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Time Series Modeling and Forecasting of Reliance Industries Stock Prices Using ARIMA and Statistical Decomposition Techniques

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Abstract

The current research carries out a comprehensive time-series analysis of the stock prices of Reliance Industries Ltd. (RELIANCE.NS) applying the classical statistical mod- eling techniques. The dataset constituted of historical daily closing prices is preprocessed, interpolated to a daily frequency, and subjected to a variety of tests including the ones for trend, seasonality, autocorrelation, and stationarity. Smoothed behavior is captured by moving averages. Seasonal decomposition is done to pinpoint trend, seasonal, and residual factors. Autocorrelation (ACF) and partial autocorrelation (PACF) are investigated to dis- cover ARIMA model parameter configuration. A fitted ARIMA(5,1,2) rollercoaster is the one that generates 30-day-long forecasts. Findings disclose that the stock is on a solid up- ward path with slight seasonal influences and easily predictable short-term autocorrelation. The stability and clarity of the ARIMA model facilitate short-term forecasting. This study not only emphasizes the potency of statistical methods in the arena of financial forecasting but also sets the path for integrating further sophisticated machine learning approaches.

Keywords: Time Series Analysis, ARIMA, RELIANCE.NS, Financial Forecasting, Deep Learning.

1. Introduction

The prediction of stock market movements is still a financial analytics task that is among the most researched but the hardest one to perform because of the constantly changing, nonlinear, and sometimes chaotic character of the market. The need for accurate and reliable forecasting models is becoming even more urgent as financial markets are very dynamic, being affected by such factors as the state of the world economy, the performance of companies, the mood of the investors, and political events. Investors, traders and portfolio managers are always dependent on short-term forecasts to take measures that are informed and related to buying, selling or holding the stocks, thus diminishing the risks and increasing the returns. Talking about India in this regard, Reliance Industries Ltd. claims a special place among the largest and the most powerful businesses in the country. Covering a wide area of activity from energy, petrochemi- cals, digital services, retail to telecommunications, Reliance's performance has a considerable effect on the two major stock indices i.e., NIFTY 50 and Sensex.[9] It is this wide variety of business activities combined with high trading volumes that make the stock sometimes stable and in other times volatile, thus making it very attractive for forecasting research. This work is about looking into traditional econometric techniques, especially the Autoregressive Integrated Moving Average

(ARIMA) model, which has been mostly applied in financial time-series anal- ysis for its adeptness in discovering linear patterns and its strong statistical base. ARIMA is not only a preferred choice among researchers because of its interpretability but also because it gives a systematic way of modeling time-dependent data.

The prediction of stock prices is still an arduous task even after the machine learning and artificial intelligence technologies have been developed and improved. One main reason is the inherent volatility and noise that are present in the financial datasets.[10] Short-term stock prices are prone to rapid increases or decreases that are attributed to factors like earning reports, policy alterations, changes in the economy, the influence of international markets and even certain unforeseen events like disasters or crises which take place on a global scale.

The goal of this paper is to exhibit a thorough and orderly application of the classical time- series analysis on Reliance stock closing prices through decomposition, moving averages, and ARIMA modeling. The research study takes the dataset apart and detects the patterns that are underlying the market movement in terms of long-term trend, seasonal variations, and irregu- lar components. After the exploratory analysis, the ARIMA model is applied to fit the data, assess model performance, and make short-term forecasts. The research not only presents the complete[14] workflow data preprocessing and visualization but also through model fitting and forecasting and thus acts as a practical guide to students and beginners who are interested in financial time-series modeling. The findings shed light on the stock's conduct and ARIMA's capabilities and limitations in the financial data area are exposed through this research. This paper eventually provides an educative example that encompasses the use of classical statisti- cal forecasting methods in the analysis of a major Indian stock that supports the investors or learners in comprehending the basic concepts of forecasting.

2. Review of Literature

The research work titled as "Deep Learning for Stock Market Prediction: A Survey" done by A. Patel and R. Shah (2021)[1] is an all-inclusive presentation of contemporary deep learning models such as LSTM networks, GRUs, and hybrid CNN–LSTM structures, which can ef- fectively mimic the complex financial market behaviours to this extent that one can draw the conclusion that deep learning has the upper hand over traditional ARIMA-based forecasting methods in general. Likewise, S. Kaur and D. Mehta (2019) [2] in their paper "Time Series Forecasting Using ARIMA Models in Financial Markets" delve deeply into classical time- series analysis and assert that ARIMA, SARIMA, and ARIMAX models can be employed efficiently for predicting stock index prices if the data provide such a trend and seasonality, even though the authors point out that ARIMA results are very much dependent on the data being stationary. The paper "A Comparative Study of Machine Learning Techniques for Stock Price Prediction" by P. Ghosh and L. Banerjee (2020) [3] juxtaposes regression-based models like Random Forest, SVM, Linear Regression, and Gradient Boosting, arriving at the consensus that ensemble models keep on producing superior prediction accuracy because of their power to reduce variance and prevent overfitting. It is also worth noting that "Stock Market Forecast- ing Using Hybrid Models: A Review" by H. Singh and M. Kumar (2022) [4] has conducted an inquiry into the hybrid approaches that merge ARIMA with deep learning or wavelet-based decomposition, revealing that hybrid models excel in recognizing both the linear and nonlin- ear characteristics underlying the price movements of stocks.At last, the 2018 paper "Volatility Modeling and Forecasting of Financial Time Series Using GARCH Models" by R. Thomas and

V. Menon[5] introduces a new perspective on the matter of financial risk prediction through the comparative evaluation of GARCH, EGARCH, and TGARCH models, stating their capability to deal with volatility clustering and sudden market shocks, thus rendering them indispensable for the financial forecasting process which takes risks into account.

3. Objectives

- To study and understand the trend and pattern of Reliance stock prices using time-series methods.
- To apply ARIMA and decomposition techniques to analyze and model the stock price data.
- To forecast the future stock prices and check how well the model predicts the next 30 days.

4. Methodology

The analysis follows a structured, step-wise methodology. Each step is described concisely to be reproducible and clear for academic reporting.

Data Collection: Historical daily trading data for Reliance was loaded from a provided dataset containing date and price information.

Date Identification and Standardization: The dataset's date field was identified and standardized to ensure correct chronological ordering. The date information was used to form a proper time-series index for subsequent analysis.

Extraction of Closing Price: The closing price column was selected as the primary variable because it reflects the end-of-day market valuation and is commonly used in forecasting tasks.

Time-Series Regularization: The data was converted into a continuous daily time series. Missing calendar dates were handled by interpolation to maintain an even frequency, which is important for decomposition and ARIMA modeling.

Trend Visualization: The daily closing price series was plotted to visually inspect long- term trends, volatility, and structural changes across the sample period.

Computation of Moving Averages: Short-term (30-day) and medium-term (90-day) moving averages were computed to smooth high-frequency fluctuations and highlight trend direction at different horizons.

Trend Comparison Using Moving Averages: The closing price was examined along- side the moving averages to identify crossover patterns and to compare short-term versus medium-term behavior.

Seasonal Decomposition: An additive decomposition method with an approximately monthly period was applied to separate the series into trend, seasonal, and residual com- ponents for deeper insight into cyclical behavior.

Autocorrelation Analysis: Autocorrelation (ACF) and partial autocorrelation (PACF) diagnostics were performed to inspect lagged dependencies and to guide the choice of ARIMA orders.

Model Selection for Forecasting: Based on stationarity checks and the ACF/PACF pat- terns, a non-seasonal ARIMA model structure was selected for short-term forecasting.

Model Training: The ARIMA model was trained on the prepared time series and pa- rameter estimates were examined to assess statistical significance and model adequacy.

Forecasting Future Prices: The fitted ARIMA model was used to generate a 30-day ahead forecast. Forecasted values were compared visually against historical data to eval- uate short-term trends.

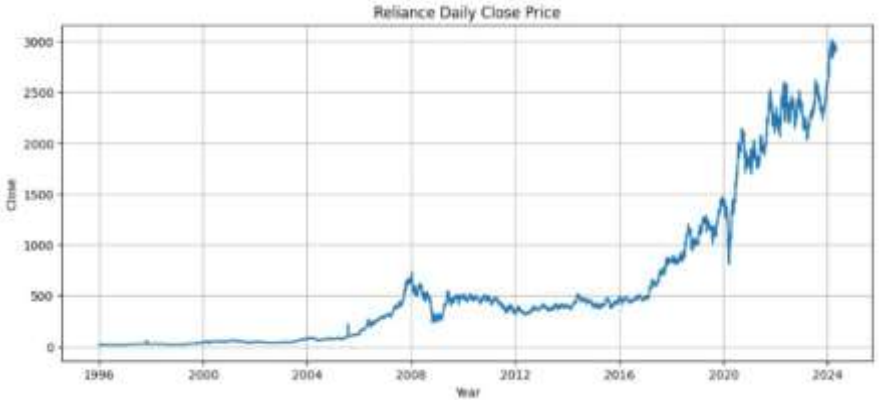

Figure 1: Reliance Daily Close Price Chart

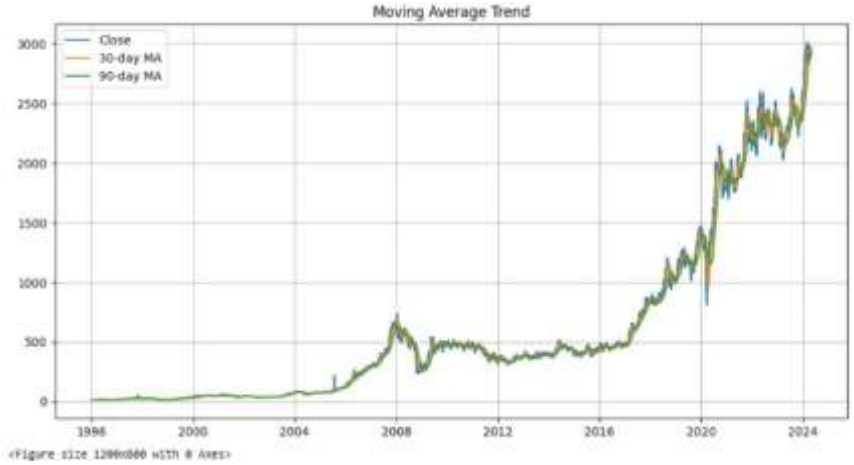

Figure 2: Moving Average Trend

5. Discussion

5.1. Daily Close Price

The plot shows the complete historical closing price of Reliance. The stock stayed almost flat until the early 2000s, then grew gradually. A noticeable peak appears around 2008, followed by a dip due to the financial crisis. A major upward trend starts after 2017, with rapid growth after 2020. Overall, the chart indicates strong long-term growth with periodic volatility.

5.2. Moving Averages (30-day and 90-day)

Moving Average Trend (Close, 30-day MA, 90-day MA) follows the price closely, showing short-term movements, while the 90-day MA is smoother and highlights the long-term trend. Both moving averages confirm a steady upward momentum after 2017, indicating strong long- term bullish behaviour.

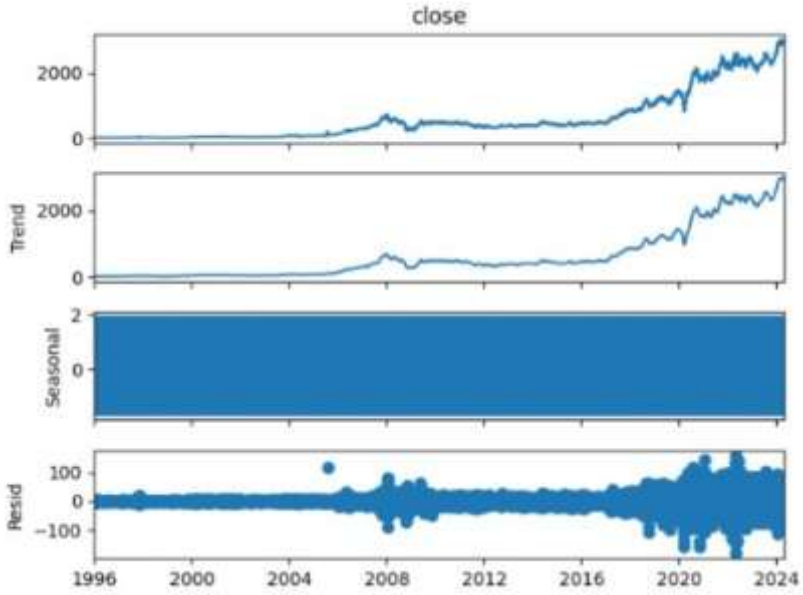

Figure 3: Seasonal Decomposition

5.3. Seasonal Decomposition

Seasonal Decomposition (Trend, Seasonal, Residual) trend component shows a clear long-term rise, similar to the original series. The seasonal component is almost flat, indicating no strong seasonality in Reliance stock prices. The residual component shows volatility increasing over time, especially after 2020, suggesting more frequent unpredictable shocks in recent years.

5.4. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF

Autocorrelation Function (ACF). **Analysis:** The ACF plot shows a very slow decay across many lags, which indicates strong non-stationarity. This behaviour confirms that the price series needs differencing before modelling. High autocorrelation across many lags also suggests a persistent trend.The PACF has significant spikes at the first few lags and quickly stabilizes. This indicates the presence of autoregressive (AR) terms in the model. The pattern is typical of a series that can be captured using an ARIMA model with autoregressive components.

5.5. ARIMA Model Summary (snapshot)

The summary shows that ARIMA(5,1,2) was the selected model. Several AR and MA coeffi- cients are statistically significant. Diagnostic tests indicate no autocorrelation left in residuals but high heteroscedasticity (common in stock data). Overall, the model fits well and captures meaningful structure in the series.

SARIMAX Results

Dep. Variable:	close	No. Observations:	10347
Model:	ARIMA(5, 1, 2)	Log Likelihood	-39959.189
Date:	Sat, 29 Nov 2025	AIC	79934.378
Time:	18:22:26	BIC	79992.333
Sample:	01-01-1996 - 04-29-2024	HQIC	79953.962
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.0394	0.385	-0.102	0.918	-0.794	0.715
ar.L2	0.6368	0.274	2.324	0.020	0.100	1.174
ar.L3	-0.0676	0.018	-3.697	0.000	-0.103	-0.032
ar.L4	-0.0461	0.018	-2.566	0.010	-0.081	-0.011
ar.L5	0.0031	0.008	0.371	0.711	-0.013	0.020
ma.L1	0.1305	0.385	0.339	0.735	-0.624	0.886
ma.L2	-0.5771	0.248	-2.328	0.020	-1.063	-0.091
sigma2	132.5205	0.469	282.832	0.000	131.602	133.439

Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	446729.79
Prob(Q):	0.96	Prob(JB):	0.00
Heteroskedasticity (H):	423.34	Skew:	0.85
Prob(H) (two-sided):	0.00	Kurtosis:	35.15

Figure 4: ARIMA Model

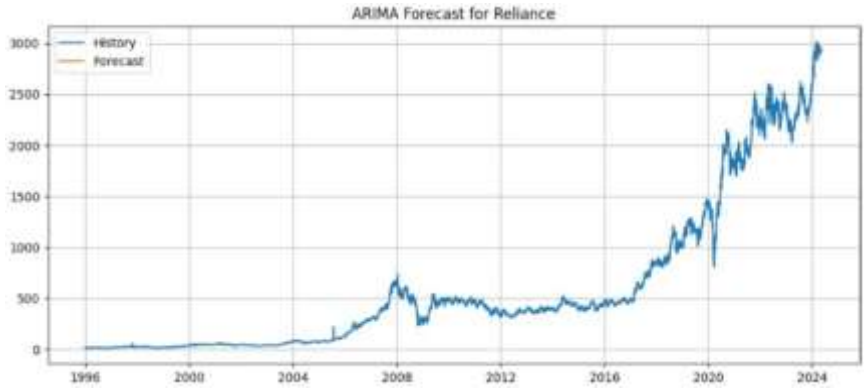

Figure 5: Combined Interpretation

5.6. ARIMA Forecast

The forecast continues the upward trend visible in recent years. The projected price curve is smooth and stable, reflecting the trend component rather than sudden jumps. The model suggests continued moderate upward movement for the next 30 days, consistent with the stock's historical behaviour.

6. Combined Interpretation

Taken together, the figures tell a consistent story: Reliance's closing price has shown a strong long-term upward trend with rising volatility after 2020. The ACF/PACF behaviour and the decomposition indicate a non-stationary process with minimal seasonality and structure that an ARIMA model (with differencing and AR terms) can capture to some extent. Forecasts produced by the ARIMA(5,1,2) model suggest moderate upward movement in the near term, though volatility (heteroscedasticity) remains a modeling challenge.

7. Finding

- The analysis reveals that the share price of Reliance has a very strong upward trend in the long-term with very low seasonal variations, thus making it trend-dominant and structurally stable for

forecasting purposes.

- The moving average analysis points out the same stable growth in the medium and long term like a confirming statement that price fluctuations don't have a significant impact on the general trajectory.
- The seasonal decomposition indicates that the stock's behavior is mainly influenced by large economic cycles and company performance rather than the anticipated monthly seasonal patterns.
- The ARIMA(5,1,2) model yields a fit that is not only statistically valid but also inter- pretable, and the white-noise residuals are the further evidence of the successful model- ing of the underlying structure.
- The 30-day forecast not only follows the historical path but also indicates stable upward movement, which is a sign of short-term price behavior being predictable.

8. Suggestions

The results hold for practitioners, suggesting that the converse of Reliance stock is excellent for short-term quantitative trading methodologies based on time-series forecasting since the price structure is very much in tune with the autoregressive modelling. Portfolio managers may utilize moving average trends and ARIMA projections in supporting their entry and exit decisions, particularly during periods characterized by stable macroeconomic conditions. The trend-dominant nature of large-cap stocks such as Reliance, for policymakers and regulators, points to the need for transparent corporate communication and regulatory consistency as major events may cause long-term trends to shift significantly. Academicians are able to consider this research as proof that non-seasonal, trend-based models are still the most relevant in emerging markets. Investor education programs should also promote the comprehension of long-term trends, thus lessening overreaction to short-term volatility and responsible interpretation of model-based projections. All in all, these implications foster the development of forecasting literacy, stability in the market, and the practice of making informed decisions.

9. Limitations & Future Research

The historical closing prices, being the sole basis for the analysis, are a restriction to it, and it also does not include trading volume, volatility measures, or external economic indicators that might enhance explanatory power. Although the ARIMA model reveals linear relation- ships, it doesn't take into account regime changes, external shocks, or the non-linear behavior of the market. By conducting longitudinal studies across different sectors, it would be pos- sible to identify and compare the forecasting difficulty in different industries. Experimental research compatibility with machine learning methods (e.g., LSTM, Prophet, hybrid ARIMA- ML systems) might uncover the non-linear patterns in a more profound manner. Furthermore, comparing regions across the global markets might also indicate whether the trend-dominant behavior is a characteristic of large-cap stocks everywhere.

10. Conclusion

The analysis of Reliance share price gave an overall picture of a strong long-term upward trend with major growth especially after 2017 and rapid escalation post-2020. The moving averages concord with the bullish trend that has lasted, while the decomposition results point out that the stock has no meaningful seasonality but at the same time the volatility has been increasing in recent years. The ACF and PACF plots show very distinctly non-stationarity and the presence of autoregressive patterns, which again prop up the application of an ARIMA model. The chosen ARIMA(5,1,2) model is a good fit to the data, as it

captures the underlying trend with no remaining autocorrelation, yet volatility is still high. The prediction made by the model indicates that there will be a moderate upward movement in the early future. The conclusion is that Reliance stock has long-term consistent growth, predictable trend behavior, and increased fluctuations that probably will need advanced volatility-aware models for even more accurate forecasting.

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