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Prediction intervals for carbon dioxide emissions in China by extreme learning machine ensemble based on particle swarm optimization

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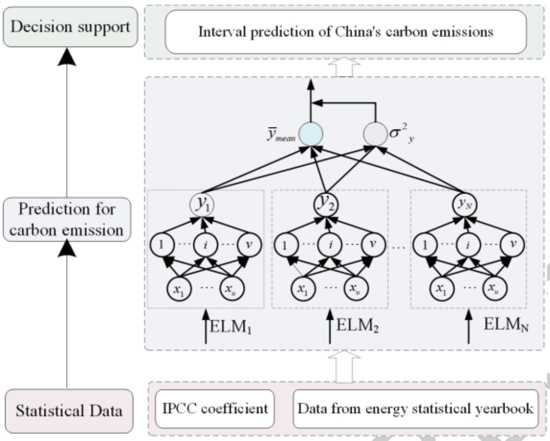
Graphical abstract



Abstract

The emission of carbon dioxide is the major cause of the greenhouse effect, which has a negative impact on human survival and sustainable economic development; therefore, it is very significant for discovering the underlying influential factors of carbon dioxide emissions. In this paper, an extreme learning machine ensemble based on particle swarm optimization approach (PSO-ELM Ensemble) are applied to predict the emission of carbon dioxide, which provide estimated values as well as the corresponding reliability. In addition, the particle swarm optimization approach is used to optimize the connection weights of extreme learning machine. The performance of the proposed PSO-ELM Ensemble is experimentally validated by carbon dioxide emissions data during the period 1978-2016 by using state-of-the-art comparative method, where the proposed approach outperforms the others in achieving the best trade-off between accuracy and simplicity.

Keywords: Extreme learning machine; carbon dioxide emissions; particle swarm optimization; influential factors

1. Introduction

With the development of economy and the progress of the society, human beings are now facing more and more global and severe environmental problems. Carbon dioxide emitted from fossil energy combustion is the main cause of greenhouse effect, which seriously threatens the safety of human life (Aldy 2006). Facing the demands of the development of low-carbon economy and the realistic pressure of the consumption of domestic energy resources, the control of greenhouse gas emission has become a prominent problem in the sustainable development of China (Assareh *et al*. 2012; Baareh 2013).

In recent years, the study of carbon emission has attracted more and more attention from researchers. The existing literatures about carbon emissions can be mainly divided into two parts, discussion on influential factors (Baareh 2018) and study on prediction models (Behrang *et al*. 2011; Chitnis and Hunt 2012). As for the influential factors, studies related to this part include the methods such as index decomposition (Coondoo and Dinda,2008) and input-output structural analysis (SILVA S.E 2013; Feng and Zhang 2012; He *et al*. 2004; Huang *et al*. 2005; Hunt and Ninomiya 2005; Khashman *et al*. 2016). With respect to forecasting techniques, there are many methods to analyze the influencing factors of carbon emissions and forecast carbon emissions. The summary of recent works in this field of the prediction of CO_2 emissions is collected in Table 1.

Utilizing time series analysis, grey models, and artificial neural networks (ANN) for carbon emissions forecasting each have their unique advantages and limitations.

Time series analysis excels in identifying and leveraging historical trends and patterns in data, making it effective for short-term forecasting. It's particularly adept at incorporating seasonal and cyclical variations. However, its reliability hinges on the quality of historical data and it may struggle with abrupt changes or external shocks, often assuming past trends will continue.

Grey models are valuable when dealing with limited or incomplete data. They can generate useful predictions even with small datasets and are good at capturing the inherent uncertainty in environmental data. The downside is their lower accuracy compared to other models, especially when data availability improves, and their basic assumption that systems are relatively stable over time.

Artificial Neural Networks, on the other hand, offer powerful capabilities in handling non-linear relationships and complex patterns in large datasets. They are adaptable to new information, making them suitable for dynamic scenarios. However, ANNs require substantial data for training and are often seen as "black boxes" due to their lack of interpretability. They also demand significant computational resources and expertise in model tuning and validation.

Applying Fuzzy rules, Principal Component Analysis-Support Vector Machine (PCA-SVM), and Genetic Programming for carbon emissions forecasting each have distinct advantages and limitations.

Fuzzy rules are beneficial for dealing with the imprecision and uncertainty inherent in environmental data. They can model complex, non-linear relationships in a way that is intuitive and easy to understand. However, their effectiveness largely depends on the quality of the rule sets developed, and they may not perform well with very large or complex datasets. PCA-SVM combines the dimensionality reduction capability of PCA with the advanced classification and regression abilities of SVM. This method is effective in extracting key features from large datasets, improving the efficiency and accuracy of SVM in forecasting. The limitation lies in the choice of kernel and parameters in SVM, which requires expertise and can significantly impact model performance. Genetic Programming offers a flexible and powerful approach, evolving programs to solve problems, including forecasting. It is especially good at discovering underlying relationships and generating novel models. The drawbacks include its computational intensity, potential for overfitting, and the challenge of interpreting the evolved programs, which can become quite complex.

Each of these methods brings a unique set of tools to carbon emissions forecasting, with their effectiveness varying based on the specific data and context of the problem.

Table 1. Carbon dioxide emissions forecasting. Summary of recent papers

Method	References
Time Series (viz. ARIMA, VAR, etc)	Liang *et al*. 2006; Lin and Moubarak 2013; Lin *et al*. 2011; Liu *et al*. 2014; Lotfalipour *et al*. 2013; Lotfalipour *et al*. 2013.
Grey Models	Nabavi-Pelesaraei *et al*. 2016; Pao and Tsai 2011; Pao and Tsai 2011; Pauzi and Abdullah 2014.
Artificial Neural Network	Pérez-Suárez and López-Menéndez 2015; Sheikhalishahi et a. 2013; Soytas and Sari 2009; Sun and Sun 2017; Sun and Xu 2016; Wang *et al*. 2015; Wang *et al*. 2013.
Fuzzy rules	Wu *et al*. 2015.
Principal Component Analysis-Support Vector Machine (PCA-SVM)	Yousefi *et al*. 2013.
Genetic programming	Zhang *et al*. 2014.

As it can be seen, a wide variety of techniques have been applied to the prediction of carbon dioxide emissions, such as time Series methods, grey models, artificial neural network, and the others. Despite their strengths in handling nonlinear relationships and adapting to new data, these methods fall short in providing an assessment of how reliable or trustworthy their predictions are. This includes not just the precision of their forecasts but also the consistency, robustness to external changes, and the clarity in understanding the uncertainty or confidence levels associated with their predictions.

Aiming the evident on demands on analyzing the underlying influence factor of carbon emissions and being motivated to capture both the future tendency and the corresponding reliability, an extreme learning machine ensemble based on particle swarm optimization approach is proposed in this study. The particle swarm optimization approach is used to optimize the connection weights of extreme learning machine. Moreover, an ensemble structure based PSO-ELM is adopted to implementation of interval prediction. In addition, the main influence factor of carbon emissions is obtained by the bivariate correlation and the significance test in the SPSS. In order to verify the overall performance and effectiveness of the proposed method, an empirical analysis of carbon dioxide emissions and influential factors was carried out in China during the period 1978-2016. The result show that the proposed approach outperforms the others in achieving the best trade-off between accuracy and simplicity.

The rest of this paper is organized as follows. Section 2 outlines the development of extreme learning machine ensemble based on particle swarm optimization, and an empirical analysis of carbon dioxide emissions and influential factors during the period 1978-2016 is presented in Section 3. Our results and discussions appear in Section 4.

2. Extreme learning machine ensemble based on particle swarm optimization

Extreme learning machine is a single layer feed-forward neural networks, which is the random initialization of the input weights and hidden biases without iterative adjustments during the learning process (Huang G B, Zhu Q Y, Siew C K. 2004; Liang N Y, Huang G B, Saratchandran P, *et al*. 2006). The salient property of ELM lies in the learning speed and avoiding numerous problems in terms of local minima and learning rate faced by others.

Given a training sample is $(X_i, y_i) \in R^u \times R^S$ .Here, X = (x_1, x_2…x_u) is a u × 1input vector and $Y=\left[y_1^T \ \cdots \ y_S^T\right]^T$ is a s×1 target vector. Assuming that ELM with νhidden nodes can approximate the S samples with zero error, therefore, the output of ELM can be define by

$$f_{\nu}(x_j)=\sum_{i=1}^{\nu}\beta_i G(a_i,b_i,x_j)=y_j, j=1,\cdots,S \quad (1)$$

$$G(a_i,b_i,x_j)=g(b_i\|x-a_i\|) \quad (2)$$

Where a_i and b_i are the learning parameters of hidden nodes and β_i the weight connecting the *i*-th hidden node to the output node. G (a_i, b_i, X_j) is the output of the *i*-th hidden node with respect to the input x.

$$H(a_1,\cdots a_v;b_1,\cdots b_v;X_1,\cdots X_S)\beta = \quad (3)$$
$$\begin{bmatrix} G(a_1,b_1,X_1) & \cdots & G(a_v,b_v,X_1) \\ \vdots & \cdots & \vdots \\ G(a_1,b_1,X_S) & \cdots & G(a_v,b_v,X_S) \end{bmatrix}\begin{bmatrix}\beta_1^T \\ \vdots \\ \beta_v^T\end{bmatrix}=\begin{bmatrix}y_1^T \\ \vdots \\ y_S^T\end{bmatrix}$$

where *H* is called the hidden layer output matrix of the network, the *i*-th column of H is the i-th hidden node's output vector with respect to inputs respect to inputs X_1, X_2 X_S and the *j*- th row of H is the output vector of the hidden layer with respect to input x_j.

When the number of hidden neurons is equal to the number of training samples, viz. S = ν, the matrix His square and invertible; therefore, ELM can approximate these training samples with zero error. However, the number of hidden neurons usually is much less than the number of distinct training samples, S«ν,H is a nonsquage matrix and there may not exist $\beta = (H^TH)^{-1}H^TT$. Thus, the way to find the specific $\hat{b}_i,\hat{\beta}_i,\hat{a}_i$ can be define by

$$\left\|H(\hat{a}_1,\cdots\hat{a}_v,\hat{b}_1,\cdots\hat{b}_v)\hat{\beta}-Y\right\| \quad (4)$$

The minimizing the cost function can be define by

$$E=\sum_{j=1}^{S}\left(\sum_{i=1}^{v}\beta_i G(\beta_i x_j+b_i)-y_i\right) \quad (5)$$

The particle swarm algorithm (PSO) is a classical artificial intelligence algorithm inspired by the foraging behavior of bird flocks (He S, Prempain E, Wu Q H ,2004) Due to the simple concept, easy implementation, and quick convergence, PSO has gained wide research in many fields (Sheikhalishahi, Ebrahimipour, *et al*.,2013). Therefore, PSO method in this study is used to search the minimum of $\|H\hat{\beta}-Y\|$,and the swarm is $\hat{\beta}=\{\beta_1^{(t)},\beta_2^{(t)},\cdots\beta_v^{(t)}\}$,the position of the i-th particle is represented by $\beta_i^{(t)}=\left(\beta_{i1}^{(t)},\beta_{i2}^{(t)},\cdots\beta_{is}^{(t)}\right)^T$, and the velocity by $\varpi_i^{(t)}=\left(\varpi_{i1}^{(t)},\varpi_{i2}^{(t)},\cdots\varpi_{is}^{(t)}\right)^T$. The optimal position of the *i*-th particle is $p_i^{(t)}=\left(p_{i1}^{(t)},p_{i2}^{(t)},\cdots p_{is}^{(t)}\right)^T$, which also can be called an individual extremum. Likewise, the best position of the whole particle swarm in the current search process is $g_i^{(t)}=\left(g_{i1}^{(t)},g_{i2}^{(t)},\cdots g_{is}^{(t)}\right)^T$,which is named as the global extremum. The structure of extreme learning machine ensemble was illustrated in Figure. 1.

The search process can be define by

$$V_{is}^{t+1}=\varpi V_{is}^{t}+c_1r_1\left(p_{is}^{(t)}-\beta_{is}^{(t)}\right)+c_2r_2\left(p_{is}^{(t)}-\beta_{is}^{(t)}\right) \quad (6)$$

$$\beta_{is}^{(t)}=\beta_{is}^{(t)}+V_{is}^{t} \quad (7)$$

Where ϖ is inertial weight coefficient, $t_{\max}$ is the maximum number of iterations, c_1 and c_2 is the learning factors, which are equal to 1.9 and 2.1, respectively. $r_1$and r_2 are independent random numbers in [0,1].

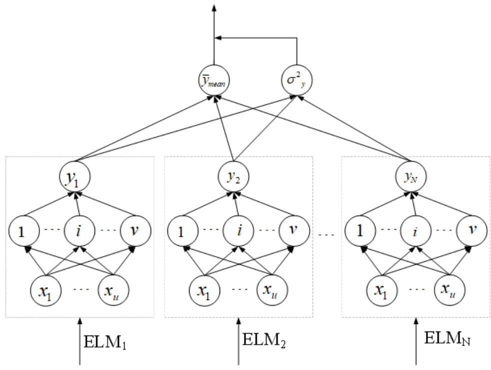


Figure 1. The structure of extreme learning machine ensemble

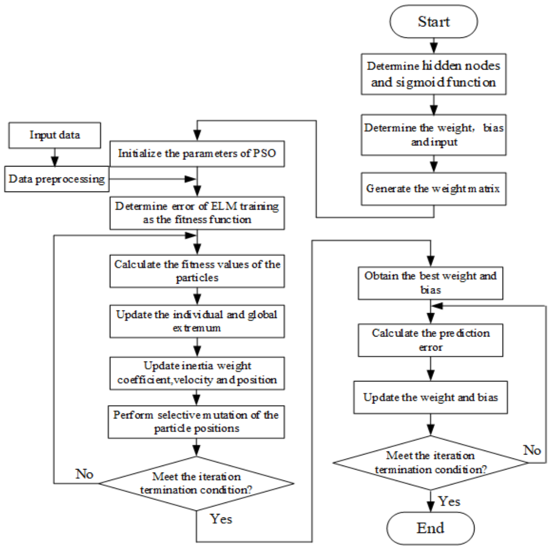


Figure.2. The flowchart of PSO-ELM

Based on the proposed structure of the ensemble, the ELM-ensemble can be formulated as

$$\bar{y}_{mean}=y+\varepsilon\approx\frac{1}{N}\sum_{i=1}^{N}y_i+\varepsilon \quad (8)$$

$$\sigma^2_{y_i}\approx E\left\{(y_i-\bar{y})^2\right\}\approx\frac{1}{N-1}\sum_{i=1}^{N}(y_i-\bar{y})^2 \quad (9)$$

Where ε is Gaussian white noise with mean zero. $\bar{y}_{mean}$ is the mean value of the output σ^2_{yi} denotes the error calculated by the squared residuals between y_i and $\bar{y}$. The flowchart of PSO-ELM was illustrated in Figure 2.

3. An empirical analysis of carbon dioxide emissions and influential factors in China

3.1. Data source and conversion

This study selects energy consumption as well as other relevant data in China during the period 1978-2016 for analysis. As the statistical data of carbon dioxide emissions cannot be directly obtained, the formula for the conversion of the relevant data can be define by

$$E=\sum_{a=1}^{o}\vartheta_a\xi_a \tag{10}$$

Where o is the number of energy category, ϑ_a is the type of energy in terms of raw coal, crude oil, natural gas, primary electricity. ξ_a is the coefficients of carbon dioxide emissions for different energy sources. In addition, primary energy consumption and the source of energy in China during the period 1978–2016 is listed in Table 2, and the coefficients of carbon dioxide emissions for different energy sources is listed in Table 3.

Table 2. Primary energy consumption and the source of energy in China over the years 1978–2016

Year	Primary energy consumption (10,000 tons of SCE)	As percentage of total energy production (%)			
		Raw coal	Crude oil	Natural gas	Primary electricity
1978	57144	40400.808	12971.688	1828.608	1942.896
1979	58588	41773.244	12772.184	1933.404	2109.168
1980	60275	43518.55	12476.925	1868.525	2411
1981	59447	43217.969	11889.4	1664.516	2675.115
1982	62067	45743.379	11730.663	1551.675	3041.283
1983	66040	49001.68	11953.24	1584.96	3500.12
1984	70904	53390.712	12337.296	1701.696	3474.296
1985	76682	58124.956	13112.622	1687.004	3757.418
1986	80850	61284.3	13906.2	1859.55	3799.95
1987	86632	66013.584	14727.44	1819.272	4071.704
1988	92997	70863.714	15809.49	1952.937	4370.859
1989	96934	73669.84	16575.714	1938.68	4749.766
1990	98703	75211.686	16384.698	2072.763	5033.853
1991	103783	78978.863	17746.893	2075.66	4981.584
1992	109170	82641.69	19104.75	2074.23	5349.33
1993	115993	86646.771	21110.726	2203.867	6031.636
1994	122737	92052.75	21356.238	2332.003	6996.009
1995	131176	97857.296	22955.8	2361.168	8001.736
1996	138948	103794.156	25010.64	2501.064	7642.14
1997	137798	98525.57	28110.792	2342.566	8543.476
1998	132214	92020.944	28426.01	2908.708	8858.338
1999	130119	88480.92	30187.608	2862.618	8587.854
2000	128000	85760	30208	3200	8832
2001	155547	105771.96	32975.964	3733.128	13065.948
2002	169577	116160.245	35611.17	3900.271	13905.314
2003	197083	138352.266	39613.683	4532.909	14584.142
2004	230281	161657.262	45825.919	5296.463	17501.356
2005	261369	189231.156	46523.682	6272.856	19341.306
2006	286467	207402.108	50131.725	7734.609	21198.558
2007	311442	225795.45	52945.14	9343.26	23358.15
2008	320611	229236.865	53542.037	10900.774	26931.324
2009	336126	240666.216	55124.664	11764.41	28570.71
2010	360648	249568.416	62752.752	14425.92	33900.912
2011	387043	271704.186	65023.224	17803.978	32511.612
2012	402138	275464.53	68363.46	19302.624	39007.386
2013	416913	280999.362	71292.123	22096.389	42525.126
2014	425806	279328.736	74090.244	24270.942	48116.078
2015	429905	273849.485	78672.615	25364.395	52018.505
2016	436000	270320	7978.8	2790.4	5798.8

Table 3. Coefficients of carbon dioxide emissions for different energy sources

Type	Coal	Petroleum	Natural gas	Hydropower, Nuclear power
C/(t/t)	0.7476	0.5825	0.4435	0

The dataset on China's primary energy consumption from 1978 to 2016 reflects significant aspects of the nation's economic and environmental evolution. A key observation is the substantial increase in energy consumption over these years, correlating with China's rapid industrial growth and urbanization. This trend is emblematic of the broader developmental trajectory experienced by China, characterized by increasing industrial activity, urban development, and a growing demand for energy resources to fuel these expansions. The ELM was used for model training, and the activation function in terms of Sigmoid and relu was selected in different ensemble learning structure; the number of neuron nodes in the input layer is set as 5, respectively. Furthermore, the proposed method was built upon the ensemble structure learning, we increase the diversity of predicted output results by selecting different hidden parameters with the randomized strategy at the interval between 50 and 500.

Within this overarching growth, the changing composition of energy sources is particularly noteworthy. Initially dominated by raw coal, which aligns with China's abundant coal reserves and its historical reliance on coal for energy, there appears to be a gradual shift towards a more diverse energy mix. This transition likely includes increased utilization of crude oil, natural gas, and primary electricity, reflecting global trends towards diversifying energy sources and the increasing importance of environmental considerations. The shift towards cleaner energy sources like natural gas and electricity could be driven by environmental concerns, highlighting China's response to global climate change imperatives and its own domestic environmental challenges.

Moreover, the fluctuations in the energy mix and consumption patterns might be influenced by significant policy shifts and global events. These include China's economic reforms, international agreements on climate change, and its integration into global trade systems. Such events often act as catalysts for changes in national energy strategies and consumption behaviors.

In conclusion, this dataset offers a comprehensive overview of China's evolving energy landscape, mirroring its economic growth, policy shifts, and increasing environmental consciousness. The transition from a coal-dominated energy mix to a more diversified one marks a critical stage in China's development, with implications for both global energy markets and environmental policies.

The data reveals that coal, with a coefficient of 0.7476, is the most carbon-intensive energy source among those listed. This aligns with global understanding that coal combustion is a major contributor to CO_2 emissions, due to its high carbon content and prevalent use in energy production, especially in countries like China with substantial coal reserves.

Petroleum, with a coefficient of 0.5825, also presents significant carbon emissions, although less than coal. Its widespread use in transportation and industry makes it a major contributor to global CO_2 emissions. The relatively lower coefficient compared to coal reflects its different chemical composition and burning efficiency.

Natural gas, with a coefficient of 0.4435, emerges as a cleaner alternative to coal and petroleum. Its lower carbon content and higher efficiency in energy production result in fewer emissions per ton consumed. This makes it an attractive option for countries seeking to transition to cleaner energy sources while balancing their energy needs and environmental goals.

Interestingly, the coefficient for hydropower and nuclear power is listed as 0, emphasizing their role as clean energy sources. These methods of energy production do not directly emit CO_2, highlighting their potential in reducing overall carbon emissions in the energy sector. However, it's important to note that while these sources have minimal direct CO_2 emissions, other environmental and safety considerations are associated with their use, such as the impact of dam construction on ecosystems and the management of nuclear waste.

In summary, this dataset provides a clear and quantitative illustration of the varying environmental impacts of different energy sources. It underscores the challenges and opportunities in managing energy consumption and CO_2 emissions, particularly for a rapidly developing and industrializing country like China. The data is a valuable tool for policymakers and researchers in assessing the environmental impact of energy choices and strategizing for a more sustainable energy future. Annual carbon dioxide emissions of China during 1978-2016 was displayed in Table 4.

Table 4. Annual carbon dioxide emissions of China during 1978-2016 (10,000 tons)

Year	CO_2 emissions	Year	CO_2 emissions	Year	CO_2 emissions
1978	38570.63997	1991	70302.71836	2004	149897.5482
1979	39526.93907	1992	73831.36532	2005	171351.2686
1980	40630.96763	1993	78051.53891	2006	187685.8448
1981	39973.54197	1994	82292.88787	2007	203788.9583
1982	41719.02920	1995	87577.04600	2008	207400.2101
1983	44299.34803	1996	93274.43071	2009	217249.6957
1984	47856.07339	1997	91071.18049	2010	229528.7214
1985	51840.50569	1998	86643.02056	2011	248898.1417
1986	54741.21461	1999	85002.18854	2012	254319.7118
1987	58737.33633	2000	83129.53600	2013	261402.5332
1988	63052.86807	2001	99939.25859	2014	262747.8929
1989	65590.73037	2002	109314.6759	2015	261805.7824
1990	66691.61343	2003	128517.4696	2016	260943.1660

The data shows a more pronounced increase in emissions in the late 20th and early 21st centuries, corresponding with China's accelerated economic growth post-economic reforms and its integration into the global market. This period is marked by large-scale industrialization and urbanization, leading to heightened energy consumption and, consequently, higher CO_2 emissions.

In an academic context, this dataset is invaluable for studying the relationship between economic development and environmental impact. It provides a case study of how rapidly developing economies face the challenge of balancing growth with sustainability. The data can also be used to model future emission scenarios, informing policy decisions and international negotiations on climate change.

In summary, the dataset on China's annual CO_2 emissions from 1978 to 2016 offers a detailed account of the country's growing environmental footprint, reflecting its economic transformation and the resulting challenges and opportunities in achieving sustainable development.

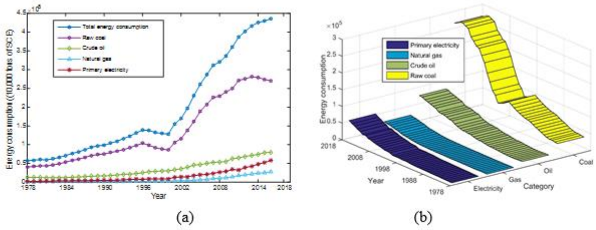


Figure 3. (a) Primary energy consumption and the source of energy in China over the years 1978–2016. (b) The 3D illustration of main sources consumption of energy in China over the years 1978–2016

Figure 3 show that the total energy consumption is increasing year by year. however, since 2010, a series of policy and regulations is adopted to reduce carbon emissions involving reducing the use of fossil energy (viz. coal, crude oil, natural gas and so forth) and increasing the use of clean energy power (primary electricity) thereby the growth rate of total energy consumption is slowing down. From Figure 4, the total amount of carbon dioxide emissions obtained by the conversion formula can be seen that China's energy saving and emission reduction measures have achieved initial results, and the growth rate of carbon dioxide emissions has slowed down significantly.

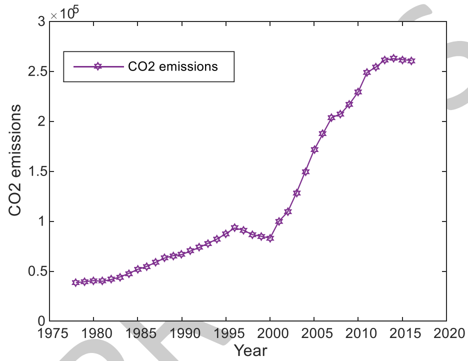


Figure 4. The total of CO2 emissions in China over the years 1978–2016

Table 5. Bivariate correlation

Factor	Pearson coefficient	Significant (bilateral)
Total energy production	0.999**	0.000
Total population	0.874**	0.000
Coal consumption	0.999**	0.000
Oil consumption	0.990**	0.000
Gross national income	0.873**	0.000
GDP	0.962**	0.000
The tertiary industry	0.724**	0.000

Note: ∗∗indicates a significant correlation at the bilateral significance level of 0.01.

Table 6. A statistical analysis of prediction intervals results

Method	$CWC_{median}(10^5)$	$CWC_{sd}(10^5)$	MAPE(%)	Time(s)
MVE MLP	0.0303	0.0056	6.78	2.14
Delta MLP	0.0334	0.0037	5.498	2.34
PSO-ELMEnsemble	0.028	0.0035	2.17	1.52

3.2. SPSS analysis for influence factor of the carbon dioxide emissions

The influence factor for prediction of the emission of carbon dioxide emissions was selected from the statistical yearbook of China. The influence factor mainly contain total energy production, total population, coal consumption, oil consumption, gross national income, GDP and the tertiary industry. Pearson correlation coefficient and the bilateral significance of the above-mentioned factors can be obtained by SPSS analysis. From Table 5, the Pearson correlation of the selected influence factors are above 0.7, therefore, we can conclude that highly significant correlation exist between the above-mentioned influence factor and carbon dioxide emissions.

3.3. Evaluation criteria of model performance

In order to verify the learning performance of the proposed algorithm, mean absolute percentage error (MAPE) is adopted, which can be define by

$$MAPE = \frac{1}{\zeta}\sum_{i=1}^{\zeta}\left|\frac{y_i - y_i^*}{y_i}\right| \tag{11}$$

Where y_i and y_i* are the prediction and real-value of the CO_2 emissions, ζ refer to the number of samples to be predicted. The smaller the values of MAPE, the better the forecasting performance of the proposed method.

As for the evaluation criteria of prediction intervals, CWC is a kind of combined index based on prediction interval coverage probability (PICP) and the mean prediction interval width(MPIW), which can be define as

$$CWC = \frac{1}{n_{test}}\sum_{i=1}^{n_{test}}\left(U_i - L_i\right) \left(1+\gamma\left(\frac{1}{n_{test}}\sum_{i=1}^{n_{test}} c_i\right)\exp\left(-\eta\left(\frac{1}{n_{test}}\sum_{i=1}^{n_{test}} c_i - \mu\right)\right)\right) \tag{12}$$

Where c_i equal 1 when the target is placed in the interval range, otherwise, c_i equal 0. η and μ are two hyperparameters that control the location and the amount of CWC jump; γ is given by

$$\gamma=\begin{cases}0, & \frac{1}{n_{test}}\sum_{i=1}^{n_{test}} c_i \geq \mu \\ 1, & \frac{1}{n_{test}}\sum_{i=1}^{n_{test}} c_i < \mu\end{cases} \tag{13}$$

Assuming that the experiments are conducted repeatedly, CWC_{median} and CWC_{SD} are the mean value and standard deviation of CWCs, respectively. CWC_{median} denotes the average results and can be used to measure the quality of the prediction intervals. The smaller the CWC_{median}, the better the performance. CWC_{SD} denotes the distribution of the CWCs around the CWC_{median} and can be used to measure the variability. The CWC_{median} and can be used to measure the variability. The smaller the CWC_{median}, the lower the variability Together, these smaller the CWC_{median}, the lower the variability Together, these two indicators reflect the performance of the prediction intervals. two indicators reflect the performance of the prediction intervals.

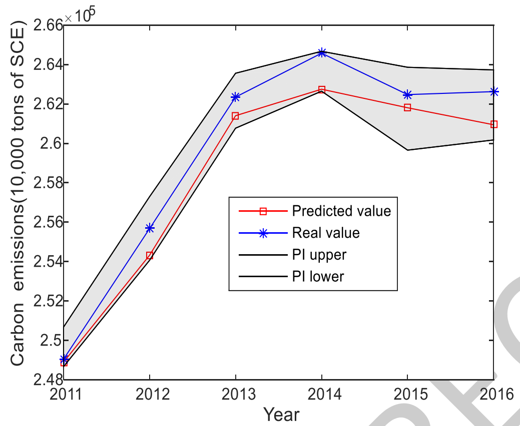


Figure 5. PIs constructed by PSO-ELMEnsemble

The experiment of CO_2 emission prediction in China is carried out based on the aforementioned related data from 1978 to 2016.However, the obtained data of CO_2 emissions are always accompanied with noise, and the existing point-oriented predictions without any indication of the accuracy are less reliable for the real-world applications. In practice, the workers usually raise more concerns on prediction accuracy and the variation intervals of CO_2 emission, with which they can design the appropriate policies.

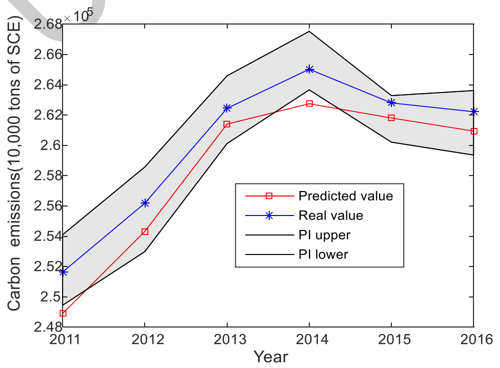


Figure 6. PIs constructed by Delta MLP

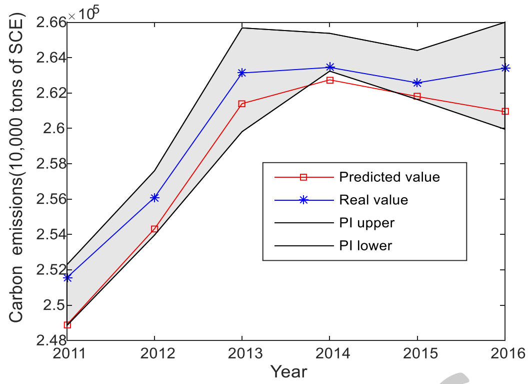


Figure 7. PIs constructed by MVE MLP

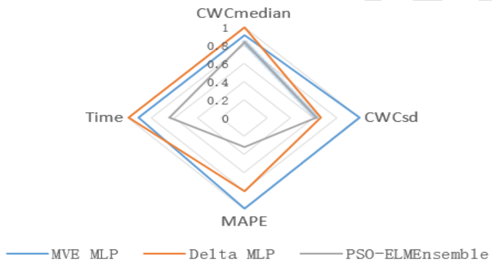


Figure 8. Comparative analysis of state-of-art PIs method

In this study, the proposed PSO-ELMEnsemble is adopted to construct the PIs for CO_2 emission. The activation function of neurons in the PSO-ELMEnsemble employs the line kernel function, and the ensemble structure has a better performance when the dimensionality equals 10. In addition, the issue of coverage probability in the proposed method is fully considered. A statistical analysis of prediction intervals results is listed in Table 6. The iterative prediction is adopted here for PIs construction, which is one-step ahead of the prediction with a rolling forecast origin. Figure 5 shows the results based on the proposed PSO-ELMEnsemble with the confidence level 95%, in which the values can be completely covered by the constructed PIs. Figures 6 and 7 respectively shows the results of the other two methods where existing points are observed outside the interval range. Given that a comprehensive comparative analysis of these methods is visualized in the Figure 8, it can be seen that the proposed method exhibits an improved accuracy performance than the others for CO_2 emissions.

4. Conclusions

Global climate change has become the greatest non-traditional security challenge faced by human development, and achieving carbon peak and carbon neutrality is of significant importance. The main objective of this study is to select the correlative factor and construct the prediction intervals for carbon emissions in China. Therefore, an extreme learning machine ensemble based on particle swarm optimization approach (PSO-ELMEnsemble) is presented, which is the novelty of this work that is helpful to understand the trend and the corresponding reliability of CO_2 emissions during the periods 1978-2016. Research shows that efficient carbon emission prediction models help better balance economic development with ecological environment. Since 2015, the rate of carbon emission growth in China has started to slow down, largely due to the government's focus on carbon emission control as a key research area, coupled with active development of new energy sources and implementation of industrial energy conservation and emission reduction policies. In the future, by incorporating more influencing factors into the carbon emission prediction models, we can further improve their accuracy. As for achieving the goals of carbon peak and carbon neutrality, the following strategies can be adopted in terms of optimizing industrial structure, raising environmental access thresholds and increasing investment in technological innovation and research & development. Frist reducing the proportion of the secondary industry in the national economy while enhancing the development level of the tertiary industry. Specific measures include accelerating the elimination of outdated production capacity, restricting the development of high-energy-consuming and heavily polluting industries, and encouraging the growth of new energy, renewable energy, and high-end manufacturing. Furthermore, strengthen environmental access standards for investment projects, guiding more funds towards green technological innovation. Finally, technological innovation plays a vital role in reducing carbon emissions. Actively increase support for industries such as clean energy, green manufacturing, green buildings, and green transportation, as well as for the research and development of green low-carbon technologies and carbon-negative technologies (such as CCS/CCUS), to enhance the role of technology in energy conservation and emission reduction.

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