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Forecasting monthly farm tractor demand for India using MSARIMA and ARMAX models

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ABSTRACT

Because of long product development cycles, effective production planning of automobiles requires accurate demand forecasting in order to effectively managing resources and maximizing revenue. Errors in demand forecasts have often led to enormous costs and loss of revenue due to suboptimal utilization of resources. Since early 2000 India has been the largest manufacturer and consumer of farm tractors in the world. This paper develops multiplicative seasonal autoregressive integrated moving average (MSARIMA) and autoregressive moving average model with exogenous variable (ARMAX) to forecast monthly demand for farm tractor. The result indicates that ARMAX with real agriculture credit has found to be outperformed MSARIMA model in forecasting demand of farm tractors in the horizon of six months. The accurate monthly forecasting of farm tractor would help the manufacturers for better raw material, inventory and supply chain management.

Key words: ARMAX, Demand forecasting, Farm tractor demand, MSARIMA.

INTRODUCTION

India has been considered as agricultural powerhouse with world's second largest arable land of 180 million hectare. It has the world's largest area under wheat, rice and cotton crop and has been the second largest producer of these crops. Agriculture growth enhances purchasing power of the rural population and pushes growth in other sectors of the economy. In the year 2017-18, agriculture sector contributes 15.11 percent to the country's gross domestic product and provide employment to more than 50.0 percent of total workforce.

The critical role of farm tractors has been well established as a major input to increase agriculture yield (Singh, 2005). Farm tractor has ensured timely completion of agriculture operations with efficiency (Bottinger *et. al.*, 2013). India has world's largest annual demand of 0.73 million units in 2017-18 for farm tractors. The primary demand of farm tractor has been coming from agricultural sector though it has also been used for haulage work. Farm tractors and machineries are vital for farm preparation in India (Gautam, 2018). The Indian government has also been supporting the demand of farm tractors with easy availability of credit for its purchase under priority sector lending.

On the supply side, the scenario for farm tractors in India has been good due to availability of cheap labour, raw materials, surplus manufacturing capacity and presence of global players in India. India is hub to global R&D centre and one of the low cost manufacturing base for farm tractor manufacturing. Hence positive demand and supply side factors have ensured the long-term growth trend in farm tractor demand in India as shown in Fig 1.

In India the farm tractor manufacturing has been started in 1961 and now it is the largest farm tractor producer in the world fulfilling one-third of global demand. Farm tractor industry is very competitive with presence of sixteen players selling tractors from 15 horse power (HP) to 110 HP (Table 1). In last ten years farm tractor sales has grown with CAGR of 13.7% whereas overall GDP has grown with CAGR of 7.5%.

Kim *et. al.*,(2013) used ARIMA model to forecast annual demand for agriculture tractor, rice transplanter and harvester for period 2012 to 2021 for South Korea. Their forecast results had periodic fluctuation and large variation in estimation. Similarly, the reliability of results was low for annual agriculture tractor demand forecast for Turkey using ARIMA model by Unakitan (2007). The paper has used the cumulative farm tractor stock as proxy for tractor demand with time trend.

Biondi *et. al.*, (1998) used both ARIMA and multivariate models to forecast annual farm tractor demand for Italy, France and United States. They had used the agriculture income, real price of tractors etc. as independent variable in their multivariate analysis. As per their study the ARIMA model had better validity for Italy and United States. The long-range forecasting models for farm tractor demand had limitation in terms of high standard error for estimated coefficients. This had led to the large confidence interval for forecast with increase in forecasting horizon. Similar

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Table 1: Major domestic players in indian farm tractor manufacturing.

Manufacturer	Collaboration	Year
Eicher Tractor Ltd.*	Gebr, Eicher Tractor, West Germany	1961
TAFE Ltd.	Messey Ferguson, UK	1964
Escorts Ltd.	Ford, UK	1965
Mahindra & Mahindra Ltd.	International Harvestor, UK	1971
HMT Ltd.	Motokov Praha, Czechoslovakia	1971
Punjab Tractor Ltd.*	CMERI, India	1974
VST Tillers	Mitsubishi, Japan	1983
Bajaj Tempo Ltd.	Own	1987
International Tractors Ltd.	Own	1998
Larsen & Tourbo Ltd.*	John Deere, USA	1999
New Holland Tractors Pvt. Ltd.	New Holland Tractors, Italy	1999
Greaves Ltd.*	Same Deutz Fahr, Italy	1999

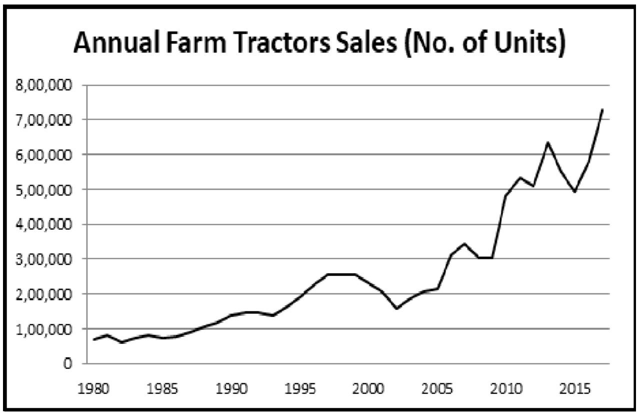

Fig 1: Long term demand trend of farm tractor.

objection on forecast reliability has been raised on using univariate econometric model for forecasting annual farm tractor demand (Evcim and Sindir, 1993; Sharan, 1995).

Mui (1986) has studied the causality between new farm tractors demand, price of diesel, price of new tractors and rural wage rate at annual level. In India the diesel prices have been under government administration and do not vary with international oil prices. The study by Pawlak (1999) has used univariate and multi variate analysis for demand of farm tractors. The multivariate analysis has showed that the farm tractor demand has been highly depended on real agriculture income which influences the purchasing power.

Previous studies revealed that significant attempts have been made to estimate and forecast farm tractor demand in long term at an annual level, however, demand forecasting on monthly level has been non-existent to the best of our knowledge. The intrinsic seasonality in agriculture operations has been influencing the monthly demand for farm tractors. So despite a long term stable positive trend, there have been significant fluctuations of the monthly demand for farm tractors. Because of long product development cycles, effective production planning of automobiles requires accurate demand forecasting in order to effectively managing resources and maximizing revenue. Errors in demand forecasts have often led to enormous costs and loss of revenue due to suboptimal utilization of resources. Raw material like steel, rubber, plastic etc. contributes almost 70% of total manufacturing cost of farm tractors. The accurate short term prediction of demand will help manufacturers to hedge against short term price fluctuation and ensure availability of raw materials. India being a geographically vast country the accurate monthly forecasting will also help in better management of supply chain.

This study tries to forecast the monthly demand of farm tractors in India using seasonal autoregressive integrated moving average (MSARIMA) complemented with autoregressive moving average with exogenous variable (ARMAX) models.

The remainder of this paper is organized as follows. Material and methods section describe the data and methodology, followed by results and discussion. Last section concludes the study.

MATERIALS AND METHODS

All India monthly farm tractor sales numbers, as a proxy to farm tractor demand, has been taken from the bulletin of Tractors Manufactures Association. The farm tractor sales numbers represent the combined sales of all manufacturers in India excluding export. The farm tractor sales have been seasonal, and demand varies with the crop cycle. The demand has been high in month of April, May, September and October due to requirement of farm tractor in crop sowing and harvesting operations as shown in Fig 2. The rural purchase has also been influenced by auspicious or festival seasons. Therefore, the month of October has observed the highest demand due to coincident of agriculture requirement and auspicious period.

For ARMAX model, this study considers following exogenous variables; real agriculture credit (AC), whole sale price index for tractor (WPI-T), index of industrial production (IIP), consumer price index agriculture labour (CPI-AL). Monthly data on these variables are available from Reserve Bank of India (RBI) and Ministry of Statistics and

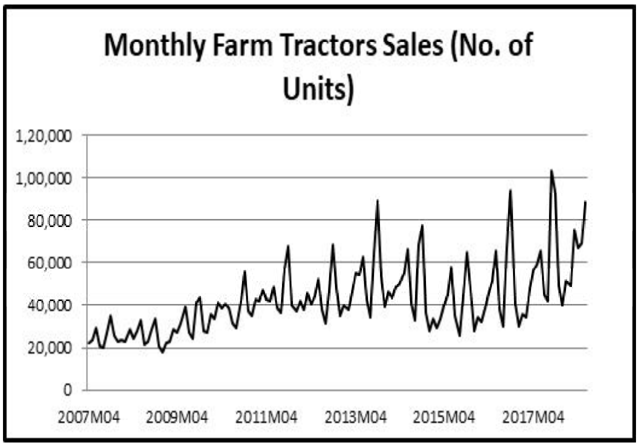

Fig 2: Monthly Tractor Sales.

Programme Implementation (MOSPI). The nominal variables are converted to real series using whole sale price index.

Agricultural credit (AC): The agriculture credit in India has been increasing exponentially over the past few years. The impact of agriculture credit on crop yield is immediate as it ensures availability of inputs like farm tractors, irrigation, fertilizers and seeds (Sreeram, 2007; Das, 2009).

The Reserve Bank of India through its special agriculture credit plan (SACP) from year 1994-95 has asked the banks to set the agriculture credit disbursement target for current year to be higher by 20 to 25 percent than last year's disbursement. The implementation of SACP greatly enhanced the disbursement of agriculture credit. Separately RBI also ensured that minimum 18 percent of net bank credit has been available to agriculture sector.

Index of Industrial Production (IIP): The index of industrial production (IIP) is the growth in the industrial activity of the economy with reference to suitable base year. IIP index enable us to measure and compare the industrial activities in the economy. There has been link between non-agriculture and agriculture sectors of the economy due to forward backward linkages. Therefore, we have studied the effect of IIP on prediction of farm tractor demand.

Consumer Price Index of Agriculture Labour (CPI-AL): Agriculture labour is a person involved in cultivation, growing and harvesting of crops including its storage and transportation. Consumer price index of agriculture labour (CPI-AL) is a measure of price level for agriculture labour on food, fuel, clothing and other miscellaneous items. CPI for agriculture labour capture the overall price level or inflation for agriculture labour.

Wholesale Price Index of Tractor (WPI-T): Whole sale price index for tractors (WPI-T) is a component of overall whole sale price index. The WPI-T measures the relative price change in tractors. It is the only reference series available to capture the price movement of farm tractors.

The data frequency is monthly and span from April 2007 - May 2014. The choice of period is on the bases of the presence of structural break in the year 2007 as evident from *Zivot-Andrews (1992)* and (b) the *Bai-Perron (1998*) unit root tests (Table 2). The government post 2004 has started different welfare schemes to promote agriculture and rural income like MNREGA, rural infrastructure project and increase in minimum support price for key crops etc. The impact of these initiatives to increase rural income has been visible from 2007 onwards. This with strengthening of agriculture credit through private banks became a turning point for tractor demand.

As mentioned earlier, the study employs multiplicative seasonal autoregressive integrated moving average (MSARIMA) complemented with autoregressive moving average with exogenous variable (ARMAX) model for estimation and forecasting of monthly tractor demand in India.

MSARIMA model is coming under the special category of time series models called 'univariate time-series'. Univariate time-series analysis incorporates making use of historical data of the concerned variable to construct a model that describes the behavior of this variable (time-series). This model can, subsequently, be used for forecasting purpose.

MSARIMA Model: A linear non-stationary stochastic process is said to be homogeneous of degree ***d*** when upon differentiating the original process by ***d*** times, the resulting transformed process has become covariance-stationary. If the original series X_t is homogeneous of degree ***d***, then

$$\Delta^d X_t = (1 - L)^d X_t = Z_t, \; t=1,2,3, \ldots, T \qquad (1)$$

is covariance-stationary . Here, L is the backward shift operator. An integrated process X_t is designed as an ARIMA (p,d,q), if taking differences of order d, a stationary process Z_t of the type ARMA (p, q) is obtained.

Table 2: Unit root tests with unknown structural breaks.

	Intercept	Trend	Both
Zivot – Andrews (1992) Test Statistics (Break Point)	-3.589506**(2007)	-5.106253***(2007)	-5.135798***(2002)
Bai-Perron (1998) Test Statistics (Break Point)	-3.523527***(2007)	-5.213596***(2007)	-5.226349***(2007)
Sample	1971 - 2014	1971 - 2014	1971 - 2014

*** significant at 1% level; ** significant at 5% level, * significant at 10% level.

The ARIMA (p, d, q) model is expressed by the function

$$Z_t = \phi Z_{t-1} + \phi_2 Z_{t-2} + \ldots\ldots.+ \phi_p Z_{t-p} + u_t - \theta_1 u_{t-1} - \theta_2 u_{t-2} - \ldots\ldots - \theta_q u_{t-q}$$

Or $\phi(L)(1-L)^d X_t = \theta(L) u_t$ (2)

Non-stationary homogeneous models with seasonal variations, ARIMA $(P,D,Q)_s$

In most of the monthly electricity time series data, seasonal variation is one of the main sources of non-stationarity. To remove seasonal non-stationarity of such series where seasonality is daily, one can proceed with seasonal differencing by s=24 times. The seasonal models ARIMA (P, D, Q) which are not stationary but homogenous of degree D can be expressed as

$$Z_t = \Phi_1 Z_{t-s} + \Phi_2 Z_{t-2s} + \ldots\ldots.+ \Phi_p Z_{t-ps} + \delta + u_t - \Theta_1 u_{t-s} - \Theta_2 u_{t-2s} - \ldots.$$

Or $\Phi_p(L^s)(1-L^s)^D X_t = + \Theta_Q(L^s) u_t$ (3)

where Φ and Θ are fixed seasonal autoregressive (AR) and moving average (MA) parameters.

General multiplicative seasonal models, MSARIMA (p, d, q) $(P, D, Q)_s$

These models take into account the effect of trend and seasonal fluctuations of a time series and are expressed as

$\Phi_p(L^s)\ \phi_p(L)(1-L^s)^D(1-L)^d X_t = \Theta_Q(L^s)\ \theta_q(L)\ u_t.$ (4)

ARIMA Model Building: For a given time series, it is important to know which ARIMA model is capable of generating the underlying series. In other words, which model adequately represents the behavior of the concerned Time Series so that the forecasts of the series under study can be done precisely. Box-Jenkins considers model building as an iterative process which can be divided into four stages: *identification, estimation, diagnostic checking and forecasting.* Identification stage basically tries to identify an appropriate ARIMA model for the underlying stationary time series on the basis of Sample Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). If the series is nonstationary it is first transformed to covariance-stationary and then one can easily identify the possible values of the regular part of the model i.e. autoregressive order p and moving average order q in a univariate ARMA model along with the seasonal part.

In the estimation stage, point estimates of the coefficients can be obtained by the method of maximum likelihood. Associated standard errors are also provided, suggesting which coefficients could be dropped.

Table 3: Estimated parameters of MSARIMA model.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4657.809	495.23	9.405345	0
MA(1)	0.655619	0.089018	7.365023	0
SMA(12)	-0.54148	0.128892	-4.20105	0.0001

In diagnostic checking stage, additional autoregressive and moving average variables can be added and their statistical significance can be examined. One should also examine whether the residues of the model appear to be white noise process. After the model has been re-specified, it will be re-estimated and diagnostic checks will be applied again until the coefficients are reasonably statistically significant and the residuals are random.

After the diagnostic checking, comes the fundamental aim of the methodology, i.e., the forecasts of the future values of the time series.

Regression Model With ARMA Errors: Let us consider the model

$X_t = Z_t'\beta + u_t$ and $\alpha(L)\, u_t = \theta(L)\, e_t$, $e_t \sim WN(0,\sigma^2)$ …….(5)

where Z_t' is a (1 x k) vector containing k exogenous variables at time t, β is a (k x 1) vector of parameters and u_t follows an ARMA (p, q) process.

RESULTS AND DISCUSSION

At the beginning, we first de-seasonalize the series as suggested by the correlogram of the original series. In the next stage, sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of de-seasonalized series have been used to identify the possible values of the regular part of the model, that is, autoregressive order *p* and moving average order *q* in a univariate ARMA model along with the seasonal part, which has then been estimated by maximum likelihood. The residuals are then inspected for any remaining autocorrelation the residual series.

The estimated parameters with their standard error, *t* statistics and probability values of the best fitted model in terms of smallest Akike information criterion (AIC) to explain the monthly tractor demand are shown in Table 3. As shown in the tables, coefficients of all AR, MA, SAR and SMA terms are statistically significant at 5% level. The stationarity and invertibility conditions for respective seasonal and non-seasonal AR and MA terms are also satisfied. In all the cases, the residual series appears to be purely white noise as shown in Table 5.

Results of the estimated ARMAX model are shown in Table 4. Real agricultural credit appears to be only statistically significant exogenous variables which influence tractor demand. The findings are consistent with earlier study

Table 4: Estimated parameters of ARMAX model.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-24163.2	9551.134	-2.52988	0.0144
AGRI_CDT	23.46724	4.674937	5.019797	0
AR(1)	0.385167	0.171473	2.246224	0.0288
SAR(12)	0.970997	0.129802	7.480626	0
SAR(24)	0.30151	0.152148	1.981688	0.0526
MA(1)	0.36404	0.171862	2.118206	0.0388
SMA(12)	-0.88828	0.036877	-24.0874	0

Table 5: Diagnostic checking of residual series.

Lags	Probability of Ljung–Box Q-statistics MSARIMA	ARMAX
1	-	-
2	-	-
3	0.25	-
4	0.317	-
5	0.462	-
6	0.349	0.174
7	0.449	0.377
8	0.528	0.557
9	0.542	0.237
10	0.608	0.345
11	0.661	0.403
12	0.747	0.472
13	0.817	0.383
14	0.483	0.414
15	0.508	0.438
16	0.536	0.519
17	0.561	0.453
18	0.617	0.507
19	0.679	0.452
20	0.733	0.444
21	0.783	0.506
22	0.739	0.577
23	0.604	0.583
24	0.533	0.639
25	0.592	0.648
26	0.572	0.698
27	0.612	0.635
28	0.645	0.669

Table 6: Forecasting performance.

Model	MSARIMA	ARMAX
RMSE	2989.94	991.26
MAE	2508.67	868.85
MAPE	5.16	1.79
Theil IC	0.03	0.01

(Mandal and Maiti, 2013). Apart from agricultural credit there are statistically significant non-seasonal ARMA (1,1) and seasonal ARMA (2,1) components. Residual series, as shown in Table 5, appears to be white noise.

Estimated MSARIMA and ARMAX models are finally used to forecast monthly tractor demand and forecasts are then evaluated using standard performance criterion such as root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) and Theil inequality coefficient. RMSE and MAE criteria depend on the scale of the variable, while the MAPE and Theil inequality coefficient are insensitive to the scale of the variable. The smaller the error, the better is the forecasting performance for the series. The Theil inequality coefficient always lies between zero and one, where zero indicates a perfect fit.

As shown in Table 6, MAPE between actual and the values predicted by MSARIMA and ARMAX models for last six months of the data span are 5.16 and 1.79 respectively. ARMAX model, thus, outperform MSARIMA model in terms of lower RMSE, MAE, MAPE and Thiel inequality coefficient.

CONCLUSION

This study forecasts monthly demand of farm tractor by employing MSARIMA model complemented by ARMAX model. ARMAX model suggests that the farm tractor demand is not influenced by farm tractor price captured by whole sale price index of tractor (WPI-T), overall increase in price level captured by consumer price index of agriculture labour (CPI-AL) and by IIP. The statistical insignificance of WPI-T and CPI-AL can be explained by considering the fact that tractor is durable capital input for agriculture, whose utility is distributed over a long period (Mui, 1986). The statistical insignificance of IIP can be explained as follows. The index of industrial production (IIP) captures the movement in non-agriculture sector i.e. manufacturing. The farm tractors are predominately used for agriculture operations and hence IIP has no significant impact on its monthly demand.

The availability of agriculture credit has directly influenced the purchasing capacity of farmers and hence increases the demand for farm tractors. The inclusion of agriculture credit as exogenous variable in our ARIMAX model has improved the overall explanatory power of the model along with forecasting performance with respect to MSARIMA model.

The contribution of this paper is in providing monthly tractor demand forecasting model. The precise monthly forecasting of farm tractor demand helps the manufacturer for better planning and utilization of their manufacturing capacity, inventory and supply chain management. The significance of agriculture credit in ARMAX model provides a tool to government to influence monthly demand of farm tractors. India, being a vast and geographically diverse country, the further extension of current work to be in studying the state specific demand of farm tractors.

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