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Forecasting of Coffee Production in India Using ARIMA Model

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Abstract— **Coffee plays vital role in India, a normal consumption of coffee, which means that three to five cups/day, is connected with a range of physiological belongings and can be fit inside healthy, impartial diet and dynamic way of life. Coffee production is conquered in the South Indian states, in Karnataka with 71%, subsequently Kerala with 21% and Tamil Nadu with 5% of on the whole production with 8,200 tonnes. Our Indian coffee is especially for the hand-picked coffee grown-up in the dark sooner than direct sunlight everywhere in this world. In India around 250,000 coffee growers are working around the country. Moreover 98% of people are small coffee producers.**

Index Terms— **ACF, ARIMA, Forecasting, Moving Average, PACF.**

INTRODUCTION

Indian's coffee is the world's best shade - grown mild coffee. It hold a remarkable place in the list of beverages, for their stimulating intensity. Among all the coffee producing regions, India is the only country where coffee is grown under shade. India withstands this great position among all the countries because of its taste, aroma, mild and less acidic nature.

Since the journey of Indian coffee production holds a long journey of around 400years ago, it holds a very special place in the historic flavor. This unique journey has been started from the hands of Yemen who has handed over seven magical beans to Bababudan, who planted it in the Chandragiri hills of Karnataka. This magical begining paved the way for the coffee with aroma, flavour, body and acidity which we are experiencing today.

Since every Indian coffee grower spend his whole time to produce coffee, it's not a miracle or a wonder that India produces an extraordinary variety of coffeee and exports it to the various parts of the world over hundred and fifty years.

TOP GROWING CONDITIONS

The goodness and the freshness of the Indian coffee is obtained from a fine organised two tier mixed shade canopy of evergreen leguminous trees. There are about 50 different varieties of shade trees in coffee plantations. The main reason for the development of Indian coffee lies in the speciality of shade trees which outstands in its work of soil erosion on sloping terrains, soil enrichment by recycling nutrients from the underground layers and prevention from seasonal fluctuations due to temperature, humidity. They also play a host to diverse flora and fauna.

Coffee plantations also support for the cultivation of spices and fruits, such as cardamom, pepper, vannila, orange, banana which are grown alongside of coffee plants.

India's diverse climatic conditions paved a great way for the cultivation of different variyaaa of coffee. The regions with high elevations are best suited for the growth of arabicas of mild quality and the regions with warm humid conditions are best suited for the growth of robustas.

II. REVIEW OF LITERATURE

India is one of the global coffee exporters and top ten leading countries where India exported coffee in the year 2017-18 are Italy, Germany, Russian federation, Belgium, Turkey, USE, Poland, Libya, Spain and Indonesia. The names of countries are arranged in descending order , i.e, largest coffee importing country from India was Italy of amount 51545 MT. There are 45 Countries name listed where India Exported 277510 MT coffee of unit value RS. 157248/ Tonne.

According to the Coffee Board of India, India produced 316000 MT coffees as per crop harvest data, out of which 95000 MT and 221000 MT were coffea arabica and coffea robusta respectively, in years 2017-18. In INDIA, top coffee producing states are Karnataka, Kerala, Tamil Nadu.

Venkatram and Deodhar (1999) in their study entitled “ Dynamic and Demand Analysis of India’ s Domestic coffee Market” highlights that coffee, although an important commodity in India’ s agricultural exports, has faced fluctuating international prices and decreasing unit value realisation, especially in the post – reform period.

International Journal of Science, Engineering and Management (IJSEM)
Vol 4, Issue 10, October 2019

Hence, domestic market for coffee cannot be neglected altogether. This suggests that Coffee Board may focus efforts on non price factors rather than price incentives in their generic coffee promotional campaign. The main issue is to withstand the quality of the coffee. The purpose was to formulate a better understanding of the role and costs of knowledge management, learning and communication in value chains and their impact on farmers and ability to integrate successfully into high value markets.

Mekuria T. (2004) in their study entitled " The status of Coffee Production and The Potential for Organic Conversion in Ethiopia" highlights in an international conference that the collapse of world coffee prices is contributing to a socio – economic decline affecting an estimate of 125 million people world – wide. The conclusion was drawn that Ethiopia has the potentials to produce certified organic high quality coffee due to the favourable growing conditions and the high quality coffee due to favourable growing conditions and the high diversity of genetic resources in coffee arabica. Conversion to organic coffee production may, however result in a significant decrease of crop productivity. A key focal point is efficient nutrient management by composting coffee husks/ pulps, and green manuring by mixed planting of suitable legumes. It also highlights how coffee farmers in southern Mexico have achieved increased earnings through partnership with conversation International, Starbucks Coffee Company and the United States Agency for International Development. Farmers can sell their coffee at premium prices to Starbucks if they adopt the specified practices.

Dorsey (1999) in his study entitled " Agricultural Intensification Diversification and Commercial Production among Smallholder Coffee Growers in Central Kenya" highlights that the research summarized in this article establishes direct links between the scale, process, and output of agricultural production by examining the dynamics of intensification, crop diversification and commercialization. Small farm survey results from Kirinyaga District, Ken, show that diversified production provides smallholders with the opportunity to select a particular crop or crops for commercial production (such as coffee, French Beans, or tomatoes) in order to increase farm – genera6ted income while meeting increasing demands for local farm produce and exports crops. The study shows that income per hectare (acre) does not consistently increase with increasing farm size, regardless of the level of commercialization, Smallholders operating at the 1.2 to 1.6 hectare (3 – 4 acre) scale appear to engage in higher – risk, more diversified, commercial production strategies than those with less area under production.

III. METHODOLOGY

Box-Jenkins (BJ) Model

This model is used as a method of extracting predictable movements in a time series manner. This model has 3 components – autoregressive component, moving average, and white noise. The time-series data to be estimated using the BJ model must not contain seasonality and mustbestationary.TheAugmentedDickey-FullerandthePhillipsPerronUnitRootTestswillbe used to check if the time-series data is stationary or –non stationary.

Method of Moving Average:

Method of Moving average models was proposed by Slutsky (1927) and Wold (1938). The series of moving average can be written as

$$Y_t = \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \theta_3\varepsilon_{t-3} - ... - \theta_q\varepsilon_{t-q} \quad (1)$$

This is called as method of moving average in the order q (MA q) here Y_t is the series which contains original data and ε_t is the error term of the series.

Method of Auto Regressive Process:

The Auto Regressive process was first proposed by Yule (1926) this regressive process is specially satisfies the following equation

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + ... + \phi_p Y_{t-p} \quad (2)$$

The present value Y_t is called as linear combination for p (AR P) also ε_t is the assumption of independent of $Y_{t-1}, Y_{t-2}, Y_{t-3} ... Y_{t-q}$.

The Auto Regressive Integrated Moving Average (ARIMA):

The ARIMA methodology was proposed by the author Box and Jenkins in the year 1976. This ARIMA model is also called as Box- Jenkins model. This model is based on the error term of the time series. To get conclude time series the data should be stationary which means, the mean, variance and covariance are constants over the time period. For this we can write the ARIMA model equation as follows.

$$\begin{aligned} Y_t &= \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + ... \phi_p Y_{t-p} + \phi_1 Y_{t-s} \\ &+ \phi_2 Y_{t-2s} + ... + \phi_p Y_{t-ps} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \quad (3) \\ &... - \theta_q a_{t-q} - \Theta_1 a_{t-s} - \Theta_2 a_{t-2s} - ... \Theta_q a_{t-qs} \end{aligned}$$

With a help of back shift operator (lag) we write the above equation as follows:

$$\phi_p(B)\phi_p(B^s)z_t = \theta_q(B)\Theta_q(B^s)a_t \quad (4)$$

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International Journal of Science, Engineering and Management (IJSEM)
Vol 4, Issue 10, October 2019

Here:

$$z_t = (1-B)^d (1-B^s)^D \ln(Y_t)$$

$$\phi_p(B) - Non\,seasonal\,operator\,of$$

$$Autoregressive\,process\,AR(p)$$

Autoregressive Integrated Moving Averages (ARIMA) Model

This is a Uni-variate Box-Jenkins (UBJ) Model used to forecast uni- variate time-series data. The basic ARIMA Model is specified as:

ARIMA (p, d, q)

Where p = auto regressive order P = Seasonal Autoregressive Order d = order of integration (# of unit roots) D = Seasonal Differencing Order

q = moving average order Q = Seasonal Moving Average Order

The ARIMA Model has four steps that is used as a cycle to determine the optimal ARIMA Model. The four steps are (1) identification stage, (2) estimation stage, (3) diagnostics stage, and (4) forecasting stage. In the identification stage, the time-series data is shown in a line graph. The unit root tests used to identify if the data is stationary or not is also conducted in this stage. A correlogram will also be used to determine which of the components possess an Autocorrelation Function (ACF) or Partial Autocorrelation Function (PACF) which will then show a certain theoretical pattern depending on the result of the ACF and PACF. This will result in the identification of the tentative ARIMA Model. The second stage consists of the estimation of the model' s parameters.

The diagnostics stage determines if the tentative ARIMA Model is a good model by identifying if the model has the characteristics of a good model. These characteristics are included being parsimonious, stationary, invertible, converging, has high quality parameter estimates, and has white noise residual series. If these characteristics are not met, the cycle is repeated from step 1. Step 4 will only be done once the ARIMA model is already adequate. The last stage, the forecasting stage, provides the estimates under the three scenarios – most-likely, worst case, and best case (Rufino, 2016).

Data Used

The time-series variable used in this study is the Production of Coffee in the India is measured in Php/kgs. This is a monthly time-series data for 6 years from 2010-2015. The data consists a total of 72 monthly observations. The data was taken from the Indian Statistics Authority (ISA) Database under their " Updates on Coffee" publications. The data is presented in Table 1

IV. RESULTS AND DISCUSSION

Graphical Analysis

The first method used in the study is to determine whether the time-series data is stationary or not by using the Graphical analysis method. It is shown on the basis of the graph, if the graph comes along in a certain wave ,then it is non-stationary. As shown in the below Figure 1 the upward motion of the wave of the time – series data, tells that the data is non- stationary. A sharp increase in the production of coffee in 4th quarter of 1970 is also viewed in the graph. From the research of coffeepedia.org the import control discharged by the National Food Authority (NFA) is the reason for the increase in the price in 1970.

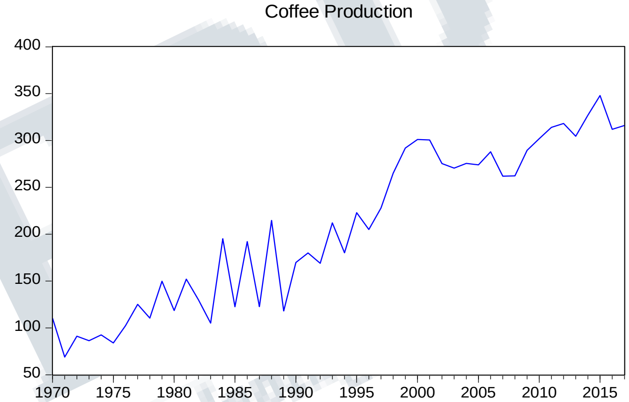

Figure 1. Graph of Coffee Production in India (1970-2015)

In the Figure 1 it shows that there is a gradual increase in the motion of Coffee Production over a period of 45 years for million tons of Coffee. However in Figure 2 there is a gradual decrease in the Coffee Production from the starting itself. The first difference of the variable production of coffee with (p - value = 0. 0000)

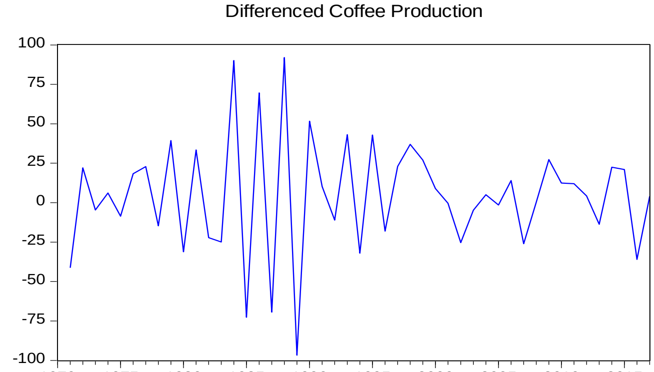

Figure - 2. Differenced Coffee Production (1970 – 2015)

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Vol 4, Issue 10, October 2019

Alternatively, the stationary of the production is tested by using unit root tests. We hereby, conduct three other different types to check the stationary of the data series.

Augmented Dickey – Fuller (ADF) Unit Root Test
Using the Augmented Dickey – Fuller (ADF) Unit Root Test, we test if the motion and intercept of the time series data is stationary at its level with 11 maximum lags. The result is presented in the table.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.796702	0.8106
Test critical values:	1% level	-3.581152	
	5% level	-2.926622	
	10% level	-2.601424	

Table 2. Augumented Dickey – Fuller (ADF) Unit Root Test

Since the absolute value of the ADF Test Statistic -0.79 is less than the absolute values of the test critical values at 1%, 5%, and 0% level, then we conclude that the ADF showed that the time – series data is non stationary at its level. Getting the first and second differences of the data might solve the problem of non stationary. The ADF Unit Root Test at its first differences is showed in the table.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	204.1948	50.70882	4.026810	0.0002
AR(2)	0.938462	0.080827	11.61079	0.0000
MA(1)	0.210896	0.148354	1.421572	0.1622
SIGMASQ	761.7891	157.3493	4.841389	0.0000

R-squared	0.890752	Mean dependent var	207.4204
Adjusted R^2	0.883304	S.D. dependent var	84.38847
S.E.of Regr	28.82781	Akaike info criterion	9.727976
Sum^2 resid	36565.88	Schwarz criterion	9.883910
Log likelihood	-229.4714	Hannan-Quinn criter.	9.786904
F-statistic	119.5849	Durbin-Watson stat	1.936620
P(F-statistic)	0.000000		

Table 3
Augmented Dickey Fuller (ADF) Unit Root Test at 1^{st} Difference

Since the absolute value of the ADF T statistic at 1st Difference -3.58 is greater than the absolute values of the test critical values at 1%, 5%, and 10% level, then we can conclude that the ADF Test showed that the time – series data is now stationary at its 1st difference.

Correlogram

Now, we generate the Correlogram of the time – series data to determine whether there is an Autocorrelation Function (ACF) or partial Autocorrelation Function (PACF). The Correlogram at its level using 32 lags is shown in the Table 4

ARIMA Modeling

The tentative ARIMA Model is ARIMA (0,1,1). Using the exact maximum likelihood as the method of equation and the transferred series as the time – series data, the optimal ARIMA Model is finally identified by the program as ARIMA (1,1,0)(0,0,0). It also shows that there are three outliners detected in the set of time – series data.

Autocor...	Partial Correlat...		AC	PAC	Q-Stat	Prob
		1	0.872	0.872	38.790	0.000
		2	0.869	0.454	78.163	0.000
		3	0.763	-0.244	109.17	0.000
		4	0.715	-0.081	137.08	0.000
		5	0.659	0.141	161.34	0.000
		6	0.573	-0.206	180.09	0.000
		7	0.545	0.082	197.46	0.000
		8	0.454	-0.058	209.80	0.000
		9	0.437	0.041	221.54	0.000
		10	0.377	0.056	230.52	0.000
		11	0.358	0.015	238.83	0.000
		12	0.306	-0.125	245.08	0.000
		13	0.251	-0.122	249.40	0.000
		14	0.208	-0.026	252.44	0.000
		15	0.154	0.035	254.16	0.000
		16	0.103	-0.143	254.96	0.000
		17	0.032	-0.131	255.05	0.000
		18	-0.033	-0.071	255.13	0.000
		19	-0.089	0.033	255.79	0.000
		20	-0.159	-0.114	257.96	0.000

Table - 4. Correlogram

It is obvious that there is a trend of continuous decline in the autocorrelation coefficient and those values are significant. This means that the time – series data is non stationary, which supports the results of the first two unit root tests. We will also get the correlogram of the 1st difference to see if it becomes stationary. The results are presented in Table 5.

International Journal of Science, Engineering and Management (IJSEM)
Vol 4, Issue 10, October 2019

Autocor...	Partial Correlati...		AC	PAC	Q-Stat	Prob
		1	-0.731	-0.731	26.781	0.000
		2	0.496	-0.084	39.371	0.000
		3	-0.298	0.073	44.026	0.000
		4	0.079	-0.195	44.358	0.000
		5	0.105	0.121	44.958	0.000
		6	-0.287	-0.208	49.573	0.000
		7	0.372	0.022	57.519	0.000
		8	-0.406	-0.076	67.242	0.000
		9	0.320	-0.144	73.446	0.000
		10	-0.271	-0.141	78.002	0.000
		11	0.162	-0.092	79.689	0.000
		12	-0.002	0.067	79.690	0.000
		13	-0.121	-0.052	80.688	0.000
		14	0.191	-0.074	83.223	0.000
		15	-0.148	0.153	84.805	0.000
		16	0.157	0.073	86.637	0.000
		17	-0.153	-0.059	88.440	0.000
		18	0.097	-0.043	89.194	0.000
		19	-0.048	-0.056	89.388	0.000
		20	0.013	0.054	89.401	0.000

Table - 5 Correlogram for 1st Difference

Diagnostic Test:
Based on the diagnostic test we decide the range of ARIMA model as (2,1,1). The table of the diagnostic test is given below.

Sr. No	ARIMA Model	R^2	AIC	BIC
1.	(1,1,1)	0.8712	9.8625	10.0185
2.	(2,1,2)	0.8887	9.7624	9.9183
3.	(1,1,2)	0.8657	10.0558	9.8998
4.	(2,1,1)	0.8907	9.7279	9.8839
5.	(3,1,1)	0.7691	10.4977	10.3567
6.	(1,1,3)	0.8317	10.1243	10.2802
7.	(3,1,2)	0.8499	10.0622	10.2181
8.	(3,1,3)	0.7736	10.4866	10.6426
9.	(4,1,4)	0.7612	10.5702	10.7262
10.	(5,1,5)	0.7103	10.7795	10.9355

Table – 6

Forecasting
We have generated a forecast for the next ten years (2015 2025). This Forecast is based on the past time serried data that were used in the identification of the ARIMA Model. The time series data has been used to generate the graph and the forecast is shown in the Figure.

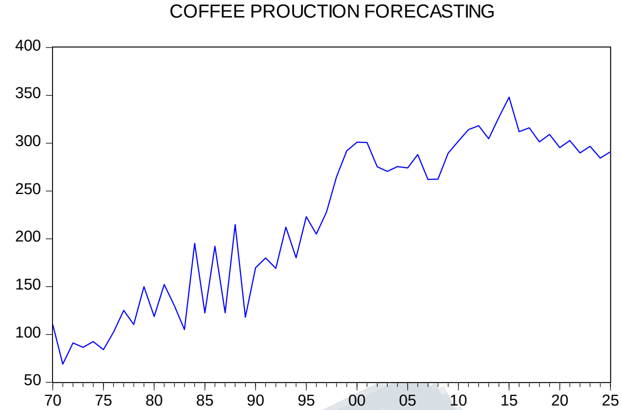

Figure 3
Forecast Stimulation Graph of the Coffee Production for the Years (2015 – 2025)

ARIMA (2,1,1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	204.1948	50.70882	4.026810	0.0002
AR(2)	0.938462	0.080827	11.61079	0.0000
MA(1)	0.210896	0.148354	1.421572	0.1622
SIGMASQ	761.7891	157.3493	4.841389	0.0000

R-squared	0.890752	Mean dependent var	207.4204
Adjusted R-squared	0.883304	S.D. dependent var	84.38847
S.E. of regression	28.82781	Akaike info criterion	9.727976
Sum squared resid	36565.88	Schwarz criterion	9.883910
Log likelihood	-229.4714	Hannan-Quinn criter.	9.786904
F-statistic	119.5849	Durbin-Watson stat	1.936620
Prob(F-statistic)	0.000000		

Table – 7

Year	Production of Sugarcane (1000 tons)	Year	Production of Sugarcane (1000 tons)	Year	Production of Sugarcane (1000 tons)
1970	110.23	1991	180	2012	318.2
1971	68.95	1992	169	2013	304.5
1972	91.07	1993	212.09	2014	327
1973	86.39	1994	180.1	2015	348
1974	92.51	1995	223	2016	312
1975	83.98	1996	205	2017	335.5326
1976	102.3	1997	228	2018	305.3658

1977	125.14	1998	265	2019	327.4503
1978	110.49	1999	292	2020	299.1399
1979	149.84	2000	301	2021	319.8654
1980	118.65	2001	300.6	2022	293.2972
1981	152.1	2002	275.3	2023	312.7472
1982	129.95	2003	270.5	2024	287.814
1983	105.03	2004	275.5	2025	306.067
1984	195.11	2005	274		
1985	122.45	2006	288		
1986	192.09	2007	262		
1987	122.71	2008	262.3		
1988	214.72	2009	289.6		
1989	118.05	2010	302		
1990	169.73	2011	314		

Table - 7

CONCLUSION

In this article, we constructed a model called ARIMA. Rooted in this model we conclude that forecasting value of Coffee production 2015 to 2026. The figure – 7 is clearly explains the future production of coffee also Table – 7 explains that the amount of change in future production. This indicates that there will be a gradual decrease production of coffee; we should take the necessary steps in order to improve the production.

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