Time Series Analysis of Indian Spices Export and Prices

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ABSTRACT

India is the land of spices and is the largest producer, consumer and the exporter of spices in the world. Spices are an important component of Indian Agricultural Exports earning valuable foreign exchange and are the source of livelihood for millions of small and marginal farmers across different states of the country. Modeling of agricultural exports in general and spices exports in particular is important in the context of spices exports being a priority area for Indian policy makers. Time series modeling of agricultural commodity exports is an active area of research in recent times. Generally Box Jenkins approach (ARIMA) is the referred technique for this purpose. When data exhibits volatility clustering, ARCH/GARCH models are used. When the data does not support linearity assumptions neutral network models are used. However, real world time series data is believed to be a combination of linear and non-linear patterns. In this context, Hybrid models which are a combination of AR models and Artificial Neural Networks are providing more accurate forecasts. The present study, using secondary data for the period from 1960-61 to 2017-18 applies three hybrid models for forecasting Indian spices exports both in terms of volume and prices. Based on the RMSE each model is evaluated and finally model with least RMSE was selected for forecasting Indian spices exports both in terms of volume and prices. Results from the study show that, Hybrid model consisting of ARIMA, Exponential Smoothing and Tbats Model with unequal weights was found to be the best model on the basis of RMSE for forecasting Indian spices exports. Thus, for both forecasting and policy formulation the hybrid model is recommended.

Key words: ARIMA, Forecasting, Forecasting accuracy, Hybrid model.

INTRODUCTION

India is still a predominantly primary sector dependent economy. In terms of employment generation and exports agriculture plays a vital role. Spices are an important component of India’s Agricultural Exports. During the financial year 2017-18, India exported 10,28,060 tons of spices valued at Rs.17929.553 crores. India exports spices to USA, UK, Germany, Japan, Iran, Hong kong UAE etc. Spices are cultivated in about 3.21 million hectares across all the states in the country. The major spices exported from India are: chilies, pepper, turmeric, cardamom, coriander, cumin, ginger etc. The leading states, producing spices in India are Andhra Pradesh, Rajasthan, Kerala, Karnataka, Madhya Pradesh, Orissa, Tamil Nadu etc. Export revenue from spices determines the livelihood of millions of small and marginal farmers in Indian government recognized spices exports as a priority activity.

In recent years Indian spices exports are facing problems in international market due to emergence of competition from countries like Brazil, Malaysia, Vietnam and China. The major problem is volatility in both quantity and prices of exports. Due to this both the area under spices and production of spices and thus exports became unpredictable, which is influencing the standard of living of millions of small and marginal farmers and also affecting the revenues of the government and industry. In this context, Indian government has recognized spices exports as one of the priority area for policy modifications. By the year 2020 it is expected that spices exports from the country will generate a revenue of Rs.25,000 (Spices Board, Annual Reports, 2016-17, 2017-18). In this context there is need for long term perceptive planning for spices sector to reach the stated objectives. To achieve this target policy measures are needed. This requires forecasts of both volume and prices of spices for the coming years .This needs building statistical models using historical data on spices. The present study is an effort in this direction.

The time series forecasting using a hybrid ARIMA and Neural Network model was presented by Peter Zhang (2003). In which a hybrid methodology which combines both ARIMA and ANN models were proposed has to take the advantage of unique strength in linear and non-linear modeling. It is noticed that a experimental results along with real data were found to be an effective way for forecasting. Subsequently Huizou et al. (2004) while analyzing time series model for forecasting used an algorithm after to
convexly combine the model for the better performance of prediction. In case of new hybrid methodology for non-linear time series forecasting Khashei et al. (2011) used ANN’s model linear problems with mixed results. Therefore the hybrid methodology combining linear models such as ARIMA and non-linear model viz ANN’s have been proposed for the time series forecasting. Further to overcome the limitations of traditional hybrid methodologies and give more general and accurate hybrid models were used. The proposed methodologies were found to be more effective way to combine linear and non-linear models together then hybrid methodologies. This alternative methodologies for hybridization in time series forecasting ARIMA, especially when higher forecast accuracy is required. Paper entitled ARIMA –ANN hybrid model for time series forecasting model (Wang et al. 2013) proposed a hybridized model which is distinguished in integrating the advantages of ARIMA and ANN modeling for the linear and non-linear behavior of the available data. The computational experienced by them indicates the effectiveness of new combinatorial was found to give more accurate forecasting results. In a system of four stage hybrid model for hydrological time series forecasting (Chongli et al. 2014) six hydrological cases with different characteristic features were used to test the effectiveness of the proposed model. The proposed hybrid model was found to perform better than conventional single models. The new model was found to be promising for complex time series forecasting. Price behavior of chillies was analyzed by Bhavani Devi et al. (2016) using seasonal index in Guntur market. They identified that the seasonal index was maximum in December in one cycle of observations. The arrivals and prices fluctuations in oil seed crops like soybeans and safflower was steadied by Sudhakarraao et al. (2016) over the period 1991-2010. They used ratio moving average method and concluded that arrivals and prices for oil seed crops were seasonal. Annesha (2017) analyzed the growth trend the rice Production in Assam using long linear model with auto correlation. In a hybrid approach of combing the forecast for linear time series model (ARIMA) and non-linear (GARCH, ANN) was found to give better forecasting performance in the analysis performed by Dipankar et al. (2017). Subsequently Panigrahi et al. (2017) which studied a system of hybrid ETS-ANN model for time series forecasting. A new hybrid methodology was developed by utilizing linear and non-linear, exponential smoothing, from innovation state space (ETS) with ANN. Trend analysis of production and productivity on major crops in Haryana was done by (Savita et al. 2018)

**MATERIALS AND METHODDS**

**METHODODS FOR TIME SERIES FORECASTING:** There are several models for time series forecasting. The classical methods are moving average (MA), decomposition, exponential smoothing and ARIMA. If the time series exhibits volatility clustering ARCH, GARCH models are used. Recently machine learning techniques like Artificial Neural Network, Support Vector Machine (SVM) are also becoming popular. However, real world time series data exhibits both linear and non-linear patterns. In this context classical methods and machine learning methods individually are unable to capture the trends and patterns in the data. The hybrid methodology which combines both classical and machine learning algorithms is found to be more reliable modeling strategy. In this context, the present study aims at building a hybrid model consisting of ARIMA, Exponential Smoothing-and ANN Models. To build hybrid models for both volume and prices of spices exports, time series secondary data, from 1960-61 to 2017-18 was obtained from the database of Indian Spices Board.

**Hybrid model methodology:** A hybrid model is described by a combination of models with mixed methodology for formulation. Zhang (2001) proposed a hybrid approach that decomposes a time series process into linear and nonlinear components. The hybrid model considers the time series $y_t$ as a combination of both linear and nonlinear components

$$y_t = L_t + N_t$$

Where $L_t$ & $N_t$ are linear and non-linear components present in the given data respective.

**The ARIMA Model:** A statistical technique that uses time series data to predict future. The parameters used in the ARIMA is $(p, d, q)$ which refers to the autoregressive, integrated and moving average parts of the data set, respectively. ARIMA modeling will take care of trends, seasonality, cycles, errors and non-stationary aspects of a data set when making forecasts.

**The Exponential smoothing model:** Smoothing Exponential smoothing is usually a way of “smoothing” out the data by removing much of the “noise” (random effect) from the data by giving a better forecast. Types of Exponential Smoothing Methods.

**The Theta Method model:** The Theta method is a combination of other methods, which proposes the decomposition of the deseasonalized time series into two other time series called “theta lines”. The first completely removes the curvatures of the data, thus accurately estimating the long-term trend.

**The Neural Network model:** ANN: Artificial neural network (ANN) is basically machine learning approach that models human brain and consists of a number of artificial neurons. Their ability to learn by example makes them very flexible and powerful. Neural networks, has its own strength to derive meaning from complicated or imprecise data and most of the time can be used to detect the pattern and trend in the data, which cannot be detectable easily from human eye or any computer techniques. We also have some of the
advantage of NN like Adaptive learning, self-organization, real-time operation, fault tolerance.

The TBATS model: The TBATS model is a generalization of BATS model which is similar except for lacking the trigonometric regressors. The TBATS model is a time series model for series exhibiting multiple complex seasonality’s. The TBATS model was introduced by DE Livera Hyndman & Snyder (2011 JASA).

RESULTS AND DISCUSSION

The actual procedure followed for modeling and forecasting is outlined as below.

Step 1: Explorative analysis of time series data: Time series plots for both total exports and prices were drawn to understand the trends and patterns in the series and detect extreme values if any. Fig 1 shows the time series plot of volume of exports and prices of Indian spices from 1960-61 to 2017-18. A perusal of this figure indicates that the volume and prices of spice exports are showing an increasing trend since 1990’s indicating the significance of economic reforms.

Step 2: Data cleaning: If any extreme values are detected in the plot, we shall clean the data and re-plot it to understand the patterns clearly. To estimate missing values and outliers replacements, linear interpolation is used on the series of the total exports and prices of Indian spices. The outliers can be seen in Fig 2 and 4 as the box plot. The graphical representation with cleaning extreme values of Total Export and Prices in India from the period 1960-61 to 2017-18 is given in Fig 3 and 5.

Step 3: Descriptive Data Analysis: The descriptive statistics of total exports and prices of spices are reported in Table 1 and Table 2. A perusal of the Table 1 indicates that average total exports of Indian spices is 2,35,619 tones. The series under consideration is positively skewed and leptokurtic. Since the CV is more than 50% it can be concluded that the total volume of exports in highly volatile. In case of export price the average is 52.29 and CV is 103.82 indicating that prices are extremely unstable.

Step 4: Building the hybrid Model: To build the optimum hybrid model for the data, the following procedure is adopted. First, a hybrid model with five components ARIMA, Exponential smoothing, Theta, ANN and Tbats with equal weights was built for both total exports by volume and prices. The Fig 6 reveals the India’s total export and prices of spices during 1960-61 to 2017-18.

Fig 1: Total export and prices of spices in India during 1960-2017.

Fig 2: Outliers in total export of spices.

Fig 3: Total export of spices in India during 1960-2017.

Fig 4: Outliers in total prices of spices.
Fig 5: Total prices of spices in India during 1960-2017.

Fig 6: Hybrid models with five components of total export and prices of spices in India during 1960-2017.

Fig 7: Hybrid models with three components of total export and prices of spices in India during 1960-2017.

Fig 8: Hybrid models with three components of total export and prices of spices in India during 1960-2017.

Fig 9: Forecast of total export and prices of spices in India during 2018-2027.
Next, a hybrid model with three components, ARIMA, Exponential smoothing and Tbats with equal weights was used for forecasting both Volume and prices of Indian spices. The Fig 7 reveals the India’s total export and prices of spices during 1960-61 to 2017-18.

Finally a hybrid model with selected three components ARIMA, Exponential Smoothing and Tbats with unequal weights was developed for forecasting the volume and Prices of Indian spices. The Fig 8 reveals the India’s total export and prices of spices during 1960-61 to 2017-18.

**Model Selection:** Of the three hybrid models used for forecasting the volume and prices of Indian spices exports, the best model is selected by Root Mean Square Error (RMSE). In Table 3 and Table 4, the ME, RMSE, MAE, MPE, MAPE, MASE, ACF1 are listed. The model with lowest RMSE (Model-III) is selected for forecasting the volume and prices of spices exports for the next 10 years. In Fig 9 presents the trend of forecasted values with their 80% and 95% confidence limits. The forecasted values of total export and prices of India for the period 2018-19 to 2027-28 are given in the Table 5 and 6. From Table 5 we find that the point estimate for total spices exports was 10,81,820 tons in 2018-19 and is projected to grow to 17,14,3391 tons by 2017-18 which is almost 60% increase in 10 years. With regard to prices of spices a point forecast indicates that from rupees 190.40 in 2018-19, it is projected to grow to 231.044 by 2027, it is 20% growth in 10 years. This indicates that

### Table 1: Descriptive statistics of Total Export of Spices.

| Statistics | Result  |
|------------|---------|
| Observations | 58      |
| Mean       | 52.29   |
| Minimum    | 2.71    |
| Median     | 28.34   |
| Maximum    | 186.4   |
| SD         | 54.29   |
| CV         | 103.82  |
| Trimmed    | 44.45   |
| mad        | 34.58   |
| range      | 183.7   |
| skew       | 66.74   |
| kurtosis   | 7.215   |

Note: SD: standard deviation; CV: coefficient of variation.

### Table 2: Descriptive statistics of Total Prices of spices.

| Statistics | Result  |
|------------|---------|
| Observations | 58      |
| Mean       | 52.29   |
| Minimum    | 2.71    |
| Median     | 28.34   |
| Maximum    | 186.4   |
| SD         | 54.29   |
| CV         | 103.82  |
| Trimmed    | 44.45   |
| mad        | 34.58   |
| range      | 183.7   |
| skew       | 66.74   |
| kurtosis   | 7.215   |

Note: SD: standard deviation; CV: coefficient of variation.

### Table 3: Accuracy measure for Total Export of hybrid forecast model.

| Model | ME   | RMSE | MAE  | MPE | MAPE | MASE | ACF1 |
|-------|------|------|------|-----|------|------|------|
| I     | 8062 | 30217| 20351| 0.921 | 12.21 | 0.8214 | 0.009 |
| II    | 7497 | 29600| 20012| 0.9654 | 12.22 | 0.8077 | 0.09  |
| III   | 7230 | 29431| 19920| 0.8986 | 12.22 | 0.804  | 0.080 |

### Table 4: Accuracy measure for Total prices of hybrid forecast models.

| Model | ME   | RMSE | MAE  | MPE | MAPE | MASE | ACF1 |
|-------|------|------|------|-----|------|------|------|
| I     | 1.453 | 5.699 | 4.177 | -0.4406 | 13.02 | 0.9367 | 0.151 |
| II    | 1.343 | 5.678 | 4.14  | 0.1363 | 13.04 | 0.9284 | 0.130 |
| III   | 1.3   | 5.658 | 4.135 | 0.1624 | 13.01 | 0.9273 | 0.122 |

### Table 5: Point Forecast of total export of spices in India during 2018-2027.

| Years | Point Forecast | Lo 80 | Hi 80 | Lo 95 | Hi 95 |
|-------|----------------|-------|-------|-------|-------|
| 2018  | 1081820        | 811170.5 | 1303017 | 680986.48 | 1433201 |
| 2019  | 1147658        | 801413.2 | 1414670 | 639093.92 | 1576990 |
| 2020  | 1214080        | 788697.5 | 1529282 | 592676.66 | 1725300 |
| 2021  | 1281708        | 772511.2 | 1647364 | 540951.76 | 1878923 |
| 2022  | 1350570        | 752528.4 | 1769242 | 483420.56 | 2038350 |
| 2023  | 1420695        | 728510.4 | 1895156 | 419718.00 | 2203948 |
| 2024  | 1492111        | 700262.1 | 2025300 | 349545.80 | 2376016 |
| 2025  | 1564847        | 667610.5 | 2159847 | 272639.21 | 2554819 |
| 2026  | 1638930        | 630392.5 | 2306866 | 188749.07 | 2740618 |
| 2027  | 1714391        | 588448.7 | 2482591 | 97631.36  | 2933618 |
Table 6: Point Forecast of total prices of spice in India during 2018-2027.

| Years | Point Forecast | Lo 80   | Hi 80   | Lo 95   | Hi 95   |
|-------|----------------|---------|---------|---------|---------|
| 2018  | 190.4052       | 136.39265 | 238.0982 | 109.47281 | 265.0181 |
| 2019  | 194.8013       | 115.22660 | 260.9950 | 76.64404 | 299.5775 |
| 2020  | 199.2267       | 98.50382  | 279.4485 | 50.61067 | 327.3416 |
| 2021  | 203.6817       | 83.95402  | 295.7289 | 27.90059 | 351.7824 |
| 2022  | 208.1666       | 70.70727  | 310.7064 | 7.18334  | 374.2303 |
| 2023  | 212.6814       | 58.32119  | 324.8232 | -12.21762 | 395.3620 |
| 2024  | 217.2263       | 46.53466  | 338.3404 | -27.90059 | 415.5767 |
| 2025  | 221.8017       | 35.17824  | 351.4275 | -48.52789 | 435.1337 |
| 2026  | 226.4076       | 24.13442  | 364.2020 | -65.87605 | 454.2125 |
| 2027  | 231.0443       | 13.31753  | 376.7496 | -82.87713 | 472.9443 |

total export revenue will not grow as fast as total volume of spice exports. This is an important aspect which policy makers need to keep in mind.

CONCLUSION

In time series modeling, forecast accuracy is an important criteria for decision making. If the underlying process exhibits linearity ARIMA methodology is best method of forecasting. However, in practice most of time series exhibits non-linearity of heteroscedastic errors. Therefore GARCH family of models is widely used in such cases. Recent development in software allows us to decompose the time series into linear and nonlinear components and then model each parts separately and ending with combining them for getting final forecast this method is called hybrid time series modeling. The above methodology was adopted in this paper for forecasting total spices exports of India by volume and unit price. Three hybrid models were fitted to the data. The hybrid model consisting of ARIMA, Exponential smoothing and Tbats with unequal weights turned out to be the best as it’s RMSE it is found to be the lowest. Thus we used the model with components: ARIMA, Exponential Smoothing and Tbats having unequal weights for forecasting the prices and quantities of total spices exports for the period 2018-19 to 2027-28. Forecasting results show that spice export quantity is expected to grow at much faster rate than export prices. This may affect the export revenues from spices and thus incomes of innumerable small and marginal cultivators of spices. Thus, Indian government needs to formulate policies to counter this trend and encourage spice exports. We recommend the hybrid model developed in this paper for long term planning of Indian spices sector.

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