ARIMA model to forecast the RSS-1 rubber price in India: A case study for textile industry

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ABSTRACT – REZUMAT

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Various rubber products are used in the textile industry. Due to increased foreign supply and synthetic rubber production, the price of natural Rubber in India has become more volatile. This paper aims to develop an appropriate model to predict the weekly price using the Box Jenkins methodology. The weekly price for Indian RSS-1 Rubber for the sample period from January 2002 to December 2019 has been collected from the official website of the Indian Rubber Board. ACF and PACF correlograms check the series stationarity and identify the model parameters. A model with the maximum number of significant coefficients, lowest volatility, lowest Akaike's information criterion (AIC), lowest Schwarz criterion and highest Adjusted R-squared is tentatively selected as the appropriate model and for the same model diagnostic check is carried out. An appropriate model to forecast the weekly price for the RSS-1 variety of Rubber is ARIMA (1, 1, 4).

Keywords: *volatility, speculative price bubbles, natural rubber price, univariate forecasting model, Box Jenkins methodology, textile industry*

Utilizarea modelului ARIMA pentru a previziona evoluția prețului cauciucului natural clasificat în categoria RSS-1 în India: Un studiu de caz pentru industria textilă

În industria textilă sunt utilizate diverse produse din cauciuc. Datorită creșterii ofertei externe și producției de cauciuc sintetic, prețul cauciucului natural din India a devenit mai volatil. Acest studiu de cercetare își propune să dezvolte un model adecvat pentru a previziona prețul săptămânal folosind metodologia Box Jenkins. Bazele de date care includ informațiile privind prețul săptămânal pentru cauciucul natural clasificat în categoria RSS-1 în India, pentru perioada de analiză din ianuarie 2002 până în decembrie 2019 au fost colectate de pe site-ul oficial al Indian Rubber Board. Corelogramele ACF și PACF verifică staționaritatea seriei și identifică parametrii modelului. Un model cu numărul maxim de coeficienți semnificativi, cea mai scăzută volatilitate, cel mai scăzut nivel privind criteriul de informații Akaike sau AIC, cel mai scăzut nivel privind criteriul Schwarz și cel mai ridicat nivel al R-pătrat ajustat se selectează provizoriu ca model adecvat și pentru același model este efectuată o verificare bazată pe diagnosticare. Modelul potrivit pentru a previziona prețul săptămânal pentru varietatea RSS-1 de cauciuc natural din India este modelul ARIMA (1, 1, 4).

Cuvinte-cheie: *volatilitate, bule speculative de preț, preț cauciuc natural, model de previziune univariat, metodologia Box Jenkins, industria textilă*

INTRODUCTION

A wide range of rubber materials is used in the textile manufacturing process. One of such key consuming areas in the rubber calendaring process in the textile industry is to make various types of fabrics. Rubber rollers, rubber moulded products, rubber coating and rubber suit are some of the other major forms of rubber consumption in the textile industry. India is the second major producer and consumer of natural Rubber globally. China, Thailand, Indonesia and Malaysia are the few other major players in production and consumption. In addition to the above-mentioned, USA and Vietnam are the major consumers and producers respectively in the world. Historically natural rubber industry in India was protected from strong tariffs and other legal protections. But today, nearly 40% of natural rubber consumption depends on imports from other countries. As India imports 40% of its natural Rubber from other counties and as the role of synthetic Rubber in the country's rubber industry is vital, the price of Natural Rubber in India is more volatile [1]. Volatile rubber prices in India have resulted in the poor lifestyle of many rubber farmers and workers. Farmers were finding it difficult to pay the loan instalments, stoppage of their children's education, entertainment and difficulty for daily livelihood. It is not just farmers and farm workers.

On the other hand, corporations taking Rubber as their core raw material will also suffer from the volatile natural rubber price [2]. The government in the central will find it difficult to balance the fair price demand of farmers and minimum cost supply expectations of the natural Rubber based industries. As the Natural Rubber price is more volatile, developing an appropriate price risk management tool is necessary. Market-based price risk management tools like futures or options will help to hedge the price risk. However, in Indian commodities exchanges, the futures on natural Rubber are not traded regularly. In this situation, the tyre makers, other rubber-dependent industries, traders, and natural rubber growers are exposed to price volatility. Hence, it is necessary to develop an appropriate statistical model to predict the price of natural Rubber [3]. Univariate time series models like AR, MA and ARIMA have become the interest of many researchers today to develop forecast models using time series data. Box Jenkins ARIMA methodology has become very popular today to forecast financial time series because of the simplicity and optimal model-building process [4]. In the univariate forecasting methodology, ARIMA will allow the investigator to model the time series even with multiple external events [5]. Using Box Jenkins methodology, this work aims to develop an appropriate univariate model to predict the price of natural Rubber in India.

Literature review

There are good numbers of literature in which discussions on price volatility in Natural Rubber have appeared. The volatility in the Natural Rubber price is increasing because of the production and supply of synthetic Rubber [6–10]. As the cost of production of synthetic Rubber is directly dependent on the cost of crude and as the cost of crude fluctuates in the market, the price of natural Rubber is also very unstable after the Second World War. Kannan, Lekshmi et al. and Khin et al. have stated that production, consumption, stock, international natural rubber price and import-export are major economic factors contributing to price instability [11–13]. Other authors have stated that Natural Rubber prices are affected by the Asian Crisis [14–16]. Thailand, Indonesia and Malaysia are large producers of natural rubber. The exchange rate between US Dollar and their domestic currencies affected the natural rubber price in these countries. All the above studies have used regression and correlation methods except Khin et al. [13, 14] have used the Vector Error Correction Model to identify the reasons for price volatility in the natural rubber industry.

Zahari et al. [3] and Kumar et al. [17] have used Box Jenkins ARIMA methodology to develop a forecast model to predict the natural rubber price in Malaysia. Sakan [18] used ARIMA, VAR and VECM methods to develop the rubber price forecast model in Malaysia. To develop the forecast model for world Natural Rubber prices, Khin et al. [19] have used ARIMA and MARMA methodology. Many studies have appeared so far on applying ARIMA methodology to develop forecast models for other agricultural commodity prices. For example, Ohyver and Pudjihastuti [20] for medium quality Rice price, Mishra et al. [21] for Potato price, Shil et al. [22] for Arecanut price, Darekar and Reddy [23] for Cotton price and Sukiyono [24] for Cacao price.

ARIMA methodology has been widely used in other disciplines as well. Some authors have used ARIMA methodology to develop the forecasting model for Gold bullion selling price, GDP, stock price, global solar radiation, private residential price, mineral commodity prices, import-exports values of the country, electricity price, rainfall, oil prices and month temperature respectively [25–38].

DATA AND METHODOLOGY

The weekly data from January 2002 to December 2019 for this study are gathered from the official website of the Indian Rubber Board which is indiannatural.com. There are five varieties of Rubbers trading in the market; RSS-1 is the highest quality among those five varieties. Hence, we consider the price series of RSS-1 in this study.

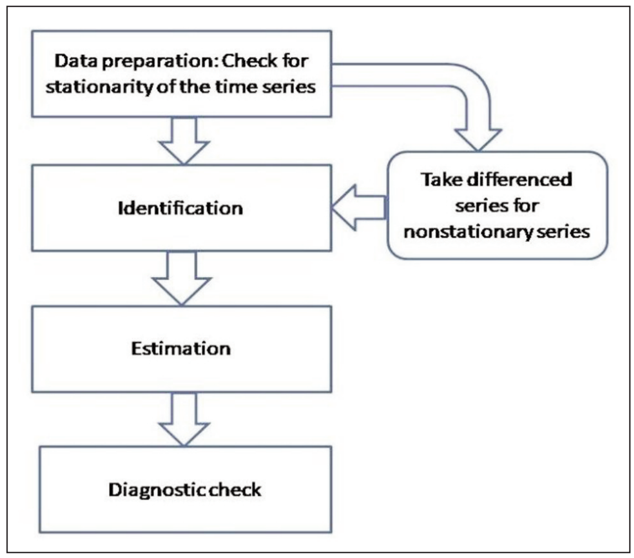

Fig. 1. Flowchart of Box-Jenkins ARIMA methodology

Box Jenkins ARIMA methodology is a systematic process which follows four steps [20–24, 28, 39, 40] have used ACF and PACF correlograms to check the stationarity of time series. We have used time plot correlograms, ACF and PACF correlograms to check the stationarity of the RSS – Rubber price series. The correlograms proved that the series is not stationary and to make the series stationary, we have taken the first-order difference of the raw series. To identify the model parameters (*p, d, q*) some authors [37, 39, 41] have advised looking at the ACF and PACF correlograms of differenced series; hence we have used the same in this study. For the identified tentative models, we have run the Box Jenkins methodology and the following five statistics are extracted and tabulated from the computer outputs. A model with the maximum number of significant coefficients, lowest volatility, lowest Akaike's information criterion, lowest Schwarz criterion and highest Adjusted R- squared is tentatively selected as the appropriate model and for the same model diagnostic check is carried out. The same authors [37, 39, 41] have suggested taking residuals of the appropriate model and using the ACF and PACF correlograms of these residuals to decide whether the selected model is statistically appropriate or not.

Linear regression is a common tool used for forecasts. The general term of a bivariate linear regression model is shown in equation 1.

$$y_t = \alpha + \beta(x_t) + \varepsilon_t \tag{1}$$

In this simple form of a linear regression equation, y_t is the dependent variable, x_t – the explanatory or independent variable, α and β are the constants, and ε_t is the error of the model [42]. The same model has been extended for multi-variate predictions; this model could be suitable when the researcher has more than one independent variable for the dependent variable of his interest. The general form of this multivariate regression model is shown in equation 2.

$$y_t = \alpha + \beta_1(x_{1t}) + \beta_2(x_{2t}) + \ldots + \beta_n(x_{nt}) + \varepsilon_t \tag{2}$$

In the second equation, we can observe multiple independent variables with names x_1, x_2, and x_n and their relationship factors β_1, β_2, and β_n with dependent variables y_t. The above two regression equations or methodology can be used only when the determinants of y_t are measurable. In the short run, although explanatory variables are constant, the y_t might vary due to market trends. In such situations, the application of univariate models such as Auto-Regressive (AR), Moving Average (MA), Auto Regressive Moving Average (ARMA), or Auto-Regressive Integrated Moving Average (ARIMA) would be most appropriate [43]. These models' very common pervasive characteristic is that the explanatory variables in all these models are the past values of the dependent series or its error terms [44]. This is evident from the following third, fourth, and fifth equations.

$$y_t = \mu + \beta_{1yt-1} + \beta_{2yt-2} + \ldots + \beta_{pyt-p} + u_t \tag{3}$$

$$y_t = \mu + u_t + \theta_{1ut-1} + \theta_{2ut-2} + \ldots + \theta_{qut-q} \tag{4}$$

$$y_t = \mu + \beta_{1yt-1} + \beta_{2yt-2} + \ldots + \beta_{pyt-p} + \\ + \theta_{1ut-1} + \theta_{2ut-2} + \ldots + \theta_{qut-q} + u_t \tag{5}$$

Equations 3–5 are the general form of the AR, MA, and ARMA process, where y_t is the value of the dependent variable. In equations 3–5, u_t denotes the white noise error term, where $p \wedge q$ denotes the optimal number of lags for the AR (p) and MA (q) processes. AR model implies the present value of the dependent variable, y, depending on its past values. MA model implies that the current value of the dependent variable is the function of the present and the past values of a white noise error term [45]. Equation five shows the characteristics of the ARIMA model, where the current value of the dependent variable, y, is the function of its past values plus the blend of the present and past values of a white noise disturbance term [43]. If the raw series is stationary at its base level, then the model applicable would be ARMA (p, q); however, if the series is not stationary, then such series calls for integrated or differenced return series to avoid spurious regression. Such differenced series would be used to identify the AR (p) and MA (q) terms for the ARMA model [46]. Hence, Box and Jenkins ARIMA modelling differs from ARMA, with additional terms 'integrated' and 'I' in the acronym.

DATA PREPARATION

Figures 2 and 3 show the time plot of the RSS-1rubber price raw series and the return series. The raw series shows trends, specifically upward trends till the end of 2011 and downward trends. Therefore, the raw series of RSS-1 Rubber price is a non-stationary time series; hence we have taken the first order difference return series to make the series stationary. In figure 3, the series does not follow any particular

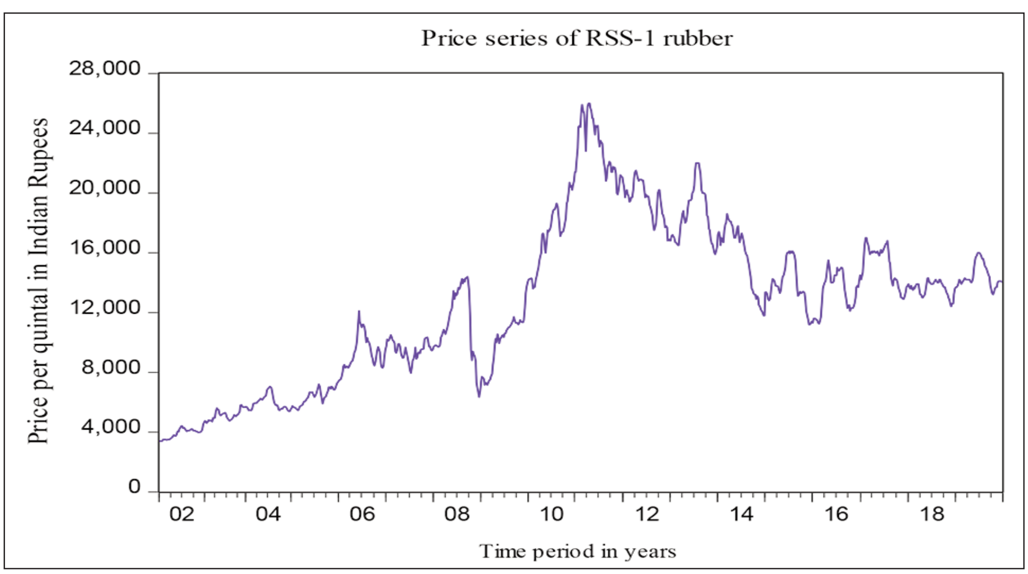

Fig. 2. Price series of RSS-1 Natural Rubber in India
(Source: authors processing using EViews package)

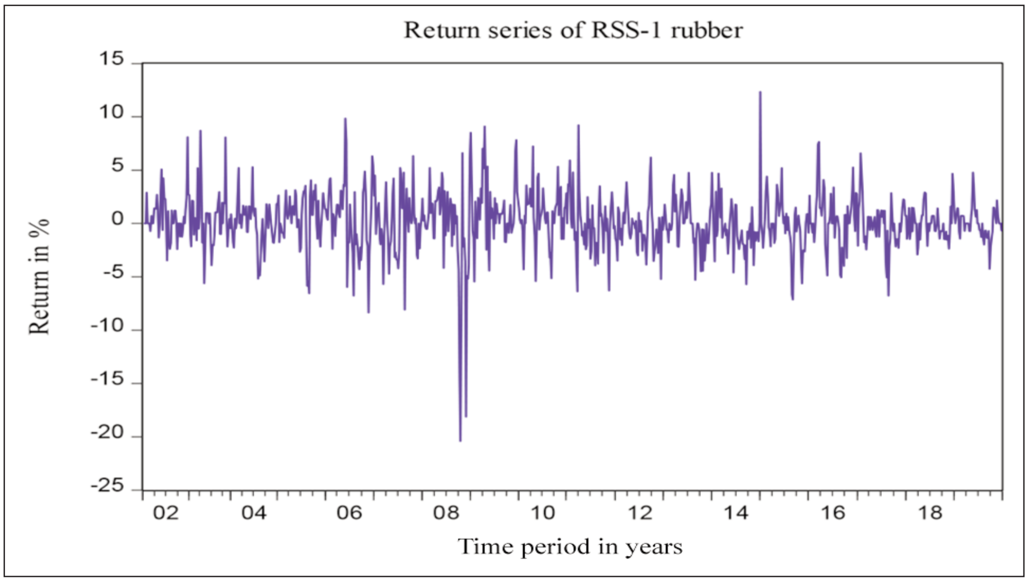

Fig. 3. Return series of RSS-1 Natural Rubber in India
(Source: authors processing using EViews package)

trend, which gives a clue that the mean of the log of RSS-1 rubber return is not changing. This perhaps indicates that the differenced RSS-1 rubber return series is stationary. But this time plot will give just an initial clue to confirm the stationarity of the series, and it is necessary to run ACF and PACF functions on the series to make the decision more precise.

Figure 4 shows the computer output for ACF and PACF with its correlograms for the RSS-1 Rubber price series for the period January 2002 to December 2019. One can observe the autocorrelation and partial Autocorrelation values up to 10 lags of the price series in figure 4. The autocorrelation coefficient at the 1st lag (0.996) is very high, and the coefficients decline slowly until the 10th lag (0.939). The correlograms of ACF for rubber price shown in figure 4 show that up to 10th lags the ACF are individually different from zero and are statistically significant. The partial autocorrelation coefficients in figure 4 show dramatically decline after the first lag, and this indicates that the RSS-1 Rubber price series is non-stationary.

Now the autocorrelation and partial autocorrelation values of the return series in figure 5 gives different interpretation compared to figure 4. The AC coefficients for the first and second lag (0.417 and 0.141) are very small compared to figure 4 values (0.996 and 0.991). Secondly, the AC coefficients in figure 4 decreased very slowly throughout up to the 10th lag and AC coefficients at each lag are not equal to zero, but in figure 5, AC coefficients decline very sharply and they have got negligible *r* value (less than 0.10) for majority lags. The ACF correlograms for the return series shown in figure 5 that is different from the correlograms of the raw series in figure 4. This confirms that the return series is not serially correlated; hence, the same is a stationary time series. As the first order differenced RSS-1 Rubber price series is a stationary series, we will carry this series for all our computations of Box Jenkins methodology. Further, as the first-order return series is stationary, the ARIMA (*p, d, q*) model identified value for *d* will be 1.

The Augmented Dickey-Fuller (ADF) test is performed to test the unit root in the RSS-1 rubber price series. The results of the ADF test are presented in table 1. The p-values of the ADF test for the price series is 0.27 and the return series is 0.00. This formally confirms that the price series of Rubber is not stationary and the return series is stationary.

Correlogram of RSS-1 rubber price series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.996	0.996	921.90	0.000
		2	0.991	-0.238	1834.4	0.000
		3	0.984	-0.029	2736.4	0.000
		4	0.978	-0.010	3627.5	0.000
		5	0.972	0.054	4508.4	0.000
		6	0.966	-0.020	5379.2	0.000
		7	0.959	-0.052	6239.4	0.000
		8	0.953	-0.006	7088.6	0.000
		9	0.946	-0.005	7926.9	0.000
		10	0.939	-0.030	8753.8	0.000

Fig. 4. AC and PAC values with correlograms for RSS-1 rubber price series
(Source: authors processing using EViews package)

Correlogram of the return series of RSS-1

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.443	0.443	181.77	0.000
		2	0.158	-0.047	205.00	0.000
		3	0.059	0.008	208.27	0.000
		4	-0.092	-0.144	216.19	0.000
		5	-0.049	0.063	218.39	0.000
		6	0.061	0.094	221.89	0.000
		7	0.063	0.006	225.62	0.000
		8	0.082	0.033	231.99	0.000
		9	0.084	0.025	238.60	0.000
		10	0.025	-0.012	239.17	0.000

Fig. 5. AC and PAC values with correlograms for the return series of RSS-1 Rubber
(Source: authors processing using EViews package)

Table 1

ADF TEST RESULTS				
Level of significance	**Price series**		**Return series**	
	t-Statistic	Probability	t-Statistic	Probability
ADF test	–2.04	0.27	–15.1485	0.00
1% level	–3.44		–3.43723	
5% level	–2.86		–2.86447	
10% level	–2.57		–2.56838	

DATA ANALYSIS & INTERPRETATION

Identification

We are using the autocorrelation function (ACF), partial autocorrelation function (PACF) of the return series and their correlograms to identify the (*p,* and *q*) values for the model. In figure 5, the PACF cut-off sharply beginning lags (0.417 to –0.0470); it can be called an AR process. Further, the partial autocorrelation coefficient in the first lag and autocorrelation coefficient in the first lag is positive and statistically significant; hence, the RSS-1 rubber return series follows the ARIMA process. The pattern of correlograms of AC and PAC in figure 5 are almost similar; hence this is an indication of the ARIMA model. In other words, the first lag of the ACF coefficient is not negative (0.417); hence it is not an MA process. Therefore adding just the AR term or MA term to the model does not make sense. The AC coefficients are statistically significant at lags 1, 2, 18, 19 and 20; the PAC coefficients are statistically significant at lags 1, 4, 5 and 6. And hence any combination of these terms may give the appropriate model. But according to Box and Jenkins, parsimonious models give a better prediction; hence we are dropping parameters 18, 19, 20, 5 and 6 from our identification process. Gujarati et al. [41] have advised doing experiments with different alternative models to select an appropriate model. Identified alternative models for the estimation process are (1, 1, 1) (1, 1, 2) (4, 1, 1) (1, 1, 4) (4, 1, 2).

Estimation

The rubber return series is used to generate the estimates for above mentioned tentative models. In the ARIMA (*p*, *d*, and *q*) model, the value for parameter *d* is already defined: the number of differences we take to make the series stationary. In the case of the RSS–1 rubber price series, the series became stationary with first-order differencing. We have extracted significant coefficients, volatility, adjusted R-squared, Akaike's information criterion and Schwarz criterion and tabulated in table 2 from the estimates of tentative models.

Among four tentative models, models (1, 1, 4) and (4, 1, 2) are the most appropriate models based on significant coefficients. Among these two models, the volatility of model (1, 1, 4) is less compared to model (4, 1, 2). Furthermore, Akaike's information criterion and Schwarz criteria for model (4, 1, 1) are lower than model (4, 1, 2). Hence the appropriate model to forecast RSS–1 Rubber price is ARIMA (1, 1, 4). The model accuracy measured by the Adjusted R-squared of ARIMA (1, 1, 4) is higher than other tentative models.

Diagnostic check

Once the appropriate model is selected and the parameters are estimated, the diagnostic check has to be made using the ACF and PACF correlograms of the residuals. ACF and PACF for model residuals (1, 1, 4) are plotted in figure 6; the correlograms of the residuals are flat in this image. The lags are within the 95% confidence level or the standard error bounce; this indicates that all the information's captured in the model. The selected model (1, 1, 4) is the perfect model because, in figure 5, the residuals are not serially correlated, which is statistically significant. This says that all the information's covered in the model and it is not necessary to look for some other ARIMA model to predict the RSS-1 Rubber price in India.

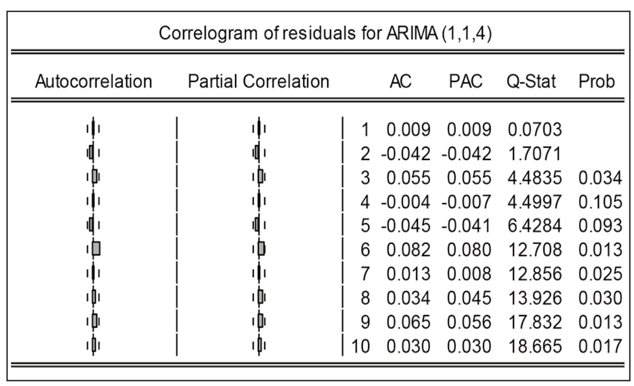

Fig. 6. Correlograms of the residuals of estimated ARIMA (1, 1, 4) model
(Source: authors processing using EViews package)

Table 2

EXTRACTED PARAMETERS					
Tentative models	**(1, 1, 1)**	**(1, 1, 2)**	**(4, 1, 1)**	**(4, 1, 2)**	**(1, 1, 4)**
Significant coefficients	2	2	2	3	3
Volatility	0.000584	0.000583	0.0005870	0.000695	0.000574
Adjusted R-squared	0.191950	0.192380	0.1877050	0.038182	0.205335
Akaike's information criterion	–4.599200	–4.599700	–4.5939000	-4.425101	–4.61583
Schwarz criterion	–4.578300	–4.578800	–4.5730000	-4.404215	–4.59494

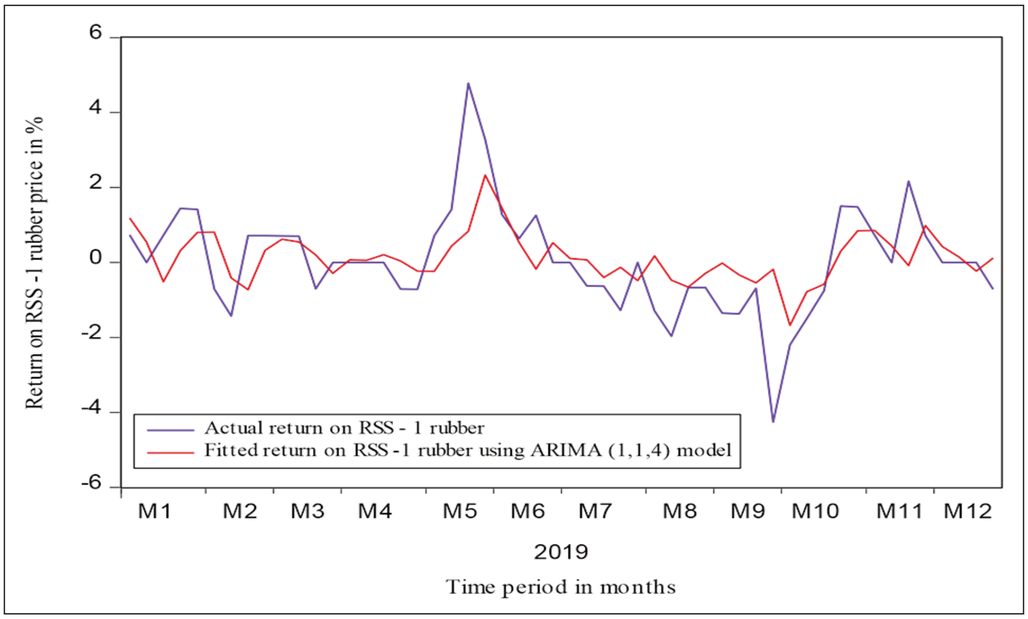

Fig. 7. Actual and fitted weekly returns on RSS-1 Rubber
(Source: authors processing using EViews package)

The estimated coefficients of the appropriate ARIMA (1, 1, 4) model are presented in equation 6. Where is the return of rubber price, 0.0015 is the intercept, 0.50 is the estimated slope for AR term, that is the autoregressive coefficient, and y_{t-1} is the first lag of the rubber return series. –0.14 is the slope for the MA term, that is, the moving average coefficient, and y_{t-4} is the 4th lag of the moving average.

$$y_t = 0.0015 + 0.50_{y_{t-1}} - 0.14_{\alpha_{t-4}} \qquad (6)$$

CONCLUSION

A wide range of rubber materials is used in the textile manufacturing process. One of such key consuming areas in the rubber calendaring process in the textile industry is to make various types of fabrics. Rubber rollers, rubber moulded products, rubber coating and rubber suit are some of the other major forms of rubber consumption in the textile industry. The price of natural Rubber in India is unstable, and market-based price risk management tools like futures and options are not regularly traded for this commodity. Natural rubber growers, traders and industrial buyers suffer from this volatile price. In this situation, looking for good price risk management tools is essential. This study aims to develop a price forecast model to manage the price risk of natural Rubber in India. Using Box Jenkins methodology, we have developed an appropriate model to forecast the price of RSS-1 Rubber in India. The selected best model for prediction is ARIMA (1, 1, 4), that is, AR (*1*), I (*1*) and MA (*4*). The AR (1) term coefficient is 0.50, and MA (4) is –0.14; the line plot of the actual and fitted values confirms that the developed model is a good fit. This model will help rubber growers, traders, corporations, and governments make accurate managerial decisions. ARIMA is a univariate time series model; many studies on different price determinants of rubber prices in the world market have identified various price determinants. Hence using multivariate models like VAR and VECM, one can develop a multivariate forecast model to predict the Rubber price in India.

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