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RESEARCH ARTICLE

MS-IHHO-LSTM: Carbon Price Prediction Model of Multi-Source Data Based on Improved Swarm Intelligence Algorithm and Deep Learning Method

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ABSTRACT Accurate carbon price prediction can help save energy and reduce emissions worldwide. Thus, this paper proposes a model that combines swarm intelligence algorithms with deep learning to predict carbon prices. In this model, we collect news related to carbon trading, construct a dictionary of carbon financial sentiment, and determine the emotional value of the carbon news. Secondly, The Harris Hawks Optimization (HHO) algorithm is improved by updating the escape energy and introducing the inertia weight. Then, the LSTM is optimized using the improved Harris Hawks Optimization (IHHO) algorithm. Finally, technical and emotional data on carbon price as multiple source input values are integrated, and the MS-IHHO-LSTM prediction model is established. The results show that the MAPE of IHHO-LSTM is 1.89%, 30.48%, and 10.30% better than that of HHO-LSTM in Hubei, Shanghai, and Shenzhen Carbon Exchanges, respectively. Similarly, MS-IHHO-LSTM showed a lower MAPE than IHHO-LSTM by 27.79%, 29.82%, and 6.33% in the corresponding regions. The results of the experiment indicate that: 1) Using IHHO to optimize LSTM hyperparameters can avoid falling into local optimal and improve prediction accuracy; 2) Incorporating emotional values can further enhance the model's performance. The MS-IHHO-LSTM prediction model facilitates low-carbon investment, technological innovation, and green production, enabling enterprises to support environmental sustainability.

INDEX TERMS Carbon price forecasting, sentiment analysis, deep learning, multiple source data, MS-IHHO-LSTM.

I. INTRODUCTION

Over the two decades, China's carbon dioxide emissions have been increasing at a rate six times higher than that of other countries and regions. China is accountable for approximately 70% of the worldwide rise in carbon dioxide emissions [1]. Since 2020, China has surpassed the European Union in per capita carbon dioxide emissions. Consequently, China has launched eight national unified carbon emission trading markets to reduce carbon emissions and tackle climate change. The fluctuation in carbon trading prices results from market changes, and investors may face increased market risk due to significant volatility in the price of carbon trading. Poor liquidity in the carbon trading market can also limit market development [2]. Accurate carbon pricing forecasts can encourage companies and individuals to participate in carbon trading and guide business trading and government policy-making. Therefore, it is urgent to implement effective carbon trading schemes, reduce carbon intensity, and develop sustainable environmental protection methods [3].

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There are three methods for predicting time series prices: traditional statistics, machine learning, and deep learning. Previous scholars generally use statistical methods to construct linear models that could match the price trend of time series data. Conventional statistical methods include the Autoregressive Moving Average model (ARMA), the Generalized Autoregressive Conditional Heteroscedasticity model (GARCH), and the Autoregressive Integrated Moving Average model (ARIMA) [4], [5], [6]. For example, the GARCH model is used to predict the volatility of stock returns in London, New York, and Tokyo, and the prediction results are satisfactory [7]. Traders can use the fuzzy gray prediction method to forecast stock prices at specific times accurately, facilitating their daily transactions effectively [8]. The ARIMA model is another technique that utilizes the inverse wavelet transform to predict future prices by analyzing the behavior of the price series [9]. Despite being user-friendly, these methods may face challenges in handling nonlinear problems [10]. The application of machine learning models eliminates the need for many assumptions inherent in statistical models. Moreover, these models demonstrate efficient nonlinear learning capabilities, resulting in superior prediction performance compared to their traditional statistical counterparts. There are several standard methods for machine learning, including Structured Multilayer Perceptrons (SMLP), Support Vector Machines (SVM), and Random Forests (RF) [11].

With the rapid development of financial technology, high-frequency trading data has become increasingly prevalent. Deep learning, recognized as a specialized form of machine learning, has gained popularity owing to its remarkable ability to process data and make more accurate predictions compared to traditional algorithms [12]. Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM) are the most widely utilized deep learning methods. LSTM is especially popular because of its effectiveness and superior forecasting abilities [13], [14], [15], [16].

When the deep learning method is used, it is crucial to consider the setting of parameters. One effective solution to this problem is utilizing swarm intelligence optimization algorithms to optimize the parameters within the prediction model. Inspired by the catching behavior of Harris Hawks, Harris Hawks Optimization (HHO) is proposed as a new swarm intelligence algorithm [17]. The HHO algorithm offers several benefits, including a wide global search range, fast convergence speed, straightforward principles, minimal parameters, effortless implementation, compatibility with other algorithms, and exceptional performance on high-dimensional problems. For example, the HHO algorithm has a particular competitive potential in stock market index prediction [18]. The HHO-NN model's results were better than those of NN, MLP, and PSO-NN in gold price prediction [19]. When predicting carbon trading prices, Zhao Feng [20] adopted an extreme learning machine and various optimization techniques to optimize parameters for more accurate predictions. The results proved that The THHO-ELM model outperformed the PSO-ELM and GWO-ELM models in predicting the outcomes. However, the HHO algorithm is prone to falling into local optimal while attempting to solve complex optimization problems. Therefore, it is essential to improve the HHO algorithm.

The carbon price prediction methods mentioned above rely on historical data from a single source. They do not consider other factors that may affect carbon prices, such as the emotional value derived from news related to carbon trading. To improve the precision of carbon price predictions, scholars should consider various sources of information, including historical data and emotional insights from news coverage.

Here, the motivations for this paper are as follows.

(1) Integrating multi-source data such as carbon trading information can improve the accuracy and objectivity of predicting carbon prices.

(2) Optimizing LSTM parameters with the improved HHO algorithm can enhance global and local searching coordination.

This paper constructs the MS-IHHO-LSTM model for predicting carbon emission trading prices. The following are the main contributions of this paper.

(1) The paper compiles carbon trading news, analyzes sentiment, and creates multi-source datasets.

(2) Adjusting the escape energy and adding the weight inertia factor improves the HHO algorithm, and a novel IHHO algorithm is obtained.

(3) The paper uses the IHHO algorithm to optimize LSTM and creates an MS-IHHO-LSTM predictive model for better accuracy.

II. LITERATURE REVIEW

A. PREDICTION MODEL FOR TIME SERIES DATA

Data-driven predictors are crucial in forecasting time series prices. They can be categorized as single and hybrid models.

The single model contains machine learning and deep learning. Scholars utilize machine learning for time series prediction due to its high resistance to over-fitting, which makes it effective even with small data samples [21]. Hansen [22] demonstrated that the Support Vector Machine (SVM) method was superior to the statistical method when forecasting the price of time series in nine domains. However, applying SVM to handle numerous data samples can increase processing time, which limits its widespread application. In recent years, significant advancements have been made in artificial neural networks (ANN), allowing for quick and precise convergence. In predicting the closing prices of five companies, the ANN method was more accurate than RF [23]. While machine learning models are generally faster at training and forecasting, certain limitations make it difficult to accurately predict the price of time series. These limitations include data uncertainty, unreliable historical data, nonlinear relationships, and unpredictable events. As a result, machine learning models may need to be improved in accurately and reliably forecasting time series prices.

Deep learning is a branch of machine learning that is highly effective in handling large and complex data sets to solve intricate problems. It is beneficial in dealing with time-series data and can accurately capture time-dependent trends between data points [24]. Therefore, more and more scholars have attempted to use different deep-learning models for making predictions [25]. Experiments have demonstrated that the Back Propagation (BP) network and Recurrent Neural Network (RNN) are better suited for handling large-scale data [26]. Cavalli and Amoretti [27] developed a one-dimensional CNN model to predict Bitcoin trends and found that it outperformed other models. In addition, experimental results showed that the LSTM neural network is more accurate in predicting Chinese stock prices compared to other methods such as Neural Network (NN), Genetic Algorithm (GA), and SVM [28]. LSTM neural network can solve the problem of gradient explosion and vanishing gradients, which deep learning models commonly face. Deep learning models have been widely used in various industries, including crude oil, steel, and carbon price forecasting [29], [30], [31]. However, deep learning models typically have numerous hyperparameters to adjust, such as learning rate, regularization parameters, and network structure. Tuning these hyperparameters requires extensive experimentation and experience, which can significantly impact the model's performance.

Some studies suggest that a single model's predictive effect is not satisfactory. Therefore, hybrid models have been developed to improve carbon price prediction accuracy [32], [33]. The existing hybrid prediction model for carbon price is mainly studied through optimization algorithms and deep learning models. It is critical to select the appropriate algorithm for optimizing the parameters of a deep learning model. Model performance can vary based on training parameters. GA, Particle Swarm Optimization (PSO), and Cuckoo Search (CS) are commonly used optimization algorithms. Most optimization algorithms efficiently handle parameter optimization problems [34]. For instance, PSO is used to discover the optimal parameters of SVM, which proves more effective than other methods [35]. Algorithms like GA and PSO prioritize local values, potentially leading to suboptimal results with multiple objective functions [36]. CS and other methods are effective for searching, but the convergence rate is slow [37]. Support vector regression (SVR) parameters are optimized using PSO and HHO algorithms. HHO-SVR demonstrates superior predictive performance in experiments [38]. The HHO algorithm is a modern and reliable method for price prediction, which is more advanced than traditional optimization algorithms like particle swarm and cuckoo optimization. This algorithm can enhance search efficiency and perform better in high-dimensional problems by utilizing Gaussian variation and dimension decision logic. Additionally, it can adapt to various issues more effectively because it is less sensitive to parameter selection.

B. FACTORS AFFECTING CARBON PRICE PREDICTION

As scholars delve into methods for forecasting carbon prices, they also analyze the various factors that affect them. Traditionally, prediction models relied solely on technical data as input features. However, many experts argue that incorporating factors like market environment conditions, the Baidu index, and emotional aspects can enhance accuracy.

Several factors in the market environment impact carbon prices, such as international oil, electricity, and coal [39], [40], [41]. European Union Allowance (EUA) and Certified Emission Reductions (CER) serve as significant alternatives that affect China's carbon market price [42]. In addition, national policies and regulations also play a role in influencing China's carbon price [43]. Furthermore, the macroeconomic development of a country can also affect the cost of the carbon trading market [44].

Some scholars rely on the search platform index to predict carbon prices. Google processes almost 80% of internet searches worldwide. In China, Baidu and Sogou serve as the primary search engines, with Baidu ranking first [45], [46]. When people search online, their behavior can reveal their interest in particular events. Studies have shown that using ten Baidu index keywords to predict carbon prices is more effective than only historical prices [47].

The sentiment of carbon trading news is a complex factor that can quantitatively affect carbon prices through text analysis. With the development of text mining technology, more and more scholars pay attention to quantifying emotion in unstructured text. They adopt natural language processing (NLP) to process text and analyze sentiment [48], [49], [50]. For instance, Farimani et al. [51] collected the economic news of 300 constituent stocks in Shanghai and Shenzhen from January 1, 2020, to May 31, 2022, and used Bi-LSTM to identify the emotion of the news. After incorporating the sentiment of the text, the prediction accuracy improved by 1%. Bai et al. [52] used LDA to mine themes from news headlines and introduced two indexes of theme emotion to predict crude oil prices. In the context of stock prices, Mu et al. [53] analyzed investor comments from a stock forum and created a sentiment dictionary to calculate the sentiment index. The experiment results showed that the prediction accuracy is improved by converting stock bar comments into emotional values and using technical indicators as input variables. To sum up, it is necessary to analyze the sentimental values of authoritative financial news to predict carbon prices.

III. METHOD

A. LONG SHORT-TERM MEMORY NETWORK (LSTM)

LSTM comprises multiple isomorphic cells, which can store information for a long time by updating the internal state. Each cell comprises three main elements: the forget layer, the input layer, and the output layer [54]. Fig. 1 displays the LSTM's cell structure diagram. The working process is as follows.

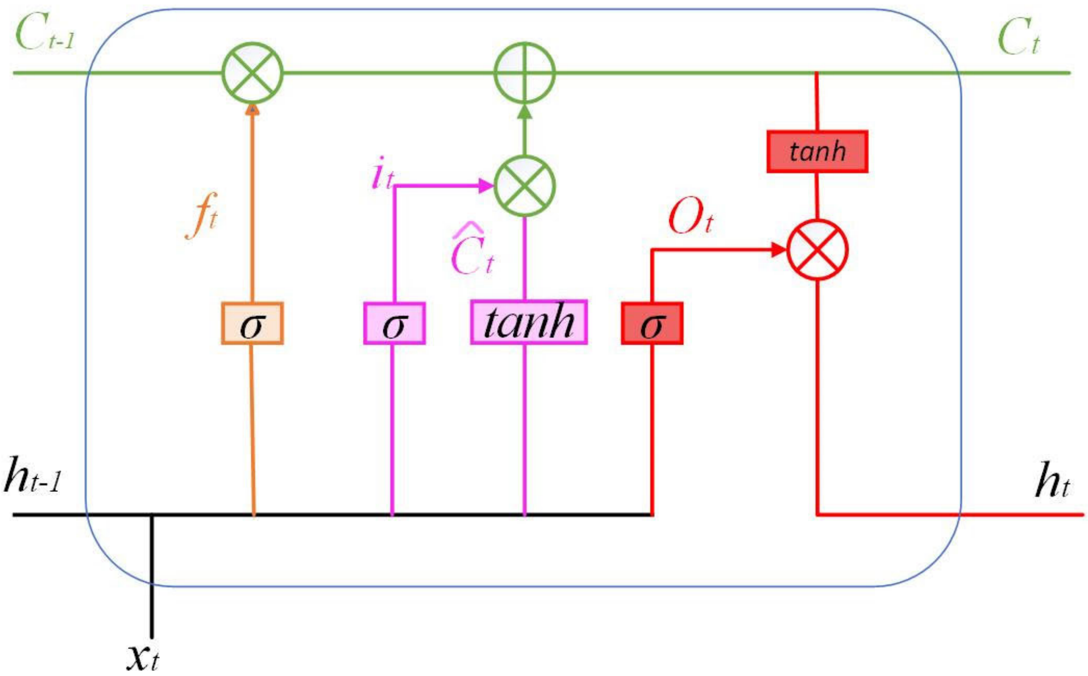

FIGURE 1. LSTM cell structure diagram.

First, the forget layer filters data and ignores useless information. The previous output h_{t-1} and current input x_t are combined, and a threshold value f_t is calculated using the sigmoid function, which ranges from 0 to 1.

$$f_t = \sigma(\mathcal{W}_f\,(x_t, h_{t-1}) + b_t) \tag{1}$$

Second, the input gate updates the status according to input and memory information. During this process, the function tanh generates a new alternative vector called $\hat{c}_t$. The input gate also produces a value, i_t, between 0 and 1 for each item in $\hat{c}_t$.

$$i_t = \sigma(\mathcal{W}_f\,(x_t, h_{t-1}) + b_i) \tag{2}$$

$$\hat{c}_t = \tanh(\mathcal{W}_c\,(x_t, h_{t-1}) + b_c) \tag{3}$$

The f_t of the forget gate and the i_t of the input gate control previous moment forgetting and new information scaling. Then, the current state c_t can be updated based on these two outputs.

$$c_t = i_t\hat{c}_t + f_t c_{t-1} \tag{4}$$

Third, the output gate outputs the current information. The sigmoid function compresses the input data x_t and the output h_{t-1} from the previous time into a value between 0 and 1. Then multiply the updated current state$c_t$with the compressed value o_t.

$$o_t = \sigma(\mathcal{W}_o x_t + V_o h_{t-1} + b_o) \tag{5}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{6}$$

In formula (1) – (6), σ is the sigmoid activation function, tanh is the activation function, W and V are the weight matrix, b is the bias vector, and x_t is the input vector at time t. h_{t-1} represents LSTM's vector output before time t, which contains short-term memory information. c_t represents long-term memory information at time t.

B. HARRIS HAWKS OPTIMIZATION (HHO) ALGORITHM

The HHO is a bionic intelligent optimization algorithm proposed in 2019. The HHO algorithm has several advantages, such as its ability to conduct a comprehensive search, compatibility with other algorithms, exceptional performance on high-dimensional problems, and versatility in solving various optimization problems [55]. The algorithm includes the seek stage, the transition stage from seek to development, and the development stage.

1) SEEK STAGE

In the Harris Hawks algorithm, the t-generation population is denoted as $P(t) = (X_1(t), X_2(t), \ldots, X_n(t))$. In the seek phase, there are two mechanisms for global search as follows.

$$X_i(t+1) = \begin{cases} X_{rand}(t) - r_1\,|X_{rand}(t) - 2r_2X_i(t)|\,, & q \geq 0.5 \\ (X_{rabbit}(t) - X_m(t) - r_3(\mathrm{lb} + r_4(\mathrm{ub} - \mathrm{lb}))\,, & q < 0.5 \end{cases} \tag{7}$$

In formula (7), $X_{rand}(t)$ is the randomly obtained eagle, $X_{i(t)}$ is the ith eagle, and $X_{rabbit}(t)$ is the global optimal solution in generation t. q, r_1, r_2, r_3, and r_4 are random numbers; lb and ub are the lower and upper limits, and $X_m(t)$

is the average of all eagle positions in generation t.

$$X_m(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t) \tag{8}$$

2) TRANSITION STAGE FROM SEEK TO DEVELOPMENT

At the beginning of the seek phase of the eagle chase, the prey rabbit has more energy. The energy setting of the target rabbit can balance the contradiction between the diversity and convergence of the search path in the search phase. The symbol E represents the energy of the prey.

$$E = 2E_0(1 - \frac{t}{T}) \tag{9}$$

where E is the prey's energy in the escape process, $E_0 \in [-1, 1]$ is the initial value of the prey energy generated randomly, the variable t represents the current iteration number, while T represents the total number of iterations.

3) DEVELOPMENT STAGE

The search methods in the development stage of the Harris Eagle are soft encirclement, hard encirclement, fast diving hard encirclement, and fast diving soft encirclement.

a: SOFT ENCIRCLING

When the prey is in $r \geqslant 0.5$ and $E > 0.5$ state, it has the energy to escape, and the eagle pursues it around and makes it tired. r is the correlation coefficient between prey and predator. It measures the degree of correlation between them and the degree to which they interact and ranges from 0 to 1. The formula is as follows:

$$X_i(t+1) = X_{rabbit}(t) - X_i(t) - E\,|JX_{rabbit}(t) - X_i(t)| \tag{10}$$

where $J = 2(1 - r_5)$ is a random jump in the prey's escape and r_5 is the random number in (0,1).

b: HARD ENCIRCLING

When the prey is in $r \geq 0.5, E < 0.5$ state, the prey's energy becomes less and can not escape. The formula is as follows:

$$X_i(t+1) = X_{rabbit}(t) - E\,|X_{rabbit}(t) - X_i(t)| \tag{11}$$

c: FAST DIVING SOFT ENCIRCLING

When the prey is in $r < 0.5$ and $E \geq 0.5$ state, the prey's energy becomes less. But the prey can still escape, and the eagle forms a soft encircling pursuit. The formula is as follows:

$$X_i(t+1) = \begin{cases} X_1, & \text{if } F(X_1) < F(X_i(t)) \\ X_2, & \text{if } F(X_2) < F(X_i(t)) \end{cases} \tag{12}$$

where F() is used to calculate fitness, $X_1 = X_{rabbit}(t) - E \cdot |JX_{rabbit}(t) - X_i(t)|$, $X_2 = X_1 + \boldsymbol{S} \times \text{Levy}(D)$. Where, $\boldsymbol{S}$ is a vector composed of random numbers of $D \times 1 \in (0, 1)$, D is the dimension, and Levy() is the Levy-Flight function.

d: FAST DIVING HARD ENCIRCLING

When the prey is in $r < 0.5$ and $E < 0.5$ state, the target has less energy and is not enough to escape. The eagle uses a hard encircle to capture. The formula is as follows:

$$X_i(t+1) = \begin{cases} X_1, & \text{if } F(X_1) < F(X_i(t)) \\ X_2, & \text{if } F(X_2) < F(X_i(t)) \end{cases} \tag{13}$$

where $X_1 = X_{rabbit}(t) - E\,|JX_{rabbit}(t) - X_m(t)|$, $X_2 = X_1 + \boldsymbol{S} \times \text{Levy}(D)$.

C. PROPOSED IMPROVED HARRIS HAWKS OPTIMIZATION (IHHO) ALGORITHM

1) UPDATE THE ESCAPE ENERGYE

In the traditional HHO algorithm, the size of rabbit escape energy E plays an essential role in regulating and transitioning global search and local mining. The energy factor E changes linearly during control development and exploration but nonlinearly during control search. The method of Harris hawks hunting rabbits in nature needs to be accurately described. An updated formula of escape energy has been introduced to enhance the coordination of global exploration and local mining and improve searchability.

$$E = 2E_0(1 - \frac{1}{1 + e^{-\alpha}}) \tag{14}$$

$$\alpha = T^{\frac{1}{3}} \cdot (\frac{2t}{T} - 1) \tag{15}$$

2) INTRODUCE THE INERTIA WEIGHT FACTOR

The algorithm enters the development stage when the escape energy E is less than 1. However, it is not guaranteed that all populations are close to the global optimal at this stage, which may lead to premature convergence and local optimization. Therefore, the inertial weight factor is introduced into four predation strategies to update the rabbit's position $\widehat{X}_{rabbit}$.

$$\omega = cos(\frac{\pi t}{2T}) \tag{16}$$

$$\widehat{X}_{rabbit} = \omega \cdot X_{rabbit} \tag{17}$$

The inertia weight factor is essential for balancing global exploration and local development. It enables the algorithm to jump out of local optimization while maintaining accuracy quickly.

D. MODEL CONSTRUCTION

1) CONSTRUCTION OF MS-IHHO-LSTM CARBON PRICE PREDICTION MODEL

This paper creates the novel MS-IHHO-LSTM hybrid model for accurately predicting carbon prices. Fig. 2 displays the model's architecture. This model combines the improved IHHO swarm intelligence optimization algorithm with the deep learning method LSTM. Technical indicators and sentiment analysis of relevant carbon market news constitute multi-source data, which improves the model's prediction accuracy. This multi-source data is then utilized as input values for the model, which performs the following steps.

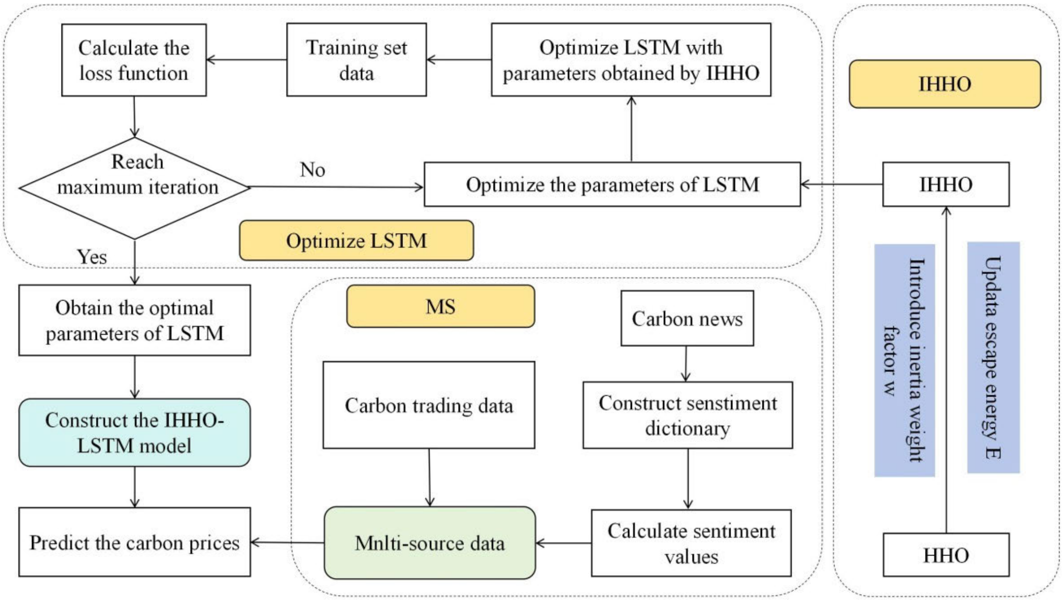

FIGURE 2. MS-IHHO-LSTM model framework.

TABLE 1. Basic transaction information of the Hubei carbon market.

Data	Open Price	High Price	Low Price	Avg Price	PreClose Price	Volume amount	Amount price	Close Price
2018/10/16	33.38	33.38	29.33	30.90	30.38	25	773.10	32.09
2019/10/16	32.78	33.75	31.81	31.95	32.78	464	14826.10	32.98
2020/10/16	28.51	29.00	28.45	28.58	29.30	22692	648455.00	28.80
2021/10/16	41.45	42.60	40.00	40.40	41.59	41977	1695766.00	41.45
2022/10/17	49.60	50.60	49.00	49.42	49.44	19604	968829.95	49.60

step 1 (Obtain Data): Identify fundamental trading indicators of carbon prices and capture news related to carbon finance.

step 2 (Calculate Emotional Values): Build a unique sentimental dictionary in the field of carbon finance and calculate the emotional weight of news related to carbon trading through sentiment analysis.

step 3 (Divide the Dataset): The multi-source index matrix includes both carbon price and emotional value, and the data is normalized before being divided into proportional train and test sets.

step 4(Propose the Improved HHO Algorithm): The HHO algorithm is improved by jumping out of the local optimal, updating the escape energy E, and introducing the inertia weight factor w.

step 5 (Optimize LSTM): The LSTM parameters are optimized using the Improved Harris Hawk Optimization (IHHO). In the training of LSTM, the error value represents the population fitness of Harris Hawks, and the goal is to minimize it.

step 6 (Create the MS-IHHO-LSTM Model): Use the dataset acquired from step 3 to train IHHO-LSTM and finally get the prediction result.

2) MODEL EVALUATION CRITERIA

In this paper, mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE) are used to analyze the validity of the model. The evaluation criteria are calculated as follows:

$$MAPE = \frac{100\%}{N} \sum\nolimits_{i=1}^{N} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \tag{18}$$

$$RMSE = \sqrt{\frac{1}{N} \sum\nolimits_{i=1}^{N} (\hat{y}_i - y_i)^2} \tag{19}$$

$$MAE = \frac{1}{N} \sum\nolimits_{i=1}^{N} \left| \hat{y}_i - y_i \right| \tag{20}$$

N is the predicted sample size, y_i is the actual price, and $\hat{y}_i$ is the predicted price. MAPE, RMSE, and MAE are used to calculate the difference between the actual and predicted

TABLE 2. Sample news related to carbon trading.

Date	News
2018/01/02	2017 China's energy trend: A new era of energy storage. Carbon emissions trading in power generation alone will top the world.
2018/03/07	The carbon market will support the development of green energy in China.
2018/11/07	Director of the Department of Climate Change of the Ministry of Ecology and Environment: Coal consumption does not affect China's carbon reduction goal.
2018/12/03	The carbon intensity reduction target is achieved three years ahead of schedule. In 2017, it was 46% lower than in 2005.
2019/01/11	Carbon trading: A double-edged sword for power generators, or worse.
2019/02/19	Truly emission-reducing electric vehicles need to be developed in tandem with renewable energy.
2019/10/31	Global investment and financing needs for green development could reach hundreds of trillions of dollars over the next decade.
2019/12/20	Shanghai carbon trading has achieved 100% compliance for six consecutive years.
2020/05/19	Will the carbon market play little role in reducing EU emissions?
2020/09/03	Cost reduction is the key to win-win cooperation.
2020/10/21	The 2050 CO_2 reduction target is a daunting task.
2020/11/16	Promote the establishment of a nationwide carbon market and support the achievement of the carbon peak target.
2021/01/13	The global carbon market gets off to a good start in 2021.
2021/02/25	The first batch of carbon-neutral 10 billion green bonds to land on the SSE National Energy Group accounts for about 50%.
2021/03/23	State Grid Jiangsu proposes 19 measures to actively implement the national grid carbon peak carbon neutral action plan.
2021/04/27	Under the double carbon goal, the electricity and carbon market has become the breakthrough point for implementing the integrated energy service business model.
2022/09/08	Promote the dual control transition as soon as possible to play the carbon market role better.
2022/10/21	The dual carbon goal creates new opportunities for green jobs.
2022/11/08	Ministry of Education supports accelerating the construction of disciplines such as energy storage, hydrogen energy, CCUS, and carbon emission trading. Maxson Energy appeared at the 2022 Climate Change and Low-carbon Development Forum at the CIIE.
2022/12/16	The price of carbon in the world's leading carbon market rose 40% in 2021 but has fallen this year.

values, and the value range is $[0, +\infty)$. The closer to 0, the better the prediction ability of the model.

IV. EMPIRICAL AND RESULT

A. DATA COLLECTION

The Chinese government set up eight carbon exchanges between 2013 and 2014 in the eastern, central, and southern regions. Based on their start-up times and geographical locations, this paper selects carbon exchanges in Hubei, Shenzhen, and Shanghai as representatives.

This paper obtains primary trading data from the CSMAR database and focuses on the carbon emission exchanges in Hubei, Shanghai, and Shenzhen from January 2, 2018, to December 30, 2022. The dataset contains nine technical

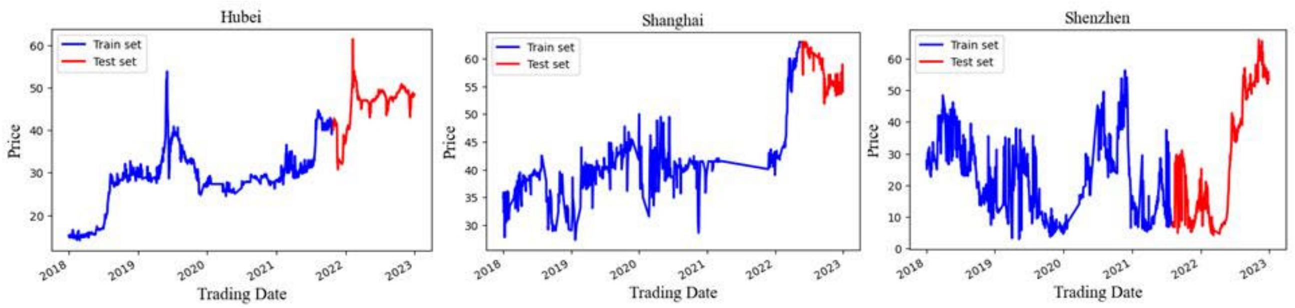

FIGURE 3. Original carbon price series. (a)Hubei; (b)Shanghai; (c) Shenzhen.

indicators: the opening price, highest price, lowest price, average price, previous closing price, change rate, volume amount, amount price, and closing price. Table 1 displays the data collected from the Hubei carbon trading market over five days.

This paper utilized the Octopus software available on the carbon trading platform (https://tanguanjia.bjx.com.cn/) to gather 1164 articles related to carbon trading. After filtering out irrelevant information, 1094 practical texts are identified. Table 2 presents four examples of carbon trading financial news per year.

B. DATA PROCESSING

Fig. 3 shows the non-stationary closing prices of three carbon exchanges due to different regional economic developments and closing price methods. The blue line represents the train set, and the red line represents the test set. Carbon market train and test sets are separated into groups based on their sample lengths. This study's train and test sets are split proportionally to ensure unbiased predictions. In the datasets for Hubei, Shanghai, and Shenzhen, the sample lengths are 1097, 707, and 942 trading days, respectively. This paper uses 75%, 80%, and 70% of data from three exchanges for training and the remaining 25%, 20%, and 30% for testing.

First, this research collects the text of news related to carbon trading and divides each sentence into several words with the Jieba participle [56]. A new emotion dictionary is then constructed, including four categories of positive, negative, denial, and degree, as shown in Table 3. Finally, the constructed emotion dictionary analyzes the selected text and emotion words and assigns corresponding weights. The paper presents a method of weight allocation for positive and negative emotion words. Positive words are given a weight of 1, while negative words are given a -1. The emotion value is assumed to follow the linear superposition principle. The sentence is then separated into individual words. The forward weight is added if the word vector contains the corresponding words. However, negative words and adverbs of degree have special rules. Negative words will cause the weight to be negative, with a value of -1. Adverbs of degree, on the other hand, will double the weight, with a value of 2. The weight of words indicates their emotional intensity. Formula (21) is utilized to calculate the sentimental value of carbon trading news.

$$\text{Sent} = \sum\nolimits_{i=1}^{n} w_i \cdot x_i \tag{21}$$

In this formula, w_i represents the weight of the corresponding part of speech, and x_i represents the number of occurrences of a particular piece of vocabulary.

This study combines technical data and sentiment values calculated from carbon market news to form a feature vector used as input to the predictive model.

C. ANALYSIS OF CARBON PRICE PREDICTION MODEL

This paper uses three class models to forecast and compare carbon prices: the single, hybrid, and multi-source data hybrid models. Table 4 shows the models. The LSTM network's hyperparameters, such as the number of iterations, learning rate, and hidden layer neurons, can be optimized using HHO and IHHO algorithms to improve the model's prediction accuracy.

1) COMPARISON EXPERIMENT OF THE SINGLE MODELS

In the single model's experiment, the performance of several methods is compared, including the traditional statistical method ARIMA, machine learning method SVM, and deep learning methods such as MLP, CNN, BP, and LSTM. The results of the model's predictions are presented in Fig. 4 to 6. The graphs depict the number of trading days in the test set on the X-axis and the carbon market closing price on the Y-axis. The red line represents the actual closing price, while the blue line represents the predicted closing price.

Fig. 4 to 6 illustrate the impact of six different models in predicting carbon prices in the carbon trading markets of Hubei, Shanghai, and Shenzhen. Firstly, according to the experimental results, the ARIMA model showed the poorest predictive performance among the six single models. The ARIMA model is a statistical method that can only make reliable predictions for linear data. However, the characteristics of carbon price data are non-linear, making it quite challenging to predict accurately. Secondly, the prediction outcome of the SVM method is unstable. The SVM method is sensitive to noise and easily disturbed by data. Carbon price data usually has significant noise and

TABLE 3. Sentimental dictionary.

Sentiment	Weight	Vocabulary
Positive	1	demonstration, promotion, carbon peak, carbon neutral, key point, reasonable, positive, encourage, development, new energy, reliable, landing, high quality, zero carbon, blockbuster, low carbon, development, rise, main, jump, countermeasures, strive, response, innovation, great, new money scene, accelerate, transformation, extensive, diversified, help, enhance, hard, first tranche, energy saving, recovery, support, resilience, wisdom, perfection, flexibility, efficiency, optimization, tackle key problems, crux, emerging, revolutionary, strive, support, priority, revelation, potential, accuracy, be pleasant to the eye, giant, first batch, chance, mature, secure, smooth, comprehensive, rapid, advantageous, sustainable, steady progress, excellent, main force, scenery, short supply, professional, unprecedented......
Negative	-1	fall back, alert, risk, trap, loss, challenge, decline, tension, falsification, blow, rumor, compensation, fraud, inefficiency, blame, punishment, pressure, in one go, crisis, danger, lesson, elimination, impact, debt, default, inappropriate, difficult, negative, controversy, motivation, weakness, neglect, slow, radical, stimulating, explosive, serious, hindrance, not enough, fall, obstacles, pollution, downturn, negligible, burden, bumpy, fever, drag hard, loophole, abandonment, dirty, slide, insufficient, extreme, subversion, unreasonable, backward, worse, end of days, rejection, anger, reflection......
Denial	-1	no, not, impossible, never......
Degree	2	very, super, slightly, a little bit, extreme, more......

TABLE 4. Prediction models.

Model type	Prediction model	Details
Single models	ARIMA	Input variable: historical transaction data
	SVM	Input variable: historical transaction data
	MLP	Input variable: historical transaction data
	CNN	Input variable: historical transaction data
	BP	Input variable: historical transaction data
	LSTM	Input variable: historical transaction data
Hybrid models	HHO-LSTM	Input variable: historical transaction data
	IHHO-LSTM	Input variable: historical transaction data
Multi-source data hybrid models	MS-LSTM	Input variable: historical trading data and sentimental data of carbon trading news
	MS-HHO-LSTM	Input variable: historical trading data and sentimental data of carbon trading news
	MS-IHHO-LSTM	Input variable: historical trading data and sentimental data of carbon trading news

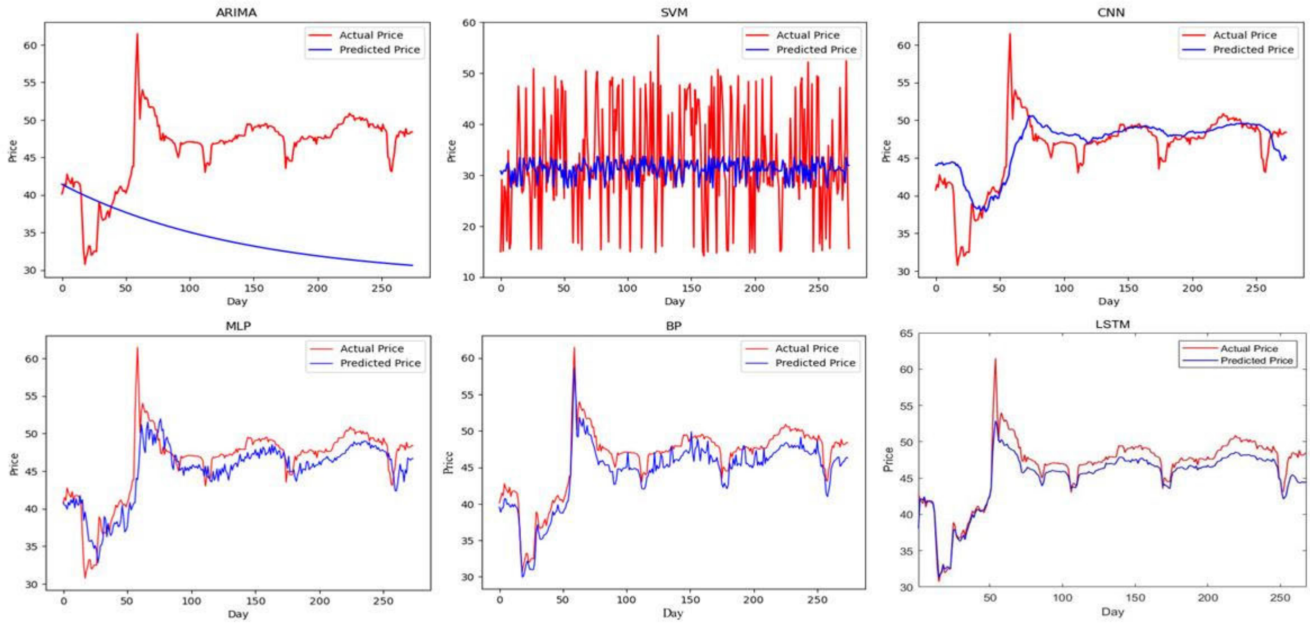

FIGURE 4. **Comparison of single prediction models in Hubei. (a)AMIMA; (b)SVM; (c) CNN; (d) MLP; (e) BP; (f) LSTM.**

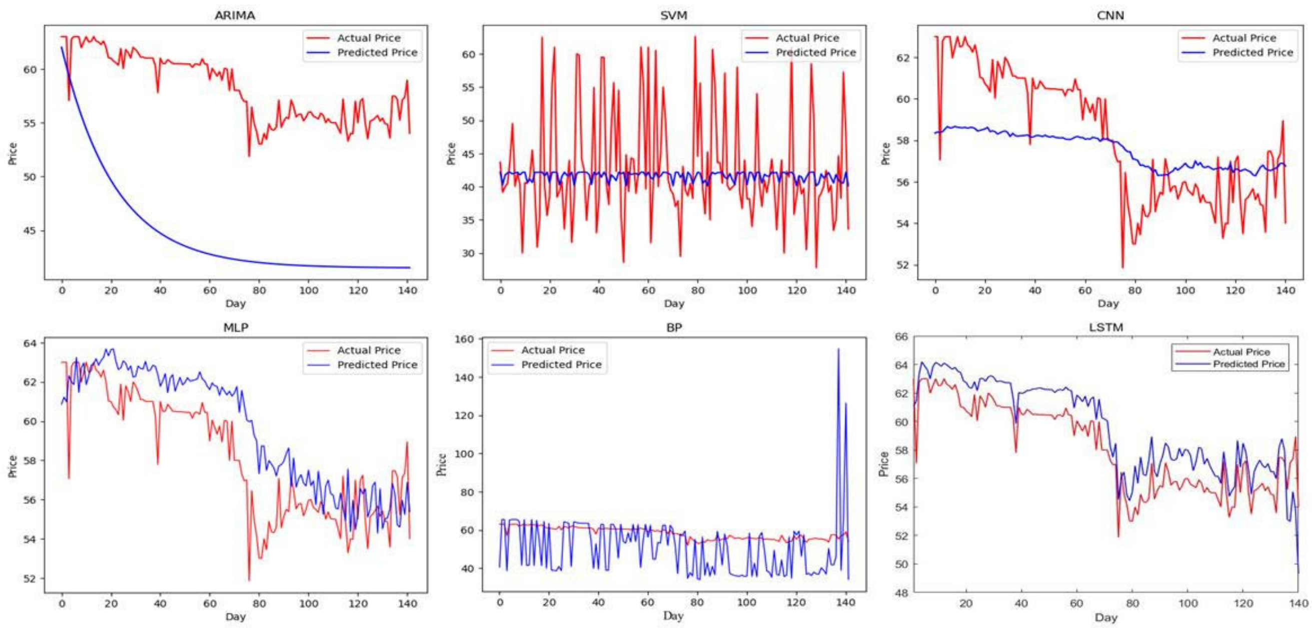

FIGURE 5. **Comparison of single prediction models in Shanghai. (a)AMIMA; (b)SVM; (c) CNN; (d) MLP; (e) BP; (f) LSTM.**

fluctuations. Thus, the experimental results are not optimal. Thirdly, the BP and CNN models for carbon prices do not accurately predict the Shanghai and Shenzhen carbon exchanges. The BP and CNN models need a large amount of data to be trained accurately to make reliable predictions. However, the quantity of transaction data available for the Shanghai and Shenzhen Carbon Exchange is lower than that for Hubei. As a result, the prediction outcomes fail to meet the desired level of satisfaction. Fourthly, LSTM has the best prediction effect among the single deep learning methods, followed by MLP. Furthermore, the ranking of the best to worst predictions among these three types of single models are deep learning methods, machine learning methods, and statistical methods. Therefore, the LSTM model is chosen, and improvements are implemented to increase prediction accuracy.

2) COMPARISON EXPERIMENT OF HYBRID AND MULTI-SOURCE DATA HYBRID MODELS

Based on the results of the single prediction model mentioned above, LSTM has a better prediction effect than other models. Therefore, all the other hybrid models are being evaluated and compared with the LSTM model. Furthermore, the following experimental comparisons are divided into hybrid

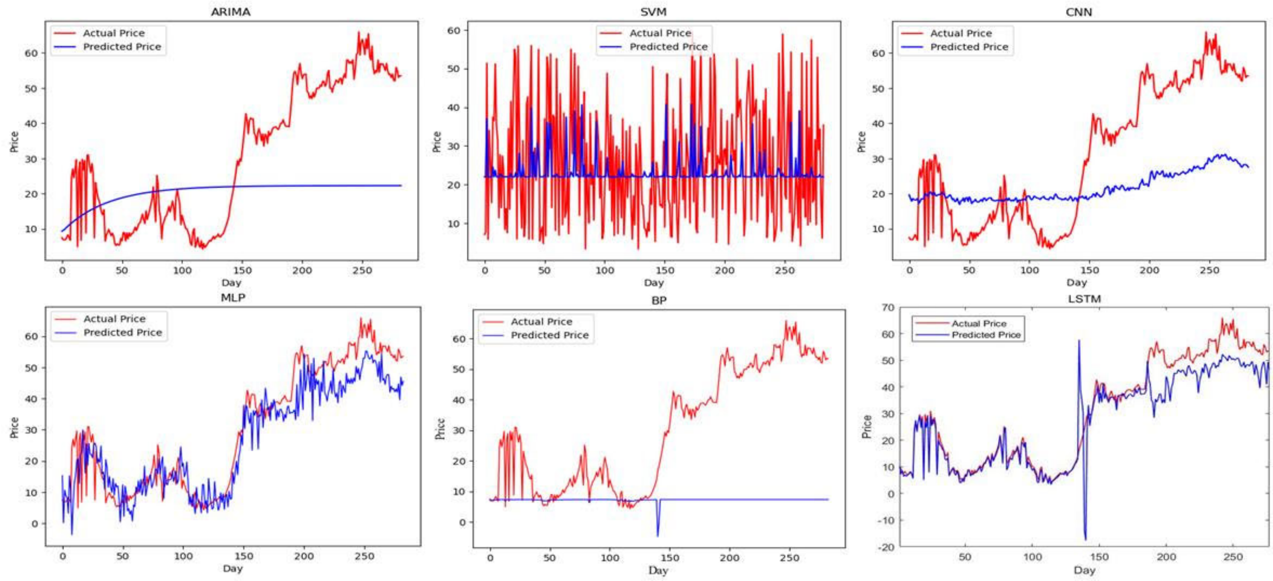

FIGURE 6. Comparison of single prediction models in Shenzhen. (a)AMIMA; (b)SVM; (c) CNN; (d) MLP; (e) BP; (f) LSTM.

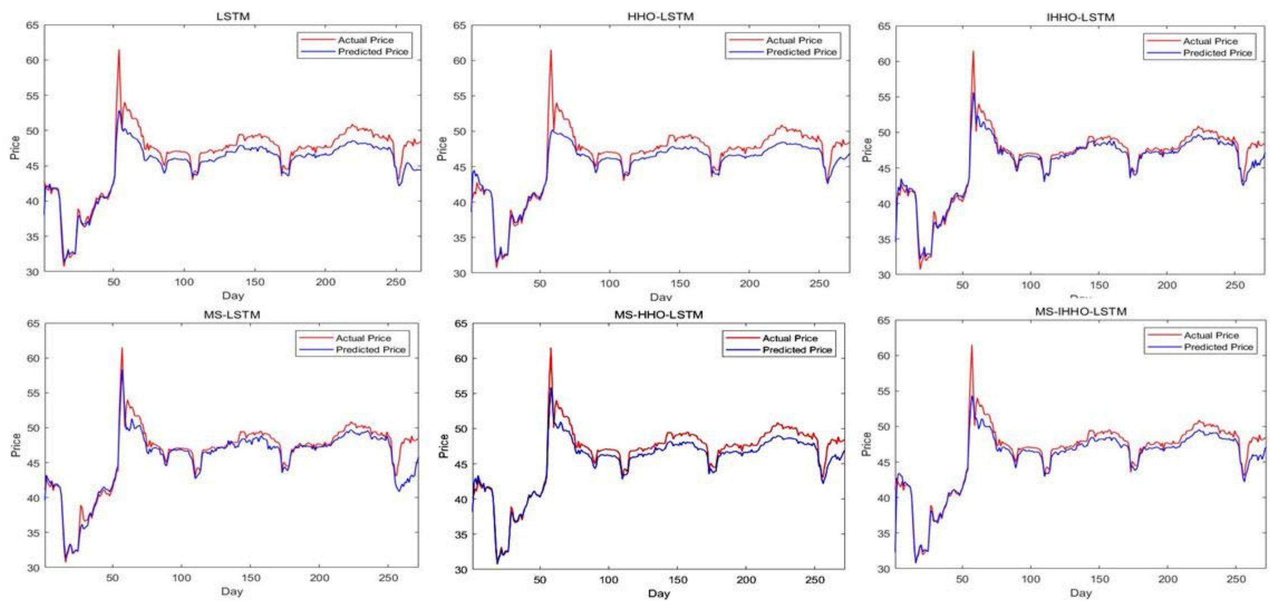

FIGURE 7. Comparison of hybrid and multi-source data models in Hubei. (a)LSTM; (b)HHO-LSTM; (c) IHHO-LSTM; (d) MS-LSTM; (e) MS-HHO-LSTM;(f) MS-IHHO-LSTM.

and multi-source data hybrid models. The HHO algorithm is chosen in this paper to optimize the hyperparameter of LSTM due to its quick convergence speed and strong robustness. However, the original HHO algorithm tends to get stuck in local optimization. Therefore, the HHO algorithm has been improved to optimize the parameters of LSTM. In addition, the carbon trading news may affect the prices in the carbon trading market. This paper uses news emotional value to predict carbon prices based on multi-source rather than single-source data.

Fig. 7 to 9 display the actual and predicted values of the carbon trading markets hybrid model and the multi-source data hybrid model in Hubei, Shanghai, and Shenzhen. By comparing the Figures horizontally, it becomes evident that the HHO-LSTM model combined with swarm intelligence outperforms the single LSTM model. The experiment results suggest that the predicted model optimized by the HHO algorithm is better than the non-optimized prediction model. Moreover, the enhanced IHHO-LSTM algorithm is superior to the HHO-LSTM model. This result shows that the improvement process of the HHO algorithm can effectively improve the model prediction accuracy. After comparing the figures vertically, it is evident that MS-LSTM outperforms LSTM, MS-HHO-LSTM outperforms HHO-LSTM, and MS-IHHO-LSTM outperforms IHHO-LSTM. The results of the above comparison show that the multi-source data

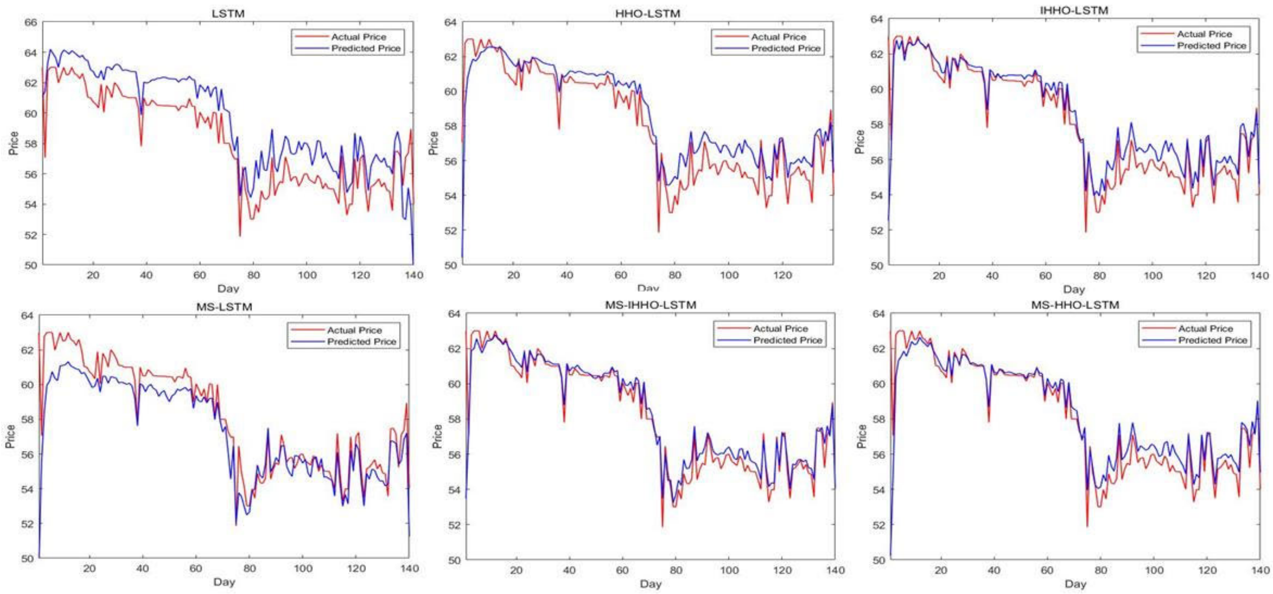

FIGURE 8. Comparison of hybrid and multi-source data models in Shanghai. (a)LSTM; (b)HHO-LSTM; (c) IHHO-LSTM; (d) MS-LSTM; (e) MS-HHO-LSTM; (f) MS-IHHO-LSTM.

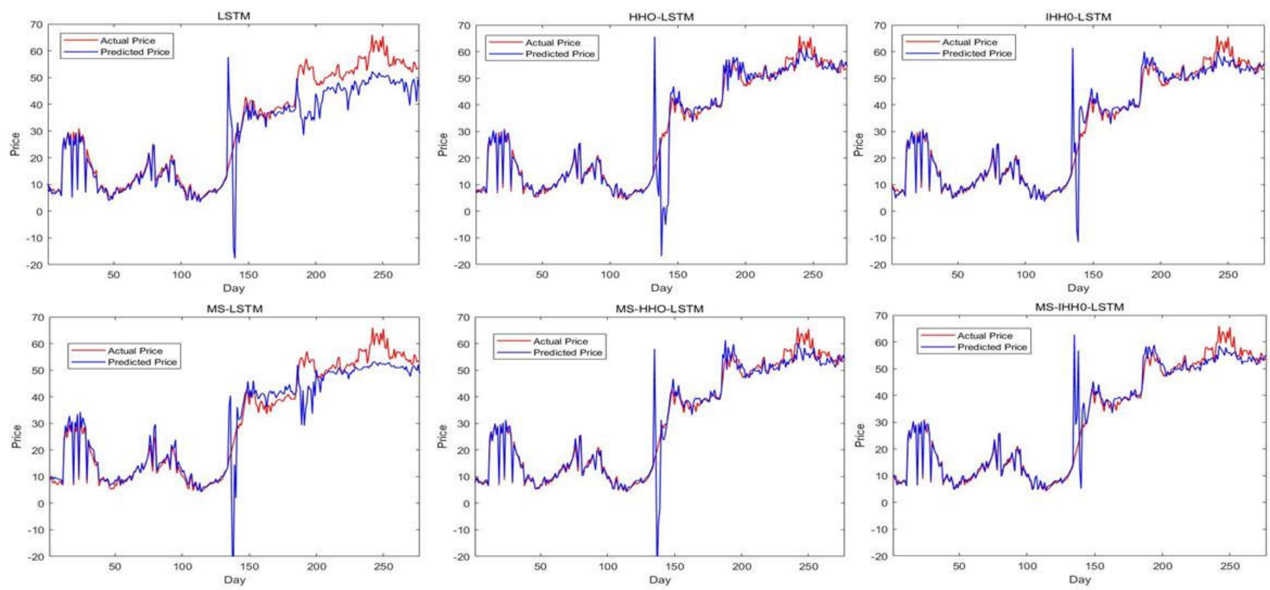

FIGURE 9. Comparison of hybrid and multi-source data models in Shenzhen. (a)LSTM; (b)HHO-LSTM; (c) IHHO-LSTM; (d) MS-LSTM; (e) MS-HHO-LSTM; (f) MS-IHHO-LSTM.

combination model is superior to the single-source model. Additionally, incorporating emotional aspects of news can enhance the accuracy of the prediction model.

Table 5 displays the evaluation criteria results for each prediction model. Bold data indicates the best experimental results.

According to the results of carbon price forecasting by the carbon exchanges in Hubei, Shanghai, and Shenzhen, the LSTM model has the highest accuracy among other single forecasting models. The study shows that the LSTM model has lower MAPE, RMSE, and MAE values than the other single models.

The performance of two hybrid models, HHO-LSTM and IHHO-LSTM, is compared with that of the LSTM model. The results show that the MAE of HHO-LSTM decreases by 10.24%, 46.12%, and 46.31% in the Hubei, Shanghai, and Shenzhen exchanges, respectively. Similarly, the MAE of IHHO-LSTM reduces by 12.37%, 62.44%, and 49.91% for the same trades. This study demonstrates that incorporating a swarm intelligence algorithm into a deep learning model can decrease prediction errors.

In addition, the experimental results of multi-source data models MS-LSTM, MS-HHO-LSTM, and MS-IHHO-LSTM compare with those of single-source data models

TABLE 5. Model evaluation index.

Models		Hubei			Shanghai			Shenzhen		
		MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE
Single models	ARIMA	0.2649	13.78253	12.6116	0.2337	13.9453	13.5510	0.7512	24.9833	22.3714
	SVM	0.2702	9.9786	7.5453	0.1291	8.1707	5.7689	0.7833	14.4931	12.2371
	MLP	0.0445	2.7146	2.0292	0.0320	2.2403	1.8360	0.3144	7.7008	7.6146
	CNN	0.0519	3.5524	2.4237	0.0358	2.4391	2.0996	0.6665	23.3687	18.6466
	BP	0.0415	2.0481	1.9253	0.2039	16.6330	11.6949	0.6452	32.1753	25.3431
	LSTM	0.0295	1.7672	1.4223	0.0299	1.8604	1.7299	0.1333	7.6222	4.4424
Hybrid models	HHO-LSTM	0.0264	1.7089	1.2766	0.0164	1.2110	0.9320	0.0951	6.1092	2.3852
	IHHO-LSTM	0.0259	1.5544	1.2463	0.0114	1.1390	0.6497	0.0853	5.1408	2.2250
Multi-source data hybrid models	MS-LSTM	0.0276	1.5417	1.2760	0.0158	1.5738	0.9423	0.1292	6.5369	3.6128
	MS-HHO-LSTM	0.0219	1.2838	1.0577	0.0105	1.2111	0.6053	0.0849	5.0454	2.0964
	MS-IHHO-LSTM	**0.0187**	**1.2766**	**0.8954**	**0.0080**	**0.9456**	**0.4631**	**0.0799**	**4.4847**	**1.9538**

LSTM, HHO-LSTM, and IHHO-LSTM. In contrast with the single-source data model LSTM, the MAE of MS-LSTM decreased by 10.29%, 45.53%, and 18.67% for the Hubei, Shanghai, and Shenzhen exchanges, respectively. Similarly, the MAE of MS-HHO-LSTM decreased by 17.15%, 12.11%, and 35.03% for the same exchanges as compared to the hybrid model HHO-LSTM. The MAE of MS-IHHO-LSTM is 28.16%, 0.1219%, and 0.2872% lower than that of the hybrid model IHHO-LSTM. These results show that using multi-source data hybrid models can improve the prediction accuracy compared to single-source data models.

After comparing the results of the MS-LSTM model and the MS-HHO-LSTM model, the MAE of the latter decreased by 17.12%, 35.76%, and 41.97% in the Hubei, Shanghai, and Shenzhen stock exchanges, respectively. Additionally, when comparing the MS-HHO-LSTM model with the MS-IHHO-LSTM model, the MAE of the latter decreased in Hubei, Shanghai, and Shenzhen exchanges by 15.34%, 23.48%, and 6.79%, respectively. These findings indicate that when using multi-source data, the model optimized using a swarm intelligent optimization algorithm outperforms the model without optimization. Furthermore, implementing a swarm intelligent optimization algorithm can improve the prediction accuracy.

The LSTM and MS-LSTM models take roughly 20 seconds to execute, with the latter taking less than a second longer than the former. After adding the swarm intelligent optimization algorithm, the model's average run time is about 8 minutes. The improved IHHO-LSTM model takes about 9.6 minutes to run, while the most time-consuming MS-IHHO-LSTM model runs at an average of fewer than 11 minutes. By analyzing the average running times of the different models, it can be seen that this proposed model has clear advantages in calculation cost and practical feasibility. Despite the increased running time of the new model, the overall time cost is still acceptable, given the significant improvement in prediction accuracy and power.

V. CONCLUSION, SUGGESTIONS, AND FUTURE WORK

A. CONCLUSIONS

This paper employs the improved HHO algorithm to optimize the LSTM model to enhance the accuracy of predicting carbon prices. The paper collects technical indicators and emotional values related to carbon trading and builds the MS-IHHO-LSTM model. Based on empirical analysis, this study has drawn the following conclusions.

Firstly, multi-source data improves prediction accuracy. The paper gathers carbon trading news from financial news platforms and builds sentimental dictionaries. Then, the carbon trading news is analyzed, and the emotional value is calculated. Finally, the input variable now includes the emotional impact of carbon trading news to reflect better how public attention affects carbon prices. Six different models were used to forecast Hubei, Shanghai, and Shenzhen carbon prices. The results showed that the MS-LSTM model had the most significant improvement in the MAPE values, with reductions of 6.44%, 47.15%, and 3.07% compared to the LSTM model for Hubei, Shanghai, and Shenzhen, respectively. Similarly, the MS-HHO-LSTM model saw reductions in MAPE values of 17.04%, 35.97%, and 10.72% compared to the HHO-LSTM model for the respective regions. Lastly, the MS-IHHO-LSTM model demonstrated reductions of 27.79%, 29.82%, and 6.33% in MAPE values compared to the IHHO-LSTM model for Hubei, Shanghai, and Shenzhen, respectively. The study suggests that incorporating sentimental values from multiple sources increases prediction accuracy compared to using data from a single source.

Secondly, deep learning performance is superior to machine learning and statistical models in terms of prediction. In a single model, the average MAPE of deep learning in these three carbon exchanges is 52.89% and 55.42% lower than that of machine learning and statistical models. Furthermore, in the deep learning model, it can be observed that the average MAPE of LSTM is 50.73%, 74.46%, and 78.38% lower than MLP, CNN, and BP, respectively, in the three carbon trading markets. Therefore, LSTM has the best prediction performance compared with other deep learning methods.

Thirdly, the hybrid model performs more effectively than the single model. In the three different carbon trading markets, it is evident that the HHO-LSTM hybrid model has a more substantial forecasting effect than the single model LSTM. The average value of MAPE of the former in the three carbon markets is 28.35% lower than that of the latter.

Fourthly, the hybrid model with an improved swarm intelligence algorithm has a better prediction effect. The Harris Hawks algorithm is enhanced by updating the prey's escape energy and introducing the inertia weight factor. Subsequently, the modified Harris Hawks algorithm is utilized to optimize the LSTM, significantly increasing prediction accuracy. In the Hubei, Shanghai, and Shenzhen carbon trading markets, the IHHO-LSTM model shows a decrease of 1.89%, 30.48%, and 10.30% in MAPE value compared to the HHO-LSTM model. Similarly, the MS-IHHO-LSTM model shows a reduction of 14.61%, 23.87%, and 5.89% in MAPE value compared to the MS-HHO-LSTM model.

The model proposed in this paper has been successfully implemented in real time. It can quickly and accurately predict carbon prices based on the latest data. The model also has strong adaptability to market dynamics. The flexible modeling method can capture new trends and changes in the market and timely adjust the forecast results to reflect the latest market conditions. The paper proposes a model that outperforms traditional forecasting methods and offers dependable market forecasting data for policymakers, enterprises, and individual investors. The model implies better planning for company production, efficient risk management, and informed strategic decisions. For individual investors, the model can assist in making better investment choices, minimizing risks, and boosting investment confidence. In conclusion, the model has broad application and is significant for market development and management.

B. SUGGESTIONS

The Chinese carbon trading market is increasingly important in reducing carbon emissions, tackling the global climate crisis, and supporting China's dual carbon goal. Accurate prediction of carbon trading prices is essential for governments, enterprises, and investors to make informed decisions about the market. To achieve these goals, three suggestions are proposed.

The government should consider price fluctuations and market demand when establishing a carbon pricing mechanism to ensure that it is stable, adequate, and reasonable. Governments can formulate policies based on predicted carbon price trends to encourage low-carbon actions, develop clean technology, and promote sustainable development. At the same time, the government should support the transformation and upgrading of enterprises through tax incentives, subsidy policies, and other means, accelerate carbon emission reduction, and create a suitable environment for the carbon market. In addition, the government should actively promote international cooperation and attract foreign investors to participate in China's carbon trading market to jointly deal with global climate change and maximize emission reduction benefits. To ensure a fair and transparent market, governments must establish a regulatory framework, strengthen market supervision and enforcement, and combat manipulation and fraud.

Enterprises can improve their competitiveness and reduce carbon costs by adjusting production plans, product pricing, and resource allocation in response to anticipated changes in carbon prices. To achieve this, they should proactively pursue innovations in emission reduction technologies and clean energy while investing in advanced equipment to optimize carbon efficiency. Moreover, enterprises should prioritize strengthening their environmental management practices by implementing robust carbon emissions monitoring and reporting mechanisms to comply with national and international standards. Establishing comprehensive environmental management systems will enable them to monitor and regulate carbon emissions effectively. Furthermore, enterprises can engage in carbon trading markets apart from actively reducing emissions. Through carbon quota trading, they can generate economic gains and mitigate the risks associated with carbon emissions, thereby fostering sustainable development.

Accurate predictions of carbon prices are crucial for maintaining stability in the market. When investors accurately anticipate the changing trends of carbon prices, they should plan portfolios more effectively, make informed decisions, and enhances their confidence and stability in the market. Moreover, investors could diversify their portfolios, reduce risks, and earn long-term returns by investing in the carbon trading market. Additionally, investors could achieve the double carbon reduction benefit by investing in low-carbon technologies and clean energy-related industries. Therefore, investors should closely focus on government policies on carbon emissions and trading markets. Proper investment behavior enables investors to adjust their investment strategies quickly, seize opportunities, and reduce potential risks and losses.

C. FUTURE WORK

This paper aims to forecast China's carbon prices. Because the proposed model has high real-time applicability and strong adaptability to the dynamic carbon market, this model can also be appropriate to other countries. As carbon finance's social media platforms are public, researchers could extract news related to carbon trading. Then, they can use the news to calculate a sentiment index predicting carbon prices.

Although the model accurately predicts carbon prices, future research could improve accuracy by categorizing related news based on more emotions such as sadness, fear, anger, and disgust. Different emotions may have various degrees of impact on the volatility of carbon prices. In addition, future studies should introduce the self-attention mechanism and converter model, which can improve the accuracy and stability of the prediction.

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