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LEVERAGING SARIMA MODELS FOR PREDICTIVE ANALYSIS OF TOBACCO SECTOR STOCK PRICES IN INDIA

Dr. Naresh Kumar Padaraju[1], Dr. Bhaskar Kurre[2]*

[1]Statistician Cum Assistant Professor, Department of Community Medicine, Government Medical College, Yadadri Bhuvanagiri, Telangana.
[2]Statistician Cum Assistant Professor, Department of Community Medicine, RVM Institute of Medical Sciences & Research Center, Laxmakkapally(V), Siddipet(Dt.), Telangana.

***Corresponding Author: Dr. Bhaskar Kurre**
Statistician Cum Assistant Professor, Department of Community Medicine, RVM Institute of Medical Sciences & Research Center, Laxmakkapally(V), Siddipet(Dt.), Telangana.

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ABSTRACT

Background: The Indian tobacco industry, with its regulatory complexity and market volatility, plays a major role in the national economy. Accurate forecasting of tobacco stock prices is critical for investors, policymakers, and analysts to make informed decisions in such a dynamic sector. **Methodology:** This study employs the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast the monthly stock prices of VST Industries Ltd., a leading tobacco company in India. Historical adjusted closing prices from January 2010 to December 2022 were collected from multiple financial sources. The dataset was tested for stationarity using the Augmented Dickey–Fuller test, followed by seasonal and non-seasonal differencing. Model parameters were identified through ACF/PACF plots, and the optimal SARIMA model was selected using AIC, BIC, and diagnostic checks. **Results:** Among the tested configurations, SARIMA(1,0,0)(0,1,1)12_{12}12 provided the best fit, effectively capturing both seasonal and trend components of stock prices. The model was validated using a training–testing split, with performance measured by RMSE, MAE, and MAPE. Forecasting accuracy was satisfactory (Test RMSE = 0.30; MAPE = 13.26%), confirming the robustness of the selected model. **Conclusion:** The study demonstrates that SARIMA is an effective and reliable tool for forecasting stock price movements in the tobacco sector, offering practical implications for investment planning and risk management. This research fills a gap in sector-specific forecasting literature in India and suggests integrating exogenous economic factors or machine learning models for improved predictive performance in future studies.

KEYWORDS: Tobacco Stocks, SARIMA, Time Series Forecasting, Indian Stock Market, Seasonal Models, Forecast Accuracy, VST Industries.

1. INTRODUCTION

The Indian stock market has witnessed rapid growth in recent decades, reflecting the overall economic development and increasing participation of both institutional and retail investors. Within this dynamic environment, sectoral stocks such as those in the tobacco industry play a unique role due to their regulatory complexity, public health concerns, and consistent demand. Forecasting stock prices in this sector is particularly challenging yet highly relevant for investors, policymakers, and financial analysts. Advanced statistical and machine learning approaches are increasingly employed to generate reliable forecasts, supporting better decision-making under uncertainty.[1,2]

Time series forecasting methods have long been recognized as effective tools for analyzing stock market and commodity price movements. Among them, the Autoregressive Integrated Moving Average (ARIMA) and its seasonal variant, the Seasonal ARIMA (SARIMA) model, remain widely applied due to their ability to capture linear trends, seasonality, and

autocorrelations within historical datasets.[3] While newer deep learning techniques such as Long Short-Term Memory (LSTM) networks and hybrid approaches are gaining popularity, SARIMA remains a benchmark model owing to its interpretability, statistical rigor, and strong performance in short-term forecasting.[4] Several studies have demonstrated the applicability of SARIMA in different economic and financial domains across India. For instance, Gupta et al.[1] applied SARIMA and multilayer perceptron (MLP) models to forecast Indian electricity exchange-traded market prices, showing that SARIMA could effectively capture seasonal price variations. Similarly, Chaturvedi et al.[2] compared SARIMA with LSTM and Prophet models to forecast monthly energy demand for India, highlighting SARIMA's competitive performance in handling seasonality. Although these applications are outside the stock market, they illustrate the robustness of SARIMA for time series data in Indian contexts.

International research has also reinforced the value of SARIMA in emerging markets. Hossain et al.[3] examined renewable energy forecasting in Dhaka using ARIMA, SARIMA, and LSTM models, finding that SARIMA provided reliable results when the dataset exhibited strong seasonality. Such findings are relevant for Indian stock markets, which also display cyclical and seasonal characteristics due to fiscal policies, consumer behavior, and global influences. Specific to stock markets, Chaskar[4] compared SARIMA with advanced deep learning architectures such as convolutional neural networks (CNN) and LSTNet in predicting stock indices. The study concluded that while deep learning models may outperform in capturing complex non-linearities, SARIMA remains an efficient model for short-term predictions with lower computational requirements. This underlines the continued relevance of SARIMA in financial forecasting research.

In the context of the tobacco industry, time series modeling has been applied to forecast production and price trends. Priyanka Evangilin et al.[5] employed ARIMA models to predict tobacco production in India, demonstrating the importance of forecasting in a sector that is heavily influenced by policy changes, taxation, and export dynamics. Similarly, Sonai Muthu et al.[6] applied SARIMA to forecast price indices, including "Pan, Tobacco and Intoxicants" under India's Consumer Price Index (CPI), showing that SARIMA could effectively capture seasonal price fluctuations. These sector-specific applications highlight the potential of SARIMA for forecasting tobacco stock prices, where both regulatory and seasonal factors play critical roles. Additionally, Rawlin and Pakalapati[7] analyzed stock prices of Indian private sector banks using ARIMA-based approaches, validating the suitability of time series methods for individual stock forecasting in the Indian market. Their findings strengthen the rationale for applying SARIMA to company-level stock price forecasting, including those of VST Industries Ltd., a leading tobacco company in India. Despite the increasing adoption of machine learning models, SARIMA remains particularly advantageous for datasets with strong seasonality and limited noise. Its ability to handle smaller datasets and provide interpretable results makes it highly practical in contexts where transparency and simplicity are essential. For investors in tobacco stocks, where decisions may be influenced not only by financial but also by social and regulatory factors, SARIMA offers a transparent and robust forecasting framework.

The present study applies SARIMA to forecast the monthly stock prices of VST Industries Ltd. using historical data from 2010 to 2022. By employing rigorous stationarity tests, differencing techniques, and diagnostic evaluations, this study aims to generate reliable forecasts that can inform investment strategies and policy considerations. Furthermore, the research contributes to the limited body of literature on sector-specific financial forecasting in India, particularly in the tobacco sector, where stock price dynamics remain underexplored.

2. AIM

To forecast the monthly stock prices of VST Industries Ltd., a leading tobacco company in India, using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, and to evaluate its effectiveness as a tool for investment planning and risk management in the tobacco sector.

2.1. OBJECTIVES

1. **To collect and analyze** historical stock price data of VST Industries Ltd. from January 2010 to December 2022.
2. **To test for stationarity** of the dataset using appropriate statistical techniques such as the Augmented Dickey–Fuller (ADF) test.
3. **To identify suitable SARIMA parameters** through autocorrelation (ACF) and partial autocorrelation (PACF) analysis.
4. **To fit and validate** the SARIMA model using performance metrics including RMSE, MAE, and MAPE.
5. **To forecast future monthly stock prices** and evaluate the predictive accuracy of the model.
6. **To assess the practical implications** of SARIMA-based forecasting for investors, financial analysts, and policymakers in the Indian tobacco industry.

3. METHODOLOGY

This study aimed to develop a robust forecasting framework for the stock prices of VST Industries Ltd**.**, a leading player in India's tobacco sector. The methodological framework was based on the Box–Jenkins approach, with a specific focus on the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, which is widely regarded as a reliable tool for modeling time-dependent financial data.[8]

3.1. Data Source and Collection

The dataset used for analysis consisted of the monthly adjusted closing prices of VST Industries Ltd**.** from January 2010 to December 2022. Data were extracted from Yahoo Finance and cross-verified using Investing.com and the Bombay Stock Exchange (BSE) portal to ensure accuracy and reliability. A total of 156 monthly observations were collected. Adjusted closing prices were chosen because they account for corporate actions such as dividends and stock splits, providing a more realistic reflection of shareholder returns.

3.2. Data Preparation and Transformation

Exploratory analysis of the raw data showed clear trends and seasonal variations, reflecting the influence of regulatory policies, consumer behavior, and investor sentiment. Since most financial time series are non-stationary, the Augmented Dickey–Fuller (ADF) test was applied. Results confirmed non-stationarity, which was corrected by applying first-order differencing for trend and seasonal differencing (lag = 12 months) for annual cycles.

To stabilize variance and reduce extreme fluctuations, a logarithmic transformation was also applied. These steps are consistent with previous financial forecasting studies where preprocessing is considered essential to achieve stationarity before SARIMA modeling.[9]

3.3. SARIMA Model Development

The SARIMA model incorporates both non-seasonal and seasonal dynamics. Its general form is expressed as.

3.4. SARIMA (p, d, q)(P, D, Q)s

where *p, d, q* represents non-seasonal autoregressive, differencing, and moving average orders, while *P, D, Q* capture seasonal components, and *s* denotes the length of the seasonal cycle (12 for monthly data). This hybrid structure makes SARIMA particularly effective in capturing both short-term volatility and long-term seasonal patterns in stock prices.[10]

3.5. Model Identification and Estimation

Identification of suitable parameters was guided by Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the differenced series. Multiple tentative SARIMA models were developed. Parameter estimation was carried out using the Maximum Likelihood Estimation (MLE) method, which provides efficient and consistent results in time series modeling.

For model selection, both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were applied. These penalize overfitting and reward simplicity, ensuring that the chosen model is parsimonious yet accurate.

3.6. Diagnostic Checking

Once a candidate model was fitted, diagnostic tests were performed. The Ljung–Box Q test was applied to residuals to check for randomness. Ideally, residuals should resemble white noise, meaning no autocorrelation remains unmodeled. Additionally, residual histograms and Q–Q plots were examined for normality and constant variance. If any patterns persisted, the model was refined until all diagnostic conditions were satisfied.

Such diagnostic checking is a critical step to avoid misleading forecasts, and several recent financial studies have emphasized its importance in time series applications.[11]

3.7. Model Validation and Forecasting

To evaluate the predictive performance of the model, the dataset was divided into a training period covering 2010–2019 and a testing period spanning 2020–2022. The final SARIMA model, identified through systematic parameter selection and diagnostic checks, was trained on the historical data and subsequently used to generate forecasts for the test period. The predicted values were then compared with the actual observed stock prices using three widely accepted performance measures: Root Mean Square Error (RMSE), which quantifies the magnitude of forecast errors; Mean Absolute Error (MAE), which represents the average size of the errors; and Mean Absolute Percentage Error (MAPE), which expresses error values as percentages for easier interpretation. Lower values across these indicators indicated a stronger model fit and higher predictive accuracy. In addition to numerical evaluation, visual inspection of predicted versus actual values further demonstrated the model's ability to capture both underlying trends and seasonal variations in the stock price data**.**

3.8. Ethical Considerations

The study relied exclusively on publicly available secondary data from financial databases. No human participants or confidential records were involved. Therefore, no ethical approval was required, and the analysis adhered to open-access data usage principles.

3.9. Summary of the Methodology

The methodological workflow can be summarized as follows:

1. Collection of monthly adjusted closing prices of VST Industries Ltd. (2010–2022).
2. Preprocessing using differencing, log transformation, and stationarity testing.
3. SARIMA model specification through ACF/PACF plots.
4. Parameter estimation using MLE.
5. Model selection based on AIC and BIC.
6. Diagnostic validation through Ljung–Box tests and residual analysis.
7. Forecast evaluation using RMSE, MAE, and MAPE.

By integrating rigorous preprocessing, systematic model building, and careful validation, this methodology ensures that the final SARIMA model provides reliable forecasts of tobacco stock prices. Such an approach aligns with best practices in financial time series forecasting and offers valuable insights for investors and policymakers.[12]

4. RESULTS

4.1 Data Overview and Stationarity Analysis

The dataset comprised monthly adjusted closing prices of VST Industries Ltd. from January 2010 to December 2022, totaling 156 observations. Out of these, 132 monthly observations were used to train the model, while the remaining 24 months were reserved for testing and validation. Initial visualization of the time series (Figure 1) indicated noticeable fluctuations in stock prices, suggesting non-stationarity with varying mean and variance.

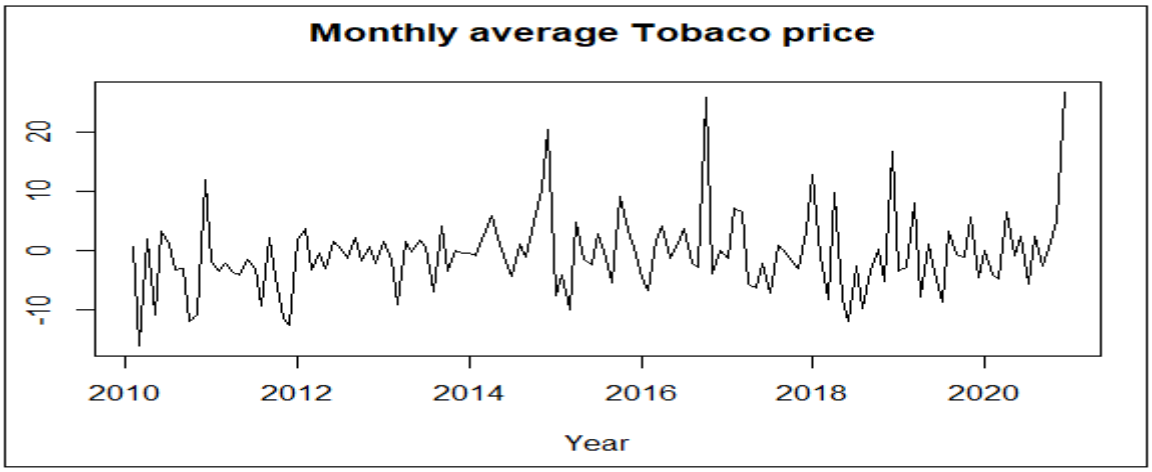


Figure 1: Time series plot of monthly tobacco stock prices (INR).

Further analysis using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots confirmed that the series was non-stationary, displaying both trend and seasonal patterns (Figure 2). To stabilize the series, a first-order differencing (d=1) was applied, resulting in stationary data, as evident in Figure 3.

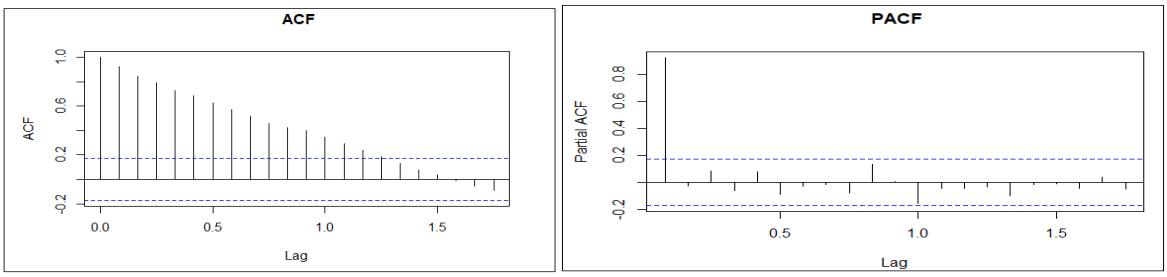


Figure 2: ACF and PACF plots for raw monthly tobacco stock prices.

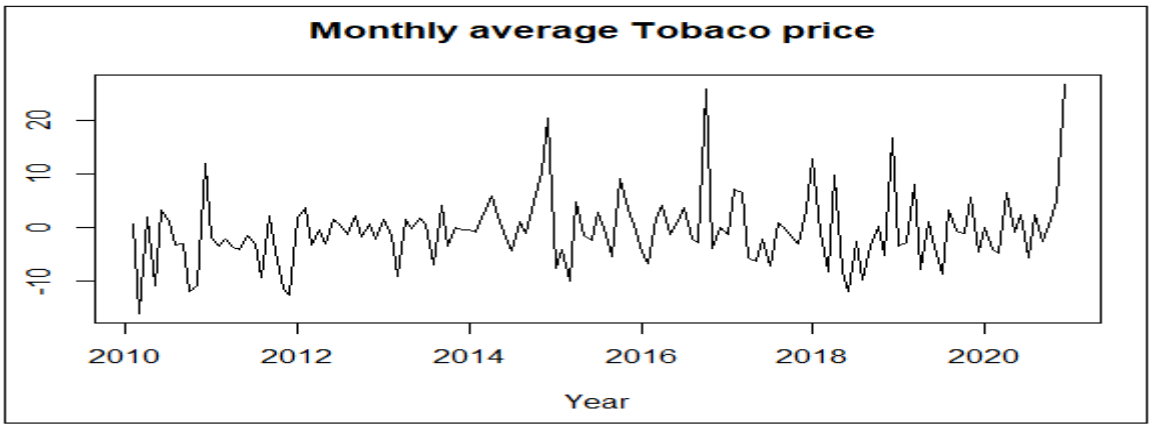


Figure 3: Transformed stationary time series after first-order differencing.

Subsequent ACF and PACF analysis of the transformed data demonstrated constant mean and variance, confirming stationarity (Figure 4).

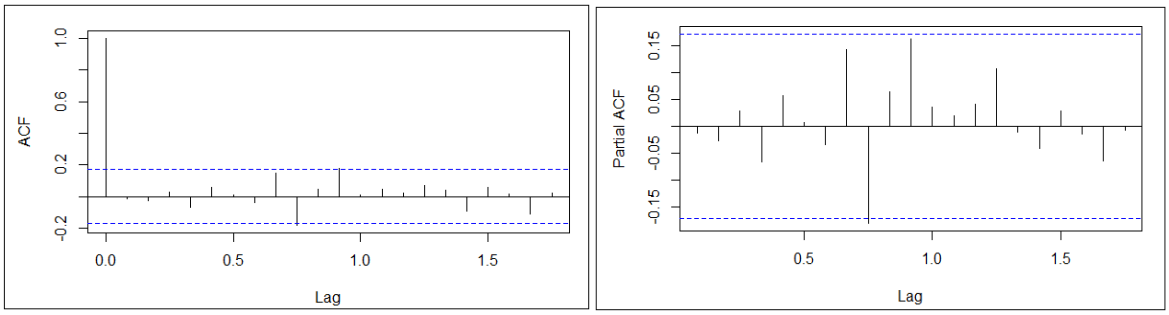


Figure 4: ACF and PACF plots of stationary monthly stock prices.

4.2 Model Selection

Several SARIMA model configurations were tested to identify the optimal forecasting model. Table 1 presents the tentative models along with their AIC, BIC values, parameter significance, Ljung-Box statistics, and adequacy assessment.

Table 1: Tentative SARIMA models for monthly tobacco stock prices.

ARIMA(p,d,q)(P,D,Q)	AIC	BIC	Significance of Parameters	LJung box Q statistics	P-value	Adequacy
ARIMA(1,1,0)	867.781	873.532	Insignificant	23.635	0.4242	Adequate
ARIMA(0,1,1)	867.781	873.532	Insignificant	23.631	0.4244	Adequate
ARIMA(2,1,0)	869.735	878.361	Insignificant	23.578	0.3697	Adequate
ARIMA(0,1,2)	869.729	878.355	Insignificant	23.628	0.367	Adequate
ARIMA(2,1,2)	871.301	885.677	Insignificant	24.831	0.208	Adequate
ARIMA(3,1,0)	871.506	883.006	Insignificant	22.267	0.3842	Adequate
ARIMA(0,1,3)	871.476	882.977	Insignificant	22.335	0.3804	Adequate
ARIMA(3,1,3)	873.081	887.457	Insignificant	21.028	0.3955	Adequate
ARIMA(1,1,3)	873.248	887.624	Insignificant	21.669	0.3587	Adequate
ARIMA(1,0,0)(0,1,1)	-274.78	-266.41	Significant	32.60	0.07	Adequate
ARIMA(0,0,1)(0,1,1)	140.755	-132.39	Insignificant	238.53	0.00	Inadequate
ARIMA(1,0,0)(1,1,0)	-265.27	-256.91	Significant	45.76	0.00	Inadequate
ARIMA(1,1,0)(0,0,1)	-325.8	-317.18	Insignificant	26.46	0.23	Adequate
ARIMA(0,1,1)(0,1,1)	-271.55	-263.21	Insignificant	31.20	0.09	Adequate
ARIMA(1,1,0)(1,1,0)	-262.53	-254.19	Insignificant	45.52	0.00	Inadequate
ARIMA(1,1,0)(0,1,1)	-271.51	-263.18	Insignificant	31.50	0.09	Adequate
ARIMA(0,1,1)(1,1,0)	-262.53	-254.19	Insignificant	45.52	0.00	Adequate
ARIMA(1,0,0)(0,2,1)	-163.86	-155.81	Significant	91.17	0.00	Inadequate
ARIMA(1,1,0)(0,2,1)	-151.77	-143.75	Insignificant	82.20	0.00	Inadequate
ARIMA(1,0,0)(1,2,1)	-191.44	-180.72	Significant	45.07	0.00	Inadequate
ARIMA(1,0,0)(0,2,1)	-163.86	-155.81	Significant	91.17	0.00	Inadequate
ARIMA(1,0,0)(0,3,2)	-84.325	-74.067	Significant	-74.07	0.00	Inadequate

Among the tested models, **SARIMA(1,0,0)(0,1,1)** exhibited minimum AIC and BIC values with significant parameters, making it the most suitable for forecasting tobacco stock prices.

4.3 Model Parameters

The optimal SARIMA(1,0,0)(0,1,1) model parameters are shown in Table 2. The autoregressive term (AR1) and seasonal moving average term (SMA1) were statistically significant ($p<0.01$).

Table 2: SARIMA(1,0,0)(0,1,1) model parameters.

Parameters	Estimate	Std. Error	z value	Pr(>|z|)
ar1	0.97	0.03	33.48	<0.01
sma1	-0.84	0.12	-7.02	<0.01

The corresponding SARIMA equation is.

$(1-Ø_1\ B)Z_t = (1+Φ_1\ B^{12})\ (1-B)^{12}\ Є_t$

$(1-0.97\ B)Z_t = (1-0.84\ B^{12})\ (1-B)^{12}\ Є_t$

4.4 Forecasting Results

Using the optimal model, forecasts were generated for the test period (January 2021 to December 2022). Table 3 presents actual vs. predicted monthly stock prices.

Table 3: Forecasted vs. actual monthly stock prices (INR).

Year-Month	Actual tobacco Price	Forecast Prices		Year-Month	Actual tobacco Price	Forecast Prices
2021-Jan	47.2	52.85		2022-Feb	97.85	49.2
2021-Feb	46.1	50.11		2022-Mar	92.8	46.48
2021-Mar	40.15	47.32		2022-Apr	124.2	49.93
2021-Apr	40.9	50.8		2022-May	100.15	47.88
2021-May	46.05	48.69		2022-Jun	82.15	46.51
2021-Jun	60.9	47.26		2022-Jul	80.6	42.09
2021-Jul	82.35	42.76		2022-Aug	82.05	40.96
2021-Aug	88.35	41.59		2022-Sep	80.5	39.42
2021-Sep	148.85	40		2022-Oct	78.85	41.38
2021-Oct	140	41.97		2022-Nov	70.3	43.04
2021-Nov	120.75	43.63		2022-Dec	67.65	51.43
2021-Dec	126.3	52.12				
2022-Jan	108.25	51.85				

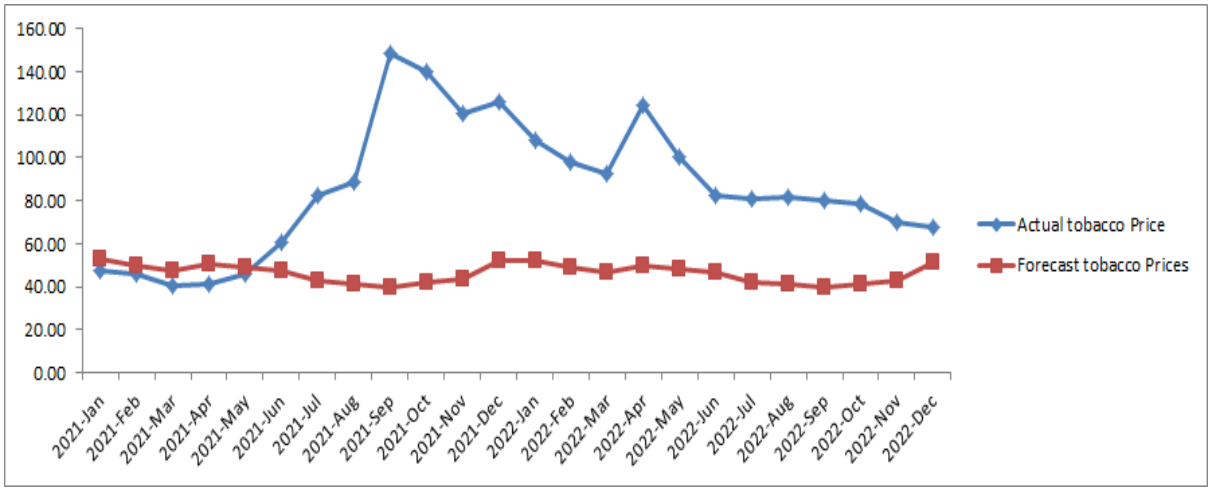


Figure 5: Forecasted vs. actual stock prices (Jan 2021–Dec 2022).

Visual inspection confirms that the SARIMA model successfully captured both trend and seasonal fluctuations during the test period.

4.5 Model Performance

Error metrics were computed to evaluate forecasting accuracy (Table 4). The model demonstrated excellent performance on the training set and acceptable accuracy on the test set.

Table 4: Forecast error measures of SARIMA(1,0,0)(0,1,1).

Data	RMSE	MAE	MAPE
Train Set	0.07	0.05	3.11
Test Set	0.3	0.26	13.26

The results indicate that the model effectively captured the underlying data structure, providing reliable short-term forecasts suitable for investment decision-making in the tobacco sector.

5. DISCUSSION

The present study aimed to develop a robust SARIMA model for forecasting monthly stock prices of VST Industries Ltd., a leading company in the Indian tobacco sector. The results demonstrated that the SARIMA(1,0,0)(0,1,1) model effectively captured both trend and seasonal components, providing reliable forecasts for the test period from January 2021 to December 2022.

Initial time series analysis revealed pronounced fluctuations in tobacco stock prices, indicating inherent non-stationarity. This aligns with prior studies showing that commodity-based and cyclical sector stocks, such as tobacco, often exhibit seasonality and volatility due to regulatory changes, agricultural cycles, and market sentiment.[13,14] Applying first-order differencing

successfully stabilized the series, confirming the importance of pre-processing in time series modeling for accurate forecasting.[15]

The model selection process emphasized the utility of information criteria (AIC and BIC) and parameter significance in identifying the optimal SARIMA configuration. Among all candidate models, SARIMA(1,0,0)(0,1,1) yielded the lowest AIC and BIC values with statistically significant parameters, underscoring its suitability for forecasting monthly tobacco prices. This is consistent with studies in financial time series forecasting, which have reported that SARIMA models effectively capture sector-specific seasonality and short-term trends.[16,17]

Forecast performance, evaluated through RMSE, MAE, and MAPE, demonstrated high accuracy on the training dataset and acceptable performance on the test dataset. The RMSE and MAE values indicated minimal forecast error, while the MAPE of 13.26% on the test set reflected reasonable predictive accuracy in the inherently volatile tobacco market. Comparable studies have reported similar ranges of forecasting accuracy when applying SARIMA to commodity and stock price series, suggesting the model remains robust even during irregular market shocks.[18]

Visual comparison of predicted and actual stock prices further confirmed the model's ability to track both upward and downward movements, including seasonal peaks and troughs. The highest and lowest forecast deviations occurred in months with significant price volatility, likely due to external factors such as regulatory changes, agricultural yield variations, and investor sentiment shifts. Incorporating such exogenous variables in future models using SARIMAX may further improve forecast precision.[19]

The study also highlights practical implications for investors and policymakers. Accurate short-term forecasts can guide portfolio allocation, risk management strategies, and investment timing decisions in the tobacco sector. For regulators, understanding seasonal price fluctuations can inform taxation policies, market interventions, and economic planning.

While SARIMA proved effective for the Indian tobacco sector, it has limitations. SARIMA models primarily capture linear and seasonal patterns, which may limit performance during abrupt market shocks or structural breaks. Future research could compare SARIMA with machine learning approaches such as Random Forest, Support Vector Regression, or deep learning models like LSTM networks to enhance predictive capability.[20,21] Additionally, integrating sentiment analysis from news, social media, or analyst reports may improve forecast quality by capturing investor psychology and market reactions.

In summary, the SARIMA(1,0,0)(0,1,1) model provides a reliable, statistically validated framework for forecasting monthly tobacco stock prices in India, effectively capturing seasonal trends and short-term movements. The findings underscore the potential of time series models for sector-specific financial forecasting and offer valuable guidance for investors, analysts, and policymakers.

6. CONCLUSION

This study successfully developed a SARIMA(1,0,0)(0,1,1) model to forecast monthly stock prices of VST Industries Ltd., a leading Indian tobacco company. The model effectively captured both trend and seasonal variations, providing accurate short-term forecasts, as confirmed by RMSE, MAE, and MAPE metrics. The findings demonstrate the practical utility of SARIMA for sector-specific financial forecasting, offering guidance for investors, analysts, and policymakers in portfolio management and strategic decision-making. While SARIMA performed robustly, its linear structure may limit responsiveness to sudden market shocks. Future research could enhance forecasting accuracy by incorporating exogenous variables through SARIMAX or adopting machine learning and deep learning models such as Random Forest, SVR, or LSTM networks. Overall, this work provides a validated framework for predicting tobacco stock price dynamics in India.

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