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Modelling and Forecasting of Meat Exports from India

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Abstract

In the present study, seasonal autoregressive integrated moving average (SARIMA) methodology has been applied for modelling and forecasting of monthly export of meat and meat products from India. Augmented Dickey-Fuller test has been used for testing the stationarity of the series. Autocorrelation (ACF) and partial autocorrelation (PACF) functions have been estimated, which have led to the identification and construction of SARIMA models, suitable in explaining the time series and forecasting the future export. The evaluation of forecasting of export of meat and meat preparations has been carried out with root mean squares prediction error (RMSPE), mean absolute prediction error (MAPE) and relative mean absolute prediction error (RMAPE). The residuals of the fitted models were used for the diagnostic checking. The best identified model for the data under consideration was used for out-of-sample forecasting along with the upper and lower 95 per cent confidence interval up to the year 2013.

Key words: Forecasting, meat export, SARIMA model, seasonality, stationarity

JEL Classification: Q13, Q17, Q22

Introduction

Fluctuations in export price of different commodities are a matter of concern for consumers, farmers and policymakers. The unforeseen variations in export prices can complicate budgetary planning. Therefore, its accurate forecast is extremely important for efficient monitoring and planning. Forecasting of meat production or meat export price for that matter is a formidable challenge. With the onset of globalization, it has become imperative to study the trends in prices of different commodities by employing sound statistical modelling techniques which in turn, will help the planners in formulating suitable policies to face the challenges ahead. India is at the top position in animal and cattle population, but meat processing industry has yet to come up. Poultry meat is the fastest growing animal protein in India. Only 21 per cent of the total meat produced is exported. Further, only 6 per cent of the poultry meat is marketed in the processed form.

In recent years, the demand for Indian buffalo meat is increasing rapidly due to its lean character and near-organic nature. Also, frozen bovine meat from India is very popular in the international markets. Thus, India has the potential to become a key player in the global meat market. Taking in view the huge scope of expanding meat exports, there is an urgent need to develop strategies for enhancing meat production in India. Since fluctuations in price for different commodities are a matter of concern for producers, consumers and policymakers, accurate forecast is extremely important for efficient monitoring and planning. Many attempts have been made in the past to develop forecast models for various commodities. Paul *et al*. (2009) have studied the fluctuations in export price of spice; Chandran and Pandey (2007) have studied the seasonal fluctuation in potato price in Delhi; Paul and Das (2010) have attempted forecasting of

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inland fish production in India by using ARIMA approach. Paul (2010) has also studied the application of stochastic modelling for forecasting of wholesale price of Rohu in West Bengal, India. Saz (2011) has used seasonal autoregressive moving average (SARIMA) model to forecast inflation rates.

In this paper time-series approach has been followed to develop an ideal model which will adequately represent the set of realizations and also their statistical relationships in a satisfactory manner. Time-series analysis is an important tool for management and decision-making as it reveals the hidden trends and seasonality patterns. Box-Jenkins autoregressive integrated moving average (ARIMA) methodology is the most widely used technique for time series analysis. The ARIMA methodology has been successful in describing and forecasting of a wide variety of species in the past. In the ARIMA approach, the forecasts are based on linear functions of the sample observations and the aim is to find the simplest models that provide an adequate description of the observed data. There are also ARIMA processes designed to handle seasonal time series; these are called SARIMA models.

There are two types of forecasting models: deterministic and stochastic. The deterministic models do not have a random variable and each prediction is made under a specific set of conditions that are always the same (William, 1986). The stochastic models, in contrast, have a random variable that represents error-terms of random factor (Box *et al.*, 2007; Liu and Hanssens, 1982). In our study, we have used a stochastic model. On plotting our data we noticed the presence of seasonality, therefore, we have opted for the Seasonal Autoregressive Integrated Moving Average (SARIMA) method. SARIMA models deal with seasonality in a more implicit manner, while ARIMA models are deficient in dealing with seasonal data. Also, SARIMA models are better if the seasonal pattern is both strong and stable over time. For the estimation of parameters, iterative least squares method is used. In the present study, SARIMA stochastic modelling has been used on the monthly total export of meat and meat preparations from India.

Materials and Methods

Data Description

The month-wise data on total exports of meat and meat preparations from India were collected from the website www.indiastat.com for the period November 1992 to December 2011 and the same are given in Figure 1. A perusal of Figure 1 reveals an increasing trend in the total export of meat and meat preparations from India over the years. At the same time, the figure also indicates that the export is highest during October-December and lowest during April-May every year. This clearly shows seasonality in the data set. Accordingly, SARIMA model was explored for modelling and forecasting of this data set.

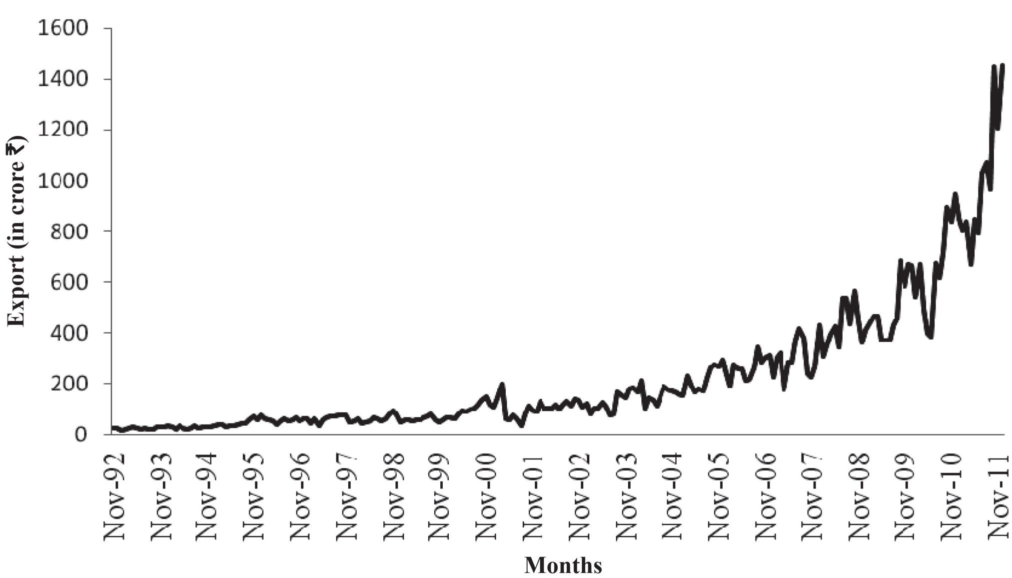

Figure 1. Monthly export of meat and meat preparations from India: Nov. 1992 to Nov. 2011

Descriptions of Models

Autoregressive Integrated Moving Average (ARIMA) Model

A generalization of ARMA models which incorporate a wide range of non-stationary time-series is obtained by introducing differencing into the model. The simplest example of a non-stationary process which reduces to a stationary one after differencing is 'Random Walk'. A process $\{y_t\}$ is said to follow an Integrated ARMA model, denoted by ARIMA (p, d, q), if $\nabla^d y_t = (1 - B)^d \varepsilon_t$ is ARMA (p, q). The model is written as:

$$\varphi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \qquad ...(1)$$

where, $\varepsilon_t \sim WN\ (0, \sigma^2)$, WN indicates white Noise, $\phi(B) = 1 - \varepsilon_1 B - \varepsilon_2 B^2 - \ldots\ldots\ldots - \varepsilon_p B^p$ and

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots\ldots - \theta_q B^q$. The integration parameter d is a non-negative integer.

Some special cases of ARIMA (p, d, q) model are:

(i) When $d = 0$, ARIMA (p, d, q) ≡ ARMA (p, q). Therefore, ARIMA (p, q) model may be represented by Equation (2):

$$\varphi(B) y_t = \theta(B)\varepsilon_t \qquad ...(2)$$

(ii) When d=0 and q=0, Equation (1) becomes AR (p) model which is represented as:

$$\varphi(B) y_t = \varepsilon_t \qquad ...(3)$$

(iii) When d=0 and p=0, Equation (1) becomes AR (q) model which is represented as:

$$y_t = \theta(B)\varepsilon_t \qquad ...(4)$$

In practice, it is frequently true that adequate representation of actually occurring stationary time-series can be obtained with autoregressive, moving average, or mixed models, in which p and q are not greater than *2* and are often less than *2*.

The ARIMA methodology is carried out in three stages, viz. identification, estimation and diagnostic checking. The parameters of tentatively selected ARIMA model at the identification stage are estimated at the estimation stage and adequacy of tentatively selected model is tested at the diagnostic checking stage. If the model is found to be inadequate, the three stages are repeated until satisfactory ARIMA model is selected for the time-series under consideration. A detailed discussion on various aspects of this approach is given in Box *et al*. (2007). Most of the standard software packages, like SAS, SPSS and EViews, contain programs for fitting of ARIMA models.

Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

The fundamental fact about seasonal time-series with period S is that observations, which are S intervals apart, are similar. Therefore, the operation $L\,(y_t) = y_{t-1}$ plays an important role in the analysis of seasonal time-series. In general, the order of SARIMA model is denoted by (p, d, q) × (P, D, Q)$_S$, and the model is represented as per Equation (5):

$$\phi_p(L)\Phi_P(L^S)\nabla^d\nabla_S^D y_t = \theta_q(L)\Theta_Q(L^S)\varepsilon_t \qquad ...(5)$$

where, $\phi_p(L)$ and $\phi_q(L)$ are the polynomials in L of degrees p and q, respectively and $\Phi_P(L^S)$ and $\Theta_Q(L^S)$ are the polynomials in L^S of degrees P and Q, respectively; p stands for the non-seasonal autoregressive order, d standing for the non-seasonal integration order, and q for the non-seasonal moving average order. In the seasonal part, P, D and Q stand for seasonal autoregressive order, seasonal integration order, and seasonal moving average order, respectively and s denotes the period or length of the season (in the monthly case 12, in the quarterly case 4). For the estimation of parameters, iterative least squares method is used. The forecasting strategy of SARIMA is given as: Data collection and examination, determination of the stationarity of the time-series, model identification and estimation, diagnostic checking, forecasting and forecast evaluation.

Testing for Stationarity

Stationarity is required for fitting a time-series into a SARIMA framework. Stationarity means that the stochastic properties, the moments (mean, variance, covariance) of the underlying time-series need to be time invariant. Time plot, Autocorrelation function (ACF), and Partial autocorrelation function (PACF) are used as a first attempt in determining the stationarity. For further conformation, augmented Dickey-Fuller test is used.

Augmented Dickey Fuller Test

The standard Dickey Fuller unit-root test performs a simple regression in the form of Equation (6):

$$\Delta y_t = (a - 1)\, y_{t-1} + \varepsilon_t \qquad \ldots(6)$$

This test is used if the underlying data-generating process is expected to have no high order lags. If higher lags are present then the Dickey Fuller test is mis-specified and the standard errors are unreliable. To correct this, the standard test is the augmented Dickey-Fuller test which takes the form of Equation (7):

$$\Delta y_t = \beta_0 + (\alpha - 1)\, y_{t-1} + \Sigma\alpha_i\, \Delta y_{t-1} + \varepsilon_t \qquad \ldots(7)$$

A unit root in this context refers to the modulus of the roots of the AR polynomial to be smaller than unity and for the MA polynomial to lie inside the unit circle, which renders the MA part non-invertible. A series is said to be stationary if it does not have a unit root. The method of differencing can be used to achieve stationarity. If there is exactly one unit root, first order difference of the series should be used and in case of two unit roots, second order difference of the series should be used.

Model Identification

On testing the presence of unit root by augmented Dickey-Fuller test, it was found that there was presence of one unit root. Accordingly, one non-seasonal and one-seasonal differencing were applied to the original time-series observations and the resulted ACF and PACF are given in Figure 2. It is observed from Figure 2 that after one differencing (for both seasonal and non-seasonal) the fate of ACF becomes more realistic, easing the identification of order of SARIMA model.

Model Estimation

The estimation of parameters for SARIMA model is generally done through non-linear least squares method. Several software packages are available for fitting of SARIMA models. In this paper, SAS 9.2 software package was used. The two statistics used were the Akaike information criterion (AIC) and Bayesian information criterion (BIC) for choosing the best fitted model for the present data under consideration. These are based on Bayesian Inference methods and require prior knowledge of parameter values and probability density functions. The values of AIC and BIC were calculated from following expressions:

$$\text{AIC} = n \log \sigma^2 + 2\,(p+q+P+Q+1)$$

$$\text{BIC} = n \log \sigma^2 + 2\,(p+q+P+Q+1) \log n$$

where, n is the number of observations, σ is the mean square error and p, q, P, Q have been defined earlier. On the basis of AIC and BIC values, the best model was found out as SARIMA (2,1,0; 1,1,0). The parameter estimates along with standard-error (SE) of estimates and their significance are given in Table 1.

Table 1. Parameter estimates of the fitted SARIMA(2,1,0; 1,1,0) model

Variable	Estimate	Standard-error	t-value	Significance
Constant	1.976	1.963	1.007	0.315
AR1	-0.412	0.068	-6.023	< 0.000
AR2	-0.155	0.070	-2.215	0.028
Seasonal AR	-0.388	0.073	-5.350	< 0.000

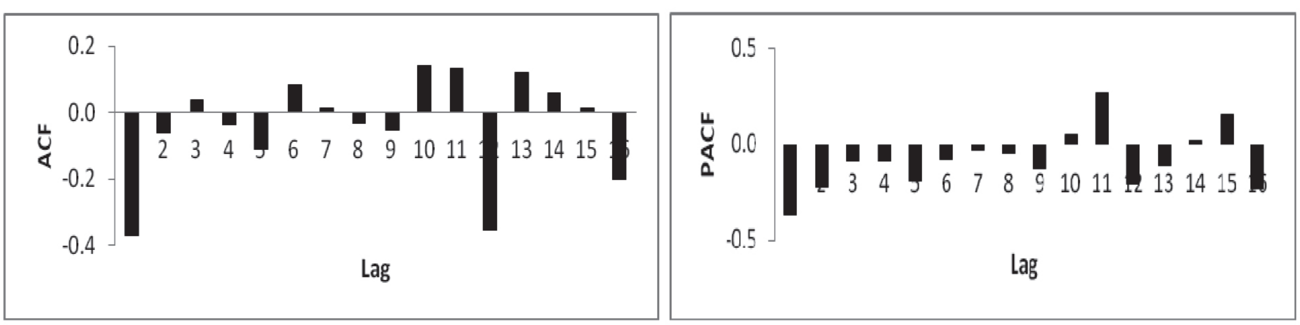

Figure 2. ACF and PACF of seasonal and non-seasonal differenced time-series

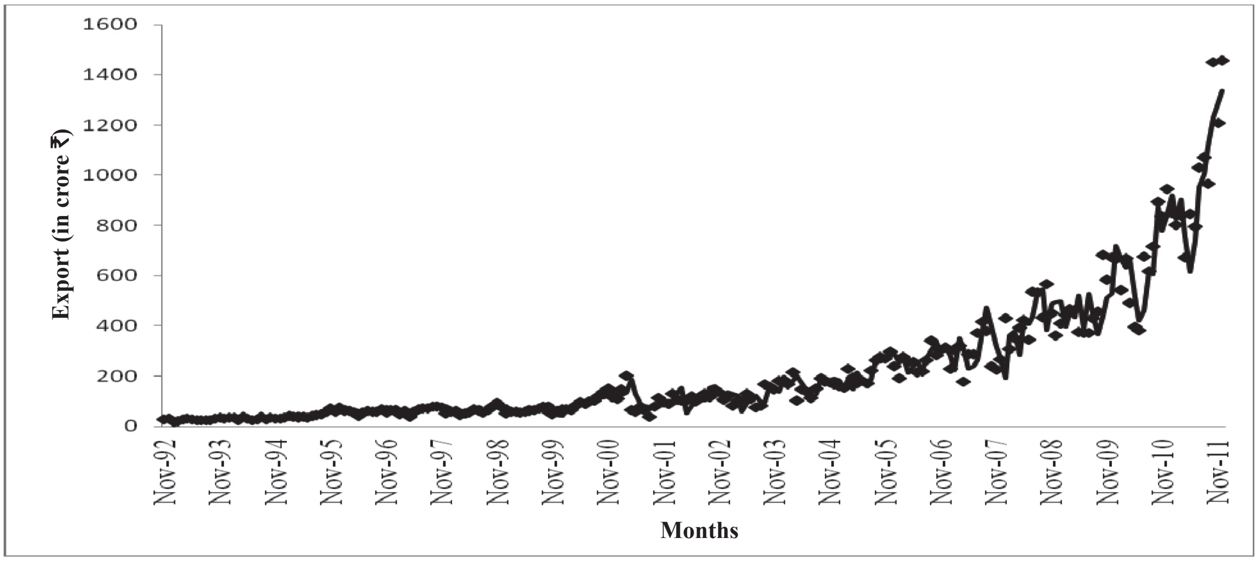

Figure 3. The fitted model along with the data points

The fitted model along with the data points have been displayed in Figure 3. A perusal of Figure 3 indicates that the fitted model is a good fit for the data under consideration.

Performance Evaluation of Fitted Model

Out of total 230 data points (November, 1992 to December, 2011), first 218 data points i.e. data from November, 1992 to December, 2010 were used for model building and the remaining 12 data points, i.e. data from January, 2011 to December, 2011, were used for model validation. The root mean square prediction error (RMSPE) value and mean absolute prediction error (MAPE) value for fitted SARIMA model were respectively computed as 109.18 and 95.11. Further, the relative mean absolute prediction error (RMAPE) value was also computed for validation of the forecast. The RMAPE was defined as per Equation (8):

$$\text{RMAPE} = 1/12\sum_{i=1}^{12}\left\{\left|y_{t+i} - \hat{y}_{t+i}\right| / y_{t+i}\right\}\times 100 \quad \ldots(8)$$

The RMAPE value for fitted SARIMA model was computed as 10 per cent. One-step-ahead forecast of export of meat and meat preparations from India has been given in Table 2.

Table 2. One-step-ahead forecast of export of meat and meat preparations from India

(in crore ₹)

Month	Actual	Forecast
Jan-2011	850.62	928.07
Feb-2011	800.87	861.44
Mar-2011	840.70	958.34
Apr-2011	671.22	852.15
May-2011	846.87	758.69
Jun-2011	793.87	751.97
Jul-2011	1029.10	929.01
Aug-2011	1071.35	919.30
Sep-2011	964.52	991.94
Oct-2011	1448.80	1290.01
Nov-2011	1206.59	1208.03
Dec-2011	1455.78	1320.92

The fitted SARIMA (2,1,0; 1,1,0) model was used for out-of-sample forecast of monthly export of meat and meat preparations from India during the period, January, 2012 to December, 2013. The forecast values along with their corresponding lower and upper 95 per cent confidence limit are given in Table 3.

Diagnostic Checking

The model verification is concerned with the checking residuals of the model to see if they contained any systematic pattern which still could be removed to improve the chosen SARIMA, which was done through examining the autocorrelations and partial

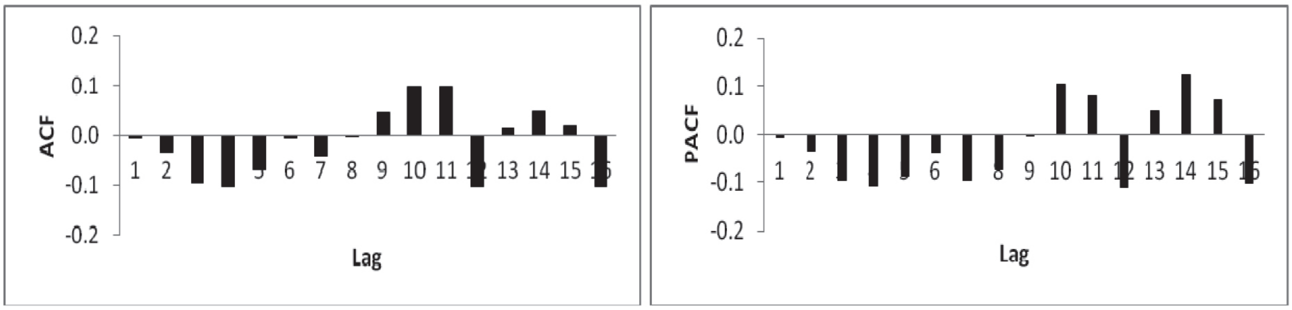

Figure 4: ACF and PACF of residual series

Table 3. Out-of-sample forecasts of monthly export of meat and meat preparations from India

(in crore ₹)

Month	Forecast	Lower confidence interval	Upper confidence interval	Month	Forecast	Lower confidence interval	Upper confidence interval
Jan-2012	1363.79	1242.08	1485.49	Jan-2013	1780.34	1459.19	2101.49
Feb-2012	1279.35	1138.16	1420.54	Feb-2013	1712.11	1368.75	2055.47
Mar-2012	1364.67	1205.54	1523.80	Mar-2013	1782.52	1417.92	2147.11
Apr-2012	1193.01	1014.72	1371.30	Apr-2013	1614.45	1228.40	2000.49
May-2012	1265.84	1071.54	1460.14	May-2013	1729.93	1324.17	2135.69
Jun-2012	1231.39	1022.22	1440.56	Jun-2013	1691.02	1266.42	2115.62
Jul-2012	1491.11	1267.92	1714.30	Jul-2013	1943.98	1501.27	2386.70
Aug-2012	1497.16	1260.85	1733.48	Aug-2013	1966.83	1506.75	2426.90
Sep-2012	1473.37	1224.61	1722.12	Sep-2013	1913.55	1436.73	2390.36
Oct-2012	1840.98	1580.38	2101.59	Oct-2013	2329.19	1836.20	2822.17
Nov-2012	1673.36	1401.42	1945.30	Nov-2013	2135.36	1626.71	2644.00
Dec-2012	1871.33	1588.51	2154.15	Dec-2013	2355.95	1832.12	2879.78

autocorrelations of the residuals of various orders. For this purpose, ACF and PACF up to 16 lags were computed and are given in Figure 4. It was also found that none of these autocorrelations was significantly different from zero at any reasonable level. This proved that the selected SARIMA model was an appropriate model for forecasting the meat export which also indicated the 'good fit' of the model.

Conclusions

The study has revealed that the SARIMA model being stochastic in nature, could be used successfully for modelling as well as forecasting of monthly export of meat and meat preparations from India. It has been found that there is a significant increasing trend in the meat export from India. The model has demonstrated a good performance in terms of explained variability and predicting power. The forecast values of meat export during January, 2011 to December, 2011 are close to the actual values. The relevant forecast interval for the out-of-sample export of meat and meat preparations can help farmers as well as policymakers for future planning. The study may help Indian meat exporters in forecasting future exports to other countries conducting long-term meat investment decisions, or identifying trends in the consumption of meats. In view of the growing meat exports the results of the study can be useful for planning expansion of meat exports to the existing destinations and to capture new markets.

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