

Time Series Analysis of Average Retail Price of Milk with Autoregressive Integrated Moving Average in R

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Abstract - The purpose of this study is to focus on forecasting weekly average retail prices of milk in Punjab, India by using historical time series data. The objective of this paper is to fitting an Autoregressive Integrated Moving Average (ARIMA) model for forecasting the weekly average retail price of milk by considering the minimum error measures. We analyze the ACF (Autocorrelation function) and PACF (Partial autocorrelation function) in detail for seasonality and parameters of AR and MA. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used for forecasting with the same scale data. The secondary data is used for this purpose and is collected from the website of the Department of Finance, Punjab. The software R is used as an important tool for forecasting and especially for studying the time series models.

Keywords — ACF, ARIMA, Average retail milk prices, MAE, PACF, RMSE.

I. INTRODUCTION

Time series forecasting is a vital area of forecasting where past observations of the same variable are collected and analyzed to develop a model to describe the relationship between past and future data. Various models are used to extrapolate the time series data into the future data. This modelling approach is particularly useful when some knowledge is available on the underlying data and when there is no satisfactory explanatory model is available to relates the prediction variable to other explanatory variables. Much effort has been devoted over the past several decades towards the development and improvement of time series forecasting models. One of the most important and widely used time series models is the Autoregressive Integrated Moving Average (ARIMA) model. Time Series contains a trend or seasonal or non stationary data, the forecasting techniques generally considered is Autoregressive Integrated Moving Average (ARIMA) model. The most of the research work about ARIMA discussed the modelling and forecasting of future data. George, E.P Box, Gwilym, M, Jenkin and Gregory, C. Reinsel [8] in their book on 'Time Series Analysis: Forecasting and Control', in the book on 'Introduction to Time series and Forecasting' by Peter, J. Brockwell and Recherd A. Davis [9] and in the book 'The Analysis of Time Series: An Introduction' by C. Chatfield [10] gave detailed knowledge on the topic and are very much useful for all time researchers.

ARIMA models are improbable and flexible class of forecasting models that utilize historical information to make predictions. ARIMA models have been already

applied to forecast various commodity prices, such as gold, tea, palm oil, household electricity consumption of etc. [5, 11, 13, 19, 20, 23]. The price of milk is also an important commodity of study during the past few years as consumption of milk is increasing day by day due to various milk products are used by mankind for its rich calcium contents. F. Ahmed, H. Shah et.al studied on milk production of Pakistan [14] whereas Hemen, D. L. and Fateh, M. S also studied milk production, but by unit root test method [15]. Forecasting of milk price in the Eastern United States was recently studied by Bolotova and Novakovic [7] and Sagar Surendra Deshmukh, R. Paramasivam also studied on ARIMA and VAR model in 2016 [22]. Apart from above research work there are also many other researchers who contributed on ARIMA models, few of them are Z. Asha Farhath, B. Arputhamary and Dr L. Arockiam [24] and established that ARIMA model is widely used for prediction, forecasting and analysis with accuracy. R. Adhikari and R.K. Agarwal [1] has been introduced a study on time series modeling and forecasting with various accuracy measures in the year 2013.

Avril Coghlan in her work "A little book of R for time series" [4], discussed in the R software and its utilization in time series analysis. Alexander Kasyoki (2015) [2] in his paper had addressed about the procedure to solve the ARIMA model in R language with various commands in R for performing a particular task. Mohamad Asad [18] and Pasapitch Chujai, Nittaya Kerdprasop and Kittisak Kerdprasop [19] were forecasting the time series data with the help of ARIMA and ARMA models taking short term periods. They have used R language for solving the

problem based on time series electric consumption in household of France and check the accuracy with the error measure by RMSE. Rob J Hydman in his research paper describe a brief description about measuring forecast accuracy [16] and in another paper along with Yeasmin Khandakar on Automatic Time Series Forecasting they used forecast package of R [21].

In recent years, high and persistent food inflation has been a matter of concern and focus of policy discussions in India. The price of milk, an important item contributing to this food inflation has been steadily rising in the domestic market. Even in the year May 2013 to May 2014, the consumer price of milk has risen by 14.5%. Consumption of milk and dairy products in the developing countries is expected to continue on the path of rising growth rate at least till 2030 (Alexandratos 2008) [3]. The total milk production in India is 165.4 million tons in 2016-17. The average per capita availability of milk in India reached 355 grams per day in 2016-17 from 178 grams per day in 1991-92. The maximum per capita availability of milk in the state Punjab of India has reached 1075 gms/day in 2016-17.

Milk is the basic source of nutrition, including protein and lactose. It provides all essential nutrients that are required for growth and development of our human body. Global protein consumption through dairy products is 10.3% of total protein intake. India is the largest producer of milk accounting for 17% of world milk production and is also the largest consumer of milk in the world. Today India contributes immense 9.5% of the global milk production. Punjab, Uttar Pradesh, Gujarat and Andhra Pradesh are the major milk producing states in India. Punjab has played important role in the milk production of our country India. The retail price of milk has been fluctuating rapidly and this frequent growth rate of price on milk affects its consumers. After 2006, growth in demand for milk in India is rising at twice the rate of milk production, 6% to 8% vs 3% to 4% with the increase demand of milk, the supply not responding to it proportionally. There is a continuous and increasing mismatch between demand and price which leads to persistence in milk price inflation. A survey report on cost of living in India till May 2018 mentioned that milk price range in all over India is lying in between Rupees 36.00 to Rs. 54.00, on average around Rs. 44.81 (source: www. numbeo.com/cost of living in India). In 2014, milk price of Punjab, India was still averaging around 38 rupees per liter but in 2018 it has seen raised to around 45 rupees per liter in Punjab, India. Bhattacharya and Rao et. al. in 2014 [6] attributed the present rise of milk price to an increased demand in domestic market with no commensurate increase in supply which indicates a structural problem and a major drive of food inflation in India.

In this paper our purpose is to throw a light on recent trends and forecast of the average retail milk price of Punjab, India. The ARIMA models were adapted to forecast the

average retail milk prices. For this purpose we take the weekly data on retail milk prices from March 2014 to January 2018. We analyze the data and emphasis are giving to fit an ARIMA model using R software (3.4.3) and forecast the future trend. For establishing the accuracy of our expected trend we use the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Lastly, an attempt has been taken to fit a best ARIMA model for forecasting the milk price of Punjab, India.

II. STUDY AREA AND RESOURCE OF DATA

Punjab is in northwestern India and has a total area of 50,362 square kilometers . Punjab is bounded by Pakistan on the west, Jammu and Kashmir on the north, Himachal Pradesh in the northeast and Haryana and Rajasthan on the south. Most of the Punjab, lies in a fertile, alluvial plain with many rivers. Its average elevation is 300 meters (980 ft) above sea level, with a range from 180 meters (590 ft) in the southwest to more than 500 meters (1,600 ft) around the northeast border. Punjab is divided into four distinct regions, namely Malwa Region, Majha Region, Doab region and Powadh region. All the regions are highly developed in agriculture and milk production. Punjab has recorded the highest per capita milk availability in terms of per capita availability of milk in the year 2010-11 in India.

In this paper our study is based on forecasting weekly average retail price of milk in Punjab, a state of India. For this purpose, we use the secondary weekly data of Punjab, India from March 2014 to Jan 2018. The source of our data is from Economic and Statistical Organization Government of Punjab (www.esopb.org). Total number of observations in data are 201. The research location of our area is shown in the following figure 1 and 2 .



Figure1: India in World Map

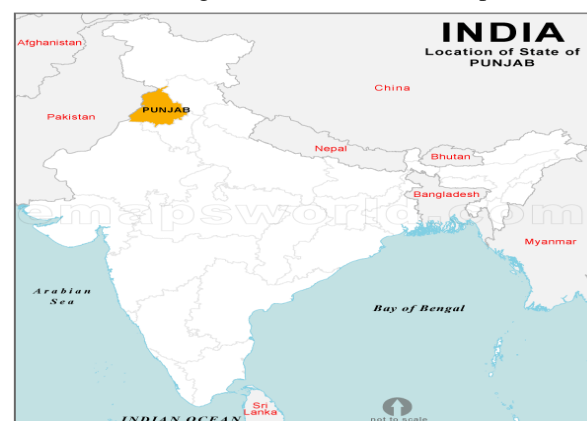


Figure2: Punjab in India Map

III. METHODOLOGY

An Autoregressive Integrated Moving-Average (ARIMA) model belongs to the one of the most used methodology approaches for analyzing time series. This is mostly because as it offers a great flexibility in analyzing various time series and also for achieving accurate forecasts. The ARIMA model methodology was first introduced by Box and Jenkins in 1976 [8], and ARIMA models are often referred to as Box-Jenkins models. This approach analyzes univariate stochastic time series, for this to be possible, the analyzed time series must be stationary. This means that the mean, variance and covariance of the series are all constant over time. However, most economic and financial time series show trends over time. So stationarity is important, if the series is non-stationary, all the typical results of the classical regression analysis will not be valid. Therefore, regression with non-stationary series is meaningless. The ARMA model as proposed by Daniel Pena, George, C. Tiao and Ruey, S. Tsay [12] in their book is as follows-

$$\phi(B)z_t = c + \theta(B)a_t \quad (3.1)$$

Originally proposed by Yule in 1927 and Slutsky in 1937 [9] and later on by Box and Jenkins, has been found useful to represent the serially dependent relation of many time series which we come across in practice. In equation (3.1) the mathematical notations are described as follows

Z_t is the observed time series, a_t is a sequence of white noise, iid as $N(0, \sigma_a^2)$, c is a constant, $\phi(B) = 1 - \phi_1(B) - \dots - \phi_p(B)$ is the autoregressive polynomial, $\theta(B) = 1 - \theta_1(B) - \dots - \theta_p(B)$ is the moving average polynomial, $\phi(B)$ and $\theta(B)$ are assumed to have no common factor. The model will be stationary if all the zeroes of $\phi(B)$ are restricted to lie outside the unit circle, and in this case $c = (1 - \theta_1 - \dots - \theta_p)\mu$, where μ is the mean of the series. When the series is non-stationary then it can be modelled by allowing some of the zeroes of $\phi(B)$ to be equal to one. Thus equation will become $\phi(B) = \phi(B)(1-B)^d$. Therefore the ARIMA equation becomes

$$\phi(B)(1-B)^d Z_t = c + \theta(B)a_t \quad (3.2)$$

Where the zeroes of, $\theta(B) = 1 - \theta_1(B) - \dots - \theta_{p^*}(B^{p^*})$, $p^* = p - d$, are all lying outside the unit circle. The model of above equation (3.2) is known as the autoregressive integrated moving average (ARIMA) of order (p^*, d, q) .

In this paper, for techniques and transforming data we are using the R software, the *tseries* package which include an *arma* function, the standard R *stats* package includes an

Arima function, the “forecast” package in R automatically selects an ARIMA model for a given time series with *auto.arima()* function. Box-Jenkins described a systematic method of identifying, fitting, checking, and using integrated autoregressive, moving average (ARIMA) time series models. The Box-Jenkins approach is iterative three-stage modeling approach – identification, estimation and diagnostic checking, and finally forecasting. The following are the three steps we followed as according to our problem:

Step1:-Model Identification – Firstly plot the original time series data and checked it whether it is stationary or not. If time series data are non-stationary, then we apply the unit root test. For making the time series data stationary we have to find the difference between observations and take their respective logarithms. Another process of checking stationary is to plot the ACF and PACF and by analyzing the trend of the graph.

Step2:-Parameter Estimation – In the estimation stage, each of the tentative models is estimated and the various coefficients are examined. The estimated models are compared using the Akaike information criterion and the Schwarz Bayesian criterion and model with the smallest criterion is chosen to get the parsimonious model. In the forecast package of R software, the user has the choice of parameter estimation method and can accordingly choose the most appropriate method based on the problem specifications. ACF and PACF also helps to find parameter values of p and q of ARIMA (p, d, q) model.

Step3:-Diagnostic Checking – After selecting the best model we feel among the various models, it is also essential to go through the diagnostic checking of the model to verify whether the applied model is accurate or not. For this the goodness of fit of the model is examined. Residuals should meet permissible error assumptions, i. e. autocorrelation, homoskedasticity and normality should be tested. If these assumptions are not satisfied, one needs to fit a more appropriate model. The main function of ARIMA models is forecasting. Their forecasting ability can be considered when compared to actual time series.

Step4:-Check the forecast accuracy – In the last stage, it is to be made sure that the results obtained from ARIMA has accurate and provide minimum error with the criteria of particular models-selection which include root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE).

IV. TECHNIQUES FOR PROBLEM SOLVING

The framework for forecasting the average retail milk prices of Punjab, India by using R are given as follows:

Step1: - At first our time series data stored in our data file with name “Milk retail Prices of Punjab” need to read it into R. This is possible by assigning our data a variable

name, for example is MP. Our data were in CSV file format, then we can use the following commands:

```
MP<-read.table("MilkPrices.csv",header=TRUE,sep=",")
OR
```

```
MP <-read.csv(Milk Prices.csv)
```

Step2: -After importing the file in R, next we store the data or variable in a time series object by using *ts()* function. Before this command we used the *View()* function in R for checking our data values. The commands are as follows :

```
View(MP)
```

```
MP time series <-ts(MP )
```

Sometimes the time series dataset collected at a regular interval that was less than one year, e.g. monthly, quarterly then we used the parameter frequency for monthly frequency =12, for quarterly frequency =4 etc. We added one more parameter "start" in *ts()* function to specify the first year that the data was collected then the command in R was written as follows:

```
MP time series <-ts(MP,frequency=?,start=c(year, ? )
```

Step3: Once we read a time series in R after that we make a plot of the time series data with the *plot.ts()* function in R with the following command:-

```
plot.ts(MP time series)
```

Step4 :- Now the time for decomposing our time series data, decomposing means to verify the time series components, whether it is following any trend, seasonality and remainder and it is used to examine and possibly to remove the seasonality components of the series. For this we use the following commands:

```
decomp = stl(MP time series ,s.window="periodic")
```

```
deseasonal_cnt<- seasadj(decomp)
```

```
plot(decomp)
```

Step5: - The stationarity of the series can be checked by using Dicky Fuller Test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and Phillips- Perron (PP) test in R. We can use these tests as according to our data requirement with the following commands:

```
adf.test(MP time series, alternative = "stationary")
```

OR

```
kpss.test(MP time series, null = c("Level", "Trend"), lshort = TRUE)
```

OR

```
pp.test(MP time series, alternative = c("stationary", "explosive"),type = c("Z(alpha)", "Z(t_alpha)"), lshort = TRUE)
```

Another method to make a time series stationary is by differencing technique by using the *diff()* function in R as follows

```
diffMP<-diff(MP time series,diff=1)
```

```
plot.ts(diffMP)
```

The *diff()* function is an iterative process and we carry on the process until our time series is stationary.

Step6: - Next on the basis of ACF and PACF plots we can identify the parameter p and q in ARIMA (p,d,q) where p is the order of AR, d is the differencing order and q is the order of MA. Commands are as follows-

```
acf(ts(diff(log10(MP time series))),main=NA)
```

```
pacf(ts(diff(log10(MP time series))),main=NA)
```

Step7: - At this stage we can fit the ARIMA model by using *auto.arima()* function or *Arima()* function which provides the best ARIMA model according to either AIC, AICc or BIC values, command are as follows-

```
FitMP<-auto.arima (MP time series)
```

OR

```
FitMP<-Arima(MPtimeseries)
```

Step8:- Now, to forecast the future values of our time series data, we follow the below command:

```
pred = predict(FitMP, n.ahead = 100)
```

And after this procedure we plot the predicted values by using the following command:

```
plot(pred )
```

OR

```
Forecast .Arima ()
```

Step9:- Finally, at this step we can check the residual of ARIMA model to ensure that no more information is left for extraction. The commands are as follows

```
par(mfrow=c(1,2))
```

```
acf(ts(MPfit$residuals),main='ACF Residual')
```

```
pacf(ts(MPfit$residuals),main='PACF Residual')
```

V. RESULT AND DISCUSSION

The average retail milk price of Punjab, India from the year March, 2014 to January, 2018 is taken into consideration to forecast the average retail milk price of Punjab, India. All the implementations are done in R [17]. In the figure 3, the average retail price of milk is shown which we take into consideration for our ARIMA modelling.

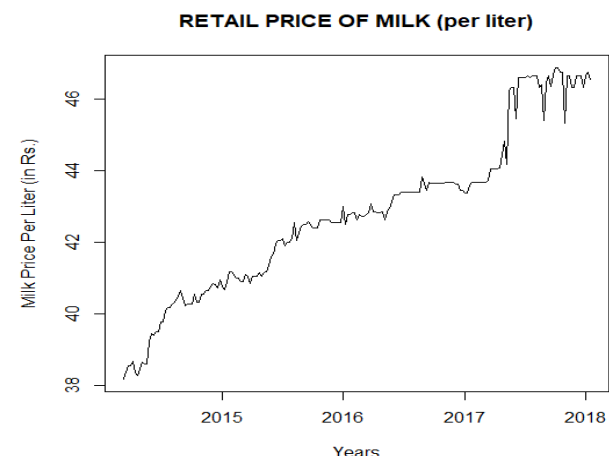


Figure 3: Graph of Average Retail Price of Milk Data

In above graph trend is linear upward trend which shows that time series is not stationary. A time series should be stationary so we converted our non stationary data into stationary for using ARIMA model. For this at first we checked the stationary of our data set on the basis of mean, at this stage it was stationary, but on the basis of variance it was coming out as non stationary.

A. Stationary Process

For converting it to stationary we again take the difference of log transformation time series and checked the stationarity at both level that is on mean and variance and gives the expected result of stationarity. The following figure 4 depicts the same.

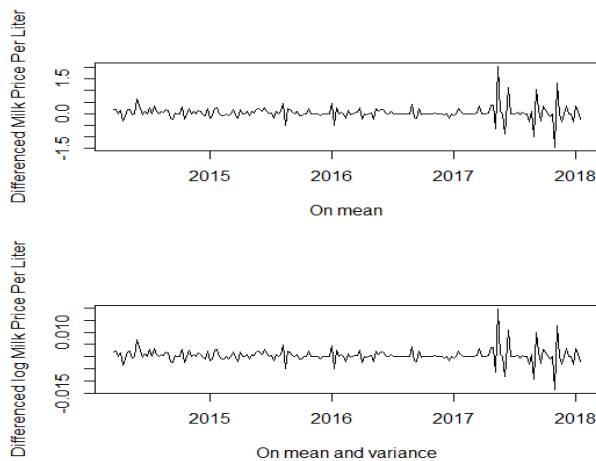


Figure 4: Graph of Time Series Data converted into Stationary

Next, we apply the Augmented Dickey Fuller (ADF) test on the mean and on both mean and variance to make our time series data stationary. We accept that time series data which will provide the p value less than 0.05. Now, as per the stationary test, we should use the $\text{diff}(\text{data})$ or $\text{diff}(\log_{10}(\text{data}))$ for fitting the ARIMA model. This means that we can use an ARIMA (p, 1, q) model.

B. Parameter estimation and Model selection

Our next step is to find out the values of p and q for the ARIMA model for this we need to plot the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the stationary time series as given below:

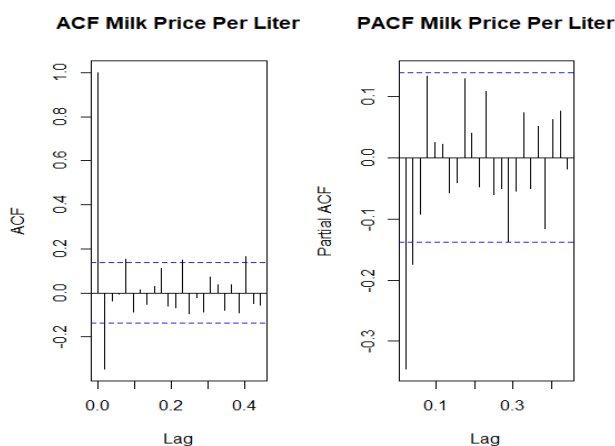


Figure 5: Graph of ACF and PACF

Since, some spikes are visible in the plots outside the insignificant zone (i.e dotted horizontal lines) from this we can conclude that the residuals are not random. This implies that there is some information available in residuals to be extracted by AR and MA models. Also, there is a seasonal component available in the residuals.

The best fit model is selected based on Akaike Information Criteria (AIC), and Bayesian Information Criteria (BIC) values. The idea is to choose a model with minimum AIC and BIC values. The following table shows the estimated value of ARIMA (5,1,0) with AIC and BIC values for our best fit model developed in R:

ARIMA(5,1,0)	AR1	AR2	AR3	AR4	AR5
Autoregressive (AR) Values	-1.2562	-1.2070	-0.9393	-0.4839	-0.1991
Standart Error (SE)	0.0697	0.1084	0.1212	0.1086	0.0696
AIC=85.52		AICc=85.96		BIC=105.28	
Estimated $\sigma^2=0.086$			log likelihood= - 36.76		

Table 1: Estimated values of ARIMA (5,1,0)

C. Decomposition of Time Series

Now, we have to remove the seasonality of time series from our data. Decomposition procedures are used in time series to describe the trend and seasonal factors in a time series. One of the main objectives for decomposition is to estimate seasonal effects that can be used to create and present seasonally adjusted values. A seasonally adjusted value removes the seasonal effect from a value so that trends can be seen more clearly. In the following graph we plot our original time series data (at top), the estimated seasonal component (second), estimated trend component (at third) and remainder components (at bottom).

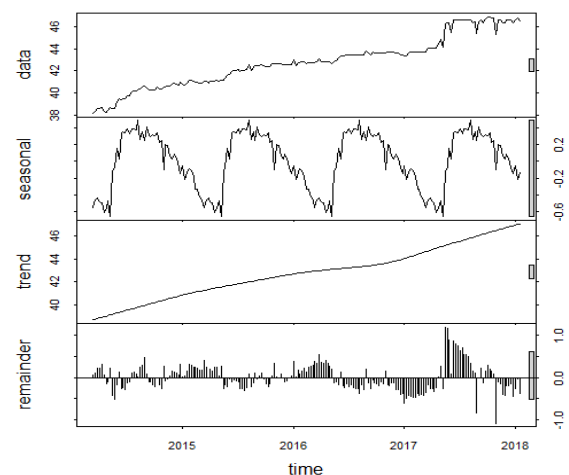


Figure 5: Graph of Time Series Decomposition

From the above graph it is clearly observed that the data is seasonal and from the trend and remainder it is clear that the estimated trend shows a small decrease in between the period 2016 and 2017 and after that a steady increase can be observed.

D. Identify the non seasonal ARIMA

ARIMA models can be fitted to both seasonal and non-seasonal data. Seasonal ARIMA requires a more complicated specification of the model structure, although the process of determining (P, D, Q) is similar to that of choosing non-seasonal order parameters. Therefore, we are interested to explore the deseasonalize of the series. For this at first, we calculate seasonal components of the data by using the STL flexible function for decomposing and forecasting the series. It calculates the seasonal component of the series using smoothing and adjusts the original series by subtracting seasonality.

Again the best fit model is selected based on Akaike Information Criterion (AIC), and Bayesian Information Criteria (BIC) values. The following table shows the estimated value of ARIMA (2,1,2) with AIC and BIC values for our best fit model developed in R are as follows :

ARIMA(2,1,2)	AR1	AR2	MA1	MA2
Autoregressive (AR) Values	0.3724	-0.4372	-0.7798	0.5247
Standard Error (SE)	0.2385	0.1364	0.2381	0.1414
AIC=8.44		AICc=8.75		BIC=24.93
Estimated $\sigma^2=0.05918$		log likelihood=- 0.48		

Table 2: Estimated values of ARIMA (2,1,2)

E. Forecasting

The MAE and RMSE are two standard statistical error measuring tools widely used in same scale data. Here we are using the measures of both to compare our data errors of ARIMA models and forecast the future data on the basis of minimum error method.

We assume that we already have n samples models error \in calculated as $(e_i, i = 1, 2, \dots, n)$. The uncertainty brought in by observation errors or the method use to compare models and observations are not considered here. We also assume that error sample set \in is unbiased. The MAE and RMSE are calculated for the dataset as

$$MAE = \frac{1}{n} \sum_{i=1}^n |e_i|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2}$$

The following table shows the MAE and RMSE values of our model

Error Measures?	MAE	RMSE
ARIMA model?		
ARIMA(5,1,0)	0.1713048	0.2888237
ARIMA(2,1,2)	0.158863	0.2408252

Table 3: Error Measures

It is seen from the above table that ARIMA (2,1,2) is the best model for forecasting retail milk price of Punjab .

Forecasts from ARIMA(2,1,2)

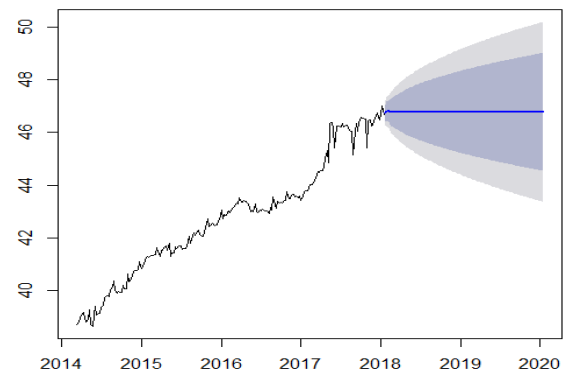


Figure 6: Forecasting of average retail milk price of Punjab with ARIMA (2,1,2)

Figure 6 shows the forecasting of average retail milk price with deseasonalized and stationary data. This is based on the assumption that there will be no other seasonal fluctuations available in our data set. Finally, we plot ACF and PACF graph of the residuals of our best fit ARIMA model (2,1,2).

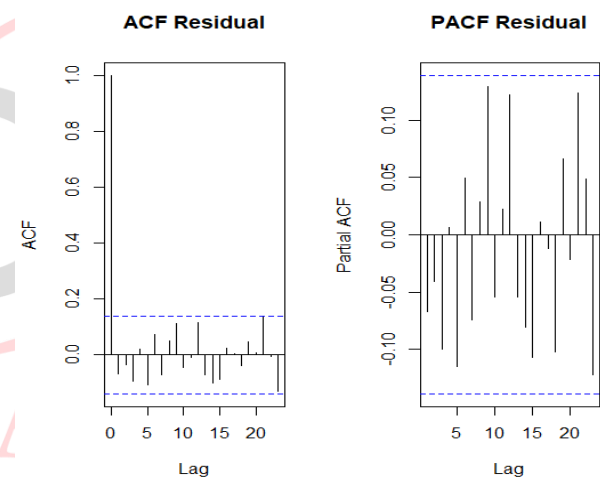


Figure7: Graph of ACF and PACF for residuals of ARIMA model

Since there are no spikes outside the insignificant zone for both ACF and PACF plots we can conclude that residuals are random with no information or juice in them. Hence our ARIMA model is working fine and we are in a state to forecast the average retail milk price of Punjab, India in coming 100 weeks.

VI. CONCLUSION

This study has focused on investigating and forecasting the average rise in retail milk price of Punjab, India up to 100 weeks by using time series data from March, 2014 to Jan, 2018. The trend of data we have taken for this research purpose is non stationary; so at first we converted it into stationary data. After the stationary test on the basis of ACF and PACF which is shown in figure 5, we checked the seasonality of the data. Next we remove the seasonality and find the best fit non seasonal ARIMA model shown in table 2. After that we choose the suitable forecasting method by

considering the smallest error measure method based on MAE and RMSE which is also shown in table 3. Thereafter it is clear from our findings that the ARIMA (2, 1, 2) model is representing the most suitable forecasting data as shown in figure 6. At last we can conclude from our findings that there will be fluctuations in average retail milk price of Punjab. Our study clearly indicated that the price will fluctuate from minimum price Rs. 44.36 to maximum Rs. 56.49. Although from figure 6, it can also be predicted that the average milk price could be stable for some time. At the end of this paper we can say that the future prospects of this research work is open and we can enhance our study to further broad areas like milk price of Northern zone or for India so that our findings can help the policymakers of India in the context of import substitution of the dairy products and also in many other ways.

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