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A low carbon management model for regional energy economies based on blockchain technology

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ABSTRACT

As the issue of sustainable energy development becomes more and more important in national economic construction, the potential dangers of climate change are gradually attracting widespread attention from countries around the world. In order to better carry out the low-carbon management of the regional energy economy, based on the analysis of the characteristics of blockchain technology, the present study utilized this technology to achieve intelligent and digital management of carbon emissions, and established a carbon emission prediction system. The cuckoo algorithm is used to improve the long-term memory network, and the improved algorithm is used in carbon emission prediction and management. The experimental results show that the improved Long Short Term Memory networks are close to the target precision in 240 iterations, and the convergence speed is fast. In the short-term regional carbon emission prediction, the average absolute error of the method is only 2%, which is highly consistent with the actual carbon emission. In the long-term carbon emission prediction, the average prediction accuracy of the upgraded long-term short-term memory networks can reach 97.26%, and the running time is only 19.46s. With high precision and running efficiency, the upgraded Long Short Term Memory networks can efficiently monitor regional carbon emission and provide a technical reference for the low-carbon management of the regional power industry.

1. Introduction

Global climate change has become a major challenge for mankind, with natural systems, including continents and oceans, experiencing varying degrees of anomalies, resulting in a continuous rise in environmental temperatures and other problems that are causing serious disasters for mankind [1]. At the same time, the proportion of China's economy in the world economy is gradually increasing, and China's pressure on energy conservation and emission reduction is growing. Statistics from the Ministry of Industry and Information Technology demonstrate that China's energy consumption and carbon emissions are among the highest in the world [2]. In addition, greenhouse gases emitted by human activities are an important factor affecting global climate change. The international community has been actively taking measures to control greenhouse gas emissions. As the world's largest energy consumer and carbon emitter, China is under increasing pressure to reduce emissions. As a result, the Chinese government has pledged to peak carbon dioxide emission reductions by around 2030. The allocation of China's carbon emission reduction targets to the provinces for implementation poses significant uncertainties about the future economic development, technological progress, and political trends of

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each province. Whether this goal can be achieved is still a question that needs to be answered. How to adhere to the sustainable development model, optimize regional energy management, and achieve low-carbon goals has become an unavoidable practical problem. With the application of blockchain technology in carbon emissions, the conditions for further optimizing the low-carbon management model are more than sufficient [3]. As a database with strong sharing function, blockchain technology is different from traditional relational database, and its advantages such as anti-tampering are favored in many fields, and has become a major development direction of China's information technology. The current management of carbon emission data is confused, with problems such as the opacity of carbon emissions and the lack of a superior methodological basis for regional low-carbon management [4].

Therefore, based on the significant advantages of decentralized, secure, transparent, and efficient blockchain technology, this study applies it to regional carbon emissions monitoring. The main contribution is to establish a settlement platform based on blockchain technology in the carbon emissions trading market, and to establish monitoring and approval institutions. Then, the carbon emission data is uploaded to the blockchain using wireless network or traffic card, and the carbon emission query function is included in each node of the blockchain to achieve the full process application of blockchain technology in carbon emission monitoring, and effectively monitor all the data. At the same time, taking the blockchain technology as the basis for the establishment of the carbon emission regulatory system, the Cuckoo Optimization Algorithm (COA) is used to improve the Long Short Term Memory (LSTM) network and apply it to the regional carbon emission prediction, so as to further achieve the goal of low-carbon management.

2. Related work

In recent years, many constructive outcomes have been obtained on the application of blockchain technology in the energy economy and carbon emissions management. Bao J et al. used blockchain technology for energy management and carbon emissions trading in response to the depletion of fossil fuels by analyzing its decentralized, transparent and anonymous underlying characteristics and managing the trading of renewable energy in distributed markets, demonstrating that the approach has a high privacy protection [5]. Sankaran K designed two projects in the field of circular economy to analyze the role of blockchain and artificial intelligence in energy transformation, including turning industrial carbon emissions into green fuel and through sensor-driven blockchain tools, and then applied the two projects together in the transformation of circular economy, the outcomes proved the effectiveness of the approach [6]. Mika B et al. proposed a service model to investigate the economic participation of potential consumers in electricity transactions by shifting the area of responsibility to the supplier and analyzed the economic value of blockchain technology in the energy supply sector, demonstrating the efficient operation of the model. The application of blockchain technology in engineering provides a methodological basis for low carbon and energy information management [7]. Zhong et al. address the issue of construction quality due to lack of trust, and design a quality information management framework based on blockchain technology that performs automated compliance checks on contracts entered into based on the analysis of participants' life cycles to ensure that all construction products meet regulatory requirements. The outcomes demonstrate that blockchain technology can provide distributed encrypted information records to ensure the security of construction quality management [8]. Zhang et al. developed a construction information management system based on blockchain technology for the digital management of engineering construction, which has multiple independent smart contracts and sets data analysis in the terminal, and integrates analytical algorithms such as deep learning for information management. The outcomes verified the high stability and security of the system [9].

The LSTM has good performance in predicting carbon dioxide emissions and has been highly appreciated by many scholars at home and abroad. Zuo Z et al. developed an LSTM combined with an extensible stochastic environmental impact assessment model to ensure that carbon dioxide emissions are always kept at a reasonable level, which can assess the drivers of carbon dioxide emissions in each region and make predictions of emission intensity and peaks. The outcomes demonstrate that the model has high operational efficiency and can be used as a reference for industrial restructuring [10]. Mele et al. proposed the use of LSTM models to predict carbon emissions and thus assess the economic development under renewable energy applications, using empirical outcomes from the Brazilian economic data to verify the accelerating effect of renewable energy on economic growth [11]. Jiang T et al. applied blockchain technology to eight industries, including electricity, chemical and steel, to address the issue of piloting carbon trading companies, and analyzed the potential of carbon pilot development through a survey on the willingness to use blockchain technology. The outcomes demonstrated that industries considering the use of blockchain technology were more willing to talk about piloting, providing guidance for the further promotion of the technology [12–15]. Sun W et al. developed the model which is capable of modeling the mapping between the target and the time lag factor. By analyzing carbon price data over a long period of time, the model was validated to be highly accurate and stable [16]. Li et al. developed an LSTM with an integrated convolutional neural network to address the imbalance in the overall energy consumption structure. The outcomes demonstrate that the method is able to better predict the energy mix [17]. LSTM has been applied in other fields and also provides a technical reference for low carbon management. The outcomes demonstrate that the LSTM model incorporating the attention mechanism improves the prediction precision and significantly reduces the time delay [18–20].

In summary, blockchain technology can ensure high data security and has the function of digital information management, which has certain application prospects in carbon emissions management. At the same time, LSTM has good performance in the long-term exploration of emissions and carbon trading market construction and management [21–23]. Most researchers have analyzed the application of blockchain technology and LSTM in low carbon management, however the study lacks the discussion on the combined use of the two and the further optimization of LSTM. Therefore, the study uses blockchain technology as the basis for establishing a low carbon management system, and then upgrades the LSTM for carbon emission prediction, in order to provide the necessary technical support for regional energy carbon emission management. The summary of all relevant studies is shown in Table 1.

3. Low carbon management of regional energy economies based on blockchain technology

3.1. Blockchain-based regional low carbon management model

The study uses blockchain technology to manage carbon emissions in regional energy economies. Firstly, the characteristics and basic structure of blockchain technology are analyzed to provide theory and techniques for low-carbon information management. The framework of blockchain technology platform achieves various functions through a layered design [24]. Blockchain adopts a five-layer architecture, which consists of data layer, network layer, consensus layer, incentive layer, and smart contract layer from bottom to top. The application layer mainly completes the accounting and transfer function by the client. The incentive layer includes issuance mechanism and incentive mechanism, and the source of incentive is transaction fees. The consensus layer mainly solves the Byzantine general problem, the proof-of-work mechanism, the double flower problem, 51% attack, etc. The network layer uses a P2P network, where each node stores all transaction records in a blockchain format. The data layer deals with issues such as what information is included in the transaction data and the encryption algorithm for the data information. Among them, the data layer is mainly used to store data and usually includes key technologies such as asymmetric encryption. Asymmetric encryption allows all nodes to have an appropriate asymmetric cipher, which is combined with hashing algorithms to ensure the security of network data and meet confidentiality requirements. The network layer is used for data communication between nodes in a P2P peer-to-peer path. All nodes in a P2P network are connected by a flat topology and do not have a centralized hierarchical structure [25]. The consensus layer is based on a specific consensus algorithm, which mainly packages and uploads the huge amount of data information. After the data is confirmed, only authorized queries or usage operations can be performed, but no corresponding deletions or changes can be made. In the blockchain platform, there is also an incentive layer to enhance the performance of the system. The contract layer usually contains key technologies such as scripting code, and finally the application layer focuses on different scenario applications of blockchain technology and corresponding case studies. Blockchain technology implements storage through a chain structure, where blocks are connected by hashes and all blocks have two parts: the block body and the block header. In a blockchain network, the hash field information is an extremely important connection method, where almost all blocks are connected to the previous block. The basic structure of the blockchain network is demonstrated in Fig. 1.

The main application of blockchain technology in low-carbon management is the monitoring of carbon emission information. For the whole carbon emission regulation system, the core part is monitoring and approval [26]. In the carbon emission trading market, it includes a complex amount of data information and links. The use of blockchain for information monitoring and verification requires the establishment of a settlement platform based on blockchain technology. Due to the economic function of the carbon trading market, its development is very immature and its security is low. Therefore, through a unified registration platform, accurate and comprehensive supervision of the carbon emission trading market can be achieved, and relevant data information can also be connected with departments. Secondly, establish a carbon emission monitoring and verification institution. The current statistical methods for greenhouse gas emissions are not very effective, and the collection and integration of carbon emission data is in a dilemma, which can easily lead to problems such as unreasonable setting of total carbon emissions. Therefore, it is necessary to optimize the carbon emission detection system based on the advantages of blockchain, and improve the accuracy and credibility of data information. Strictly follow the requirements of blockchain technology, increase and update monitoring equipment, and gradually implement and control emission units to build a carbon emission control and management system under big data technology. The specific implementation path of the carbon emission control and management system is shown in Fig. 2.

The study uses edge devices to collect carbon emissions data. All edge devices are capable of receiving carbon emissions data from a number of carbon emissions meters, which can be uploaded to the blockchain with the help of a wireless network or a traffic card. At the same time, the edge devices are able to store carbon emission port data with low overall power and maintenance costs, and the frequency of collection is automatically controlled and centrally packaged for upload. Wireless edge devices are networked with ZigBee or Lora, allowing data to be uploaded using satellite communications even in the event of network outages or fluctuations. In addition, a carbon query function is built into each node of the blockchain, allowing queries for specific carbon emissions, greenhouse gas emissions and hash values for a certain period of time [27–29]. Before deleting block records, most nodes are backed up and the backup information is not tampered with. In blockchain technology, the regulation of carbon emission data is mainly determined by the alarm messages received by the nodes and the checks are artificially implemented at the carbon emission collection points.

Table 1
Summary table of all relevant studies.

Author	Time	Achievement
Bao J [5]	2020	High privacy protection
Zhong B [6]	2020	Availability
Zhang Y [7]	2022	High stability and safety
Sankaran K [8]	2019	Availability
Mika B [9]	2021	Efficient operational efficiency
Zuo Z [10]	2020	High efficiency
Mele M [11]	2021	Verify the promoting role of renewable energy
Jiang T et al. [12–15]	2022	High fitness
Sun W [16]	2020	High-precision
Li Y [17]	2022	Strong predictive ability

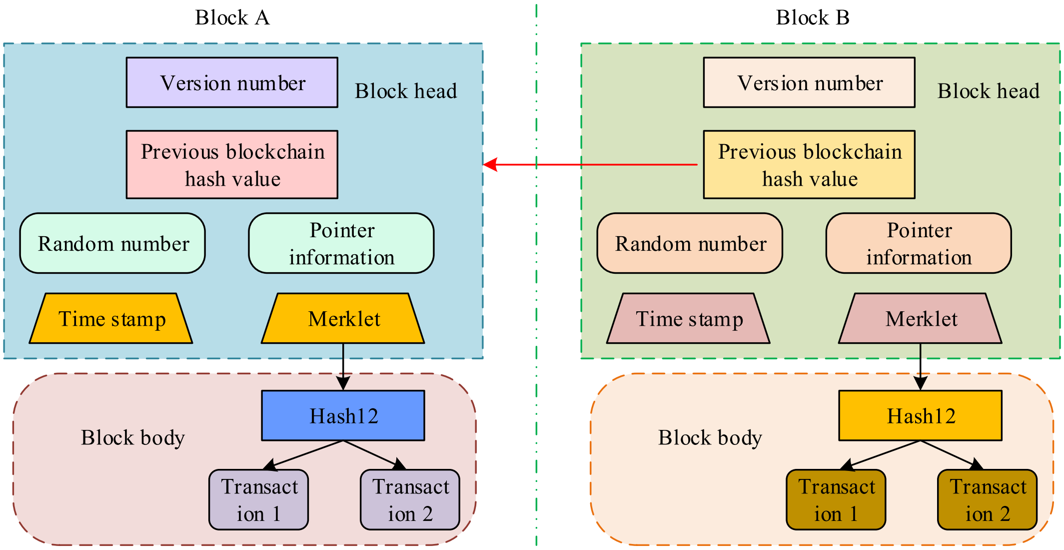

Fig. 1. Fundamental structure of blockchain network.

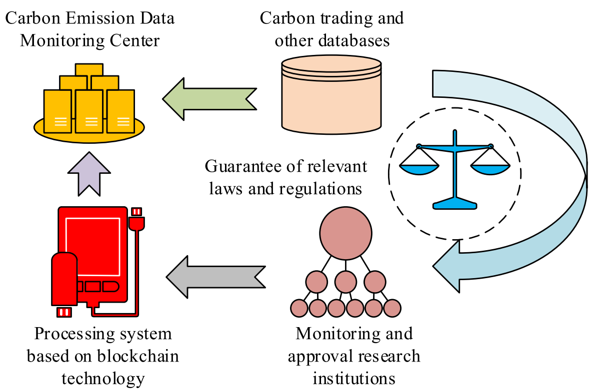

Fig. 2. The specific implementation path of carbon emission control and management system.

3.2. LSTM-based carbon emission prediction

On the basis of blockchain technology to manage low-carbon information of regional energy economy, carbon emissions are predicted by LSTM to achieve low-carbon management. Blockchain technology provides a decentralized platform for data collection and sharing among various actors in the energy economy, such as energy suppliers, energy consumers, and regulators. The data includes information on energy consumption, energy production and carbon emissions. The LSTM model can use this data to make predictions about carbon emissions and make these predictions available to participants in the blockchain network. At the same time, blockchain technology is used to monitor and verify the accuracy and authenticity of carbon emissions data in the energy economy. By recording carbon emissions data on the blockchain, data tampering and falsification can be prevented. The LSTM model can be used to predict carbon emissions data and compare it with actual data to further verify the accuracy of the data. LSTM is actually optimized from recurrent neural network, which is an extension of recurrent neural network and better handles the problem of gradient explosion or disappearance [30]. LSTM inherits the “memory” property of recurrent neural network and can analyze the correlation of data sequence at different moments and is not prone to training increase. In response to the shortcomings of the gradient descent algorithm, which cannot guarantee convergence to the global optimal solution, the LSTM introduces a new recurrent structure to extract the data correlation of the input signal sequences, in order to deal with a large number of signal sequences, avoiding the increase of prediction due to data redundancy. In LSTM, the gate structure is mainly divided into three types: forgetting gate, input gate and output gate. The forgetting gate is mainly used to determine whether the information passes or not, the input gate is mainly used to determine which information can enter the storage unit, and the output gate is mainly used to determine which information can leave the storage unit. The gate structure and the storage unit are used to form a new cycle structure. By analyzing the data correlation of the input signal sequence, some redundant data are removed, and the gradient problem in the network training process caused by the surge of input data is effectively solved. The cell structure of the LSTM is demonstrated in Fig. 3.

The LSTM uses gradient descent to search for core parameters, and the storage units and gate structures introduced by the LSTM itself come into play when the amount of data increases dramatically. The gate structure is a selective pass-through mechanism that protects or controls information in combination with the activation function layer of the neural network and dot product operations, while the storage unit essentially functions in the same way as a neuron [31]. The main function of the input gate is to determine whether the information can be input into the energy storage unit. The calculation process is shown in equation (1).

$$i = f(b_i + \omega_i \cdot [h_{t-1}, x_t]) \tag{1}$$

in equation (1), f is the activation function; ω_i is the weight; x_t represents the current input; h_{t-1} represents the output at the previous moment; b_i is the bias value. In the new memory cell, the construction vector must be stored to obtain the candidate state of the cell as demonstrated in equation (2).

$$\overline{C_t} = \tanh(\omega_c * [h_{t-1}, x_t] + b_c) \tag{2}$$

in equation (2), $\overline{C_t}$ is the new candidate state. The union between the new candidate state and the forgetting gate updates the old cell as shown in equation (3).

$$C_t = i_t \Theta c_t + f \Theta c_{t-1} \tag{3}$$

in equation (3), Θ represents the joint update action; C_t is the new cell state; c_{t-1} and c indicates the old unit status. The forgetting gate is a sigmoid function whose main function is to determine whether the information has been passed from the new storage cell, while the output gate is used to determine the outcome and update the memory of the storage cell. The calculation of the output gate and the forgetting gate is demonstrated in equation (4).

$$\begin{cases} f_t = f\left(b_f + \omega_f \cdot [h_{t-1}, x_t]\right) \\ o_t = f(b_o + \omega_o \cdot [h_{t-1}, x_t]) \end{cases} \tag{4}$$

in equation (4), f_t represents the information retained by the forgetting gate and o_t is the output gate processing outcome. The implicit layer output information is demonstrated in equation (5).

$$h_i = o_t \Theta \tanh(c_t) \tag{5}$$

in equation (5), the output outcome of the implied layer is represented. The final prediction outcome of the output layer is obtained as demonstrated in equation (6).

$$\overline{\overline{x_t}} = b + h_t * \omega_y \tag{6}$$

in equation (6), $\overline{\overline{x_t}}$ indicates the prediction outcome. The LSTM is difficult to expand for operation and the gradient still disappears when the sequence length exceeds a certain range. Therefore, the study introduces the COA algorithm for improvement. The COA algorithm is developed from the cuckoo bird's egg-laying behavior by nesting and Levi's flight, which performs a fast search in the whole domain and achieving a more accurate optimal solution location, thus achieving a fast optimal solution for the parameters at the overall and local levels [32]. The COA algorithm performs the position update mainly in the form of nest replacement. The COA algorithm first needs to start a global search, and the position update is calculated as demonstrated in equation (7).

$$x_i^{t+1} = \alpha \oplus levy(\lambda) + x_i^t \tag{7}$$

in equation (7), t is the nesting algebra, α is the search step factor, usually 0.01. $levy(\lambda)$ is the Lévy flight, x_i^{t+1} is the position to be updated, and x_i^t is the actual position. The equation required to search for a path using Lévy flight is demonstrated in equation (8).

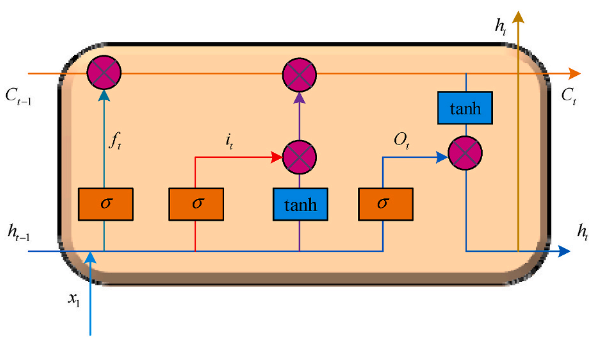

Fig. 3. Unit structure diagram of LSTM.

$$levy = \frac{\varphi u}{|v|^{1/\beta}} \tag{8}$$

in equation (8), β is the scale factor, usually 3/2, and $u \sim v$ follows the normal distribution. The calculation of φ is demonstrated in equation (9).

$$\varphi = \frac{\Gamma(\beta+1)\sin(\beta\pi/2)}{\Gamma\left[2^{(\beta+1)/2}\cdot\beta\cdot((1+\beta)/2)\right]} \tag{9}$$

in equation (9), Γ is the gamma function. All nests are randomly assigned the corresponding probability, and the decision to produce a new nest is made by comparing the magnitude between the maximum detection probability and the random number [33,34]. When the former is larger, the nest is retained and, conversely, the nest is abandoned and a new nest is obtained, whose location is shown by equation (10).

$$x_i^{t+1} = \zeta\left(x_i^t - x_j^t\right) + x_i^t \tag{10}$$

in equation (10), ζ denotes a random number. The improvement of the LSTM by COA algorithm is mainly to find the core parameters of the LSTM for carbon emission prediction in order to improve the convergence speed of the core parameters and obtain better prediction results. The flow of the improved LSTM for carbon emission prediction is demonstrated in Fig. 4.

In Fig. 4, when improving LSTM for regional carbon emission prediction, the collected data sequence must first be checked when the improved LSTM predicts regional carbon emissions. When it is judged as abnormal data, it is repaired and supplemented through coefficient interpolation method. Then, the filtered and normalized data sequence is divided according to an appropriate proportion to obtain the training and validation dataset. The optimized LSTM of the COA algorithm is used to train the training dataset and obtain core parameters such as thresholds. Finally, it determines whether the conditions are met and, if so, outputs the result. When it is determined that the collected data sequence is not abnormal data, it is directly processed by the LSTM and COA algorithms on a standardized basis before determining whether to output the results. It should be noted that the sample selection was conducted using official data from a specific region. Due to the proposed model being able to inspect the collected data sequence, the data preprocessing is achieved by conventional methods such as noise elimination. The calculation process of repairing and supplementing with coefficient interpolation method is shown in equation (11).

$$x_i = \alpha x_{i-1} + \beta x_{i+1} \tag{11}$$

in equation (11), x_i represents the repaired anomalous data value; x_{i-1} represents the previous anomalous data value; x_{i+1} represents the next anomalous value; α and β represent the scale factor, which usually takes the value of 0.5. Different influencing factors are likely to cause prediction errors, and the study implements the normalization of the data series by the most valuable method, whose calculation process is demonstrated in equation (12).

$$\bar{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{12}$$

in equation (12), x is the actual value of the original data series; $\bar{x}$ is the normalized value, and $x_{\max}$ and $x_{\min}$ are the maximum and

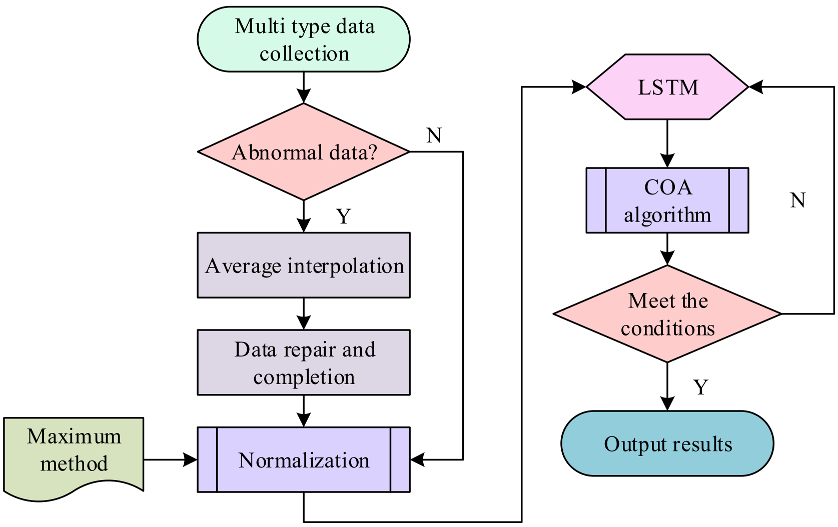

Fig. 4. The upgraded LSTM carbon emission prediction process.

minimum values of, respectively. The training and validation data sets were obtained by dividing the filtered and normalized data sequences according to appropriate ratios, and the COA algorithm was used to optimize the LSTM to train the parameters on the training data set to obtain the core parameters such as thresholds. To validate the prediction results, the mean absolute percentage error is calculated as demonstrated in equation (13).

$$R_{MAPE} = \sum_{i=1}^{m} \left| \frac{x_i - \hat{x}_i}{x_i} \right| \cdot (m / 100) \tag{13}$$

in equation (13), m represents the predicted value; x_i is the initial value and m is the amount of data included. The root mean square error is calculated as demonstrated in equation (14).

$$R_{RMSE} = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (x_i - \hat{x}_i)^2} \tag{14}$$

The Hill inequality factor is calculated as demonstrated in equation (15).

$$R_{TIC} = \frac{\sqrt{\frac{1}{m} \sum_{i=1}^{m} (x_i - \hat{x}_i)^2}}{\sqrt{\frac{1}{m} \sum_{i=1}^{m} \hat{x}_i^2} + \sqrt{\frac{1}{m} \sum_{i=1}^{m} x_i^2}} \tag{15}$$

in equation (15), R_{TIC} represents the Hill inequality coefficient, usually between 0 and 1, the smaller the value, the higher the prediction precision.

4. Analysis of application effects

The study establishes a carbon emission management model based on blockchain technology, and enhances the LSTM with the COA algorithm to form the COA-LSTM for carbon emission prediction. Performance tests of the COA-LSTM method were first conducted to compare it with Back Propagation (BP) networks, LSTM and Convolutional Neural Networks (CNN). The experimental settings for the four methods selected for performance testing are demonstrated in Table 2.

The improved COA-LSTM method is compared to CNN, BP network and LSTM. To compare the prediction performance of the four methods, the commonly used Alpha Vantage dataset was selected. The dataset is an online platform providing financial market data, which provides a set of API interfaces to obtain real-time and historical data of financial assets such as stocks, forex, cryptocurrencies, and can accurately reflect the predictive performance of the algorithm. The prediction time of the four models is 7 days of data. The randomness of artificial neural networks are addressed by increasing the number of tests. When training and classifying the model, the samples are randomly divided into 70% of the training set and 30% of the testing set, with 650 iterations and a batch training size of 16. Accuracy is highest when the Adam optimizer is used to update parameters at a learning rate of 0.01. At the same time, all models are fully adjusted and tested, and the results are shown in Fig. 5. In Fig. 5, the horizontal coordinate is the number of iterations, the vertical coordinate is the error rate, the solid line is the target accuracy to be achieved by the four methods, and the dashed line is the four methods for comparison. From Fig. 5, the differences between the four methods are more obvious. In particular, the BP network evolves to the target accuracy at about 490 generations, with a smaller gap between the BP network and the CNN up to 400 generations, while the CNN has reached its goal at about 380 generations. Compared with BP and CNN, LSTM has a certain lead, as it reaches the target at 325 generations, 165 and 55 generations ahead respectively. The upgraded COA-LSTM, on the other hand, converges to the target accuracy at 240 generations compared to the first three methods, which is 85 generations ahead of the LSTM and is the fastest of the four methods, indicating its optimal convergence performance.

Fig. 6 shows the comparative results of the prediction accuracies of the four selected methods on the Alpha Vantage dataset. The horizontal and vertical coordinates in Fig. 6 represent the number of iterations and the precision rate respectively, and the precision rate of the BP network grows relatively slowly before 80 generations and starts to remain around 84% after 80 generations. The precision rates of both LSTM and CNN improve rapidly up to 20 generations and demonstrate a slow growth after 40 generations, with the maximum values of 92% and 90%, respectively, which is a relatively small difference, and the maximum values are upgraded by 8% and 6%. The COA-LSTM, on the other hand, showed the largest and fastest increase in accuracy up to generation 20. It was already close to 90% at generation 20, and the growth slowed down after generation 80 remaining close to 98%, with a maximum of 99%.

Table 2
Experimental environment for performance testing of the four selected methods.

Operating environment	Product name
CPU	Intel Core i7-9750H 2.60 GHz
Operating system	Windows 10
Graphical Tools	Matlab 2018b
Internal storage	8.00 GB

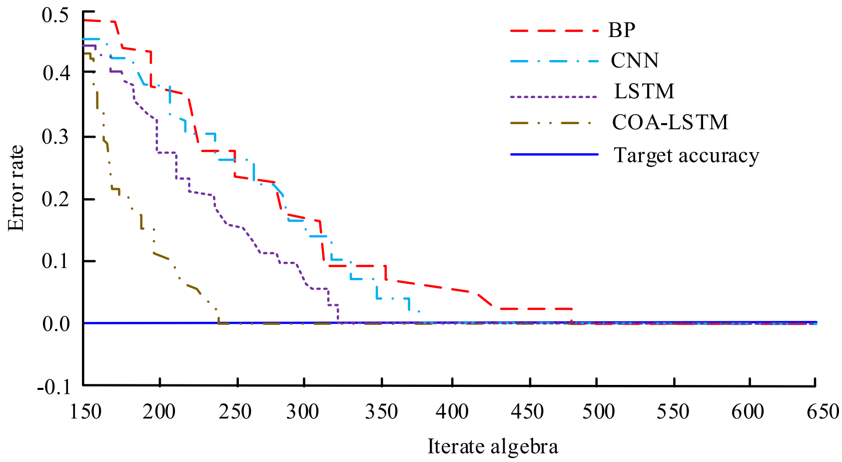

Fig. 5. Training outcomes of COA-LSTM method, CNN, BP network and LSTM in the Alpha Vantage dataset.

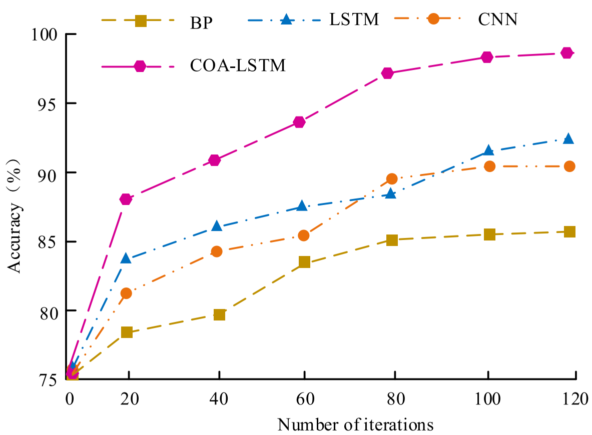

Fig. 6. Comparison outcomes of prediction precision of the four selected methods in the same dataset.

Compared with the highest precision values of CNN, BP and LSTM, COA-LSTM has upgraded by 9%, 15% and 7% respectively, which is a more significant improvement.

The prediction errors and performance comparisons of the four methods are demonstrated in Table 3. The error comparison includes R_{MAPE} (%), R_{RMSE} and R_{TIC}, while the performance comparison includes effective prediction time, training time and invalid prediction time. In this context, R_{RMSE} (Relative Root Mean Square Error) stands for relative root mean square error. R_{MAPE} (Relative Mean Absolute Percentage Error) is a relative mean absolute percentage error that can be used to estimate the average percentage error of the predicted value relative to the true value. R_{TIC} (Relative Technical Indicator) is a relative technical indicator error used to evaluate a time series prediction model. In Table 3, the R_{RMSE} of COA-LSTM, CNN, BP network and LSTM are 1.2415, 1.7264, 2.0360 and 1.6163 respectively, and the root mean square error of COA-LSTM is the smallest, which indicates that the prediction error of this method is low. Meanwhile, the R_{MAPE} value of COA-LSTM is 11.57 and the R_{TIC} value is 0.565, both of which are the smallest among the four methods and are comparable to the BP network, indicating that the prediction error of this method is significantly lower. In terms of training time, COA-LSTM takes only 0.565s, while CNN, BP network and LSTM take 0.1047s, 0.1246s and 0.0972s respectively, which is longer. In the comparison of effective and ineffective prediction times, COA-LSTM was 5860 min and 1732 min respectively, both better than the other three methods, indicating that COA-LSTM has better performance and lower prediction error.

Table 3
Prediction error and performance comparison of four methods.

Prediction method	R_{RMSE}	R_{MAPE} (%)	Training time(s)	R_{TIC}	Effective forecast duration (min)	Predicted failure time (min)
COA-LSTM	1.2415	11.57	12.348	0.0565	5860	1732
CNN	1.7264	16.75	28.271	0.1047	3154	2960
BP	2.0360	19.34	30.536	0.1246	2147	3008
LSTM	1.6163	14.21	26.874	0.0972	4263	2679

The COA-LSTM was then applied to the actual carbon emission projections. The four methods were used to forecast carbon emissions in a randomly selected region in China where the energy industry is important, and the outcomes are demonstrated in Fig. 7. The red solid line represents the actual carbon emissions in the region, and the dashed line represents the prediction outcomes of the different methods. It can be seen from Fig. 7 that the predicted value of the BP network is quite different from the actual value, which is generally small, and the Mean absolute error is about 15%. Compared with BP, the prediction value obtained by CNN has a relatively obvious improvement, and the Mean absolute error is about 8%. The prediction results of COA-LSTM are generally consistent with the actual values, and it can be clearly seen that the curve changes at several peaks are almost equal to the actual values, with an average absolute error of about 2%, which has a high prediction accuracy.

Finally, in order to improve the scientific and reliability of the results, the proposed COA-LSTM is applied to the long-term carbon emission prediction in this region. At the same time, this method is compared with the literature [34–36]. The prediction time of the study was 6 months, and the comparison results of the average prediction time and prediction accuracy are shown in Fig. 8. Fig. 8 (a) represents the average prediction accuracy results, and Fig. 8 (b) represents the average prediction time comparison. Fig. 8 (a) shows that the average accuracy of COA-LSTM, literature [34], literature [35] and literature [36] are 97.26%, 89.53%, 85.01% and 91.87%, respectively. Compared with literature [34], the proposed COA-LSTM method is improved by 12.25% and is the best among the four methods. As can be seen from Fig. 8 (b), the average running time of literature [34] is the longest, which is 38.57s, and those of literature [35,36] are 30.12s and 29.63s, respectively. However, COA-LSTM is only 19.46s, and the maximum increase is 19.11s. In summary, this method has both high efficiency and high accuracy, and has high applicability in carbon emission prediction and low-carbon management. Analyzing the reasons, the proposed COA-LSTM prediction model first checks the collected data sequence when predicting regional carbon emissions. If it is judged as abnormal data, it is repaired and supplemented through coefficient interpolation method, and the data sequence is divided and screened according to appropriate proportions. Due to the different influencing factors that can easily cause prediction errors, the model also uses the maximum value method to normalize the data sequence, thus ensuring the accuracy of the results as much as possible.

5. Discussion

The research uses blockchain technology to establish a carbon emission management model, applies COA algorithm to improve the LSTM, and performs carbon emission prediction. The experimental results show that in the performance test, the BP network evolved to the target accuracy in about 490 generations, LSTM reached the target in 325 generations, and COA-LSTM approached the target accuracy in 240 generations, 85 generations ahead of LSTM. When comparing the prediction accuracy on the same data set, the accuracy of LSTM and CNN both improved rapidly within 20 generations, and increased slowly after 40 generations, with the maximum of 92% and 90%, respectively. COA-LSTM has the largest increase in accuracy rate before the 20th generation, and its speed is fast. The R_{RMSE} of COA-LSTM, CNN, BP network and LSTM are 1.2415, 1.7264, 2.0360 and 1.6163 respectively, and the root mean square error of COA-LSTM is the smallest. In terms of training time, COA-LSTM needs only 0.565s, while CNN, BP network and LSTM are 0.1047s, 0.1246s and 0.0972s respectively, which are longer. In comparing the effective and ineffective prediction time, COA-LSTM was 5860 min and 1732 min respectively. In the prediction of actual carbon emissions, the prediction results of LSTM are generally larger than the actual carbon emissions, with an average absolute error of 6%. The predicted results of COA-LSTM are generally consistent with the actual values, with an average absolute error of about 2%. In the long-term regional carbon emission detection, the accuracy rate of the improved method is as high as 97.26%, and the time is only 19.46s. It shows that the proposed method has higher quasi accuracy and efficiency in carbon emission management, better performance and better practical application effect.

6. Conclusion

The sustainable development of energy and economy places higher demands on regional carbon emission management. The wide application of blockchain technology has provided a new way to achieve the low-carbon goal. In this study, blockchain technology is applied to regional energy economy carbon emission management, and the carbon emission data collection method is established. Further, the COA algorithm is introduced to improve LSTM, and the improved method is applied to regional carbon emission prediction. The results show that in the prediction error comparison, the root mean square error of the method is 1.2415, the required training time is 0.565s, and the effective prediction time is up to 5860 min. In the one-month regional carbon emission prediction, the prediction curve obtained by this method is equal to the actual carbon emission at several peaks, with an average absolute error of about 2%, which is increased by 6%, 13% and 4%, respectively compared with CNN, BP and LSTM. In the long-term regional carbon emission detection, the improved method is as high as 97.26%, which only takes 19.46s and is more efficient. It shows that the LSTM prediction method proposed by the research has high accuracy and efficiency in carbon emission management based on blockchain technology, and can be better applied to regional low-carbon management. However, there are still some limitations in the scalability, performance, and privacy protection of current blockchain technology. For example, due to the distributed nature of blockchain, its processing speed is relatively slow and cannot meet the needs of large-scale energy transactions. In addition, transaction information on the blockchain is public and may raise issues of trade secret protection and personal privacy. In the future, it is necessary to continue to research and improve the blockchain technology to enhance its scalability, performance, and privacy protection capabilities. For example, the use of sharding techniques, side chains, or other consensus mechanisms can be explored to improve the processing speed and throughput of the blockchain and provide better privacy protection mechanisms.

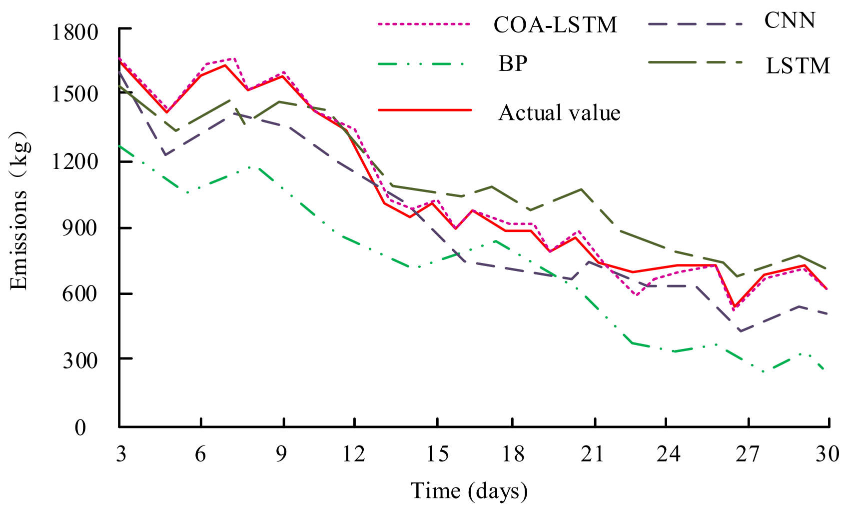

Fig. 7. Outcomes of four methods in regional carbon emission prediction.

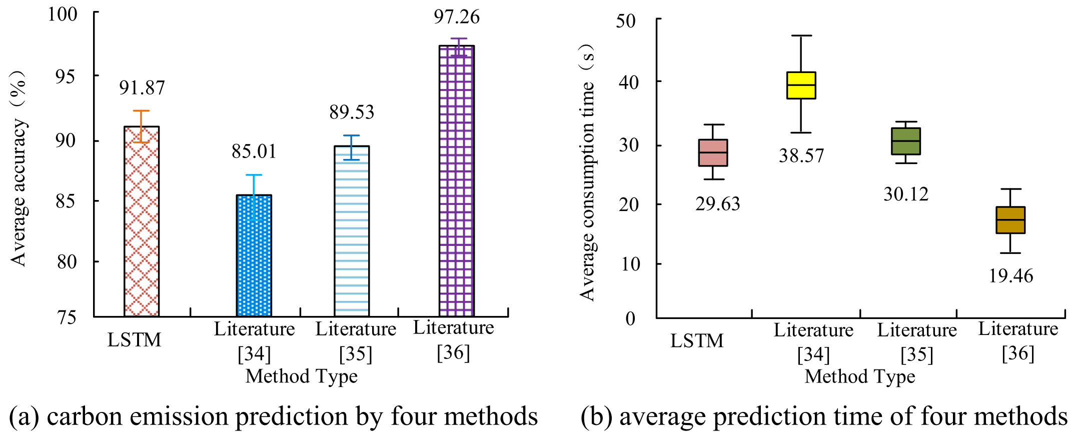

Fig. 8. Comparison of average prediction time and precision of regional carbon emissions by four methods. (a) carbon emission prediction by four methods (b) average prediction time of four methods.

Author contribution statement

Siyue Tan: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Guangmin Liu: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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