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Stock price forecast model for CATL based on BP neural network regression

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Abstract. With the introduction of the "Dual Carbon" policy and the increasing environmental awareness among residents, the new energy vehicle industry is experiencing positive growth momentum. New energy vehicles use non-traditional energy sources as their power supply, effectively reducing carbon emissions, enhancing energy efficiency, and contributing to the improvement of China's existing energy landscape, thus supporting environmental protection and the early realization of "carbon peak" and "carbon neutrality" goals. Contemporary Amperex Technology Co., Ltd. (CATL), a prominent and competitive player in China's emerging clean energy industry, focuses on researching, developing, manufacturing, and marketing power battery and energy storage systems specifically designed for new energy vehicles. Moreover, in recent years, machine learning and deep learning have gained wide application in various domains, including stock price prediction and financial investment. This paper constructs a stock price prediction model for CATL based on a BP neural network regression, considering factors related to traditional energy, carbon trading, environmental aspects, and industry-specific factors.

Keywords: Stock Price Forecast, BP Neural Network Regression, CATL.

1. Introduction

Presently, from a macro perspective, the development of China's new energy vehicle industry presents opportunities at three levels: energy landscape transformation, government policy support, and environmental protection requirements.

Regarding the transformation of the energy landscape, China's total energy usage in 2022 reached 5.41 billion tons of standard coal, signifying a 2.9% upturn compared to the prior year. Coal consumption constituted 56.2% of the overall energy consumption, indicating a 0.3 percentage point increase from the preceding year. Traditional energy sources continue to maintain a predominant position in China's energy makeup. In the face of international energy supply constraints and continuous increases in oil prices, the rationality and security of China's energy structure necessitate a gradual shift toward new energy sources.

In terms of government policy backing, China has been actively promoting the growth of the new energy vehicle sector since 2015, aligning with the goals of achieving a "carbon peak" and "carbon neutrality".[1]The government has introduced policies such as unrestricted driving, no purchase restrictions, and purchase subsidies for new energy vehicles, aiming to establish a comprehensive automotive technology system and industry chain. At the macro-policy level, China has set the development goal of achieving a 20% share of new energy vehicle sales by 2025.

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Concerning environmental protection requirements, the importance of environmental conservation and ecological balance has become increasingly recognized. The idea of "sustainable development" has been given significant emphasis. Concerning energy preservation and emissions reduction, new energy vehicles exemplify the principles of being "environmentally friendly and highly efficient." Compared to traditional fuel vehicles, they can save 2.3 kilograms of standard coal per hundred kilometers, leading to a substantial decrease in carbon dioxide, sulfur, and nitrogen emissions. They have a 13% to 68% reduction potential in overall pollution emissions. The widespread adoption of new energy vehicles provides fresh impetus for environmental protection and green development.

Contemporary Amperex Technology Co., Ltd. (CATL), a highly prominent and competitive player in the new energy sector, stands as one of the early domestic manufacturers of power batteries with international acclaim, boasting a market capitalization of CNY 995.8 billion. [2]CATL is fully committed to the research, development, production, and marketing of power battery systems and energy storage solutions tailored for new energy vehicles, with a steadfast dedication to delivering cutting-edge solutions for global applications in the new energy field. The company's core technologies encompass the entire industry spectrum, spanning materials, battery cells, battery systems, and even battery recycling and repurposing. CATL's position as a leading enterprise in the new energy domain, along with its pivotal role in the upstream segment of the new energy vehicle industry, not only mirrors the evolving dynamics of the power battery sector but also underscores broader trends within the overall new energy arena.

In the 1990s, mathematical models, particularly neural network models, began to be widely used for stock market prediction. It's worth highlighting that the BP neural network model was introduced in 1986 by a U.S. research team led by Rumelhart. Subsequently, in 1987, White became the first to employ the BP neural network model to forecast stock market patterns, particularly identifying the optimal buying and selling moments for a specific stock within a specified time frame.Although the experimental results were not satisfactory, this forecasting experiment laid the foundation for other scholars to apply BP neural networks to time series data prediction. In 1990, Kamijo used the BP neural network to predict stock market patterns with good results, demonstrating the effectiveness of the BP neural network. Subsequently, BP neural networks gained popularity and further development for stock market prediction abroad. In China, numerous scholars have conducted research on using BP neural networks to predict stock markets. Li and Wang proposed an improved BP neural network prediction method that performed better than traditional BP neural networks for short-term predictions of highly nonlinear stock price changes [3]. Sun Quan and Zhu Jiang adjusted the parameters of activation functions dynamically and combined existing BP improvement algorithms for stock price prediction, achieving good results [4]. Ouyang Jinliang and Lu Liming addressed the slow convergence and susceptibility to local minima problems of standard BP neural network algorithms, proposing a comprehensive improved BP algorithm combining additional momentum and dynamically adjusting the learning rate. The improved algorithm significantly accelerated network convergence and proved effective and feasible for short-term stock price prediction, achieving high accuracy and practical value [5]. Guo Jianfeng et al. constructed an LM-BP neural network to predict stock market data and then optimized the initial parameters of the model using a genetic algorithm, resulting in the composite model GA-LM-BP. This model overcame some of the drawbacks of BP neural networks, enhancing prediction accuracy[6]. Qin optimized BP neural networks for stock market data prediction using a genetic algorithm, and the error in the prediction results of GA-BP neural networks was lower than that of traditional BP neural networks [7].

Considering the context provided, utilizing machine learning algorithms to forecast stock price movements and growth patterns of leading firms within the new energy sector can serve as a valuable tool for gauging the broader dynamics within the new energy industry as a whole. It can also support the "Dual Carbon" policy and energy landscape transformation, providing reasonable advice and references for government decision-makers, regulatory agencies, and individual investors.

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2. Model theory

2.1. BP Neural Network Regression

A BP (Backpropagation) neural network is a type of multilayer feedforward neural network distinguished by its two main stages: forward signal propagation and backward error propagation. Specifically, for a neural network model comprising just one hidden layer, the BP neural network process can be divided into two key phases:

1. Forward Propagation: This stage involves the transmission of signals from the input layer, passing through the hidden layer, and eventually arriving at the output layer. Each layer processes and transforms the signals as they move forward.

2. Backward Propagation: During this stage, errors are retroactively propagated in the reverse direction, starting from the output layer and moving back through the hidden layer to the input layer. Throughout this process, the weights and biases connecting the hidden layer to the output layer and those linking the input layer to the hidden layer are iteratively adjusted to minimize errors and enhance the network's performance.

Let's consider a three-layer BP neural network as an example (figure 1).

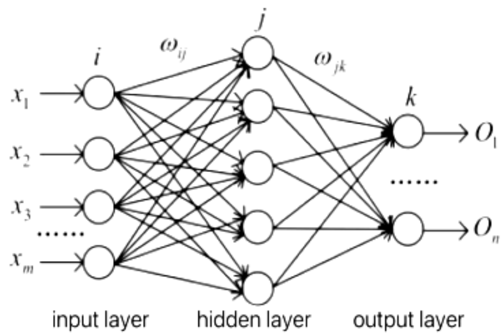

Figure 1. Three-layer BP neural network structure.

The output of the hidden layer is denoted as Fj, and the output of the output layer is denoted as Ok. The activation function of the system is represented as G, and the learning rate is denoted as β.The mathematical relationships among these three layers are as follows:

$$\begin{cases} F_j = G(\sum_{i=1}^{m} w_{ij}\, x_i + a_j) \\ O_k = \sum_{j=1}^{l} F_j\, w_{jk} + b_k \end{cases} \tag{1}$$

If Tk represents the expected output of the system, then the system's error E can be expressed as the variance between the actual output and the target value. The specific relationship is as follows:

$$E = \frac{1}{2}\sum_{k=1}^{n}(T_k - O_k)^2 \tag{2}$$

By setting $e_k = T_k - O_k$, and utilizing the gradient descent principle, the update formulas for the system's weights and biases are as follows:

$$\begin{cases} w_{ij} = w_{ij} + \beta F_j(1 - F_j)x_i \sum_{k=1}^{n} w_{jk} e_k \\ w_{jk} = w_{jk} + \beta F_j e_k \end{cases} \tag{3}$$

$$\begin{cases} a_j = a_j + \beta F_j(1 - F_j)x_i \sum_{k=1}^{n} w_{ij} e_k \\ b_k = b_k + \beta e_k \end{cases} \tag{4}$$

2.2. XGBoost

XGBoost, short for "Extreme Gradient Boosting," is an ensemble learning algorithm that combines base learners (typically decision trees) with weights to form a composite algorithm for superior data fitting. XGBoost is known for its strong generalization ability, scalability, and fast execution speed, making it popular in the fields of statistics, data mining, and machine learning since its introduction in 2015.[8]

For a dataset containing n data points with m features, an XGBoost model can be represented as follows:

$$y_i^{\wedge} = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathrm{F} \quad (\mathrm{i} = 1,2, \ldots \mathrm{n}) \tag{5}$$
$$\mathrm{F} = \{f(x) = w_{q(x)}\}(\mathrm{q}: \mathrm{R^m} \rightarrow \{1,2, \ldots, \mathrm{T}\}, \mathrm{w} \in \mathrm{R^T})$$

Where, F represents a collection of CART (Classification and Regression Trees) decision tree structures, q represents the mapping of samples to leaf nodes in the tree structure, T is the number of leaf nodes, and w represents the real-valued scores assigned to leaf nodes.

When building an XGBoost model, optimal parameters need to be found based on the principle of minimizing the objective function. The objective function of an XGBoost model consists of two components: the loss function term L and the model complexity term Ω. The objective function can be written as:

$$\begin{gathered} \mathrm{Obj} = \mathrm{L} + \Omega \\ \mathrm{L} = \sum_{i=1}^{n} (\mathrm{y_i} - \hat{\mathrm{y}}_i)^2 \\ \Omega = \gamma \mathrm{T} + \frac{1}{2} \lambda \sum_{j=1}^{\mathrm{T}} \mathrm{w_j}^2 \end{gathered} \tag{6}$$

Where $\gamma\mathrm{T}$ is the L1 regularization term, and $\frac{1}{2}\lambda \sum_{j=1}^{\mathrm{T}} \mathrm{w_j}^2$ is the L2 regularization term.

During the training of the XGBoost model with the training data, a new function f is added to the model while keeping the original model unchanged. The objective is to maximize the objective function, which is achieved by minimizing the objective function. The process involves:

$$\begin{gathered} \hat{y}_i^{(0)} = 0 \\ \hat{y}_i^{(1)} = \hat{y}_i^{(0)} + \mathrm{f_1(x_i)} \\ \hat{y}_i^{(2)} = \hat{y}_i^{(1)} + \mathrm{f_2(x_i)} \\ \ldots\ldots \\ \hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \mathrm{f_t(x_i)} \end{gathered} \tag{7}$$

Where $\hat{y}_i^{(t)}$ is the prediction of the model at the t-th iteration, and $f_t(x_i)$ is the new function added at that iteration. The objective function is given by:

$$\mathrm{Obj^{(t)}} = \sum_{i=1}^{n} [\mathrm{y_i} - (\hat{y}_i^{(t-1)} + \mathrm{f_i(x_i)})]^2 + \Omega \tag{8}$$

In the XGBoost algorithm, to efficiently search for optimal parameters that minimize the objective function, a second-order Taylor expansion of the objective function is performed to obtain an approximate objective function. When the constant term is removed, the objective function only depends on the first and second derivatives of the loss function. Therefore, the objective function can be approximated as:

$$\mathrm{Obj^{(t)}} \approx \sum_{i=1}^{n} \left[\mathrm{g_i w_{q(x_i)}} + \frac{1}{2} \mathrm{h_i w_{q(x_i)}}^2\right] + \gamma \mathrm{T} + \frac{1}{2} \sum_{j=1}^{\mathrm{T}} \mathrm{w_j}^2 = \sum_{j=1}^{\mathrm{T}} \left[(\sum_{i \in I_j} \mathrm{g_i}) \mathrm{w_j} + \frac{1}{2} (\sum_{i \in I_j} \mathrm{h_i} + \lambda) \mathrm{w_j}^2\right] + \gamma \mathrm{T} \tag{9}$$

Where the objective function is minimized with respect to the scores w_j for each leaf node. This minimization problem is essentially finding the optimal solution for a quadratic function.

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$$w_j^* = \frac{-\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i + \lambda}$$

$$\mathrm{Obj} = -\frac{1}{2}\sum_{j=1}^{T}\frac{(\sum_{i\in I_j} g_i)^2}{\sum_{i\in I_j} h_i+\lambda} + \gamma T \tag{10}$$

The $\mathrm{Ob_j}$ value serves as a scoring function to evaluate the model. A smaller $\mathrm{Ob_j}$ value indicates a better model performance. By recursively building decision trees and optimizing their structures, XGBoost constructs an ensemble of regression trees to build the best XGBoost model.

2.3. Random Forest

Random Forest (RF) is a supervised machine learning method that combines decision trees as base learners through an ensemble approach. [9]RF introduces randomness during both sample selection and feature selection in the training process, making it robust against overfitting and noise.

1) Random Sample Selection: In RF, each decision tree is trained on a randomly sampled subset of the original dataset using a technique called bootstrap sampling. This means that each subset can contain duplicate samples, and different subsets are independent of each other.

2) Random Feature Selection: Unlike individual decision trees that consider all features for splitting nodes during the tree-building process, RF randomly selects a subset of features to consider at each split. This introduces feature selection randomness and contributes to the model's diversity.

The steps of the Random Forest algorithm are as follows:

A) Bootstrap Sampling: Randomly select n samples with replacement from the original dataset to create k subsets. These subsets are used as training datasets for each decision tree. The subsets may overlap because of the with-replacement sampling.

B) Building Decision Trees: Build a decision tree for each subset using the standard tree-building algorithm (e.g., CART). During tree construction, only a random subset of features is considered for each split.

C) Ensemble Decision Trees: For classification tasks, the ensemble of decision trees predicts the class label by a majority vote. For regression tasks, the ensemble predicts the average or weighted average of the individual tree predictions.

2.4. Gradient Boosting Decision Trees (GBDT)

Gradient Boosting Decision Trees (GBDT) is a boosting algorithm that uses CART regression trees as base learners. GBDT, originally proposed by Friedman, focuses on optimizing general loss functions and aims to minimize the residuals of the previous round of base learners. This iterative process gradually reduces the residuals, allowing the model's predictions to approach the true values.

The core idea of GBDT is to fit the negative gradient of the loss function with respect to the model's output in each iteration. [10]This fitting ensures that each round of training adjusts the model's predictions in the direction that minimizes the loss function, resulting in faster convergence toward a local or global minimum.

2.5. Gradient Descent

Gradient Descent is an optimization method based on searching for the minimum of a loss function. It is commonly used for minimizing loss functions in machine learning model parameter optimization, particularly in unconstrained optimization problems. Gradient Descent stands out as one of the most frequently utilized techniques for training machine learning models. It operates by iteratively adjusting the model's parameters to minimize the loss function (figure 2).

The key idea of Gradient Descent is to update the model's parameters in the direction of the negative gradient of the loss function with respect to those parameters. This iterative process aims to reach a minimum point of the loss function, which corresponds to optimal model parameters.

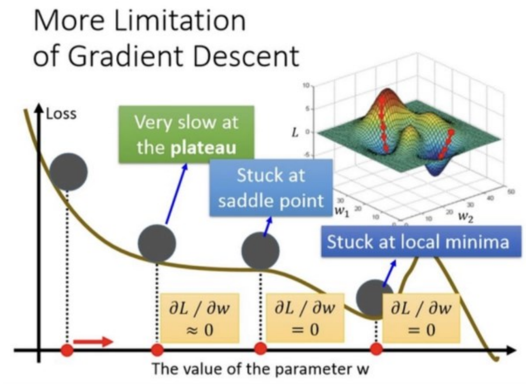

Figure 2. Gradient Descent algorithm graph

3. Variable selection

3.1. Traditional Energy Factors

Traditional energy refers to finite and non-renewable energy sources, such as coal, oil, and natural gas, which have limited reserves. Currently, China's energy landscape is still dominated by traditional energy sources. New energy started relatively late in China and had a lower market share. However, with recent policy support, the new energy market has been growing.

The stock prices of new energy companies are notably sensitive to fluctuations in the conventional energy market, with oil prices exerting the most significant influence. In the oil market, research by Tang and Tang (2010) using cointegration equations found that as international oil prices rise, the total consumption of new energy increases, leading to an increase in the stock prices of new energy companies. The connection between international oil prices and the new energy vehicle industry is particularly strong. CATL, as a developer of power batteries, is positioned upstream in the new energy vehicle industry, and its stock prices are inevitably influenced by fluctuations in international oil prices.

Therefore, to comprehensively consider the impact of domestic and international markets on the stock price of CATL, this study selects Brent crude oil prices and Daqing crude oil prices as representatives of traditional energy market factors (table 1). Figure 3 shows the price trends for these factors.

3.2. Carbon Trading Factors

The carbon trading market is a significant institutional innovation aimed at promoting the development of a green and low-carbon economy and reducing greenhouse gas emissions. The carbon trading market increases the production costs of high-carbon companies, prompting them to increase their demand for new and renewable energy sources. It also provides additional carbon trading revenue for new energy companies by allowing them to sell carbon quotas. This, in turn, creates more market demand for the technology, equipment, and services of new energy companies, leading to increased revenue and stock prices for these companies. The carbon trading market provides policy incentives for the development of the new energy industry [11]. CATL, as a representative company in the new energy industry, has a close relationship between its stock price trends and the carbon trading market.

Therefore, this study selects the Beijing carbon trading market and the European carbon emissions futures prices as representative factors for carbon trading. Figure 4 shows the price trends in these two markets.

3.3. Environmental Factors

The Air Quality Index (AQI) is a dimensionless index used to quantitatively describe air quality conditions. The smaller the AQI value in a region, the lower the air pollution. Research has shown that carbon emissions from new energy vehicles are only one-fourth of those of traditional fuel vehicles, and

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the proportion of emissions of air pollutants such as carbon monoxide, sulfur dioxide, and nitrogen dioxide is even lower, close to one-sixth. Therefore, the application of new energy meets the need for air quality and environmental protection. CATL, as a representative company in the new energy sector, may have a certain relationship between its stock prices and the AQI. This study selects the AQI in Beijing as the environmental representative factor. Figure 5 shows the time series of AQI in Beijing.

3.4. Industry Factors

CATL, positioned as a power battery manufacturer within the upstream segment of the new energy vehicle industry, experiences substantial impacts based on the progress of the new energy vehicle sector. The state of affairs in the new energy vehicle industry is intricately linked to the broader evolution of the automotive industry. For this study, the stock prices of the Shanghai Stock Exchange Automobile Index and the New Energy Vehicle Index have been chosen as representative factors for the industry. Figure 6 illustrates the time series data for the stock prices of these indices.

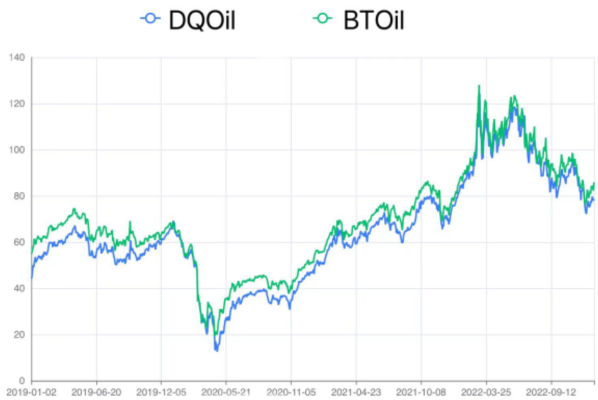

Figure 3. Time series of DQOil and BTOil

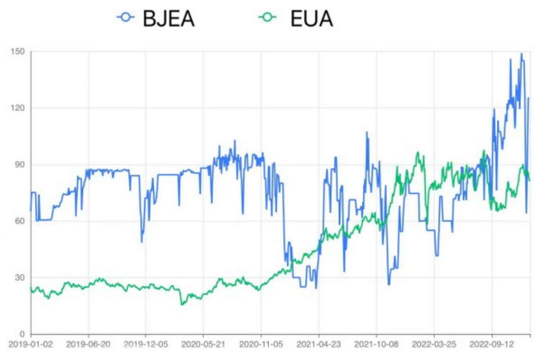

Figure 4. Time series of BJEA and EUA

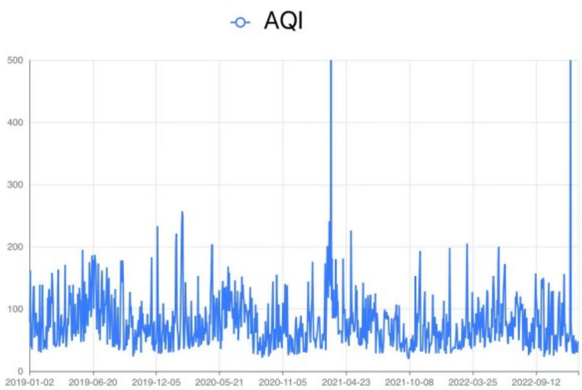

Figure 5. Time series of AQI

Figure 6. Time series of SZ and XN

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Table 1. Specific Explanatory Variables

Variable Category	Variable Name	Symbol
Traditional Energy Factors	Continuous Futures Settlement Price - Brent Crude Oil	BTOil
	Daqing Crude Oil Price	DQOil
Carbon Trading Factors	Beijing Carbon Emissions Allowance-Average Transaction Price	BJEA
	Continuous Futures Settlement Price - European Union Emission Allowances	EUA
Environmental Factors	Air Quality Index (AQI) - Beijing	AQI
Industry Factors	New Energy Vehicles	XN
	Shanghai Stock Exchange Automobile Index	SZ

3.5. Descriptive Statistical Analysis

Considering the three factors of variable selection: accessibility, quantifiability, and effectiveness, this study selects Brent crude oil prices, Daqing crude oil prices, European power coal price index, Beijing carbon trading price, European carbon emissions futures, Beijing air quality index, new energy vehicles (399417), and Shanghai Stock Exchange Automobile Index (950070) as explanatory variables. CATL (300750) is selected as the dependent variable. The data covers the period from January 1, 2019, to December 31, 2022, with daily closing prices. The data sources are from the Wind database. As some data contain missing values, after removing missing values and non-trading days from all samples, there are 1041 remaining data points. The table 2 shows the descriptive statistics results.

Table 2. Descriptive Statistics Results

Variable Name	Sample Size	Maximum	Minimum	Mean	Standard Deviation	Median	Variance	Kurtosis	Skewness	Coefficient of Variation (CV)
New Energy Vehicles	1040	5418.966	1463.115	3088.364	1225.131	3165.755	1500946.492	-1.325	0.228	0.397
Shanghai Stock Exchange Automobile Index	1040	7101.979	3488.031	5094.075	991.631	5003.514	983332.885	-1.276	0.203	0.195
CATL	1040	688	66.87	300.635	187.276	311.3	35072.168	-1.387	0.187	0.623
Air Quality Index (AQI) - Beijing	1040	500	20	77.802	43.941	69	1930.806	16.54	2.564	0.565
Continuous Futures Settlement Price - European Union Emission Allowances (EUA)	1040	97.67	15.24	45.973	24.536	32.31	602.025	-1.277	0.561	0.534
Beijing Carbon Emissions Allowance (BJEA) - Average Transaction Price	1040	149	24	76.628	21.063	81.445	443.663	1.111	-0.122	0.275
Continuous Futures Settlement Price - Brent Crude Oil	1040	127.98	19.33	69.266	21.882	66.58	478.801	-0.228	0.309	0.316
Spot Price - Crude Oil (Daqing, China): Circum-Pacific	1040	124.18	12.56	64.089	22.57	61.245	509.394	-0.245	0.347	0.352

3.6. Pearson Correlation Analysis

Figure 7 shows the results of correlation analysis.

Figure 7. Results of Pearson Correlation Analysis shown in heat map

4. Model Establishment

4.1. BP Neural Network Regression

Table 3 summarizes the performance of BP Neural Network Regression. Figure 8 presents the forecast trend of CATL stock price based on BP Neural Network Regression.

Table 3. Performance of BP Neural Network Regression

	MSE	RMSE	MAE	MAPE	R^2
Training Set	379.383	19.478	13.82	6.803	0.984
Testing Set	1273.35	35.684	27.703	6.018	0.829

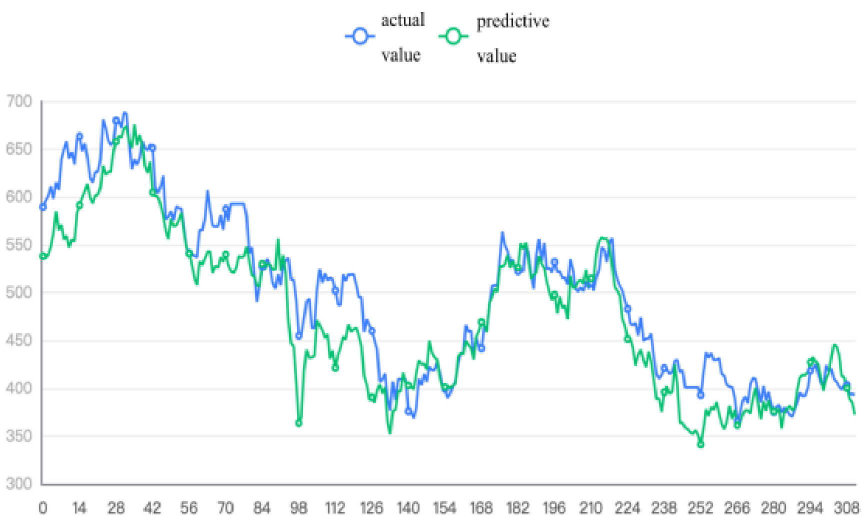

Figure 8. Forecast trend chart of CATL stock price based on BP Neural Network Regression

4.2. XGBoost Regression

Table 4 summarizes the performance of XGBoost. Figure 9 presents the forecast trend of CATL stock price based on XGBoost Regression.

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Table 4. Performance of XGBoost Regression

	MSE	RMSE	MAE	MAPE	R^2
Training Set	0.09	0.3	0.206	0.15	1
Testing Set	3896.043	62.418	47.856	9.792	0.478

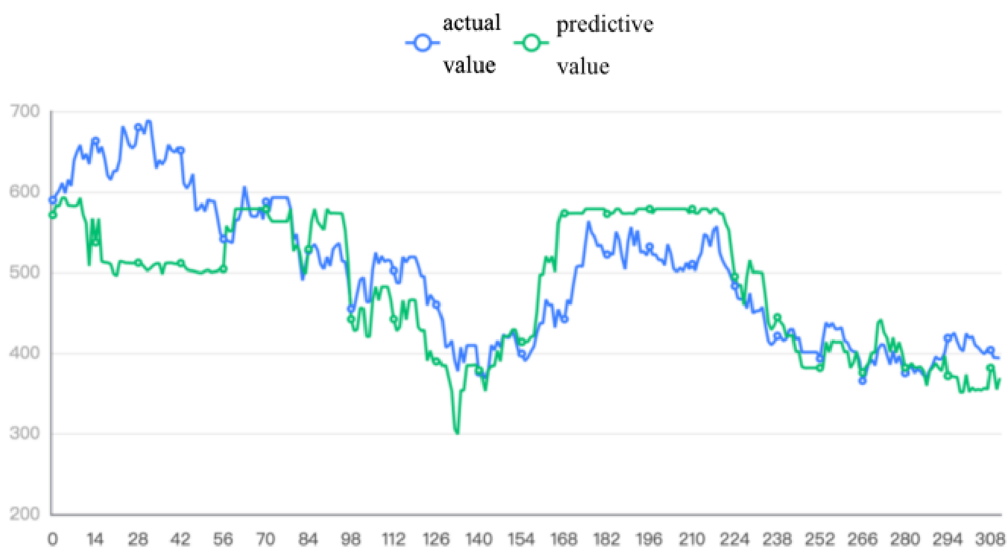

Figure 9. Forecast trend chart of CATL stock price based on XGBoost Regression

4.3. Random Forest Regression

Table 5 summarizes the performance of Random Forest Regression. Figure 10 presents the forecast trend of CATL stock price based on Random Forest Regression.

Table 5. Performance of Random Forest Regression

	MSE	RMSE	MAE	MAPE	R^2
Training Set	31.179	5.584	4.14	2.341	0.999
Testing Set	3601.637	60.014	44.015	9.095	0.517

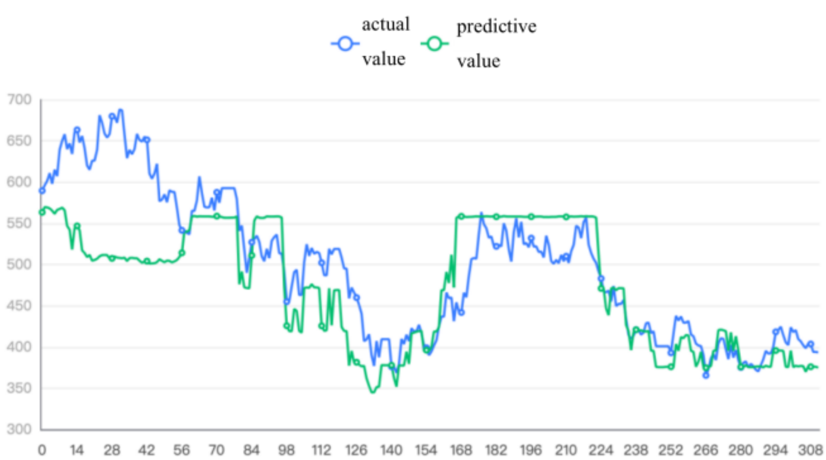

Figure 10. Forecast trend chart of CATL stock price based on Random Forest Regression

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4.4. Gradient Boosting Decision Tree (GBDT)

Table 6 summarizes the performance of GBDT. Figure 11 presents the forecast trend of CATL stock price based on GBDT.

Table 6. Performance of Gradient Boosting Decision Tree (GBDT)

	MSE	RMSE	MAE	MAPE	R^2
Training Set	0.261	0.511	0.412	0.312	1
Testing Set	3988.213	63.152	48.318	9.629	0.466

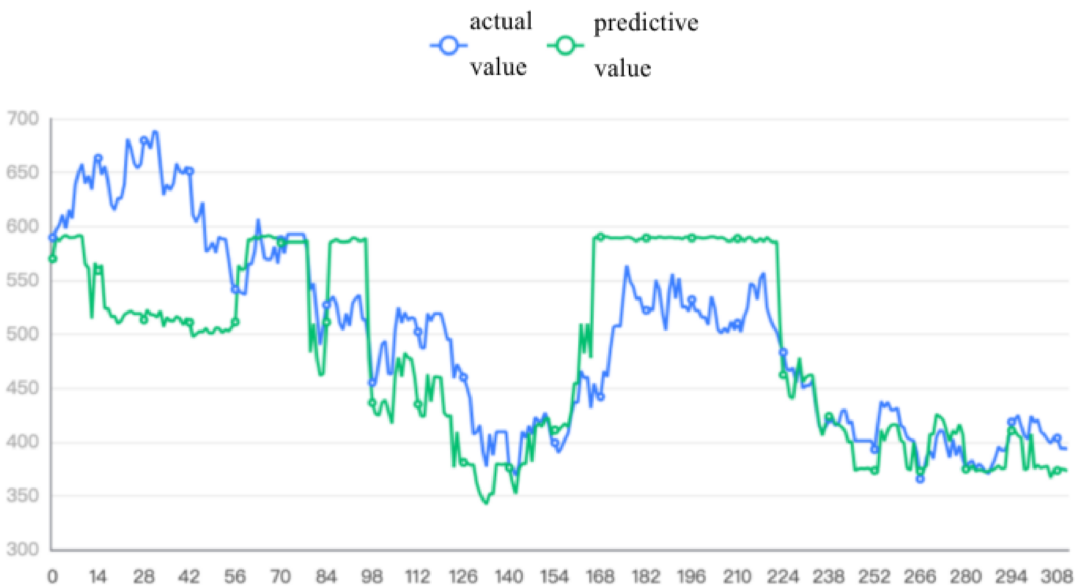

Figure 11. Forecast trend chart of CATL stock price based on Gradient Boosting Decision Tree(GBDT)

4.5. Gradient Descent

Table 7 summarizes the performance of Gradient Descent. Figure 12 presents the forecast trend of CATL stock price based on Gradient Descent.

Table 7. Performance of Gradient Descent

	MSE	RMSE	MAE	MAPE	R^2
Training Set	362.844	19.048	13.505	6.872	0.984
Testing Set	1312.889	36.234	27.722	6.024	0.824

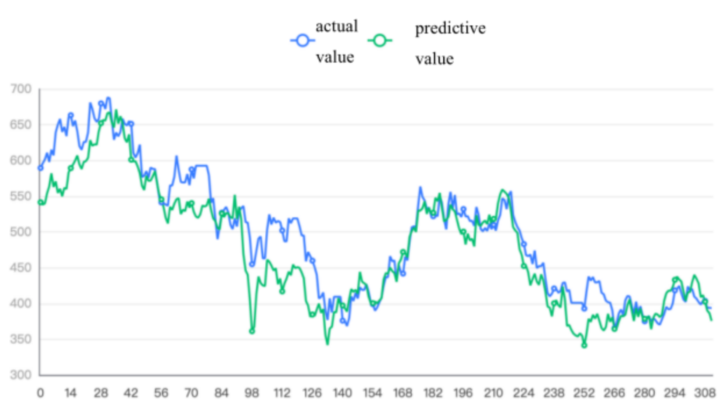

Figure 12. Forecast trend chart of CATL stock price based on Gradient Descent

5. Conclusion

China is currently in a crucial period of energy structure transformation. To meet the needs of environmental protection and energy security, Chinese policies strongly support the development of the new energy industry, which is showing positive overall development trends. This study selected CATL, a representative company in the new energy industry, as the analysis subject. Considering factors such as traditional energy, carbon trading, environmental protection, and industry, this study selected Brent crude oil prices, Daqing crude oil prices, Beijing carbon trading prices, European carbon emissions futures, Beijing air quality index, new energy vehicles, and the Shanghai Stock Exchange Automobile Index as explanatory variables. The stock price of CATL was selected as the dependent variable. Five stock price prediction models were established, including BP neural network regression, XGBoost regression, random forest regression, gradient boosting decision tree (GBDT), and gradient descent. After comparative analysis, the BP neural network regression-based model performed the best in predicting the stock price of CATL, with an RMSE of 35.684 and an MAE of 27.703.

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