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Forecasting stock prices : Endeavors in the renewable energy sphere for a greener future

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Abstract

Renewable energy research in India is critical to providing energy security, reducing reliance on fossil fuels, and achieving long-term economic and environmental improvement. Precise stock price prediction in the renewable energy sector is crucial for optimizing investment choices, improving market returns, and facilitating India's shift to a clean energy economy. The nation aims to become a global leader in renewable energy, with forecasting models serving a vital function in directing investors, enterprises, and government towards sustainable development. This study assesses Elastic-Net regression models for NHPC, Reliance Industries, Tata Power, and Borosil Renewable, considering volatility, market capitalization, and data limitations. Our results indicate that Forecast Distance Modeling with Differencing (FDM + Diff) enhances accuracy, whereas hybrid alpha regularization without differencing is effective for NHPC's smaller dataset. These findings underscore the significance of customized models for optimized resource allocation in India's growing renewable sector. India's leadership in clean energy will be enhanced by strategic forecasting,

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which will accelerate the transition, reduce financial risk, and motivate global sustainability initiatives.

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1. Introduction

Given the focus on sustainable development, renewable energy is vital to the global and Indian economies. India, one of the fastest-growing economies, has increased renewable energy output to meet rising energy needs and reduce carbon emissions. The National Solar Mission vows to net-zero emissions by 2070 are focussing policymakers, investors, and scholars on renewable energy [1]. Renewable energy companies have attracted investment, making them a stock market focus in India. These companies' financial performance suggests growth potential and sector economic and policy trends. Investors, analysts, and policymakers need to forecast stock values for optimum resource allocation.

This study examines Reliance Industries, NHPC, Borosil Renewable, and Tata Power. Renewable energy firms that contribute to solar, wind, hydropower, green hydrogen, battery technology, and electric vehicle charging infrastructure were chosen. These companies' varying market capitalisations and broad energy portfolios make them excellent for studying renewable energy stock prices. The volatility of stock prices and the massive amount of data make forecasting challenging [2]. Time series analysis uses statistical methods like ARIMA on historical data and artificial intelligence models like LSTM to find detailed patterns [3]. These models use past trends to predict future prices, helping investors choose [4]. As data grows, these methods must be improved for accurate forecasts. Hence, methods like Elastic Net Regression and LSTM improve stock price prediction on high-dimensional and noisy financial datasets by finding relevant features, addressing multicollinearity, reducing overfitting, and improving generalization [5][13].

2. Literature Review

Statistical models and machine learning (ML) are often used to predict stock prices in financial markets [6] . Time-series forecasting has traditionally used statistical models like ARIMA [7] and GARCH [8].

These approaches predict stock prices using past price trends and stationarity. However, their failure to account for financial data non-linearity has led researchers to examine more advanced machine learning models.

Recent advances in ML and DL have improved stock price forecasting accuracy [9]. Financial time-series data has been analysed using SVMs [10], Random Forests[11], and Neural Networks [12]. ML models excel at large datasets and complex price movements. Financial forecasting has embraced the Elastic-Net Regressor[13], a regularised linear regression method that prevents overfitting and improves generalisation. This study introduces a hybrid ARIMA-LSTM model for forecasting stock prices and evaluates its efficacy relative to independent ARIMA and LSTM models [3].

ML-based stock prediction has been extensively studied, but renewable energy's growing impact on financial markets has not. Government policies, technological advances, global energy consumption, and environmental challenges affect renewable energy firm stock prices[14]. Moreover, there is a direct relation between the growth of the economy and renewable energy adoption. This study explores how FDI, ECBs, and renewable energy sector economic growth in India are related. It investigates how increased foreign direct investment (FDI) and external commercial borrowings (ECBs) could accelerate the shift from fossil fuels to renewable energy and recommends policy changes to attract more foreign investment [15].

Most renewable energy equity research has used ARIMA, LSTMs, and other models, but few have used Elastic-Net Regression with Forecast Distance Modelling. Four variants of the Elastic-Net Regressor are used in this study to predict stock prices for prominent Indian renewable energy companies. This research uses many forecasting methods to create a comprehensive renewable energy predicting framework. Comparing model performance using MSE, MAE, MASE, and MAPE provides a complete predicted accuracy assessment.

3. Data and Methodology

3.1 *Data Description*

Yahoo Finance provided daily stock price data for renewable energy companies. The data includes daily stock prices and trading volume for each company, reflecting their listing histories and data availability as seen in Table 1. From Table 2, we can get the basic statistics of the stock prices' data. The closing price was the main forecast variable.

Table 1

Data Period and Observations

Company	Start Date (MM/DD/YYYY)	End Date (MM/DD/YYYY)	Number of Observations
Reliance	1/1/1996	1/9/2025	7275
Tata Power	1/1/1996	1/9/2025	7275
NHPC	9/1/2009	1/9/2025	3788
Borosil Renewable	1/3/2000	1/9/2025	6113

Table 2

Company Data Statistics

Company	Mean Close Price	Std Dev	Min Close Price	Max Close Price	Skewness	Market Capitalisation
Reliance	320.35	396.03	5.49	1600.9	1.61	17.10LCr
Tata Power	83.37	87.31	4.31	485.5	2.23	1.16LCr
NHPC	30.87	18.03	15.05	115.81	2.69	78.83KCr
Borosil Renewable	118.06	178.44	0.14	780.15	1.61	7.12KCr

3.2 *Exploratory Data Analysis (EDA)*

This section helps us in choosing suitable predictors by analysing price, volume, and market trends. It is witnessed from Figure-1 that distributions are right-skewed across all companies. We can also notice that Rolling Mean and Standard Deviation Plots in Figure-2 that indicate non-stationarity. The data appears non-stationary due to its fluctuations. The Augmented Dickey-Fuller (ADF) Test indicates a p-value beyond 0.05, signifying that the dataset is non-stationary.

3.3 *Feature Engineering*

Feature engineering is indispensable in the prediction of stock prices, as it improves the accuracy of the model, captures market patterns, and enhances the quality of the data, thereby enabling more accurate

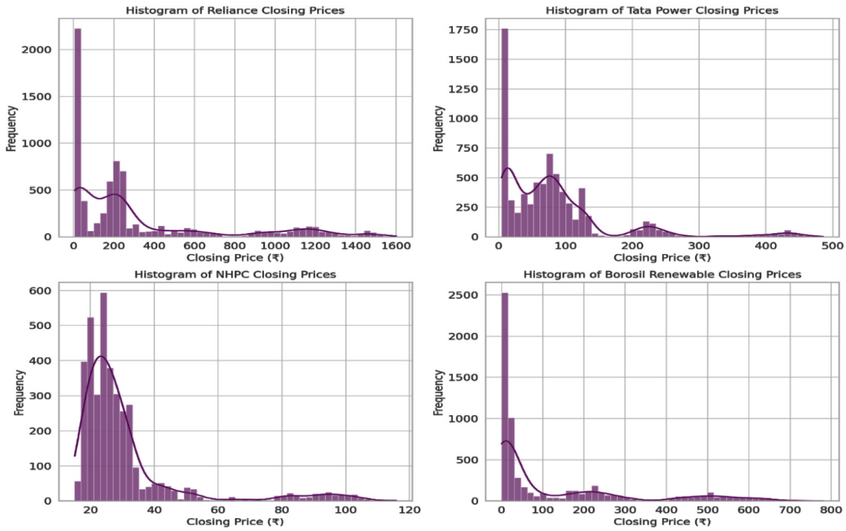

Figure 1

Histograms

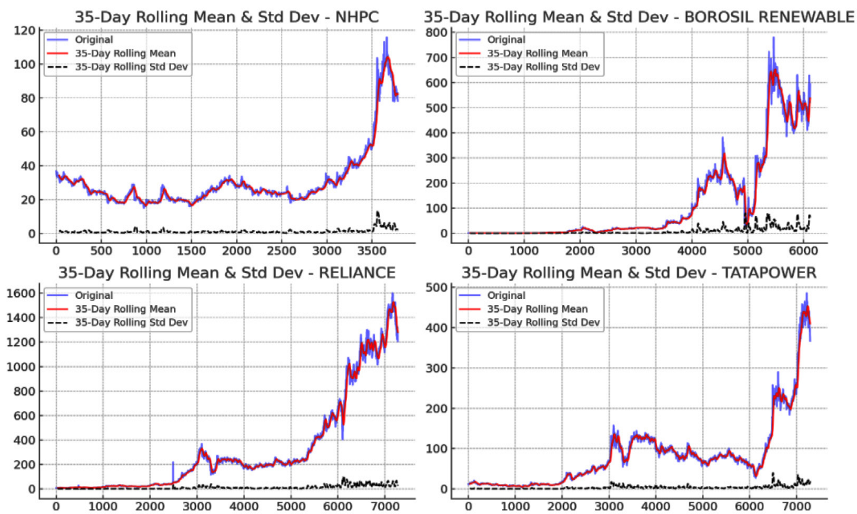

Figure 2

Rolling Mean and Standard Deviation Plots

forecasting. Hence, to create relevant stock price predictors, stock price datasets were feature engineered using a methodical and financially informed process. Stock prices are stochastic, hence statistical transformations, time series lagging, seasonality extraction, and rolling window approaches were used.

The constructed features capture market structures, trend persistence, and volatility characteristics needed for robust Elastic-Net regression modelling. Log-transforming the closing price stabilised variance and addressed multiplicative patterns. Stationarity was achieved by differencing the log-transformed pricing.

Log-transformed closing price moving averages were constructed for 7, 14, 30, and 35 days. Smoothed values show price fluctuations and reduce short-term noise, capturing trends at many scales.

Multiple features were produced by comparing the current price to the previous month's values to allow for monthly seasonality. These included variations from the previous month's end, the same weekday, and one month previously. Similar monthly reference points were used to derive "naive" seasonal values. These features try to capture monthly patterns. To capture short-term dependencies and momentum effects, log-transformed closing price, differenced closing price, and monthly difference characteristics were lagged 1 to 5 days.

3.4 *Model Description*

Financial data is noisy due to market volatility, external economic factors, and unpredictability among investors. Elastic Net Regression improves prediction by combining L1 (Lasso) and L2 (Ridge) regularisation, which reduces overfitting, handles multicollinearity, and improves accuracy in noisy financial data. This reduces overfitting by keeping only the most important predictors and penalising excessive complexity due to stock prices' dynamic character. The following Elastic-Net model versions were tested for regularisation, differencing, and weighting:

- Elastic-Net Regressor (L2 / Gamma Deviance) with Forecast Distance Modelling and Differencing: These models used target variable differencing to induce stationarity, which our model needed. The hyperparameter tuning process chose 0.0 alpha. This shows that the optimisation process found that decreasing the coefficients of less influential features was best for our prediction objective.
- Linearly Decaying Weights and Forecast Distance Modelling: This variant used linearly decaying weights in the Elastic-Net architecture without differencing. Linearly decreasing weights stress recent data items, claiming they are more predictive.

- Elastic-Net Regressor (L2 / Gamma Deviance) with Forecast Distance Modeling (No Differencing): This model was similar to the best-performing model but without differencing the target variable. This variation was explored to assess the impact of differencing on model performance.
- Elastic-Net Regressor (mixing alpha=0.5 / Gamma Deviance) with Forecast Distance Modeling and No Differencing: This version explored a 50/50 mix of L1 and L2 regularization (alpha = 0.5) without differencing. This was tested to see if a combination of feature selection (L1) and coefficient shrinkage (L2) would improve performance.

3.5 *Cross-Validation Approach*

Model performance was assessed using 5-Fold Cross-Validation (CV) backtesting to ensure robustness and generalisability. Rolling window backtesting is a strategy that trains a model on a fixed-size sliding window of past data and tests it on the next period, emulating real-world forecasting. It is critical because it eliminates data leakage, provides consistent evaluation across time, and assesses the model's adaptability, resulting in more reliable and robust performance. The dataset was first divided to keep the past 30 days as a holdout set for final analysis. The remaining data was used for five rounds of backtesting, each with a training window of 210 days and a validation window of 30 days. Each round, the training and validation windows were moved ahead in time without overlap to simulate real-world forecasting circumstances. This method evaluates the model's consistency and flexibility across time periods, reducing overfitting and ensuring more trustworthy performance insights.

Every model is trained and tested on the Training and Validation Sets, logging performance metrics. After training on all data except the Holdout_Set, a model is evaluated on the holdout data for unbiased judgement.

4. Results and Discussion

Elastic-Net Regressor (L2 / Gamma Deviance) using Differencing and Forecast Distance Modelling (Diff + FDM) was the most effective model across all datasets of the four models assessed as can be seen in Table 3. It consistently achieved lower RMSE, MAE, and MAPE values, making it the most accurate stock price forecasting approach. It performs better because differencing eliminates long-term trends and stabilises data, enhancing model efficacy. FDM also ensures adaptation across prediction scopes, improving a generalisation.

Case-Specific Observations:

The shortest data history (3,788 observations) limits long-term trend analysis for NHPC. Alpha, No Diff, and FDM produced better results, demonstrating that differencing removed much valuable information from the confined dataset. Borosil Renewable's low market cap (7.12K Cr) increases volatility, confounding predictive analytics. However, Diff + FDM outperformed all other models, proving that differencing reduces volatility.

Table 3

Results on Holdout

Company	Model	RMSE	MAE	MASE	MAPE (%)
Reliance	Diff + FDM	29.42	21.68	1.04	1.59
	Decay + FDM	34.94	27.26	1.3	2.01
	No Diff + FDM	35.28	27.38	1.31	2.02
	Mix Alpha + No Diff + FDM	29.74	21.7	1.04	1.59
Tata Power	Diff + FDM	13.79	9.79	0.4	2.59
	Decay + FDM	14.67	10.99	0.45	2.91
	No Diff + FDM	14.63	11.02	0.45	2.91
	Mix Alpha + No Diff + FDM	15.9	12.16	0.49	3.17
Borosil Renewable	Diff + FDM	25.27	17.03	1.03	3.35
	Decay + FDM	27.62	20.01	1.21	3.98
	No Diff + FDM	26.58	18.75	1.13	3.7
	Mix Alpha + No Diff + FDM	25.27	16.91	1.02	3.32
NHPC	Diff + FDM	3.96	3.02	0.5	3.25
	Decay + FDM	4.62	3.69	0.61	3.99
	No Diff + FDM	4.64	3.7	0.61	3.99
	Mix Alpha + No Diff + FDM	3.59	2.62	0.43	2.78

5. Conclusion

Renewable energy companies like Reliance, Tata Power, NHPC, and Borosil Renewable are shaping India's sustainable energy sphere, making stock price estimates crucial for investors. This study used Elastic-Net regression models and found that Differencing and Forecast Distance Modelling (Diff + FDM) worked well in most cases. Differentiation improves stationarity and prediction precision, especially for large and volatile datasets, but model selection must match dataset properties. This research enhances stock projections, helping investors optimise strategies, minimise risks, and link financial progress to sustainability for data-driven renewable energy investments.

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