast of previous Demand is used for calculation of forecasting.

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

Here α is the smoothing factor and its value is decreased as we move towards the past. The decrease follows an exponential pattern thus the name Exponential Smoothing.

4.5 Simple Linear Regression

Simple Linear Regression is a mathematical technique that relates to one variable, that is, an independent variable , with another variable called the dependent in the form of a linear equation. The linear regression equation is -

$$y = a + b \cdot x$$

Where y is the dependent variable, a is the intercept , b is the slope of the line, and x is the dependent variable. The variables a and b are given by -

$$a = \bar{y} - b\,\bar{x}$$

$$b = \frac{\sum xy \; - n(\bar{y})\,(\bar{x})}{\sum x^2 \; - n\,(\bar{x})^2}$$

Where a is constant and b of the coefficient of variable x , x is time and y is Demand.

The coefficient of correlation shows the strength of correlation between 2 variables. The linear regression model of forecasting is only used when coefficient of correlation(r) is high i.e. near to 1. Correlation variable is a measure of strength of the relationship between the independent (time) and dependent (Demand) variable. It is given by :

$$r = \frac{\sum_{t=1}^{n}(x_t - \bar{x})\,(y_t - \bar{y}\,)}{\sqrt{\sum_{t=1}^{n}(x_t - \bar{x})^2}\sqrt{\sum_{t=1}^{n}(y_t - \bar{y})^2}}$$

4.6 Auto Regression

An auto regressive model predicts future behavior based on past behavior. It is used for forecasting when there is a sum correlation between values in a time series and values that precede and succeed them. The process is a linear regression of the current series's data against one or more past values in the same series. An AR(p) model is an auto regressive model where specific lagged values of y_t are used as predictor variables. The value for p is called the order. The order of an autoregression is the number of immediately preceding values in the series that are used to predict the value at the present time. The general equation for AR(p) model is as follows:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \ldots\ldots + \phi_p y_{t-p} + \varepsilon_t$$

$$\phi_0 = (1 - \sum_{i=1}^{p} \phi_i)\,\mu$$

Where μ refers to process mean and ε_t refers to the white noise or shock / randomness in the data which ranges from $(0 , \sigma)$.

AR(1) model refers to an autoregressive process in which the current value is based on the immediate preceding value. Equation for first order auto regression model is as follows :-

$$y_t = \phi_0 + \phi_1 y_{t-1} + \varepsilon_t$$

4.7 Auto Regression Moving Average (ARMA)

In the statistical analysis of time series, autoregressive–moving-average (ARMA) models provide a parsimonious description of a (weakly) stationary stochastic process in terms of two polynomials, one for the autoregression (AR) and the second for the moving average (MA). It is the basic model for analyzing a stationary time series. A stationarity time series is defined formally in terms of the behavior of the autocorrelation function (ACF) through Wold's decomposition. Several simple cases of the ARMA model are then introduced and analyzed, with the partial autocorrelation function (PACF) also being defined, before the general model is introduced.

Finding appropriate values of p and q in the ARMA(p,q) model can be facilitated by plotting the partial autocorrelation functions for an estimate of p, and likewise using the autocorrelation functions for an estimate of q. Further information can be gleaned by considering the same functions for the residuals of a model fitted with an initial selection of p and q.

$$y_t = \phi_0 + \varepsilon_t + \sum_{i=1}^{p} \phi_i\, y_{t-i} + \sum_{i=1}^{q} \theta_i\, \varepsilon_{t-i}$$

ARMA(1,1) model refers to an autoregressive moving average process in which the current value is based on the immediate preceding forecast and residual value. The equation for the first-order auto regression model is as follows:-

$$y_t = \phi_0 + \varepsilon_t + \phi_1\, y_{t-1} + \theta_1\, \varepsilon_{t-1}$$

4.8 Auto Regression Integrated Moving Average (ARIMA)

An autoregressive integrated moving average model is a form of regression analysis that gauges the strength of one dependent variable relative to other changing variables.

Each component functions as a parameter with a standard notation. For ARIMA models, a standard notation would be ARIMA with p, d, and q, where integer values substitute for the parameters to indicate the type of ARIMA model used. The parameters can be defined as:

p: the number of lag observations in the model; also known as the lag order.

d: the number of times that the raw observations are differenced; also known as the degree of differencing.

q: the size of the moving average window; also known as the order of the moving average.

Differencing (back- shift) operator :

$$\begin{aligned} \Delta y_t &= y_{t-1} \\ (1-\Delta)\, y_t &= y_t - y_{t-1} \\ \Delta^d y_t &= \Delta^{d-1} y_{t-1} \\ &= y_{t-d} \end{aligned}$$

Re-writing AR(p), MA(q) and ARMA(p,q) using the back-shift operator will simplify the mathematical representation of the ARIMA model.

4.9 Holt Winter Linear Trend model

Holt (1957) extended simple exponential smoothing to allow the forecasting of data with a trend. This Method involves a forecast equation and two smoothing equations (one for the level and one for the trend):

Forecast equation $y_{t+h|t} = \ell_t + hb_t$

Level equation $\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1}+b_{t-1})$

Trend equation $b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1},$

where ℓ_t denotes an estimate of the level of the series at time t, b_t denotes an estimate of the trend (slope) of the time series at time t, α is the smoothing parameter for the level, $0 \le \alpha \le 1$, and β is the smoothing parameter for the trend, $0 \le \beta \le 1$.

As with simple exponential smooth (SES), the level equation here shows that ℓ_t is a weighted average of observation y_t and the one-step-ahead training forecast for time t, given by $\ell_{t-1}+b_{t-1}$. The trend equation shows that b_t is the weighted average of the estimated trend at time t based on $\ell_t - \ell_{t-1}$ and b_{t-1}, the previous estimate of the trend.

The forecast function is no longer flat but trending. The h-step-ahead forecast is equal to the last estimated level plus h times the last estimated trend value. Hence the forecasts are a linear function of h.

5. NUMERICAL ILLUSTRATIONS

Year	Actual Sales	Volume Produced	Naïve Method	Simple Moving Average	Weighted Moving Average	Exponential Smoothening	Holt Winter Linear Trend	Simple Regression	Auto Regression	ARMA	ARIMA
2010	12,795	17,916	9,598	8,444	8,555	9,198	10,887	7,332	10,095	10,858	9,370
2011	14,120	20,382	12,795	10,346	9,842	11,715	12,556	7,552	11,030	11,856	11,935
2012	17,625	20,626	14,120	12,171	11,360	13,398	15,026	7,771	11,732	12,946	12,279
2013	18,422	21,500	17,625	14,847	13,681	16,355	17,130	7,990	12,717	14,136	13,918
2014	19,724	23,358	18,422	16,722	15,636	17,801	19,062	8,210	13,602	15,436	15,861
2015	20,469	24,016	19,724	18,590	17,445	19,147	20,628	8,429	14,687	16,856	17,182
2016	21,863	25,314	20,469	19,538	18,812	20,072	22,118	8,648	15,752	18,405	19,366

2017	24,981	29,094	21,863	20,685	20,147	21,325	24,169	8,867	16,974	20,098	21,477
2018	26,266	30,914	24,981	22,438	21,855	23,883	26,019	9,087	18,231	21,946	23,547
2019	21,546	26,362	26,266	24,370	23,540	25,550	25,530	9,306	19,626	23,963	26,148

Table 1 : Actual Sales , Vehicles Produced and Forecasting Result for Different Time Series Forecasting Techniques (all values are in thousands)

In Table 1 values of forecasted results for different techniques have been shown along with the actual sales and actual vehicle produced for each year. For simple moving average Method, calculations were conducted to find the most optimal period duration and the 3-period moving average gave the least MAPE value. For the exponential smoothening Method, the most optimal solution is for the smoothening factor 0.69. Analysis for Holt Winter Linear Trend gave minimum MAPE value for alpha :0.35 and beta:0.25. While considering the case for simple regression , the intercept value came out to be -1658 and x variable value 219. A comparison was drawn between different AR order models [AR(1) , AR(2) , AR(3)]. AR(2) model was the most precise model and had least MAPE value. Comparing ARMA [(1,1) ; (1,2) ; (2,2)] order models for same data set, ARMA(1,1) had least MAPE value. Forecasting using different ARIMA order models without constant [(1,2,2) ; (1,1,1) ; (2,2,2) ; (1,2,3) ; (3,2,1) ; (3,2,3) ; (3,3,3) ; (4,3,2)] were quite comparable but ARIMA(3,3,3) produced most precise result among all. All the models are trained using data for the past 40 years (1970 – 2009) and were deployed to forecast values for the next 10 years (2010 – 2019). Table 2 highlights MAPE value for all the techniques used for forecasting with the most optimum order or smoothening factor among themselves.

Forecasting Technique	MAPE
Naïve Method	11%
Simple Moving Average	19%
Weighted Moving Average	22%
Exponential Smoothening	15%
Holt Winter Linear Trend	8%
Simple Regression	57%
Auto Regression	27%
ARMA	18%
ARIMA	19%

Table 2 : MAPE for Different Time Series Forecasting Techniques

6. RESULT AND CONCLUSIONS

According to the conducted experiments the Holt Winters Linear Trend achieves the minimum Mean Absolute Percentage Error (MAPE) and Simple Regression has the maximum MAPE value for the chosen data set of vehicles sold in India for the past 50 years (1970 – 2019). The study demonstrates that Holt Winter Method is the most precise and accurate model for Indian Automotive industry in all available time series forecasting techniques. The Holt-Winters model's relative ease of use makes the model useful in forecasting comprehensive market trends. Some results obtained from other time series forecasting techniques were quite comparable. Methods such as Exponential Smoothening , ARMA , Moving Average , ARIMA also had relatively less MAPE value but Holt Winters proved to be the best among them.

The actual vehicles sold in an year were compared with the actual production of the number of vehicles produced that year. The average overproduction percentage came out to be a staggering 18%. The analyzed results emphasize that there is a necessity for better and improved production planning strategies to minimize the losses faced by companies due to over or under production. The primary step involved in the improvement of production strategy is to have precise forecasted results. Improving on the accuracy of estimation is imperative to the reasonable allocation of scarce resources, this signifies the call for enhanced forecasting techniques and the research will help Indian automobile industry and parts manufacturers to build effective strategies.

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