

# Price and Production Forecasting Model of Okra – A Case Study

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## Abstract

Okra (*Abelmoschus Esculentus*) is perishable in nature and its variable prices as well as arrivals depend on the supply and demand in the market. Approximately 73% of worldwide Okra is cultivated in India. This research incorporates seasonal variation in the forecasting of arrivals and three categories of prices, which were de-seasonalized to achieve a regression line. Initial values of level, trend and seasonality were exploited from the regression line and were used to perform static time series forecasting analysis. The same initial values were then updated for every new data entry for the adaptive time series forecasting model (Winters Model). The errors and fit of model were seen on the basis of MSE, MAD, MAPE and  $R^2$  values. A database for the arrivals as well as the maximum, minimum and modal prices of Okra was gathered for 12 years (Jan'10 to Dec'21). The static model gave a MAPE of about 19.33% for the prices and almost 207% for arrivals of Okra. On the other hand, the adaptive winter's model, which incorporated the previous as well as the current data, streamlining itself after every new entry, gave an average error of 13.9% for the prices and about 18.9% for arrivals. This adaptive model predicted the modal price of Jan 2022 and Feb 2022 to be Rs. 5800/quintal and Rs. 5600/quintal, and the actual values observed are Rs. 5700/quintal and Rs. 5200/quintal.

## Keywords

Okra, De-seasonalization, Adaptive Forecasting, Regression and Prediction.

## 1. Introduction

India is known for the producing numerous fruits, dairy products, spices, meat, vegetables, fibrous crops like jute and is also among the top five agricultural producers in the world. The vast geographical region of India allows for the production of a wide variety of fruits and vegetables owing to the different temperature conditions. India accounted for almost 14% of global production of fruits and vegetables in 2021 (Apeda.gov report, FY 2022). Okra, commonly known as Ladyfinger or Bhindi, comes under the *Malvaceae* family and the genus *Abelmoschus*. India produced 58207.8 thousand quintals of okra annually in financial year 2022, accounting for 74 percent of global production whereas Gujarat's data for okra in FY-22 was reported at 9248 thousand quintals (NHB reports, 2022). The crop can be sown in all kinds of soils in between January-March and June- August. Reddy et al. (2018) mentioned that high fluctuations from season to season, is a reason why farmers do not always capitalize on the best price for the crop. One of the most critical prerequisites for boosting Supply Chain efficacy is demand prediction. Vegetables are not gathered from the farmers in some months due to a lack of market demand. During other times produce is unavailable for various causes, resulting in price increases (Rais and Sheoran 2015). Even Zhang et al. (2014) described how accurate forecasting of agricultural products can be useful for developing a proper balance between supply and demand.

## 2. Methodology and Analysis

### 2.1 Database Collection

The scope of this research is restricted to the APMC markets in Ahmedabad, Gujarat, and the time series data were obtained from AGMARKNET website as well as the APMC Ahmedabad website. The data of daily arrivals, minimum price, maximum price, and modal price were collected from January 2017 to December 2021, but later it was found out to be insufficient, mainly due to the impact of Covid-19, thus additional data from January 2010 to December 2021 (12 years) was gathered. The average value of all the available dates was taken which represented that month's data. Below graphs (Figure 1 and Figure 2) show the database of Arrivals (in Quintals) and Prices (Rupees per Quintal) extended to a period of 12 years.

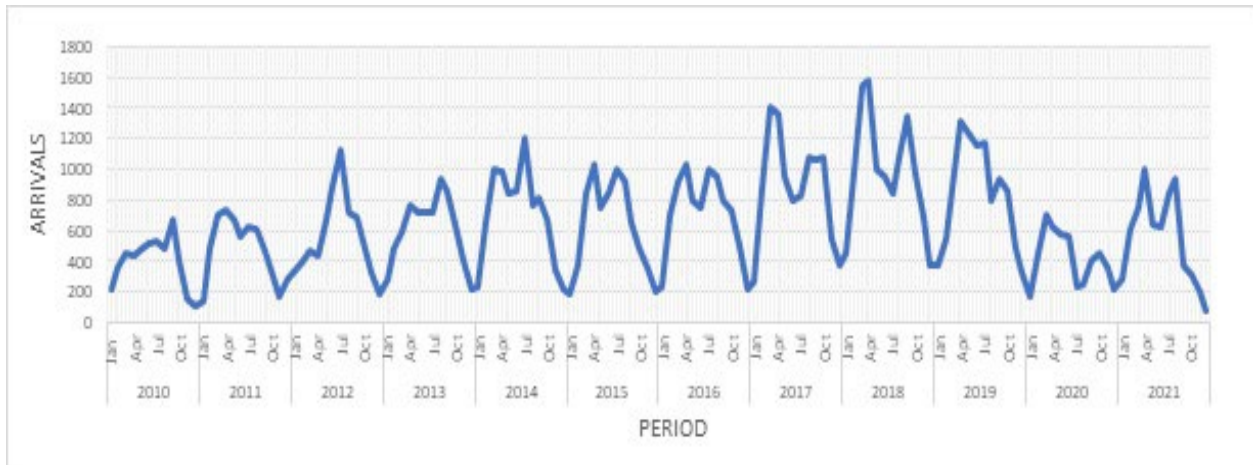


Figure 1. Arrivals Database from 2010 to 2021

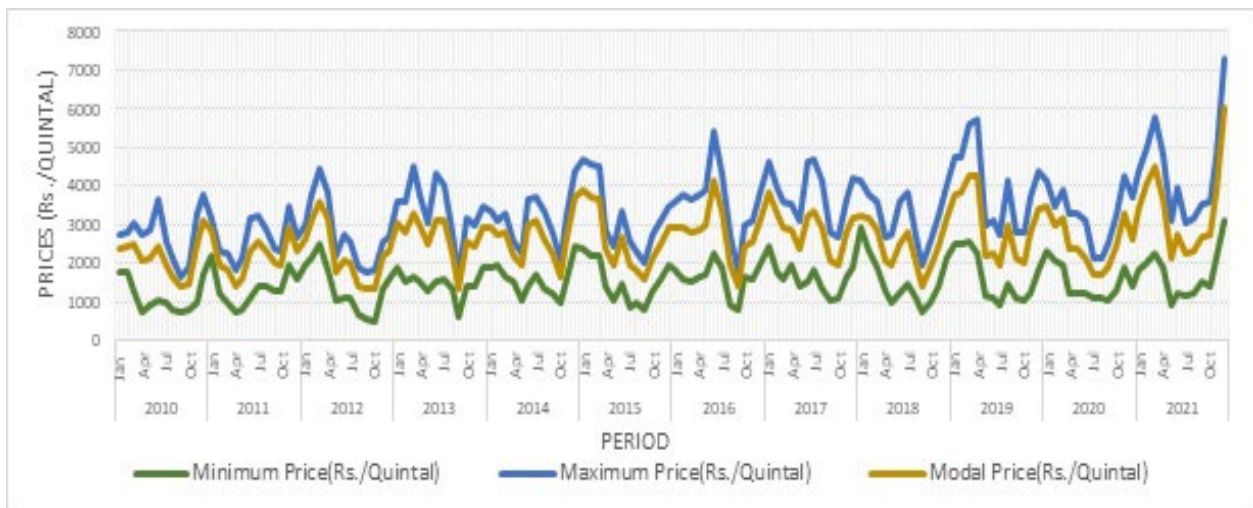


Figure 2. Maximum, Minimum and Modal Price database from 2010 to 2021

The inverse relationship between the price and supply of Okra can be evidently seen in Fig. 3 that shows the arrivals of Okra in Ahmedabad APMC markets against the modal price over the years (Figure 2 and figure 3).

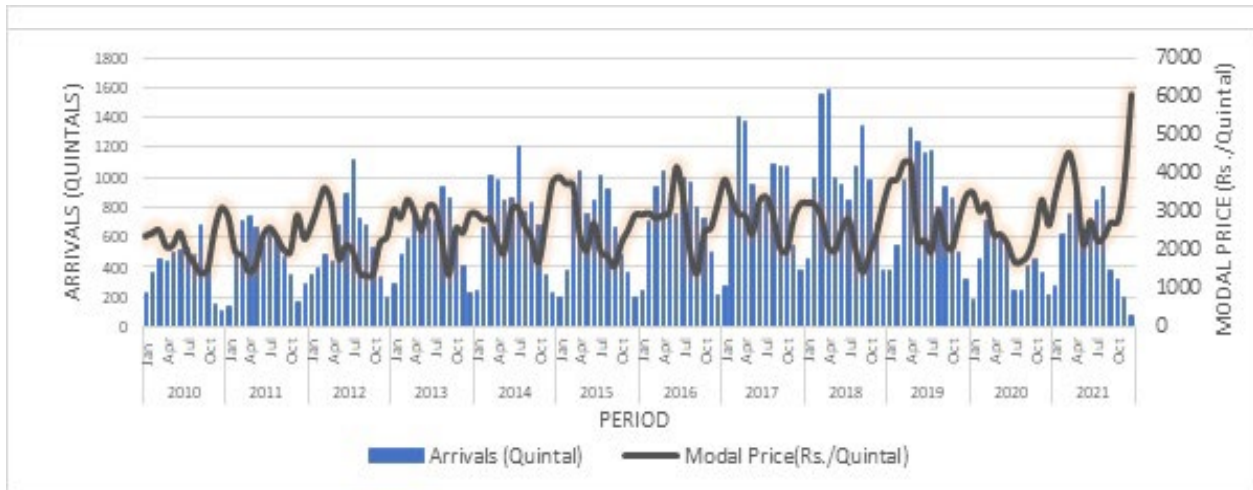


Figure 3. Arrival v/s Modal price over the years

### 2.2 De-seasonalizing the data

Seasonality usually causes the series to be non-stationary and thus has to be dealt with. It is difficult to perform analysis on seasonal data so it needs to be de-seasonalized. De-seasonalizing helps represent data that otherwise would show a recurring trend because of the seasonal variations (Bodily and Weatherford 2008). The pattern of arrivals and prices of Okra tends to repeat every 12 months, thus periodicity taken in this research equals 12, which is even. When de-seasonalizing the values, the average of  $p$  consecutive periods of values was used to provide equal weightage to every season. The average of demand from Period  $N + 1$  to Period  $N + p$  yields the de-seasonalized demand for Period  $N + (p + 1)/2$ . This method provided the de-seasonalized demand at a point between Period  $N + (p/2)$  and Period  $N + 1 + (p/2)$ , when even periodicity is observed. Clutching the average of de-seasonalized demand provided by Periods  $N + 1$  to  $N + p$  and  $N + 2$  to  $N + p + 1$ , de-seasonalized demand for Period  $N + 1 + (p/2)$  was

easily obtained. Here,  $\bar{D}_t$  = De-seasonalized arrivals,  $D$  = Arrivals,  $p$  = periodicity,  $t$  = period number. The minimum value of  $t$  taken here was 7. Fig. 4 and 5 depict the deseasonalized graphs for arrivals as well as the various analysed prices (Figure 4).

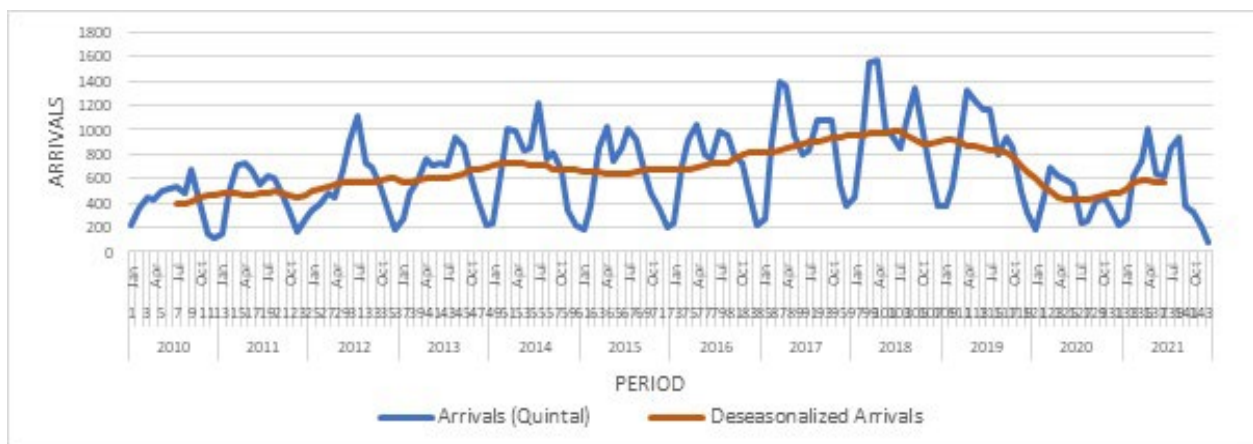


Figure 4. De-seasonalized Values of Max., Min. and Modal Prices

### 2.3 Linear Regression

Linear regression was then applied to calculate the systematic de-seasonalized component. In this paper, the level or the initial de-seasonalized value is represented by L whereas the trend or the rate of growth is represented by T. With the aid of a regression line, L was estimated as the intercept of the derived regression line and T being the coefficient of variable x, was the slope of the derived regression line. These regression line equations (Figure 5 and Figure 6) were then used to calculate the de-seasonalized values for all the corresponding periods. Regression equations came out as:

$$\text{Arrivals} = 539.0615 + (1.81544865926719 * t);$$

$$\text{Max. Price} = 2727.88335281704 + (8.19412927526387 * t);$$

$$\text{Modal Price} = 2264.0821148987 + (4.79532509578944 * t);$$

$$\text{Min. Price} = 1329.2416 + (2.3173595 * t)$$

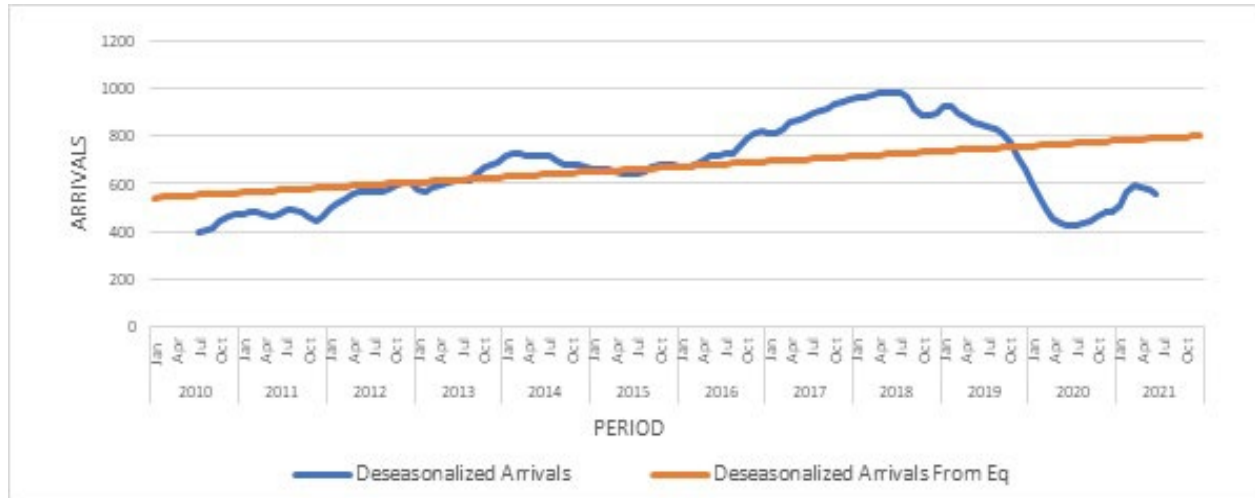


Figure 5. Regression lines for Deseasonalized Arrivals

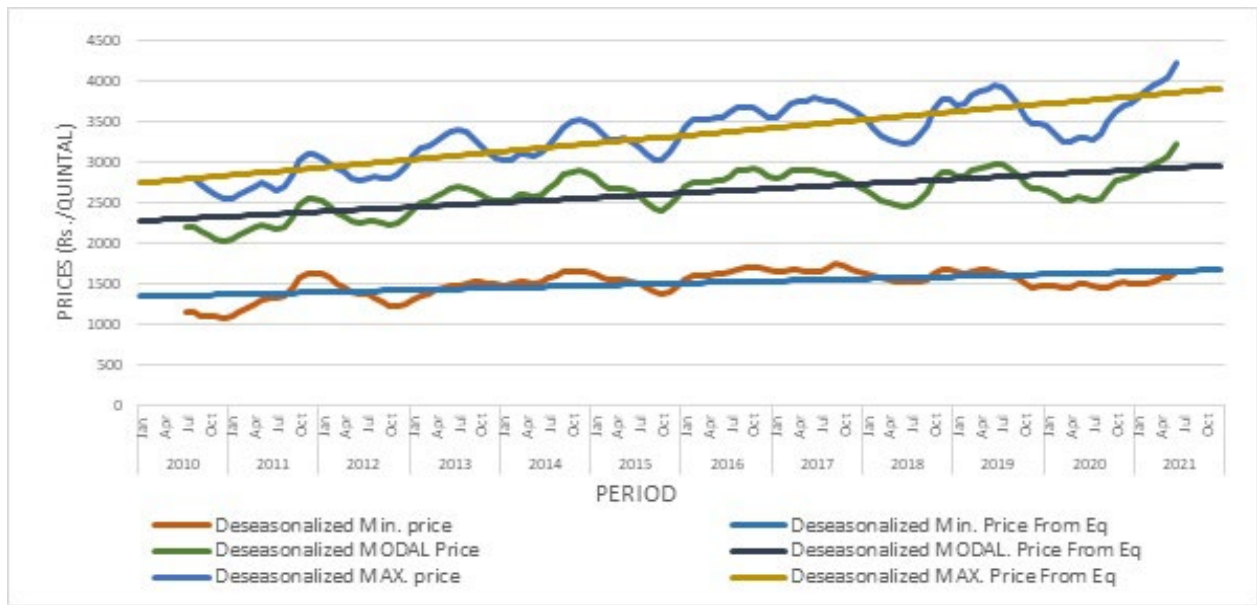


Figure 6. Regression lines for all Deseasonalized Prices

## 2.4 Seasonal Factor

For any time-period,  $t$ , the seasonal factor is defined as the ratio of original values to the de-seasonalized ones. The database here is of 12 years, thus 12 values one for each month of every year is taken. Later average of each month's seasonal factor is obtained. The Table 1 lists down the mean seasonal factors of all the above considered attributes.

Table 1. Mean seasonal factors

	Arrivals	MAX Price	Modal Price	MIN Price
<b>Jan</b>	0.402740515	1.169294232	1.229017897	1.455158923
<b>Feb</b>	0.866133298	1.134250829	1.189456123	1.284141947
<b>Mar</b>	1.288324558	1.210619605	1.221853506	1.22391135
<b>Apr</b>	1.395901347	1.03722179	1.031467483	0.993916158
<b>May</b>	1.164059479	0.857731591	0.834031846	0.758578177
<b>Jun</b>	1.154770326	1.13311117	1.049693475	0.903689487
<b>Jul</b>	1.270096286	0.993450095	0.962584274	0.887753289
<b>Aug</b>	1.181979738	0.855926138	0.826816812	0.75356866
<b>Sep</b>	1.130201511	0.68692497	0.680007662	0.627633553
<b>Oct</b>	0.917600299	0.786168021	0.778076179	0.7568687
<b>Nov</b>	0.551696629	1.027534225	1.038801966	1.038327431
<b>Dec</b>	0.342651362	1.176288048	1.21857752	1.299679869

## 2.5 Winters Model:

Holt-Winters model was developed by Charles Holt where this model takes into account the seasonal nature of data. This model involves adaptive forecasting by integrating the latest data. Level, trend and seasonality are revised based on the new appended data. Considering period,  $t$ , having the estimates of level,  $L_t$ , trend,  $T_t$ , and seasonal factor,  $S_t$ , the forecast for the upcoming period was predicted as a mixed systematic component based on the preceding values (Makridakis et.al. 1999) Here,  $L_0$  and  $T_0$  were obtained from the regression line of de-seasonalized values. Mathematically, the forecast for period 1 and the Upcoming predictions of level, trend and seasonal factors are revised as follows:

$$F_1 = (L_0 + T_0) * S_1$$

$$L_{t+1} = \alpha \left( \frac{D_{t+1}}{S_{t+1}} \right) + (1 - \alpha)(L_t + T_t)$$

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1 - \beta)T_t$$

$$S_{t+p+1} = \gamma \left( \frac{D_{t+1}}{L_{t+1}} \right) + (1 - \gamma)S_{t+1}$$

Here the smoothing constants for level, trend, and seasonal factors were  $\alpha$ ,  $\beta$ , and  $\gamma$  respectively, where  $0 \leq \alpha, \beta, \gamma \leq 1$ . Every revised value for level, trend and seasonality was in fact a weighted mean of the observed value and the previous estimate. The initial values of  $\alpha$ ,  $\beta$ , and  $\gamma$  were assumed to be 0.1, 0.2, and 0.3 respectively. All the values of forecasts were calculated using this method for the forementioned dataset.

## 2.6 Errors in Forecasting

A forecasting approach that routinely produces a positive or negative error is overestimating or underestimating the systemic component respectively and must be adjusted (Dielman and Terry 1986). In this research work, Mean squared error (MSE), Mean absolute deviation (MAD) and Mean absolute percentage error (MAPE) were calculated to see the performance the proposed model. The  $R^2$  value was also derived to see how good the fit of the model is. MSE was chosen to be the key indicator to be minimized as it showed the largest magnitude of error. Next, in excel, the solver was used to minimize MSE and to find the optimum values for alpha, beta and gamma.

## 3. Observations and Results

### 3.1 Numerical Observations

Time series forecasting models were applied on the historical data. Both Static as well as adaptive models were evaluated, where the static time series forecasting model does not revise itself after addition of new data. As we are in the month of May 2022, we have the database of the first four months of the year. The various errors obtained in forecast values of year 2022 after applying the Static Model in all the attributes are shown in Table 2.

Table 2. Error analysis of Static Model

Error Type	Arrivals	Modal	Max	Min
MSE	269235.424	1113398	1054433	1522010
MAD	493.3828	688.412	687.6287	961.9967
MAPE	2.07082337	0.136098	0.115314	0.261004

It was observed that the Mean Absolute Percentage Error for Arrivals was 207%, which highlights the exact reason why static time series forecasting model is incapable of delivering a good forecast. Post this, the errors of Winters model were calculated based on optimum value of  $\alpha$ ,  $\beta$ , and  $\gamma$  as shown in Table 3.

Table 3. Optimum values and mean errors for all attributes

	Arrivals	MIN	Modal	MAX



$\alpha$	0.93104	0.614801	0.84919	0.933457
$\beta$	0	0	0	0
$\gamma$	0	0	0	0
<b>MSE</b>	21034.74	90638.11	205500.3	331216.6
<b>MAD</b>	106.9044	241.6279	346.2757	441.8795
<b>MAPE</b>	0.189564	0.178116	0.139854	0.139523
<b>R2</b>	0.800388	0.653269	0.631583	0.623284

The optimum values of  $\beta$  and  $\gamma$  came out to be 0 or we can consider them to be very low. This means that trend and seasonality are present in the data but they did not change or weren't revised with the addition of new data. The mean absolute percentage error was 18% for this model for arrivals and 13.9% in the prediction of modal price.

### 3.2 Graphical Results

Using the optimum values of  $\alpha$ ,  $\beta$ , and  $\gamma$ , graphs 8 to 11 were plotted for each attribute showcasing the fit of the model to the original data. For arrivals, the power of results determined using regression were astonishingly good ( $R^2 = 80\%$ ), whereas for price attributes the fit was adequate ( $R^2 = 63\%$  for Modal Prices). Figure 7, Figure 8, Figure 9 depict the fit of the model for all the concerned attributes.

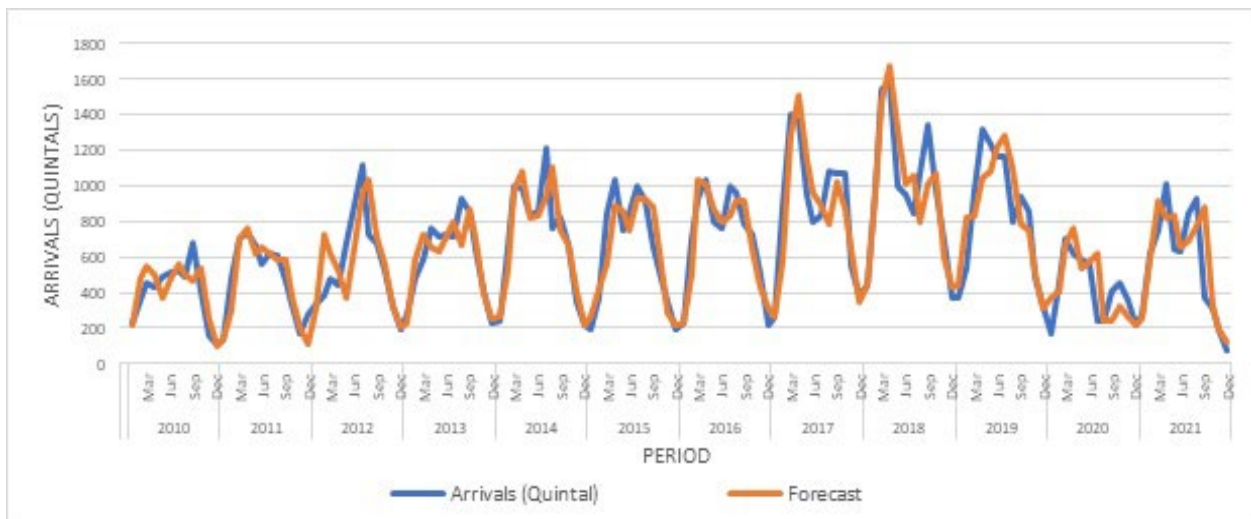


Figure 7. Fit of forecasting model for Arrivals

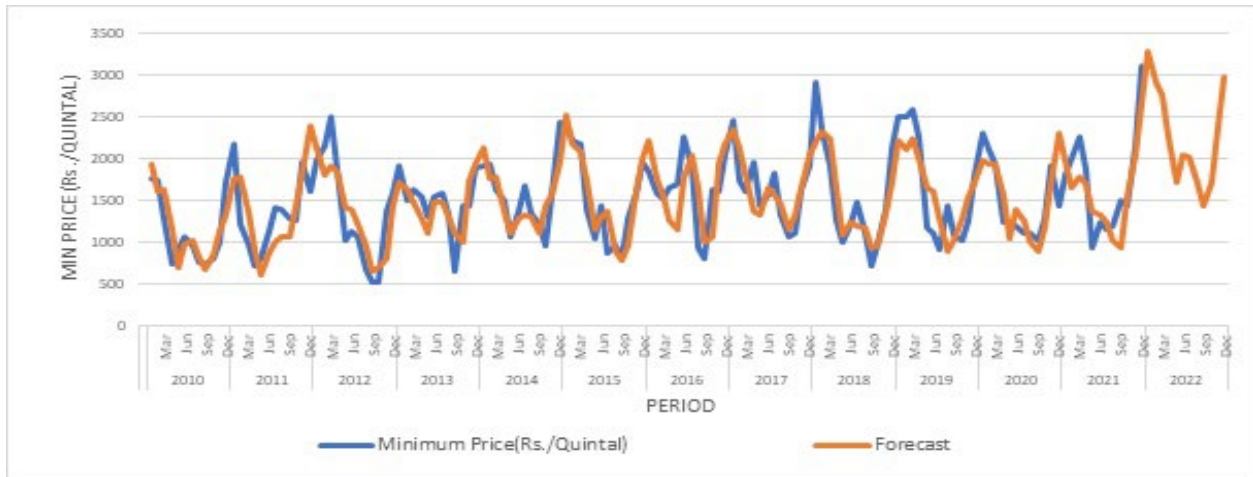


Figure 8. Fit of forecasting model for Maximum Prices

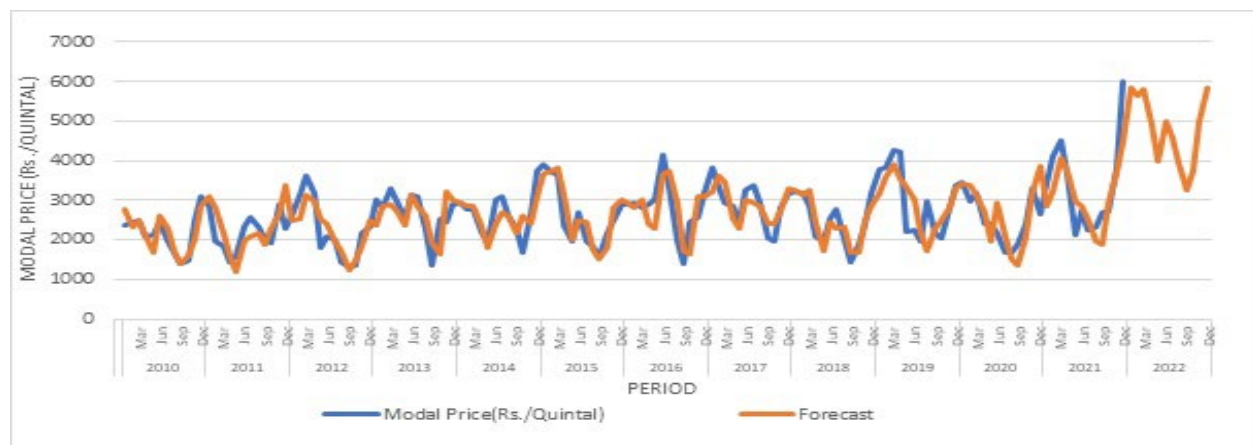


Figure 9. Fit of forecasting model for Minimum Prices

## 4. Conclusion and Future work

### 4.1 Conclusion

There is a high need to apply the concepts and methodologies of supply chain management to the agricultural sector to reduce the wastage of food and other resources. Most of the products in this sector are perishable and there is a need to anticipate the needs and plan accordingly well in advance. On analysing the data available, it was observed that there was seasonality present which repeated itself every year. The static model and adaptive winter's model were used to analyse and forecast the data of okra productions and prices. The errors and fit of model were seen on the basis of MSE, MAD, MAPE and  $R^2$  values.

The Static model gave a mean absolute error of about 19.33% for the prices and almost 207% for arrivals of Okra. This huge difference is because of the COVID-19 pandemic which disrupted the supply chains in every sector. On the other hand, the adaptive winter's model, which incorporates the previous as well as the current data and updates itself after every new entry, gave an error of 13.9% for the prices and about 18.9% for arrivals. This adaptive model predicted the modal price of Jan 2022 and Feb 2022 to be Rs. 5800/quintal and Rs. 5600/quintal, and the actual values observed from were Rs. 5700/quintal and Rs. 5200/quintal.



#### **4.2 Proposed Improvements/ Future work**

In this report we have used 2 main methods for forecasting. There are many more such methods which can be tested such as ARIMA, SARIMA, Artificial neural network and other machine learning algorithms. Here complete data for year 2020 is considered because the market is still recovering from Covid-19 but over the next 5-6 years when the economy has been fully recovered, covid-19 related data of the year 2020 can be omitted as it will be an outlier in the database.

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#### **Biographies**

**Mr. Atharva Ratnaparkhe** is graduated in Mechanical Engineering from Institute of Technology, Nirma University in 2022. He did an internship in SEW Eurodrive where he applied mechanical theoretical and practical knowledge which he learnt in his university. Atharva previously worked as a Research Assistant under Prof. Hiren Prajapati in the field of Magneto Rheological (MR) Fluids. He has also presented a conference paper titled “Design Calculations and Fabrication of a Foot Operated Hand Sanitizer Dispenser” at RIME-2021 held at Nirma University. His research and subject of interests involve Operations research, Maintenance engineering and Supply chain management. He is currently pursuing his MBA in Marketing.

**Mr. Somya Kothari** has completed his undergraduate, 4 year BTech course specialized in Mechanical Engineering from Institute of Technology Nirma University, Ahmedabad. During his BTech he acquired theoretical as well as practical knowledge of the subject. He has hands-on experience with softwares like AutoCAD, Creo-Parametric, Solid works and had studied additional subjects including Work study, Operation research, Rapid prototyping, Financial and Project management. He did his internship at JK Tyres & Industries Ltd. (Rajsamand), using the subject domain understanding and learning new management skills. Somya previously worked under Prof. Hiren Prajapati, prof. of Nirma University, in the field of Magneto Rheological (MR) Fluids for his minor project. Currently he is pursuing a 2 year MBA programme.

**Dr Bimal Kumar Mawandiya** is working as Associate Professor in Mechanical Engineering Department of Nirma University since 2008. He has experience of more than 28 years in the field of teaching, research and industry. He obtained BSc (Engineering) in Production Engineering and Management in 1992 from the National Institute of Technology Jamshedpur. Dr Mawandiya obtained MTech degree in Industrial Engineering and Management and PhD degree in 1996 and 2016, respectively from IIT Kharagpur. He has published more than 30 papers in national and international conferences, book chapters and journals with h-index of 5 and i-10 index of 2 in the areas of Industrial and Mechanical Engineering. He has guided 22 PG dissertations. He is presently guiding 1 PhD students for their research work. His research interest includes Supply Chain Management, Closed-loop Supply Chain

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**Mr. Siddharth Bhatia** has recently completed his undergraduate study in the field of Mechanical Engineering from Institute of Technology, Nirma University Ahmedabad. He is currently with Flipkart India Pvt. Ltd. at their Hyderabad Mother Hub and is Interning there with the Supply Chain (Operations) Team as a part of his 8th semester Industrial Training project. Siddharth's previous interning experiences have been with Schaeffler India (Vadodara Plant) and Nissan (Vadodara), where he has successfully applied the theoretical and practical knowledge earned from his university professors. Siddharth previously worked as a Research Assistant under Prof. Hiren Prajapati in the field of Magneto Rheological Fluids and now works under the guidance of Prof. Bimal Mawandiya in the field of supply chain. Siddharth has also presented a conference paper titled "Design Calculations and Fabrication of a Foot Operated Hand Sanitizer Dispenser" at RIME-2021 held at Nirma University, Ahmedabad. His research and subject of interests involve Supply Chain, Planning, Operations Research, Quality, Ergonomics, and Industrial Engineering.