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Optimal production with carbon trading market in China

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Abstract

As a significant carbon dioxide-emitting country globally, China has set a concrete short-term target of carbon dioxide emissions peak in 2030 and an ambitious long-term plan to reach carbon neutrality by 2060. One essential policy is to set up a carbon trading market to reduce high-pollution enterprises' carbon emissions by rationally allocating carbon quotas among different firms and regions and setting carbon quotas trading market.

In reality, firms obtain carbon quotas in three ways, initial allocation from the government, carbon market trading, and purification. By using carbon quotas, firms are required to meet the limitation of carbon emissions by regulations. To help firms make the cost-optimal decision in both short-term and long-term management, this paper focuses on the impact and trading of carbon quota for emission-depending firms.

The short-term optimal production model suits firms less than a year from meeting emission limitation requirements. It is considered that during this time, firms cannot upgrade production equipment with less carbon emission but can only sell or buy carbon quotas in the carbon trading market. Furthermore, this paper builds a carbon quota price predicting model based on the long-short-term memory neural networks(LSTM) method to help firms develop a better trading strategy. In the long term, firms can update their technique to less carbon-emitting production technology. Therefore, a long-term optimal production model is established, and variable purifying levels are discussed. Finally, this paper calculates the optimal production strategy under different restraints of carbon emission.

Keywords: optimal production model; carbon quota; emission permits and trading

1 Introduction

Ever since the world began to pay attention to the impact of climate warming on the human living environment, the real establishment of a carbon emission trading system experienced 20 years of development. After difficult negotiations, the IPCC adopted the 'United Nations Climate Change Framework' in 1992. In December 1997, the United Nations Framework Convention on Climate Change called for the third Conference of the Parties. Representatives from 149 countries signed the 'Kyoto Protocol,' a complementary document to the United Nations Framework Convention on Climate Change, hoping to remove greenhouse gases from the atmosphere. The Kyoto Protocol stipulates three flexible carbon Emission Trading mechanisms: Emission Trading, Clean Development Mechanism, and Joint Implementation Mechanism. The carbon trading market has emerged.

Carbon trading is a market-based mechanism for reducing emissions, and it has been implemented in China since 2021 when the long-awaited national emissions trading system (ETS) was launched. As the largest carbon market in the world, China's carbon trading system will be more than ten times larger than California's, doubling the share of global emissions covered under such a system and covering approximately one-tenth of global carbon dioxide emissions. In the first phase, the market will be focused exclusively on the power sector, covering over 2,200 businesses, comprising more than 40 percent of the nation's emissions, and with plans to incorporate other sectors (i.e., steel and cement) - and the regional pilot markets - in the future.

China has set a concrete short-term target of carbon dioxide emissions peak in 2030 and an ambitious long-term plan to reach carbon neutrality by 2060. To achieve such a goal, China's government mainly uses a combination of different jurisdictions-carbon quota, carbon tax, offsets(not available after 2017 in China), carbon trading scheme, and penalty. Initially, firms will receive carbon quota allocation from the government for free. When a firm's carbon emission exceeds its initial allocation, it must pay the penalty for emitting excessively. However, firms can buy or sell carbon quotas in the carbon trading market to reduce emissions and avoid penalties. At last, enterprises need to pay taxes based on their volume of total carbon emissions.

This paper establishes two mathematical models to help enterprises earn the maximum profit under the carbon trade system and variable constraints. Section 2 briefly reviews the status of China's carbon trading system and theories of carbon quotas. Section 3 explains the LSTM model's function and how it helps carbon market traders predict prices and builds two cost-optimal models for profit maximization in both short-term and long-term situations. And section 4 shows the predicted carbon quota price of the LSTM model. Section 5 concluded.

2 Literature review

The theoretical carbon trading system originates from the "emission trading" theory proposed by economist Dales in the 1960s. And the solution to the greenhouse gas problem in the form of emissions trading is mainly motivated by the consideration of "internalizing externalities." Externality was first proposed in 1890, and Pigou further proposed two concepts of external diseconomies and external economies in Welfare Economics[1].

Coase proposed a new idea to solve negative externalities by introducing the concept of tradable property rights. That is, the behavior that causes negative externalities is considered a tradable right. According to Hardin (1968), the tragedy of the Commons will occur only when individuals treat public resources in their way and use unrestrained resources. Due to the lack of property rights for goods of public nature, users lack the motivation to protect public goods, resulting in their damage or disappearance[2]. From this perspective, Coase believed that under zero transaction cost and clear property rights, voluntary transactions could converge the private cost and social cost of economic activities to solve the externality problem and realize the optimal allocation of resources.

The production decisions of firms directly affect the carbon emissions of firms. When there is a carbon quota constraint, the production cost of enterprises changes directly due to the increase in carbon cost. Therefore, the mechanism and trend of enterprise cost change have been studied [3-10]. Taking the article by Damailly D [4] and the article by Robin Smale [10] as an example, they analyzed the impact of the European carbon trading system on the cost and profit of enterprises in different ways. They believed that the increase in firms' marginal cost led to reduced output, but the increased product price could be greater than the extra cost. At the same time, they can also benefit from free emission allocation, so firms do not necessarily lose profits from implementing a carbon trading system. Based on the cost structure, CO_2 emissions, electricity consumption, and quota allocation data, Tomas RAF evaluated the impact of the implementation of carbon quota trading on the chemical industry in Portugal. Their study comprehensively considered the increase in direct and indirect production costs and compared the results with those of other EU countries and industries. The results showed that The impact of carbon quota trading on the chemical industry's competitiveness in Portugal is not great, which may be lower than that of other industrial sectors [3]. Damailly D and Quirion P discussed the impact of the EU carbon trading system on the competitiveness of the iron and steel industry from two aspects of production and profit. The study concluded that the constraint of carbon quota did not greatly impact the industry's competitiveness. Therefore, the author believed that the opposition to implementing stricter emission reduction targets by the EU in the second stage of implementing carbon trading should be based on other reasons. Not for reasons of loss of competitiveness in the industry.

The author further analyzes the robustness of marginal abatement cost, demand, transaction elasticity, and cost transfer rate [4]. Chan HS analyzed the changes in the competitiveness of power, cement, and steel industries due to carbon quota constraints from three levels: unit material cost, employment rate, and profit. The research shows that the carbon quota constraint does not impact the cement and steel industries' competitiveness. In contrast, for the electric power industry, the carbon quota constraint positively affects the unit material cost and profit. The positive effect on the cost reflects the increase of the carbon constraint on the cost of enterprises. The increase in profits reflects the behavior of power enterprises transferring the cost increase to consumers[6]. Lee M analyzed the potential cost increase of Korean power enterprises after participating in carbon trading[7]. Kara analyzes the impact of a carbon trading system on the Nordic electricity market and assesses the location of various market participants. According to the research, the participation of the power industry in the carbon trading system leads to the rise of electricity prices, which in turn leads to a heavy impact on private consumers and the metal industry. In contrast, developing nuclear power will limit electricity price growth to a certain extent[8]. In addition to discussing the cost changes of enterprises under the constraint of carbon quota, scholars also adopt modeling and Numerical analysis methods to study the changes in firms' production decisions under carbon trading.

Furthermore, Zhang and Xu(2013) used the profit maximization model to analyze the optimal output and carbon trading decision and discuss the impact of the carbon price and total carbon quotas on production capacity, decision, and total profit when the carbon quotas trading was small, with multiple project production plans and independent and random demand of each project[11].

3 Methodology

In reality, firms obtain carbon quotas in three ways, initial allocation from the government, carbon market trading, and purifying. By using carbon quotas, firms must meet the limitation of carbon emissions by regulations in both short-term and long-term management. In the short term, we build a cost-optimal model with the help of carbon quota price prediction conducted by the LSTM method. We discuss firms' optimal production strategy under variable purifying levels in the long-term cost-optimal model.

Before establishing our cost-optimal models, a few assumptions are made as follows.

3.1 Preparation for the models

3.1.1 Assumption and Justifications

(1) Free trading of emission rights

Considering that many industries and enterprises participate in carbon emission trading in the current market, and afforest organizations have a large supply capacity of emission permits, this paper assumes that the emission permits market is sufficient for individuals in the carbon emission trading market within a certain range.

(2) High-emission industries with monopolistic or oligopolistic nature

Currently, mainly seven industries with a monopoly or oligopoly nature are allowed to enter the carbon trading market -electricity, building materials, cement, steel, petrochemical, paper production, and civil aviation. Therefore, this study assumes selling price in the product market is determined by the output.

(3) Constant unit output

Technological improvement in production is not considered in this paper because of its relatively standardized industrialization process in these industries.

(4) Short-term and long-term strategy

After conducting many market investigations, we found that some firms cannot achieve clean technology updates to reduce emissions per output unit before the current year's carbon quota cost performance deadline. However, firms can finally achieve clean technology updates in the long term through continuous technology iteration and capital investment. Therefore, this study will discuss both the short-term and long-term situations.

(5) Purification cost assumption

In the long run, this study believes that firms have sufficient time to purify their production technology and obtain emission-right savings.

(6) Purification technology assumptions

This study assumes that the update of purification technology only reduces the emissions per unit of product but does not increase the output and reduce the emissions simultaneously, which is consistent with most situations.

3.1.2 Notations

The notations used in this paper are listed.

Symbols	Definition
E_g	Initial allocation of carbon quota by government
E_m	The amount of carbon quota purchased or sold in the carbon market by firms
E_p	Carbon emissions reduced by purification
p^*	Carbon quota trading price which the LSTM model can predict
β	Carbon emission per unit of product produced by firms
$E(q)$	Actual carbon emission output $E(q) = eq$
$P(q)$	Product price $P(q) = \omega - uq$
α	Purification level
C_0	Marginal production cost of products
t	The carbon tax rate of an industry
$C(\alpha)$	Cost of purification

3.2 Prediction of carbon quota price based on the LSTM Network Method

Deep learning methods such as long-short-term memory neural networks (LSTM) can better handle highly correlated financial time series problems and achieve higher accuracy when dealing with nonlinear trends and sequence-related data issues. Therefore, this paper uses LSTM neural networks to acquire the time series characteristics of historical trading data of carbon quotas and establish an LSTM neural network prediction model.

Before experimenting, we performed data per process and checked abnormal and missing values. For the missing values in non-trading days, we removed the data for continuous forecasting of national carbon quotas.

Later, we performed abnormal value detection on the data. As the data in this experiment was taken from publicly available trading data[12] rather than real-time data, we assumed there were no abnormal values. Furthermore, we normalized the data by creating a MinMaxScaler object and converted all numerical variables to values from 0 to 1.

$$x_i' = \frac{x_i - \overline{x}}{\max(x) - \min(x)}$$

In this paper, MAE and RMSE, as well as the Learning time and Convergence speed of the model, are selected as evaluation indicators for the performance of the LSTM neural network prediction model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \widehat{y_i}\right|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)}$$

n is the size of the data set, Y_i is the actual price of the carbon quota, and $\widehat{Y_i}$ represents the model's predicted value.

This paper mainly tunes three model parameters: the number of hidden layers, learning rate, and maximum training iterations. The range of the number of hidden units in the LSTM neural network can be calculated based on empirical formulas.

$$n = \sqrt{m+n} + a$$

Parameter q represents the number of hidden layers, m represents the number of input layers, n represents the number of output layers, and a is a constant between 1 and 10. In the experiment, m is set to 20, n is set to 1, and the value ranges from 1 to 10. According to the formula, the range of the number of hidden layers is calculated to be between 5 and 15. To determine the specific number of hidden layers, the q values are set to integer values between 5 and 15 while keeping m and n constant for simulation and verification.

After multiple experiments, it is observed that the error rate of the LSTM neural network decreases continuously from 5 hidden layers. The MAE and RMSE values reach their minimum when the number of hidden layers is 12, and the error rates increase continuously when the number of hidden layers is between 12 and 14. Therefore, the optimal number of hidden layers for the LSTM neural network is 12, where the MAE and RMSE values are the lowest, and the prediction results are more accurate.

Learning rate parameters: When the learning rate is 0.01, the results shown in the figure shows that the loss function frequently fluctuates with the increase of the number of training times, which means that the model parameters skip the optimal value in each update, resulting in the instability of the training process and even failure to converge. After reducing it to 0.01, the right figure shows the effect.

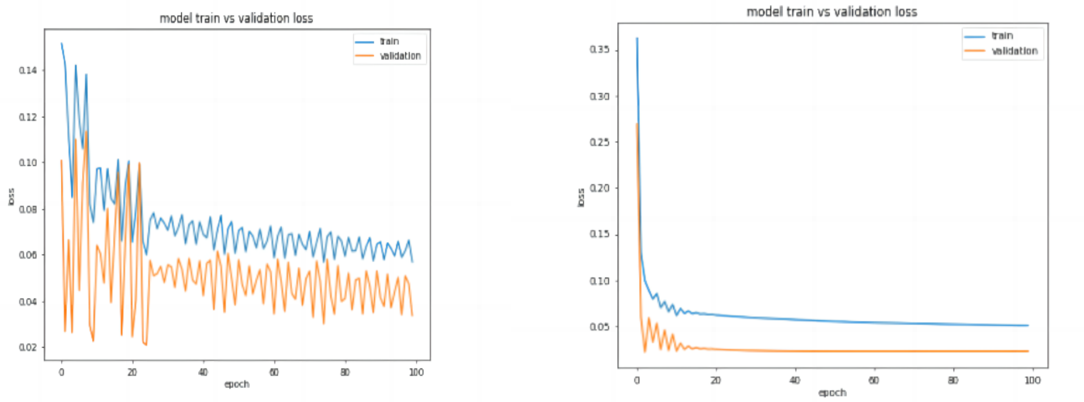

Figure 1: The loss function when the learning rate parameter is set at 0.01 and its effect.

Data source: Publicly available trading data from the Shanghai Environment and energy exchange(SEEE)

Batch size parameter: Batch size refers to the number of samples used in each training. Using batch training can significantly accelerate the training process and improve the model's generalization ability. A large batch size can speed up the training speed of the model, but at the same time, it may lead to an increased risk of model overfitting. However, although a small batch size can reduce the risk of model overfitting, it may lead to low efficiency of model training.

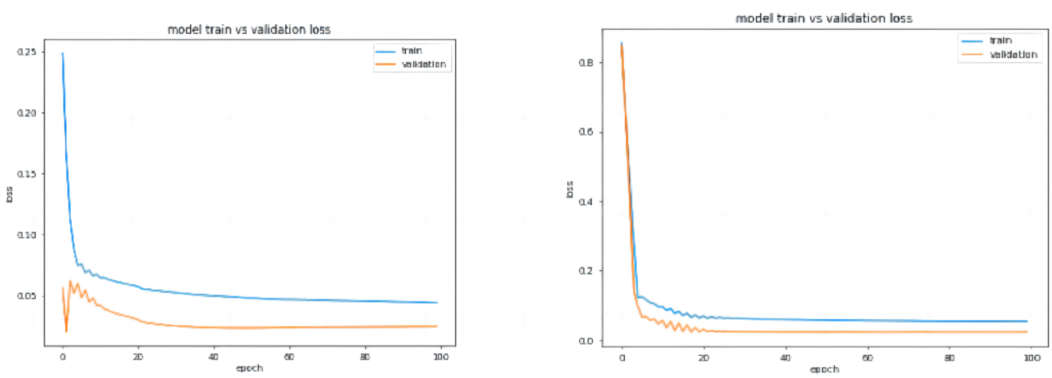

Figure 2: The function loss of batch sizes from 2 to 16.

Data source: Publicly available trading data from the Shanghai Environment and energy exchange(SEEE)

Step parameter: The time step refers to the point at which each sequence element is input into the model, and the number of time steps determines the length of the input sequence that the model can take into account. The selection of time steps needs to consider the model's computational and storage complexity. The three groups with time steps equal to 20 were compared.

When time steps equal 25, there is a large oscillation from 3 to 5 epochs, which may be affected by the randomness of the model. Regarding the carbon quota price change trend, we use the data of the first 20 trading days to predict the closing price data of the 21st day. This is because the data of more than 20 days has little influence on the data of the 21st day, and the accuracy of prediction may be affected by factors such as seasonality and trend. Therefore, we choose time steps equal to 20 as the time step parameter of this model.

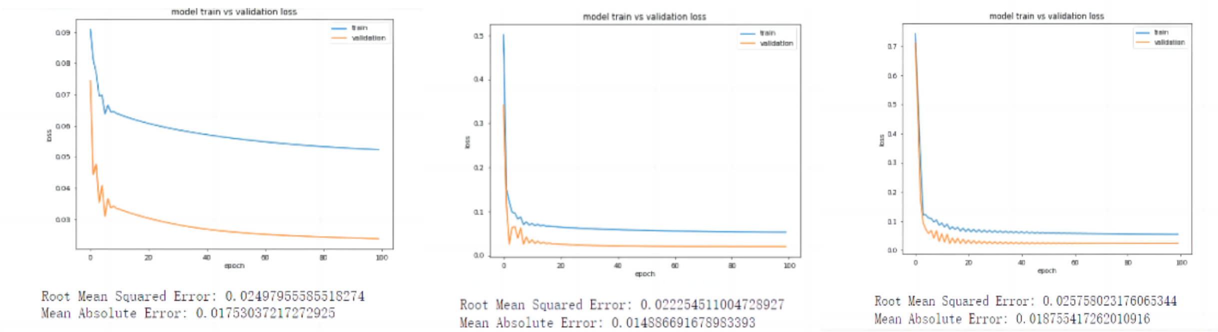

Figure 3: The function loss of time steps.

Data source: Publicly available trading data from the Shanghai Environment and energy exchange(SEEE)

3.3 Short-term Cost Optimization Model

In the short term, we believe firms cannot upgrade a cleaner technology in the short term due to the time limitation. Therefore, this model aims to discuss the impact of emission permits on the output decision of production enterprises in the short term, and only the emission-related costs and production costs need to be considered. In contrast, other costs can be ignored, not affecting the analysis results. The firm's profit function is

$$\pi = \left[P(q) - c_0\right]q - p^{\mu}\left[E(q) - E_g\right] - tE(q)$$

$$\textbf{s.t.}\ \ E_g + E_m \le E(q)$$

$\left[P(q) - c_0\right]q$ is the product profit which equals net revenue per unit of product multiple by the quantity sold. $P^*\left[E(q) - E_g\right]$ is the cost or benefit of purchasing or selling carbon quota. tε_c is the carbon tax payable by a certain firm under the condition of the carbon tax rate of a certain industry.

Because firms have profit maximization goals, the restriction will become

$$\textbf{s.t.}\ \ E_g + E_m = E(q)$$

When $E(q) = E_g$, the initial emissions allocated by the government are greater than the emissions. Firms are faced with deciding whether to sell the remaining carbon quota for profit or completely use the carbon quota to continue production. To solve this problem, we need to analyze continuing production's marginal cost and marginal benefit.

Suppose the profit obtained by selling the carbon quota is greater than that obtained by completely using the carbon quota to continue production. In that case, the firm will choose to sell the remaining carbon quota. Therefore, the profit function of the enterprise will become the following form:

$$\pi = \left[p(q) - c_0\right]q + p^*\left[E(q) - E_g\right] - tE(q)$$

$$\textbf{s.t.}\ \ \beta p^* > p(q) - c_0$$

Suppose the profit from selling the carbon quota is less than the profit from continuing production by completely using the carbon quota. In that case, the firm will choose to continue production by completely using the carbon quota.

$$\pi = \left[P(q) - c_0\right]q - tE(q)$$

$$\textbf{s.t.}\ \ \beta p^* < P(q) - c_0$$

When $E(q) < E_g$, the initial emissions allocated are less than the natural emissions of the enterprise, the firm decides to minimize the loss cost, which turns into whether to purchase a carbon quota for cost fulfillment or reduce emissions by reducing production.

Suppose the carbon quota price predicted is higher than the profit lost when reducing production. In that case, the enterprise will choose to reduce production to reduce emissions and finally realize the cost performance, and its profit function becomes the following form:

$$\pi = \left[P(q) - c_0\right]q - tE(q)$$

Suppose the carbon quota price is lower than the profit lost when reducing production. In that case, the enterprise will purchase a carbon quota to fulfill the contract rather than giving up the output already produced or continuing production. In this case, the profit function becomes the following form:

$$\pi = \left[P(q) - c_0\right]q - p^4\left[E(q) - E_g\right] - t\varepsilon_c$$

3.4 Long-term Cost Optimization model(LCO model)

In the long term, we consider the carbon quota of producers mainly comes from three channels: initial government allocation, carbon quota savings obtained from purification, and purchase from the carbon trading market. We will discuss situations of constant purification levels and alterable purification levels.

3.4.1 Constant purification level

When the producer's emission purification level α is constant, we will need to find the specific correlation between profit(π) and E_p to determine the optimal output and emission reduction.

$\dfrac{c(\alpha)}{\alpha}$ is the purification cost per unit. When $\dfrac{c(\alpha)}{\alpha} < p^*$, the purification cost per unit is less than the carbon quota price, it can be concluded that $\dfrac{\partial\pi}{\partial E_p} > 0$ and the cost of reducing carbon emissions through purification is lower than that of purchasing carbon quota from the market when the cost is fulfilled. Therefore, The optimal strategy of the producer is to preferentially purify all emissions, purchase the insufficient part from the trading market and put the surplus part into the trading market to earn the difference.

$$\pi = \left[a - bq - c_0\right]q - eq\left[\left(p^*(1-\alpha) + C(\alpha)\right] - tE(q)\right.$$

$$\textbf{s.t.}\ \frac{\partial x}{\Delta q} = 0$$

$$\textbf{s.t.}\ P(q) = a - bq$$

The optimal production will be

$$q^* = \frac{a - e\left[\left(p^*(1-\alpha) + c(\alpha)\right]\right.}{2b}$$

Under optimal production, the maximizing profit should be

$$E_p = eq^*$$

$$E_g = \alpha eq^*$$

$$E_m = (1-\alpha)E\left(q^*\right) - E_g$$

$$\pi^* = q^*\left[a - ep^*(1-\alpha) - eC(\alpha))\right] - \alpha\left(q^*\right)^2 + p^*E_g$$

When $\dfrac{c(\alpha)}{\alpha} = p^*$, the purification cost per unit is equal to the price of the carbon quota purchased per unit; under this condition, the cost of purification is equivalent to the purchase carbon quota in the market. Any value has no impact on the profits of firms.

If the firm decides to purchase carbon quota in the market instead of purification, the function of profit will be

$$\pi = \left[a - bq - c_0\right]q - p^\mu\left(eq^\mu - E_g\right) - teq$$

$$\textbf{s.t.}\ E_m + \alpha E_p + E_g = eq*$$

The optimal production will be

$$\frac{\partial\pi}{\partial q} = a - 2bq - p^*e - te = 0$$

$$q^* = \frac{\theta\left(t - p^-\right) - a}{2b}$$

When $\dfrac{c(\alpha)}{\alpha} < p^*$, the purification cost per unit is less than the price of carbon quota purchased per unit in the market. In this case, the profit π of the enterprise is a monotonically decreasing function. Therefore, when the enterprise takes profit maximization as the premise, it will not choose purification but simply buy carbon quota from the market.

$$E_p = 0$$

In this case, the producer's revenue is still

$$\pi = \left[a - bq - c_0\right]q - p^*\left(eq^* - E_g\right) - teq$$

$$\textbf{s.t.}\ E_m + \alpha E_p + E_g = eq*$$

The optimal production will be

$$\frac{\partial\pi}{\partial q} = a - 2bq - p^*e - te = 0$$

$$q^* = \frac{\theta\left(t - p^-\right) - a}{2b}$$

3.4.2 Alterable purification level

In the case of variable purification level, it becomes a decision variable in the interval of 0 to 1, and in this case, the construction function is

$$f(\alpha) = p^{*}\alpha - C(\alpha)$$

The economic significance of this time is the set of purification levels in which the carbon emissions of enterprises in production purification treatment is better than the carbon quota traded in the market, which is called the "purification area."

When the purification area is empty, and there are no satisfactory results in the feasible space, the enterprise will not carry out purification during production, and the income obtained from production is irrelevant.

When the purification region is not an empty set, the enterprise must find the optimal coefficient solution in the purification space.

The existence of the purification space needs to meet the following proof.

Proposition 1: The necessary and sufficient condition for the existence of purified space is

$$\frac{\partial C(0)}{\partial \alpha} < P^{*}$$

Proposition 2: If there is a purified space, the function $f(\alpha)$ has a maximum value, and the corresponding a^{*} must be in the purified space.

Let's assume

$$C(\alpha) = \frac{\alpha C_0}{1-\alpha}$$

Then,

$$\alpha^{*} = 1 - \sqrt{C_0 / C_m}$$

The optimal production q' will be

$$q^{*} = \frac{a + eC_0 - 2e\sqrt{C_0 / C_m}}{2b}$$

And under optimal production, the maximizing profit should be

$$E_p = \frac{ea + e^2 C_0 - 2e^2\sqrt{C_0 / C_m}}{2b}$$

$$E_s = \alpha e q^{*}$$

$$\pi = \frac{\left(a + \theta C_0 - 2\theta\sqrt{C_0 / C_m}\right)^2}{4b} + C_m E_g$$

4 Results

Through the establishment of the LSTM model, this study predicts the predicted the carbon quota prices in the next ten days as follows:

[56.592484][56.58412][56.6348][56.688324]
[56.738155][56.784977][56.829556]
[56.873077][56.916122][56.95909]

The loss function value of the final training is

$$\text{RMSE} = 0.02337$$
$$\text{RAE} = 0.01482$$

After comparing the predicted values with the actual values, we have drawn the following chart to visualize the model-predicted values with the actual values.

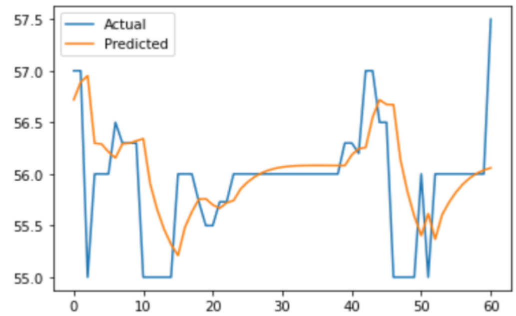

Figure 4: Fitted plots of predicted and actual values

From the comparison curve between the predicted value and the actual value of the model, we can see that the prediction accuracy of the model is high within 50 days, and the average male of the error between the predicted value and the actual value is 0.34983, which is 0.64208% of the average opening price. From the model's accuracy, we can conclude that the model's prediction is reasonable. At the same time, we obtained the results using the Arima model and the LSTM prediction model. We calculated the average error of the prediction results using the data in the last ten days of the table as the benchmark. The average error of the Arima model is 0.7343, and the average error of the LSTM model is 0.2953.

5 Discussion

The gradual implementation of China's policy establishes a unified national carbon emission trading market. The outcome of this research has provided new insight into the relationship between firms and the carbon trading market. Most of the existing studies do not consider the short-term and long-term problems firms face in actual production. In the short term, usually less than six months, firms cannot upgrade their production equipment to a less emission one, and their product strategy is highly correlated with carbon quota price in SEEE. Therefore, when reaching the carbon quota fulfillment deadline set by the government, firms can only choose to purchase carbon quotas in the carbon trading market. This situation often occurs in the early stage of the carbon trading market. In the long term, firms can update their technique to less carbon-emitting production technology. Therefore, a long-term optimal production model is established, and constant and alterable purifying levels are discussed.

Furthermore, this empirical paper is not only limited to theoretical discussion but also uses the long-short-term memory neural networks(LSTM) model to predict the carbon quota price, which firms can use directly to develop the best production strategy.

However, the results should be interpreted with caution due to the limitation of current research.

The chapter ends with several recommendations for further research. Firstly, it is highly important to consider different cooperative emission reduction mechanism designs among supply chain firms. Each node in the supply chain can cooperate to reduce emissions through coordination mechanisms such as cost sharing and buyback, which is also one of the important future research directions. In the long term, suppliers and distributors can also cooperate to reduce emissions, including those led by manufacturers and those led by distributors. Also, other situations firms may come across are also not considered. They are multi-period problems allowing intertemporal use of emission permits, emission permit trading contract problems with stochastic product demand, and nonlinear emission factors considering economies of scale.

6 Conclusions

This paper mainly studies the impact of China's emission permit trading scheme on the production strategy of emission-dependent firms. In this paper, we consider the case of single cycle and single emission, and it is assumed that the producers will face both short-term and long-term compliance. In the short term, firms cannot upgrade their production equipment to a less emission one, and their product strategy is highly correlated with carbon quota price in SEEE. An LSTM carbon price predicting model is developed to help firms make the best trading strategy during this period. In the long term, firms can obtain emission permits through three channels: initial government allocation, market trading, and purification treatment. The best strategy should both strike a balance among the three channels and maximize profits.

The research has a certain enlightenment for confused enterprises in the launch stage of carbon trading. It clarifies the impact of carbon emission intensity on the production strategy and external relations of firms, helping them to understand and actively participate in carbon trading and flexibly respond to the impact caused by carbon quota constraints. On the other hand, this paper analyzes the reaction of enterprises to the carbon quota constraint. It provides a reference for the design of the carbon emission permit system at the national policy level.

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Appendix

Import code

```
import numpy as np
import pandas as pd
import tensorflow as tf
from keras. models import Sequential
from keras.layers import Dense, LSTM
from sklearn.preprocessing import MinMaxScaler
import tensorflow as tf
from tensorflow.keras import backend as K
from keras.optimizers import Adam
```

Data standardization

```
data=pd.read_excel('new_index.xlsx')
df=pd.DataFrame(data,columns=['Date','Open'])
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(df['Open'].values.reshape(-1, 1))
```

Divide the test set and training set

```
time_steps = 20
train_size = int(len(scaled_data) * 0.8)
test_size = len(scaled_data) - train_size
train_data = scaled_data[:train_size, :]
test_data = scaled_data[train_size:, :]
```

Time series data definition

```
def generate_time_series(data, time_steps):
X = [ ]
y = [ ]
for i in range(len(data) - time_steps):
X.append(data[i:i+time_steps])
y.append(data[i+time_steps])
return np.array(X), np.array(y)
def rmse(y_true, y_pred):
return K.sqrt(K.mean(K.square(y_pred - y_true)))
learning_rate = 0.01
adam = Adam(lr=learning_rate)
X_train, y_train = generate_time_series(train_data, time_steps)
X_test, y_test = generate_time_series(test_data, time_steps)
```

LSTM model training

```
model = Sequential()
model.add(LSTM(11, input_shape=(time_steps, 1)))
model.add(Dense(1))
model.compile(optimizer=adam, loss=[ rmse , 'mean_absolute_error'])
history = model.fit(X_train, y_train, epochs=100,batch_size=16,validation_data=(X_test, y_test), shuffle=False)
```

Model fitting effect test

```
predictions = [ ]
```

```
for i in range(len(X_test)):
    X_input = X_test[i].reshape((1, time_steps, 1))
    y_pred = model.predict(X_input, verbose=0)
    predictions.append(y_pred[0])
rmse = np.sqrt(np.mean((predictions - y_test)**2))
print('Root Mean Squared Error:', rmse)
mae = np.mean(np.abs(predictions - y_test))
print('Mean Absolute Error:', mae)
```

Model adjustment

```
predictions = scaler.inverse_transform(np.array(predictions).reshape(-1, 1))
y_test= scaler.inverse_transform(np.array(y_test).reshape(-1, 1))
last_20_days = scaled_data[-time_steps:]
X_input = last_20_days.reshape((1, time_steps, 1))
predicted_data = []
for i in range(10):
    y_pred = model.predict(X_input, verbose=0)
    predicted_data.append(y_pred[0])
X_input = np.append(X_input[:, 1:, :], y_pred.reshape((1, 1, 1)), axis=1)
predicted_data = scaler.inverse_transform(np.array(predicted_data).reshape(-1, 1))
print('Predicted open prices for the next 10 days:')
print(predicted_data)
```