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PM_{2.5} concentration prediction in Lanzhou, China, using hyperchaotic cuckoo search—extreme learning machine

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Abstract

Recently, Northwest China has been suffered PM_{2.5} pollution. Through a case study of Lanzhou city, capital of Northwest China's Gansu province, a hyperchaotic cuckoo search-extreme learning machine (HCCS-ELM) approach is proposed to establish a PM_{2.5} concentration prediction model. The cuckoo search is used to generate the number of hidden layer neurons in ELM. The hyperchaotic system is innovatively introduced to improve the accuracy of the algorithm with its good randomness and convergence. HCCS-ELM has a similar memory footprint as ELM, while experiments using observed data from four monitoring stations in Lanzhou during 2016 to 2018 show that HCCS-ELM has higher accuracy in PM_{2.5} hourly and daily concentration prediction.

Keywords: PM_{2.5} prediction, Hyperchaotic system, Cuckoo search, Extreme learning machine

1 Introduction

PM_{2.5} is still one of the environmental problems in China, and Lanzhou, as the most important industrial city in China, is facing more serious PM_{2.5} pollution. And artificial neural network has been widely used in air pollution prediction. Researchers have developed several PM_{2.5} concentration prediction models such as statistical and machine learning methods [1, 2]. Recently, the performance of compound models has considerably increased with the development of computer hardware and software technologies, which has attracted significant attention in developing various prediction models. For example, convolutional back-propagation neural networks [3, 4], image contrast-sensitive features and weighted bagging based neural network can be integrated to predict air pollution [5]. However, a hybrid convolutional neural network combined with the high-level features extracted from the convolutional layer with ground-truth PM_{2.5} can learn haze-relevant classified mapping and train support vector regression, indicating cheapness, quickness, and convenience [6]. Besides, neural networks can derive a kind of multivariate Bayesian uncertainty processor to predict the probabilities of PM_{2.5} [7] or develop an air quality early-warning system by phase-space reconstruction and multi-objective optimization [8]. In addition, the AOD-PM_{2.5} model uses a combination of multiple linear regression, back propagation neural networks, classification and regression trees, and random forest estimation methods to predict PM_{2.5} concentrations, and improves accuracy in East China by adding meteorological elements that vary with time and height [9].

Deterioration of air quality has affected people in China [10–12]. Chinese researchers [13] proposed a hybrid model that can rapidly estimate particulate pollution based on a data-driven artificial neural network (ANN). At the regional level, Zhao et al. [14] used recurrent neural networks to analyze hourly air quality in the Northwest of China. Besides, Wang et al. [15] exploited an ANN to predict and analyze the PM_{2.5} in Chongqing, China. In terms of small-scale predictions, Tong et al. [16] and Xu et al. [17] investigated machine learning to analyze PM_{2.5} in the households in Hong Kong and near the Beijing railway station, respectively.

Air quality is an environmental and major survival issue [18, 19]. As an important city in Northwest China, Lanzhou has been plagued because of air pollution for a long time. The PM_{2.5} concentration in Lanzhou far exceeds the Chinese warning line. In March 2021, Lanzhou encountered a severe sand-storm. In Figure 1, the red dotted line represents the PM_{2.5} concentration limit of China. While the blue one represents the PM_{2.5} concentration in Lanzhou, which severely exceeds China's standard in recent years. The PM_{2.5} concentration is dynamic, related to time series, and presents seasonal changes. Thus, an accurate prediction of PM_{2.5} concentration is of great significance for strengthening the prevention and control of air pollution [20].

Most of the existing algorithms are aimed at the prediction of short-term or long-term pollutant concentration. There is currently no algorithm that can

Fig. 1: 2016-2019 $\text{PM}_{2.5}$ concentration in Lanzhou, China

perform well in long-term and short-term $\text{PM}_{2.5}$ forecasts. The inherent neural network is complicated to calculate, occupies a lot of system resources, and has poor prediction accuracy for $\text{PM}_{2.5}$ concentration. There is a correlation between $\text{PM}_{2.5}$ concentration and time series, so we use an extreme learning machine (ELM) method to predict $\text{PM}_{2.5}$ concentration. Avoiding manual adjustment, cuckoo search (CS) algorithm can be provided to calculate the optimal number of hidden layer neurons of ELM. For the good convergence and randomness of hyperchaotic systems [21], its join can reduce the computational cost of CS algorithm and improve the accuracy of ELM [22]. Inspired by the above, this paper proposes hyperchaotic CS-ELM (HCCS-ELM) to predict the $\text{PM}_{2.5}$ concentration in Lanzhou. The proposed HCCS-ELM is validated using the measured data selected from four monitoring stations in Lanzhou. The results show that HCCS-ELM has good performance in predicting $\text{PM}_{2.5}$ hourly or daily concentration in Lanzhou. Compared with ELM, HCCS-ELM utilizes a similar memory footprint, and it is conducive to the accurate and efficient prediction of $\text{PM}_{2.5}$ concentration. Besides, it can reduce the cost and the time required for prediction under the condition of ensuring the same accuracy. By accurately predicting the $\text{PM}_{2.5}$ concentration, preventive and effective measures can be taken in advance to minimize the losses caused by heavy pollution weather [23].

2 Method

2.1 Study Area

Lanzhou is the capital city of Gansu, located at 36°03'N and 103°40'E. The terrain is high in the southwest and low in the northeast. Surrounded by mountains in the north and south of the urban area, the Yellow River passes through the city, forming a narrow long valley between gorges and basins. The frequency of calm winds and temperature inversion in the Lanzhou River Basin is high, which is not conducive for the diffusion of endogenous pollutants. And the transfer of external dust in the surrounding area results in severe PM_{2.5} pollution.

2.2 Air Quality Monitoring and Meteorological Data

The meteorological data comes from website (<http://data.cma.cn/>), and the pollution data comes from website (<http://www.mee.gov.cn/>). In this paper, four stations provide the data, which geographic positions are shown in Figure 2. Station 1 is located in Xigu District, Lanzhou City, next to Lanzhou Petrochemical, and has relatively low traffic. Station 2 is located around the city of Lanzhou, with low traffic and no factories nearby. Stations 3 and 4 are located in the residential area of Lanzhou City, with heavy traffic and no factories nearby. The four stations do not affect the surrounding environment, which means they are hidden. For example, if people know where the stations are, they may go away, reducing traffic flow and resulting in inaccurate data. We select daily and hourly meteorological data such as wind direction, wind speed, temperature, relative humidity and pollutant (CO, SO₂, NO₂, O₃ and PM_{2.5}) data from 2016 to 2018 as research samples [24–26].

2.3 Hyperchaotic System

In this section, we adopt a hyperchaotic real system and its corresponding complex system to generate the input weights and hidden layer biases of HCCS-ELM to obtain better prediction results than models for comparison. The hyperchaotic real system is given as follows [22, 27]:

$$\begin{cases} \dot{\xi}_1 = -a\xi_1 + \xi_2\xi_3 + \xi_4, \\ \dot{\xi}_2 = -\xi_1 + c\xi_2, \\ \dot{\xi}_3 = \xi_1\xi_2 - b\xi_3, \\ \dot{\xi}_4 = d\xi_1 + e\xi_2, \end{cases} \quad (1)$$

where a , b , c and d are real constants, and ξ_1 , ξ_2 , ξ_3 and ξ_4 are real variables. The dots denotes derivatives with respect to time t . The corresponding hyperchaotic complex system is given by

Fig. 2: Geographic positions of four stations in Lanzhou, China (From left to right are Station 1, 3, 4 and 2)

$$\begin{cases} \dot{\eta}_1 = -a\eta_1 + \eta_2\eta_3 + \eta_4, \\ \dot{\eta}_2 = -\eta_1 + c\eta_2, \\ \dot{\eta}_3 = \frac{1}{2}(\bar{\eta}_1\eta_2 + \eta_1\bar{\eta}_2) - b\eta_3, \\ \dot{\eta}_4 = d\eta_1 + e\eta_2, \end{cases} \quad (2)$$

where $\eta_1 = u_1 + ju_2$, $\eta_2 = u_3 + ju_4$, $\eta_3 = u_5$, and $\eta_4 = u_6 + ju_7$ are complex variables, and $j = \sqrt{-1}$. The over bar represents the complex conjugate of the variables. The real version of System (2) is given as follows:

$$\begin{cases} \dot{u}_1 = -au_1 + u_3u_5 + u_6, \\ \dot{u}_2 = -au_2 + u_4u_5 + u_7, \\ \dot{u}_3 = -u_1 + cu_3, \\ \dot{u}_4 = -u_2 + cu_4, \\ \dot{u}_5 = u_1u_3 + u_2u_4 - bu_5, \\ \dot{u}_6 = du_1 + eu_3, \\ \dot{u}_7 = du_2 + eu_4. \end{cases} \quad (3)$$

The hyperchaotic sequences are shown in Figure 3 for the ξ_3 - ξ_2 - ξ_1 and ξ_2 - ξ_1 - ξ_4 planes.

(a)

(b)

Fig. 3: Phase diagrams for System (1) in the (a) ξ_3 - ξ_2 - ξ_1 plane, (b) ξ_2 - ξ_1 - ξ_4 plane

2.4 Hyperchaotic Cuckoo Search

The CS algorithm is a behavior simulation proposed by Yang et al. [28] based on the interesting breeding behavior such as brood parasitism of certain species of cuckoos. Meanwhile, they introduced the breeding behavior of cuckoos and characteristics of Lévy flights of some birds and fruit flies' trajectories. In nature, cuckoo birds fly in random or similar random ways to find the location of the nest suitable for laying eggs. The CS algorithm has three ideal conditions as the premise [28, 29]:

- (1) Each cuckoo lays only one egg at a time, and randomly selects a nest location for hatching.
- (2) In a randomly selected set of nests, the high-quality ones will be retained for the next generation.
- (3) The number of available nests is fixed, and the probability of bird's nest owner finding the foreign egg is $P_a \in [0, 1]$. When the owner finds a foreign cuckoo egg, he will throw it away or build a new nest.

Based on the above, the operation steps of cuckoo algorithm are as follows:

- (1) Setting parameters such as population size, searching space dimension, and maximum number of iterations. The position of the nest is initialized randomly as X_i , $i \in [1, n]$, and the objective function is defined as $f(x)$, $x = [x_1, x_2, x_n]^T$, where T denotes transpose.
- (2) Calculating the objective function value of each nest location and comparing it to obtain the current optimal function value.
- (3) Using hyperchaotic sequence to update the position and state of other nest except the optimal one, calculating the objective function value and comparing the obtained function value with the current optimal one. If it is better, the current optimal value is updated.
- (4) After position updating, random numbers r and P_a are used for comparison. If $r > P_a$ is used, the nest position is randomly updated once. Otherwise, it remains unchanged.
- (5) If the maximum number of iterations or search accuracy requirements are met, the next step will proceed, or it will go back to Step (3).
- (6) Outputting the location of the globally optimal nest.

2.5 Hyperchaotic Extreme Learning Machine

The hyperchaotic ELM is divided into three parts: input, hidden and output layers. In the network, neurons of input, hidden and output layers are completely connected. Assume that the model has n input layer neurons and its corresponding input has n data variables, j neurons in the hidden layer, and m in the output layer so that its corresponding output has m data variables [30]. W is the connection weight matrix of input and hidden layers. It is represented using the following matrix:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{l1} & w_{l2} & \cdots & w_{ln} \end{bmatrix}_{l \times n} \quad (4)$$

where w_{ji} is the connection weight between the i^{th} input and the j^{th} hidden neurons.

β is the connection weight between the hidden and output layers as shown in Eq. 5:

$$\beta = \begin{bmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1m} \\ \beta_{21} & \beta_{22} & \cdots & \beta_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{l1} & \beta_{l2} & \cdots & \beta_{lm} \end{bmatrix}_{l \times m} \quad (5)$$

where β_{kj} is the weight from the hidden neuron j to the output neuron k . Both W and the status of neuron threshold in the hidden layer are generated using the above mentioned hyperchaotic system.

Hyperchaotic sequences generated using the above hyperchaotic functions are used to replace the hidden layer threshold matrix randomly generated using the ELM. The running steps of hyperchaotic ELM are as follows:

- (1) Importing data and starting training.
- (2) Generating the connection weight matrix between the input and hidden layers randomly.
- (3) Generating threshold matrix of hidden layer using the hyperchaotic function.
- (4) Calculating the connection weight matrix between the hidden and output layers using the least square method.
- (5) Importing the test data into the hyperchaotic ELM and outputting the prediction results after the training.

2.6 HCCS-ELM

Figure 4 shows the structure diagram of HCCS-ELM. First, the training data are input. Then, the chaos equation runs to generate the hyperchaotic sequence. Sequence 1 is selected to replace the Lévy flight in the cuckoo algorithm. It realizes the jump by randomly selecting the value in sequence without repetition. Sequence 2 is selected to replace the randomly generated connection weight matrix of the input and hidden layers. Sequence 3 is used to generate the hidden layer threshold matrix in the ELM. The improved cuckoo algorithm is used to traverse the sample data to generate the number of hidden layer neurons in the ELM. After the training process of ELM, the test data is imported, and the prediction results are obtained.

To reduce the system computational cost, the hyperchaotic system is used to generate a sequence instead of the Lévy flight. The hyperchaotic system

Fig. 4: System chart of HCCS-ELM

is only required to generate a sequence once, and then each iteration randomly selects a value from the sequence, which greatly reduces the resource occupation. Besides, CS is exploited to traverse the samples to generate the number of hidden layer neurons, which could effectively improve the algorithm's adaptability and avoid repeated parameter adjustments. Considering the convergence phenomenon of chaos, the hyperchaotic sequence is used to replace the hidden layer threshold matrix in ELM, and regression could be understood as a convergence phenomenon. Thus, the convergent sequence is used to replace the random one, which improves the ELM's accuracy and generates highly accurate results in $PM_{2.5}$ concentration prediction, saving the use of system resources.

Table 1: The amount of data on daily pollutant concentrations of four stations in each season

Amount Station	Season	Spring	Summer	Autumn	Winter
	Station 1	183	186	168	178
	Station 2	183	186	183	178
	Station 3	183	186	183	178
	Station 4	183	186	183	178

3 Experiments and Results

3.1 Long-term Prediction

This study uses HCCS-ELM, back-propagation (BP), multiple linear regression (MLR), ELM, Long Short-Term Memory(LSTM) and Prophet to predict the PM_{2.5} concentration of four observing stations. Besides, it compares and analyzes the results similar to that of [31]. Seventy percent of the historical observation data are used to train the model, and the remaining 30% data are used to test the model. Since the PM_{2.5} concentration varies across seasons, so that it is predicted for different seasons. For the instrument failure and other irresistible making historical observations incompletable, the invalid data are deleted if one or more kinds of variables are missing. However, special days, such as rainy days, holidays, or night time are not a criterion for filtering data. Thus, only two months in each season are selected for prediction. Table 1 presents the amount of filtered data. There are 500 samples in the training set of PM_{2.5} prediction at station one, and 215 samples in the test set. There are 511 samples in the training set of PM_{2.5} predictions of station 2, 3 and 4, and 219 samples in the test set. Eight impact factors are located in the input layer. The predicted PM_{2.5} concentration is output in the output layer. Both HCCS-ELM and ELM have the same parameters, which are sigmoid function, "regression" model, and 10 hidden layer neurons. However, the BP network has 10 hidden layer neurons, 100 epochs, 0.1 learning rate, and 0.4 goals. All parameters of the six models remain unchanged during the experiment. The root mean squared error (*RMSE*) and the coefficient of determination R^2 are selected as the evaluation criteria. The formulas of *RMSE* and R^2 are given as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{model,i})^2}{n}} \quad (6)$$

$$R^2 = 1 - \frac{RMSE}{Var} \quad (7)$$

where n is the number of samples, $X_{obs,i}$ is the observed value of PM_{2.5} concentration, $X_{model,i}$ is the predicted value of PM_{2.5} concentration, and $Var(\cdot)$ is the variance. The smaller the *RMSE* and the closer R^2 is to 1, it indicates that the prediction effect is better.

MLR, LSTM and Prophet are run with Python. Figure 5 shows the HCCS-ELM prediction results. Tables 2 and 3 present the $RMSE$ and R^2 of HCCS-ELM, ELM, BP, MLR, LSTM and Prophet. The analysis of the above chart show that the $RMSE$ of HCCS-ELM are smaller than the other five models, and the R^2 are larger than the other models, which could predict the concentration and the trend of $PM_{2.5}$ more accurately. Table 2 shows the results obtained by the daily concentration from 2016 to 2017 as the training set and the 2018 daily concentration as the test set; Table 3 uses the first two months of each quarter in 2018 as the training set, and the last month as the test set.

Fig. 5: Long-term prediction results of HCCS-ELM (Year)

Table 2: $RMSE$ and R^2 values by station and method (Year)

	$RMSE$						R^2					
	HCCS-ELM	ELM	BP	MLR	LSTM	Prophet	HCCS-ELM	ELM	BP	MLR	LSTM	Prophet
Station 1	4.6255	9.3645	15.7328	17.7866	16.5247	16.5238	0.9627	0.8842	0.6079	0.4131	0.4858	0.4929
Station 2	5.7935	11.8354	17.8923	21.3147	18.5391	21.1809	0.9686	0.8497	0.6627	0.4296	0.5626	0.4366
Station 3	4.6431	8.9009	24.6076	15.7897	13.6778	15.5725	0.9470	0.8244	0.6607	0.3524	0.5006	0.3601
Station 4	4.7172	8.4336	20.3576	19.1319	16.2429	17.6423	0.9625	0.8931	0.6853	0.3979	0.5423	0.4588

Table 3: *RMSE* and R^2 values by station and method (Season)

		<i>RMSE</i>						R^2					
		HCCS-ELM	ELM	BP	MLR	LSTM	Prophet	HCCS-ELM	ELM	BP	MLR	LSTM	Prophet
Spring	Station 1	5.0233	9.1717	19.1538	20.9775	16.7506	18.1760	0.9371	0.8384	0.6513	0.1443	0.2827	0.1386
	Station 2	7.1416	9.7955	13.7006	26.1891	17.3320	19.0321	0.8987	0.8513	0.7429	0.0236	0.2708	0.1075
	Station 3	4.8586	15.2012	10.1559	18.5039	14.5123	15.4039	0.9236	0.6557	0.8090	0.0760	0.2200	0.1156
	Station 4	5.2844	14.7320	8.8194	22.7076	16.6815	17.3568	0.9278	0.7330	0.8115	0.0135	0.2602	0.1880
Summer	Station 1	3.4992	5.9359	5.1225	10.7228	10.6803	9.9579	0.9111	0.7087	0.8219	0.0551	0.0420	0.1275
	Station 2	3.6244	7.8195	7.2272	14.7589	11.8178	9.9890	0.9165	0.7533	0.7443	0.0161	0.0637	0.1125
	Station 3	2.2680	5.7048	4.3199	10.1234	8.9888	8.1486	0.9360	0.7222	0.7889	0.0081	0.0007	0.1425
	Station 4	2.2604	4.5818	4.4368	11.1462	9.5097	8.7015	0.9481	0.7903	0.8476	0.032	0.0127	0.1496
Autumn	Station 1	6.5007	11.3300	13.9920	13.7498	17.1170	17.4268	0.9106	0.7194	0.6930	0.5252	0.1574	0.1389
	Station 2	8.1300	13.2583	19.2205	29.0382	23.7319	24.6825	0.9543	0.8987	0.8456	0.4161	0.5688	0.5220
	Station 3	7.9112	13.8340	14.1030	21.6965	14.2278	15.3461	0.9164	0.7875	0.8581	0.3124	0.6511	0.5855
	Station 4	6.1445	14.5434	15.9177	21.5627	17.2101	18.1260	0.9555	0.7317	0.7966	0.4725	0.6487	0.6050
Winter	Station 1	7.2779	12.7341	10.5278	17.0671	20.9554	20.6743	0.9457	0.7307	0.8011	0.5285	0.1664	0.1717
	Station 2	8.4257	20.8565	23.9630	19.5162	24.5324	22.5306	0.9271	0.7488	0.8243	0.5172	0.0012	0.1391
	Station 3	3.8454	12.7414	16.3453	17.1244	18.5874	17.4310	0.9590	0.7347	0.7582	0.2818	0.0216	0.1277
	Station 4	5.9452	13.5708	13.3386	22.1096	22.2022	20.4694	0.9344	0.7172	0.8402	0.3632	0.0277	0.1453

3.2 Short-term Prediction

The short-term extremely high $\text{PM}_{2.5}$ concentration is usually the object of the attention of the meteorological department. High $\text{PM}_{2.5}$ concentration is harmful to human health. In this paper, data with $\text{PM}_{2.5}$ concentrations exceeding China's national standard are selected, and the data division is consistent with the above. Figure 6 shows that HCSS-ELM is still efficient for prediction of short-term extremely high $\text{PM}_{2.5}$ concentration. Due to the missing data, hourly concentration data is incomplete. In Figure 6, the test set is the hourly concentration of the date in the figure, and the training set is the effective value of the hourly concentration fourteen days before the test date.

Fig. 6: Short-term prediction results of $\text{PM}_{2.5}$ based on HCSS-ELM

3.3 Performance Evaluation

The running time and memory usage are used to evaluate the performance of HCSS-ELM and ELM. Tables 4 and 5 present the time and memory results.

Table 4 shows the performance of the two algorithms in processing the daily concentration data of each station from 2016 to 2018, and Table 5 shows the performance of the two algorithms in processing the daily concentration data of four stations in each quarter. It shows that HCCS-ELM needs more running time than ELM, while they have similar occupied memory. That's because HCCS-ELM need to generate hyperchaotic sequences during operation. The differences in running time and memory usage of the same model can be attributed to the software.

Table 4: Performance comparison between HCCS-ELM and ELM (Year)

	Running time (s)		Memory (MB)	
	HCCS-ELM	ELM	HCCS-ELM	ELM
Station 1	2.2436	0.2049	2026	2004
Station 2	2.2767	0.1598	2026	2004
Station 3	2.2693	0.1683	2028	2003
Station 4	2.2826	0.1716	2028	2013

Table 5: Performance comparison between HCCS-ELM and ELM (Season)

		Running time (s)		Memory (MB)	
		HCCS-ELM	ELM	HCCS-ELM	ELM
Spring	Station 1	2.1104	0.0222	2067	2113
	Station 2	2.1132	0.0164	2074	2104
	Station 3	2.3861	0.0165	2073	2083
	Station 4	2.1071	0.0167	2072	2082
Summer	Station 1	2.1414	0.0188	2063	2067
	Station 2	2.2904	0.0184	2062	2067
	Station 3	2.1173	0.0204	2063	2066
	Station 4	2.1473	0.0161	2061	2065
Autumn	Station 1	2.1230	0.0163	2081	2160
	Station 2	2.1389	0.0162	2079	2161
	Station 3	2.1251	0.0183	2078	2147
	Station 4	2.1200	0.0228	2078	2147
Winter	Station 1	2.1002	0.0227	2062	2072
	Station 2	2.1172	0.0160	2060	2062
	Station 3	2.4589	0.0171	2069	2069
	Station 4	2.1337	0.0158	2076	2060

4 Discussion

In March 2021, most parts of China suffered a severe sandstorm. From the perspective of environmental protection, people should improve the environmental protection system, adopt an environmentally friendly way of life, and insist on the harmonious coexistence between man and nature. For the improvement of the global ecological environment, it is necessary to set up and

practice the concept that clear waters and green mountains are as valuable as mountains of gold and silver.

Machine learning has fast and accurate performance in prediction and is commonly used to predict the trend of pollutant concentration transformation. Accurate prediction of pollutant concentrations can help local governments take more effective preventive measures. Therefore, based on existing methods, this paper proposes the HCCS-ELM algorithm, which has the following advantages in analyzing PM_{2.5} concentrations in Lanzhou. First, HCCS-ELM simplifies the analysis process, while traditional numerical weather forecast methods are very complex and require a lot of calculations. And then, air quality forecasting cost is reduced. The proposed HCCS-ELM is similar to other neural networks in that it is independent of the complex relationship between the parameters and outputs. However, it depends on constant change of weights so that the parameters and outputs are closely related and tedious mathematical modeling is avoided. Second, HCCS-ELM has good generalization. Since there is no mathematical modeling process, combined with similar and available data, HCCS-ELM can theoretically be applied to all cities in China that set up air quality monitoring stations without being affected by differences in geographical environment and the level of economic development. Third, considering the HCCS-ELM data processing characteristics, the concentration of other pollutants can be predicted only by simple transformation of the columns in the data matrix to avoid a complicated adjustment process in the meteorological equation. Finally, the prediction accuracy of the multivariate linear regression model is positively correlated with the number of input parameters. Compare with that, HCCS-ELM is independent of the number of input parameters. So that HCCS-ELM can reduce the number of input parameters while maintaining a high prediction accuracy.

5 Conclusion

In areas such as Lanzhou where PM_{2.5} is high, the monitoring and control of PM_{2.5} concentrations are very important. This paper investigates HCCS-ELM model to predict the PM_{2.5} hourly and daily concentration in Lanzhou. Firstly, the hyperchaotic system generates chaotic sequences, and the values of chaotic sequences are randomly chosen instead of Lévy flights for iteration to improve the CS algorithm. Subsequently, the improved CS algorithm is used to generate the number of hidden neurons of the ELM. Moreover, considering the convergence phenomenon of chaos, hyperchaotic sequences are used to generate the input-to-hidden weight matrix and the hidden layer threshold matrix of the ELM. Finally, according to the input PM_{2.5} daily concentration or hourly concentration train data, the predicted result of the daily concentration or hourly concentration is obtained. Research on the experimental data obtained from four monitoring stations in Lanzhou shows that the proposed HCCS-ELM model can effectively predict the PM_{2.5} hourly and daily concentration, which is significantly better than the traditional neural network and regression

statistical model. It is greatly significant to pollution control, and the addition of hyperchaotic system provides a new idea for improving neural networks.

Experiment Platform

CPU Intel i7-8700, GPU Nvidia RTX2060, RAM 16GB

Data Source

Meteorological data: <http://data.cma.cn/>

Pollutant data: <http://www.mee.gov.cn/>

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