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Long-term forecasting of stock prices using time series models: Evidence from solar industries India Ltd

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Abstract

Long-term stock price analysis is essential for understanding market dynamics and supporting investment decisions. Using data from the National Stock Exchange, the study focuses on Solar Industries India Limited's closing prices between January 1, 2000, and December 31, 2024. The primary objectives are to use time series analysis to model and predict closing prices, identify underlying trends, and investigate relationships with trading activity. An ARIMA model was used with Minitab software to account for data noise, trends, and seasonal fluctuations. Statistical criteria guided the model selection process, providing optimal fit and reliability. These charts helped determine trends, patterns, and seasonal elements. A total of 729 monthly observations were examined, and the best-fitting model was chosen using the Akaike Information Criterion (AICc). The Ljung-Box test verified that the ARIMA (0, 2, 1) model was the best model, as it had the lowest AICc and strong residual diagnostics ($p > 0.05$ for most lags). The forecasts showed anticipated pricing ranges with increasing uncertainty over time. Further statistical analysis was conducted to investigate the relationships between trading activity and stock price. While insights into the relationship between trade volume and price movement provide useful perspectives for market analysis, a strong forecasting model can help stakeholders make well-informed decisions. Overall, the integration of exploratory research with time series modeling provides a comprehensive framework for analyzing stock price behavior and forecasting future trends.

Keywords: ACF, ARIMA, Forecasting, PACF, Regression, Stock Price.

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1. Introduction

A key element of the global economy, the stock market represents the state of the economy and the mood of investors across various industries. Accurate stock price forecasting is crucial for investors, decision-makers, and financial analysts to make informed choices. Many methods, from sophisticated machine learning algorithms to conventional statistical models, have been developed in recent decades to forecast changes in the stock market.

1.1. Time Series Analysis in Stock Price Forecasting

The foundation of stock price forecasting has always been time series analysis. Time series models examine past pricing data to identify underlying trends, patterns, and seasonalities that can be used to forecast future changes. Within this field, one of the most popular statistical models is the Autoregressive Integrated Moving Average (ARIMA) model. Autoregression, differencing (to achieve stationarity), and moving averages are all combined in ARIMA models to capture different facets of time-dependent data. To ensure that ARIMA models are suitable for forecasting, the Box-Jenkins methodology provides a systematic way to identify, estimate, and diagnose them [1].

The effectiveness of ARIMA models in forecasting stock prices has been demonstrated in recent research. For example, an in-depth study of the ARIMA (Autoregressive Integrated Moving Average) model's ability to predict the returns of the S&P BSE Sensex and S&P BSE IT indices. Particularly in developing countries like India, their study offers important insights into how well time series models forecast stock market performance [2]. Likewise, studies on the stock prices of Maersk employed the ARIMA model to evaluate its predictive power, using the Box-Jenkins method for model identification and validation [1].

1.2. Challenges and Limitations of Traditional Models

Traditional time series models, such as ARIMA, are widely used, but they have drawbacks, especially when it comes to representing the complex and nonlinear character of financial markets. Economic data, corporate performance, geopolitical events, and investor psychology are just a few of the many variables that affect stock values, which makes them inherently volatile and unpredictable. The complex connections seen in financial data may not be adequately captured by traditional models, which frequently assume linear correlations [3].

1.3. Emergence of Machine Learning and Hybrid Models

Researchers are increasingly using hybrid models and machine learning techniques to overcome the shortcomings of classic statistical models. For instance, long short-term memory (LSTM) networks and recurrent neural networks (RNNs) are designed to process sequential data and have demonstrated promise in identifying the temporal connections in stock values. The performance of RNN, LSTM, and ARIMA models in stock price prediction was compared in a study that highlighted the advantages and disadvantages of each strategy [4].

Hybrid models, which blend machine learning algorithms with conventional statistical techniques, have also become popular. The integration of ARIMA with Support Vector Machines (SVM), for example, combines the advantages of both techniques, using SVM to capture nonlinear relationships and ARIMA to capture linear patterns. In comparison to solo models, these hybrid models have shown better predictive ability when used to forecast stock indexes [5].

1.4. Incorporating External Factors and Relational Data

The historical price data of a single stock is the main focus of traditional time series models, which may ignore the impact of related stocks and outside variables. In the stock market, where the prices of related stocks can have a substantial impact on one another, a recent study highlights the significance of taking linkage effects into account. Relational data and external variables can be incorporated into models to provide a more comprehensive picture of market dynamics and produce predictions that are more accurate [6].

1.5. The Case of Solar Industries India Limited

Solar Industries India Limited, a prominent player in the industrial sector, has experienced significant growth and transformation over the past few decades. Examining its stock price changes provides important information about the variables affecting its success and serves as a case study for using different forecasting techniques. The company's stock price is influenced by a variety of intricate elements due to its exposure to both domestic and foreign markets, which makes it a prime choice for time series analysis and forecasting.

The study's objective is to provide an extensive time series analysis of Solar Industries India Limited's closing prices. The study looks for underlying patterns, trends, and seasonality in the price movements of the stock by using the ARIMA model. To provide a comprehensive understanding of the elements impacting the stock's performance, the study will also investigate the relationship between trading activity and closing prices.

For investors, analysts, and policymakers, it is essential to understand the mechanics of stock price changes. By utilizing exacting time series analytic methods on an extensive dataset, this research adds to the corpus of information already available on stock price prediction. In the end, the results can help create more informed and effective financial markets by influencing regulatory decisions, risk management procedures, and investment strategies. With sophisticated machine learning techniques and hybrid approaches complementing and, in many circumstances, replacing older statistical models, the field of stock price forecasting has seen tremendous change. By utilizing the advantages of these approaches, this study aims to provide both academically sound and practically applicable insights into the analysis and forecasting of Solar Industries India Limited's stock price fluctuations.

Despite the extensive body of work on stock price forecasting, there remains a critical need for focused, long-term analyses of individual stocks within emerging markets such as India. Solar Industries India Limited, given its substantial growth, strategic importance in the industrial sector, and exposure to both domestic and international markets, presents a unique opportunity to investigate how advanced time series methods can enhance price prediction accuracy. Accurately forecasting its stock price can support better decision-making for investors and stakeholders, particularly in high-volatility sectors.

While numerous studies have applied ARIMA and hybrid models to broad market indices or multiple stocks, there is limited research focused on the long-term forecasting of an individual company's stock, particularly within the Indian context. Moreover, few studies integrate trading activity data, such as the number of traders with time series models to explore how trading behavior interacts with price movements. This study aims to fill that gap by combining ARIMA-based time series forecasting with trading activity analysis, offering a more holistic view of stock price dynamics.

2. Literature Review

The implications of stock market forecasting for investing strategies, risk management, and economic policymaking have made it a significant topic of study for scholars and financial experts. Various levels of accuracy have been achieved in stock price prediction using both contemporary machine learning approaches and traditional statistical models [7]. The best forecasting techniques must be identified by comprehending both historical and contemporary developments.

Forecasting stock prices has extensively utilized the ARIMA (Autoregressive Integrated Moving Average) model because of its capacity to handle non-stationary data. It forecasts future movements by using linear dependencies and historical values [8]. A study using ARIMA on the Shanghai Stock Exchange discovered that it provided steady projections but struggled with extremely volatile stocks [9]. Financial time series volatility clustering is frequently captured by Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. According to a study, GARCH models perform better than ARIMA in managing stock market volatility, especially when reacting to external economic shocks [10].

The capacity of machine learning methods, especially deep learning, to identify intricate patterns in data has led to their increased use in stock price predictions. Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs) have demonstrated notable advancements over conventional models by integrating memory cells that store historical data [11]. According to a study, for S&P 500 stocks, LSTMs outperformed ARIMA in terms of predicting accuracy [12]. CNNs, which are usually used for image processing, have been modified to forecast financial time series. By extracting significant temporal information, a study combined CNNs and LSTMs to improve the accuracy of stock price predictions [13].

Hybrid forecasting models have been created by fusing machine learning methods with conventional time series models. The advantages of both statistical and deep learning models are combined in hybrid models like ARIMA-LSTM. According to a study, LSTM manages nonlinear dependencies, whereas ARIMA successfully captures linear trends, producing better prediction results [14]. ARIMA has been used with Support Vector Machines (SVM) and SVR to enhance stock price forecasts. According to a study, ARIMA-SVR models forecast the NASDAQ index better than standalone ARIMA models [15].

Stock prices are greatly impacted by macroeconomic factors, including GDP, inflation, and interest rates. According to a study that examined the connection between macroeconomic variables and stock market movements, adding these variables to forecasting models improves prediction accuracy [16]. Sentiment analysis of news articles and social media data has gained traction in stock market prediction. A study demonstrated that Twitter sentiment strongly correlates with stock price fluctuations [17]. Likewise, research found that news headlines might more accurately forecast S&P 500 movements [18].

Economic announcements, mergers and acquisitions, and corporate earnings reports all have a significant influence on stock prices. The impact of quarterly earnings reports on stock price volatility was examined in a study that also highlighted the function of event-based forecasting models [19]. In one study, stock price swings after central bank announcements were predicted using event-driven machine learning models [20].

A hybrid ARIMA-LSTM model was used in a recent study to forecast Microsoft's stock values, demonstrating better accuracy than conventional models [21]. According to a study that examined how well deep learning predicted the prices of the BSE Sensex and NIFTY 50 indexes, hybrid models performed better than independent models [22].

Interpretability has become more important as AI-based models become more complicated. According to a study, explainable AI methods are crucial for financial forecasting in order to increase investor trust and transparency [23]. In financial forecasting, quantum computing is becoming a new frontier. Early indications of possible advances were found in a study that investigated quantum machine learning techniques for stock price prediction [24].

Forecasting stock prices has changed dramatically over time, moving from conventional time series models like GARCH and ARIMA to sophisticated deep learning methods and hybrid strategies. Adding outside variables such as sentiment analysis and macroeconomic indicators further improves prediction accuracy. Future studies should focus on developing explainable AI models and utilizing quantum computing to enhance the precision of stock market forecasts. This study outlines potential research directions for future investigations and provides a comprehensive analysis of current developments in stock price forecasting.

3. Methodology

The study involves stock market data for Solar Industries India Limited, obtained from the NSE. The dataset includes information on daily trading and covers the period from December 13, 2021, to December 11, 2024, and includes 729 observations. The number of traders and the closing price are the main variables of utility in this study. For time series analysis, the data was cleaned and organized to remove any missing values or inconsistencies.

Time series analysis was conducted using Minitab software to analyze trends in stock price fluctuations and the impact of trading activities. The seasonal period, which captured monthly changes in stock prices, was set at 12. After testing several ARIMA models, the best model was selected based on the minimum corrected AICc [25].

Using maximum likelihood estimation (MLE), the selected ARIMA model was estimated. The adequacy of the final model was confirmed using residual diagnostics, such as Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to identify patterns in the residuals and the Ljung-Box test to determine whether the residuals show randomness, which guarantees the model captures all systematic variations in the data [26, 27].

Following the model estimate, 95% confidence intervals, and out-of-sample forecasts for future stock prices were produced. A time series plot of closing prices with trendlines and forecasts was created to evaluate the forecast accuracy by comparing the expected values with the actual stock prices.

A scatter plot and correlation matrix were created to examine the relationship between the closing price and the number of traders. To determine the direction and strength of this relationship, a linear regression model was also developed. The statistical confirmation of the relationship between trading activity and price changes was provided by the Pearson correlation coefficient (r), which was calculated with a 95% confidence interval.

The methodological approach offers insights into the market dynamics of Solar Industries India Limited by providing an in-depth study of price behavior and its relationship to trading activity.

4. Analysis and Results

4.1. Trend and Pattern Visualization

A graph was made to show the trends and patterns seen in the closing price data, as shown in Figure 1. Examining this graphical representation is a crucial first step in understanding the stock's overall behavior based on its closing values throughout the specified time period.

Figure 1.
Close Price from 13 Dec 2021 to 11 Dec 2024.

The closing price analysis aims to provide a deeper understanding of the stock's performance by considering the specific values at the end of each trading day. Patterns in closing prices may offer further insights into market trends, investor sentiment, and potential turning points.

4.2. Model Selection for Forecasting

The closing price was predicted by the study using a Seasonal Autoregressive Integrated Moving Average (SARIMA) model. A 12-month seasonal period was utilized because the data were collected on a monthly basis. By examining various combinations of autoregressive (p), moving average (q), seasonal autoregressive (P), and seasonal moving average (Q) terms, multiple model modifications were examined in order to identify the optimal SARIMA configuration. For regular differencing, the differencing parameters were set at d = 2, and for seasonal differencing, D = 0 in order to guarantee stationarity. The tested models are given in Table 1.

Table 1.
Model Selection Summary.

Model (d = 2, D = 0)	Log-Likelihood	AICc	AIC	BIC
p = 0, q = 1, P = 0, Q = 0*	-4695.68	9395.4	9395.4	9404.5
p = 2, q = 1, P = 1, Q = 0	-4776.2	9562.5	9562.4	9585.3
p = 2, q = 0, P = 1, Q = 0	-4794.2	9596.5	9596.4	9614.8
p = 2, q = 0, P = 0, Q = 0	-4795.69	9597.4	9597.4	9611.1
p = 2, q = 0, P = 0, Q = 1	-4795.15	9598.4	9598.3	9616.7
p = 1, q = 0, P = 1, Q = 0	-4827	9660	9660	9673.8
p = 1, q = 0, P = 0, Q = 0	-4828.23	9660.5	9660.5	9669.6
p = 1, q = 0, P = 0, Q = 1	-4827.55	9661.1	9661.1	9674.9
p = 0, q = 0, P = 1, Q = 0	-4929.75	9863.5	9863.5	9872.7
p = 0, q = 0, P = 0, Q = 1	-4929.81	9863.6	9863.6	9872.8
p = 0, q = 0, P = 1, Q = 1	-4929.19	9864.4	9864.4	9878.1
p = 2, q = 1, P = 1, Q = 1	-5165.03	10342.2	10342.1	10369.6
p = 2, q = 0, P = 1, Q = 1	-6071.62	12153.3	12153.2	12176.2

Note: * Best model with minimum AICc. The output for the best model follows.

Table 1 presents the evaluated SARIMA models along with their respective log-likelihood, AICc, AIC, and Bayesian Information Criterion (BIC) values. The model with p = 0, q = 1, P = 0, Q = 0 was identified as the best model based on the lowest AICc value of 9395.4.

The optimal model was chosen, and its parameters were estimated as shown in Table 2. At a coefficient of 0.9866 ($p < 0.05$), the moving average (MA) term was statistically significant. To guarantee stationarity, the model was subjected to two levels of differencing (d = 2).

Table 2.
Final Model Parameters.

Type	Coefficient	Standard Error	T-Value	P-Value
MA (1)	0.986593	0	2.72E+11	0

Table 3 presents the model summary, including degrees of freedom (DF), sum of squares (SS), mean square (MS), and information criteria (AICc, AIC, and BIC). The model's variance of residuals, known as the white noise series variance, was 23738.8.

Table 3.
Model Summary.

DF	SS	MS	MSD	AICc	AIC	BIC
726	1,72,58,109	23,771.50	23,738.80	9395.39	9395.37	9404.55

Hence, the final selected model is a Seasonal Autoregressive Integrated Moving Average (SARIMA) model with parameters (0,2,1)(0,0,0,12).

4.3. Residual Diagnostics

4.3.1. Ljung-Box Q Test

The Ljung-Box Q test was used to determine if the residuals showed autocorrelation at several lag levels (12, 24, 36, and 48). An uncorrelated residual is indicated by a non-significant p-value, confirming the model's validity. The result of the Ljung-Box test is shown in Table 4.

Table 4.
Modified Box-Pierce (Ljung-Box) Test Results.

Lag	Chi-Square	DF	P-Value
12	12.77	11	0.309
24	29.14	23	0.176
36	61.86	35	0.003
48	70.67	47	0.014

From Table 4, at lags 12 and 24, the p-values are greater than 0.05, suggesting no significant autocorrelation at these lags. However, at lags 36 and 48, the p-values fall below 0.05, indicating mild autocorrelation in longer lags.

4.3.2. Autocorrelation and Partial Autocorrelation Analysis

The plots of the ACF and PACF were created as shown in Figure 2 in order to further verify the residual behavior. Any remaining correlation patterns in the residuals can be found with the use of these visuals.

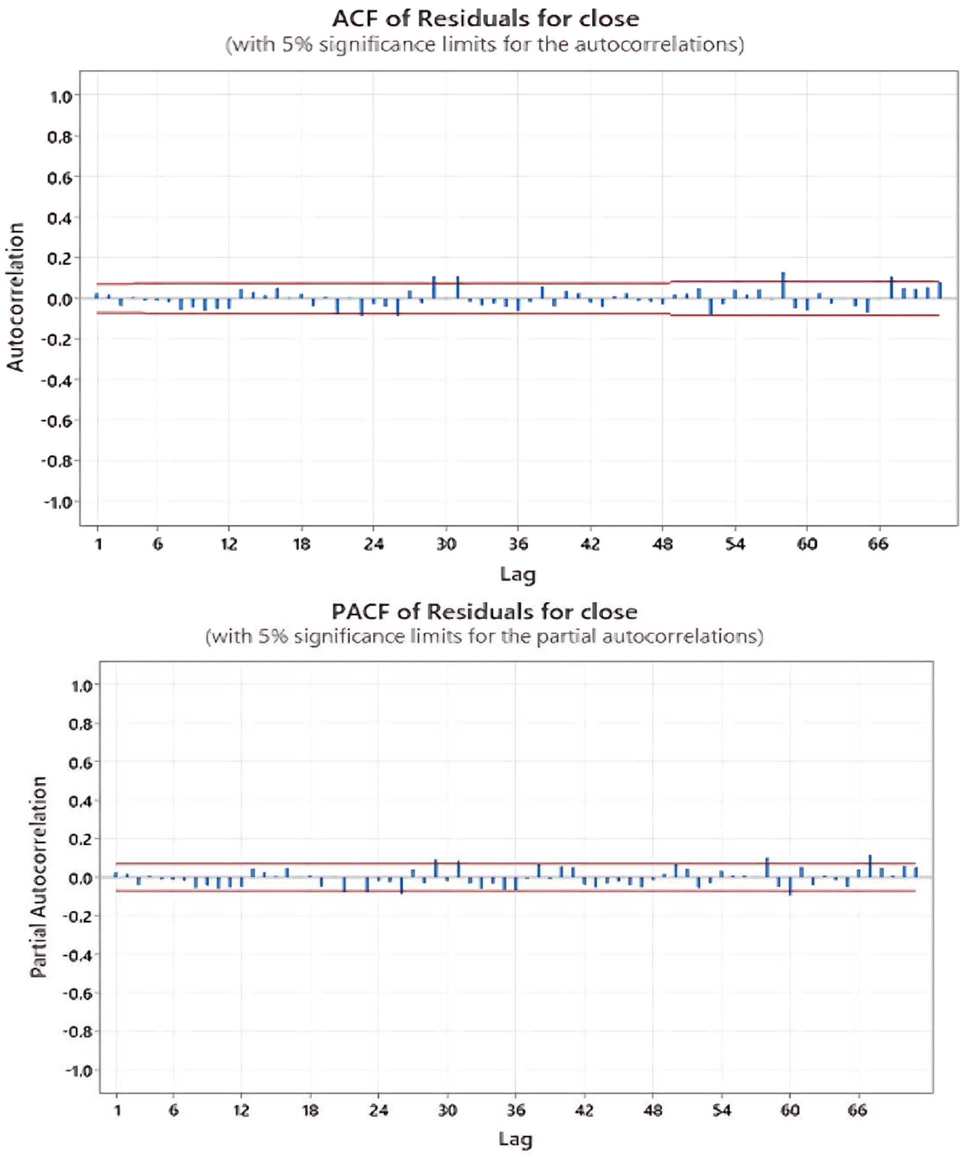

Figure 2.
ACF and PACF Plot.

Form Figure 2, the model accurately depicts the dependence structure, as evidenced by the residual autocorrelations in the ACF plot, which are primarily within the confidence limits. The PACF plot supports the idea that the residuals are roughly equal to white noise because no notable spikes outside of the confidence bands were seen.

4.3.3. Standardized Residuals Analysis

Randomness and constant variance were checked by looking at a plot of standardized residuals against observation order is shown in Figure 3. There were no noticeable trends or regular tendencies in the residuals, which seemed to be evenly distributed around zero. This implies that there are no omitted structures or heteroscedasticity issues with the model.

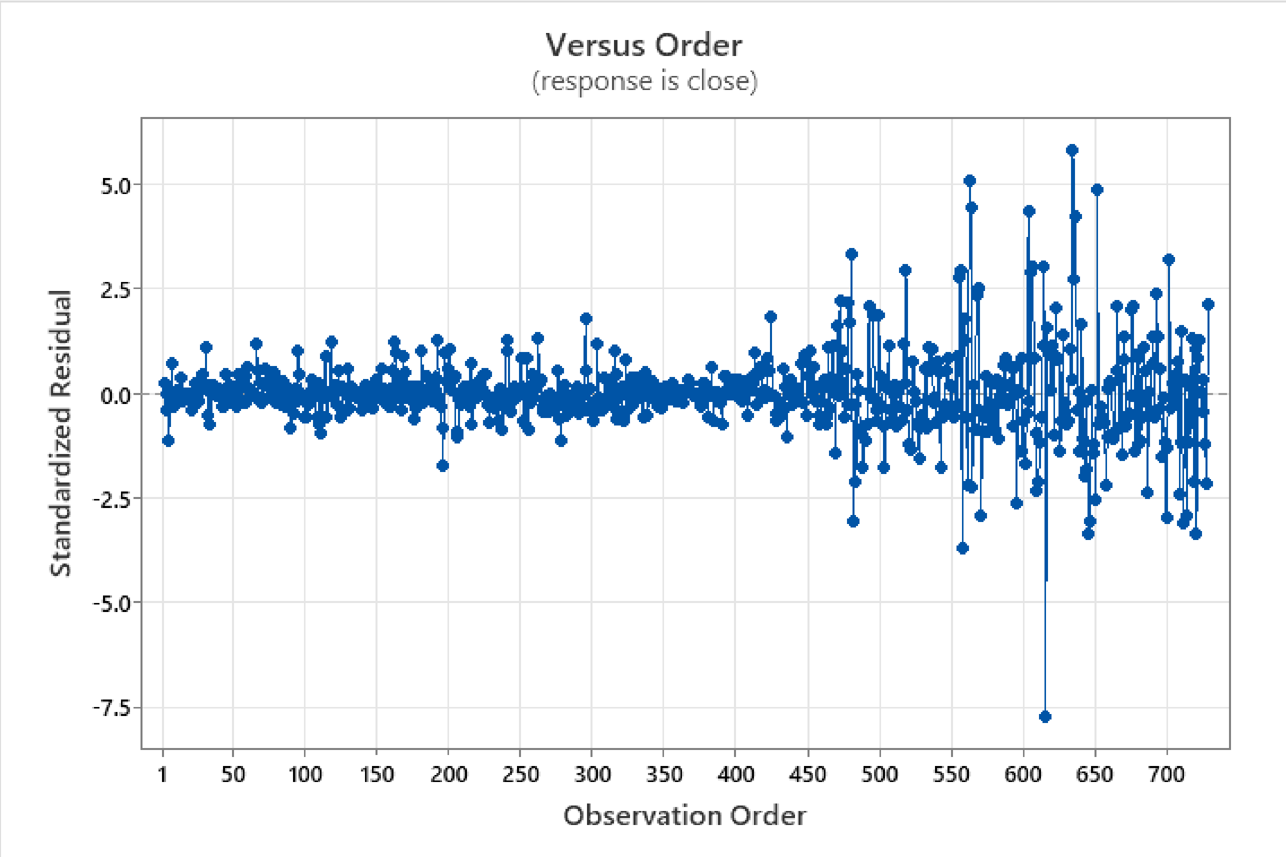

Figure 3.
Standardized Residuals Plot.

4.4. Forecasting Closing Price

The closing price of Solar Industries India Limited had been predicted out-of-sample from 730 to 759 using the SARIMA (0,2,1) (0,0,0,12) model as shown in Table 5. In order to account for prediction uncertainty, the model offers point forecasts in addition to 95% CIs.

Table 5.
Forecasted Closing Prices with 95% Confidence Intervals.

Time Period	Forecast	SE Forecast	Lower 95% Limit	Upper 95% Limit	Actual Closing Price
730	10008.2	154.18	9705.96	10310.5	9,726.40
731	10007.9	219.51	9577.56	10438.2	9,983.50
732	10007.6	270.64	9476.98	10538.1	9,973.50
733	10007.2	314.6	9390.49	10624	10,036.95
734	10006.9	354.06	9312.79	10701	9,961.95
735	10006.6	390.42	9241.19	10771.9	10,233.30
736	10006.2	424.47	9174.1	10838.4	10,291.70
737	10005.9	456.75	9110.49	10901.3	10,893.35
738	10005.6	487.61	9049.65	10961.5	10,681.20
739	10005.2	517.32	8991.08	11019.4	10,540.65
740	10004.9	546.07	8934.39	11075.4	10,479.55
741	10004.6	574.01	8879.27	11129.9	10,673.35
742	10004.2	601.27	8825.51	11183	10,826.50
743	10003.9	627.94	8772.89	11234.9	10,808.30
744	10003.6	654.09	8721.29	11285.8	10,962.90
745	10003.2	679.8	8670.55	11335.9	10,792.95
746	10002.9	705.12	8620.59	11385.2	10,863.95
747	10002.6	730.1	8571.3	11433.8	-
748	10002.2	754.76	8522.6	11481.9	-

749	10001.9	779.16	8474.44	11529.4	-
750	10001.6	803.32	8426.75	11576.4	-
751	10001.2	827.26	8379.48	11623	-
752	10000.9	851.02	8332.58	11669.2	-
753	10000.6	874.6	8286.02	11715.1	-
754	10000.2	898.03	8239.76	11760.7	-
755	9999.9	921.32	8193.76	11806.1	-
756	9999.6	944.49	8148.01	11851.2	-
757	9999.2	967.55	8102.46	11896	-
758	9998.9	990.52	8057.11	11940.7	-
759	9998.6	1013.4	8011.92	11985.2	-

With a continuous rise in forecast uncertainty over time, the forecasts stay comparatively stable around 10,000. Although there are some variations between the actual closing prices and the predicted values, they mostly lie within the 95% confidence intervals, suggesting that the prediction performed reasonably well. The standard error of forecasts (SE Forecast), which is common for time series forecasting, rises with time, indicating an increase in long-term prediction uncertainty.
A forecast plot was created to visualize the projected closing prices along with confidence intervals, as shown in Figure 4.

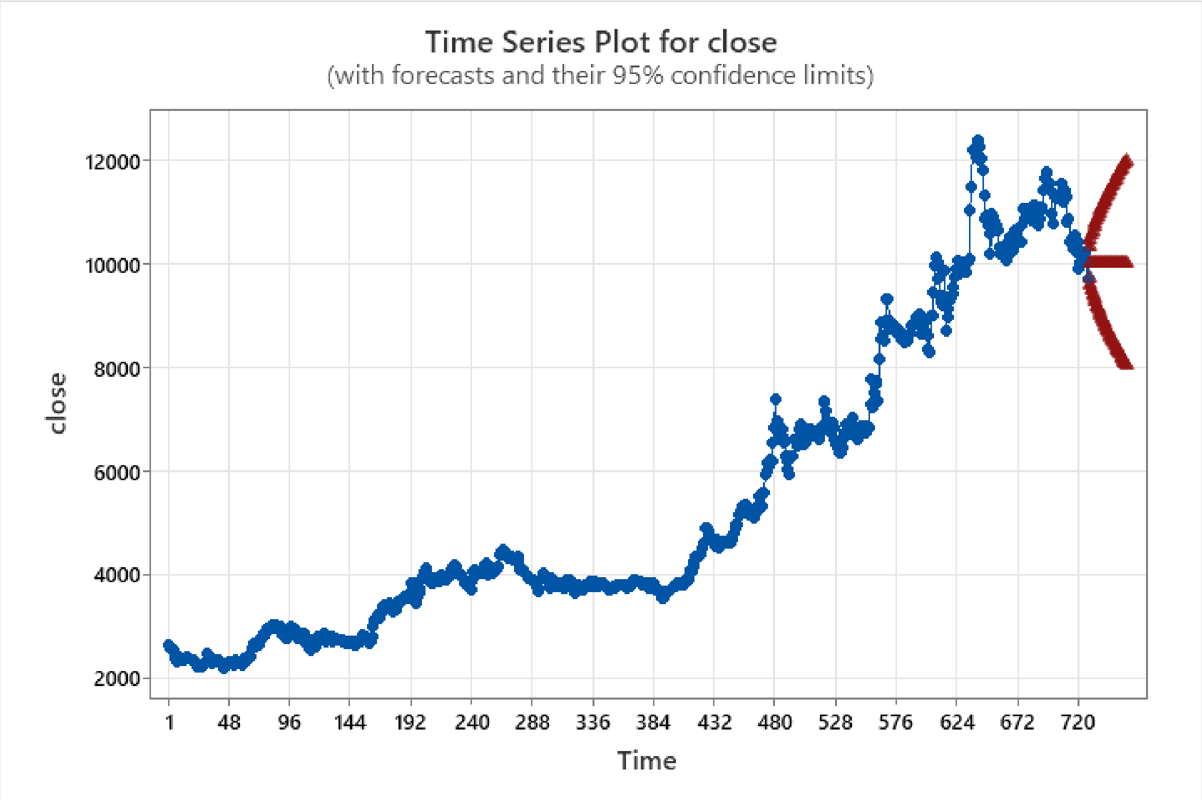

Figure 4.
Forecast Visualization.

4.5. Correlation Analysis

A correlation matrix and scatter plot were created in order to investigate the connection between the closing price and the number of traders, as shown in Figure 5. A moderately favorable association between these factors was confirmed by the Pearson correlation coefficient (r = 0.492) with a 95% confidence interval of (0.435, 0.545). This implies that although the link is not strong enough to show a direct causal relationship, the closing price tends to climb as trading activity increases. The relationship's validity under nonparametric assumptions may be ascertained with the aid of further analyses, such as Spearman's rank correlation. Furthermore, to determine whether historical trading volumes have an impact on future price changes, possible lag effects could be investigated.

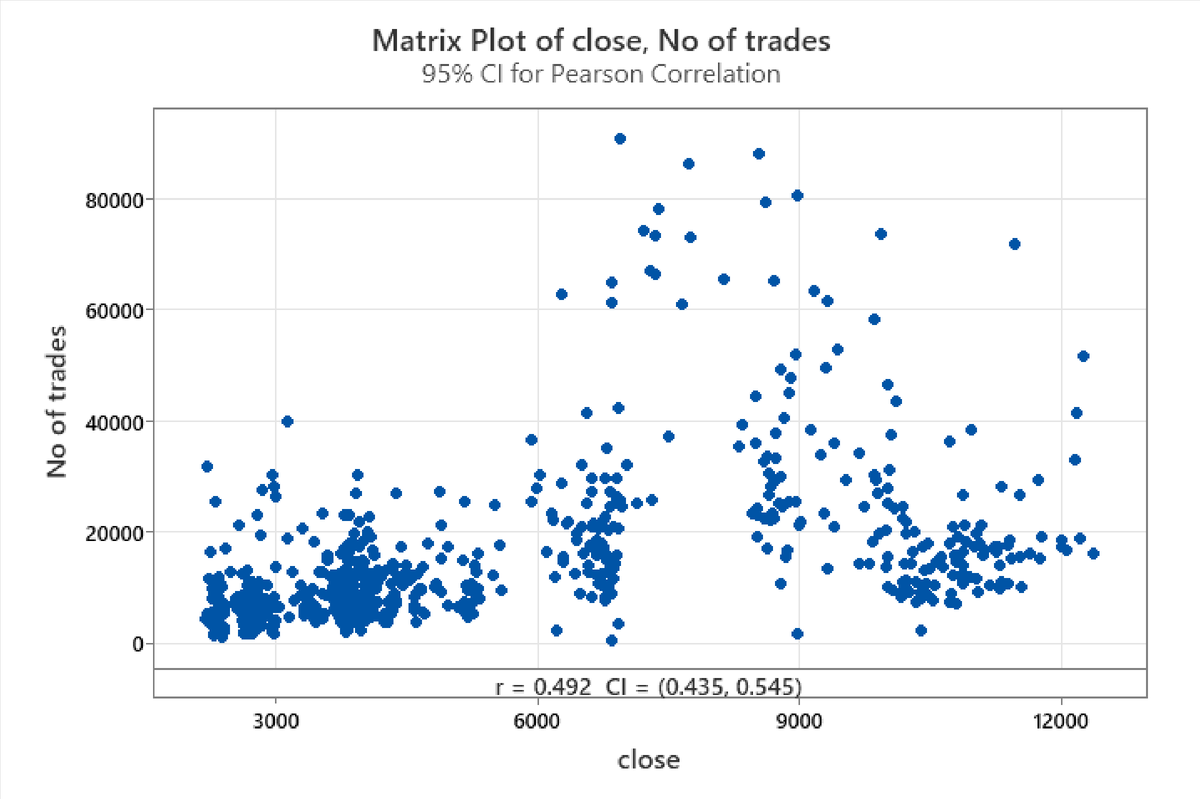

Figure 5.
Matrix Plot.

4.6. Regression Analysis

A simple linear regression model was developed to quantify the relationship between the closing price and the number of traders. The estimated regression equation is given as follows,

$$close = 3934 + 0.1026(No. of\ traders)$$

The fitted line plot is shown in Figure 6.

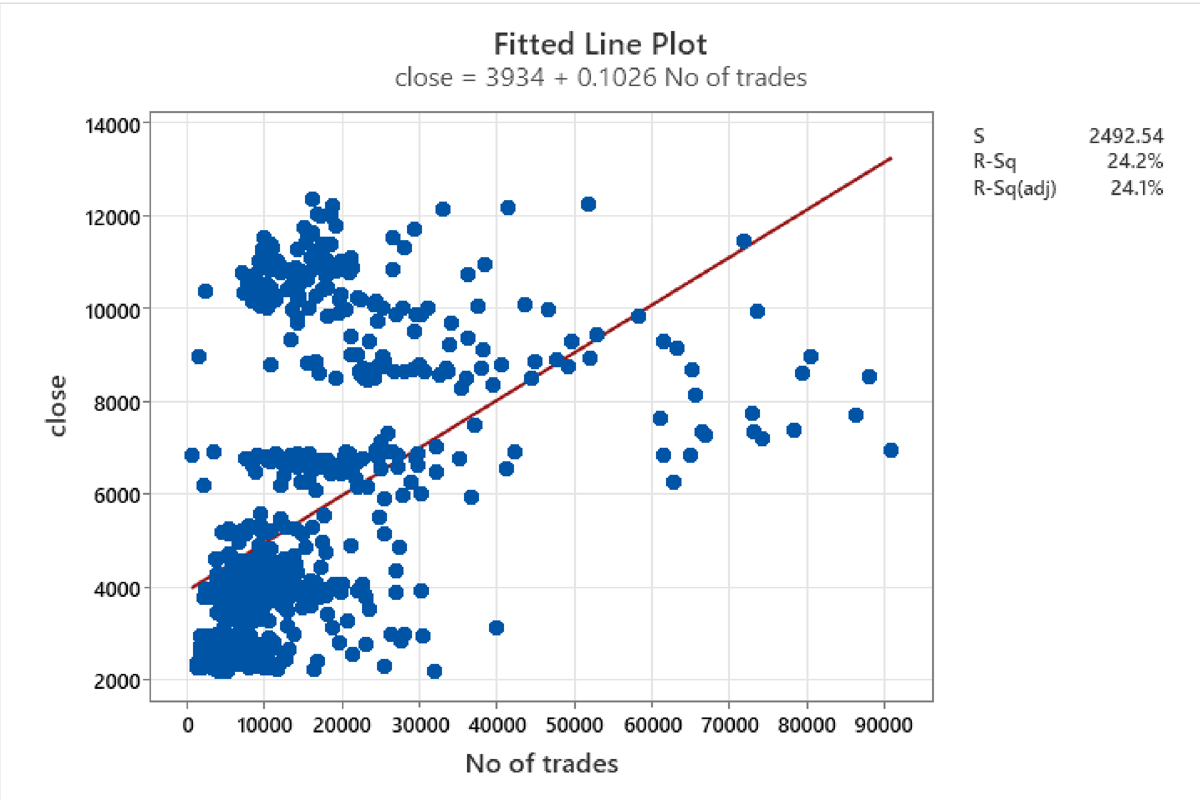

Figure 6.
Fitted Line Plot.

The model accounted for 24.2% of the closing price variation (R^2 = 24.2%, adjusted R^2 = 24.1%), suggesting that a moderate amount of price changes are caused by trading activity. The degree of residual dispersion was indicated by the regression's standard error (S), which came out as 2492.54. The comparatively low R^2 indicates that other factors impact price changes, even though the model offers statistically significant insights into the relationship. Plotting residuals against fitted values is one type of residual diagnostic that may be used to identify patterns like heteroskedasticity or nonlinearity. Furthermore, the model's explanatory power may be increased by adding lagged variables, moving averages, or interaction terms.

5. Discussion

The study used predictive modeling, correlation analysis, residual diagnostics, and time series forecasting to analyze the closing price of Solar Industries India Limited. White noise behavior was checked by residual diagnostics utilizing the Ljung-Box Q test and ACF/PACF plots, guaranteeing the suitability of the chosen model. With growing standard errors over time and larger confidence intervals, the forecasting results showed a generally consistent trend in the anticipated closing prices. Even while the model was able to capture general patterns, variations from real data points to possible short-term market swings. According to the correlation study, there is a somewhat positive relation (r = 0.492) between the closing price and the number of traders, suggesting that higher closing prices are typically associated with more trading activity.

The importance of high-frequency data in enhancing forecast accuracy has been highlighted in a study by Chen et al. [28]. Although our analysis relies on daily closing prices, using intraday data may yield more detailed insights into price fluctuations. Additionally, research has examined how external factors like commodity prices and geopolitical events affect stock market changes [29]. This could be important for firms in the defense and explosives sector, like Solar Industries India Limited. The research's main novelty is the way it validates prediction performance by combining conventional forecasting models with a strict residual diagnostic methodology. Furthermore, Solar Industries India Limited, a business with distinct market dynamics that have not been properly investigated in previous studies, is the special focus of the study. The modest relationship between trading volume and price changes points to a direction for future research, indicating that adding other macroeconomic data or market sentiment analysis could improve prediction models.

The study has several limitations despite its contributions. The forecasting model might not adequately account for the intricacies of stock price fluctuations since it makes the assumptions of stationarity and linear linkages. The regression analysis's comparatively low R^2 suggests that price variations are influenced by additional macroeconomic, industry-specific, or investor sentiment factors.

However, this study is limited by its reliance on historical data and linear modeling, which may not fully capture sudden market shifts or nonlinear relationships. Future research could explore the use of advanced machine learning and hybrid models, as well as the inclusion of macroeconomic indicators and sentiment analysis, to improve prediction accuracy and capture a broader range of market influences.

6. Conclusion

Using ARIMA modeling, this study offers a thorough time series analysis and forecasting method for Solar Industries India Limited's closing prices. The underlying patterns and trends in the stock's historical data were successfully captured by the ARIMA (0, 2, 1) model, which was chosen based on the corrected AICc and confirmed by residual diagnostics. White noise behavior in the model's residuals demonstrated its suitability and dependability for forecasting.

One of the study's main conclusions is that, according to correlation and regression studies, there is a somewhat positive association between trading activity (as shown by the number of traders) and the closing price of the stock. This suggests that price changes are influenced by trade volume.

This study makes two main contributions: (1) applying a robust statistical model to a 25-year-old dataset, and (2) including trading activity data to enhance the interpretability and applicability of stock price predictions. Compared to models that rely solely on price history, these components offer a more comprehensive view of stock price movements. From a practical standpoint, the results provide valuable information for analysts, investors, and policymakers. The verified ARIMA model is a reliable tool for predicting future prices, aiding risk management and investment decisions. Furthermore, incorporating trading behavior highlights the importance of considering market activity in financial modeling, as this can lead to more accurate and useful predictions for practical applications.

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