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A Data-Driven Rule-Base Approach for Carbon Emission Trend Forecast with Environmental Regulation and Efficiency Improvement

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Abstract: Greenhouse gas emissions are widely recognized as the primary cause of global warming, leading to a growing attention on carbon emission management. However, the existing studies still failed to propose a feasible approach to directly forecast carbon emission trends and also did not take into account both environmental regulation and efficiency improvement. Hence, this study aims to propose a novel carbon emission trend forecast model based on data-driven rule-base with considering the intensity coefficient of environmental regulation and the management efficiency of carbon emissions. Carbon emission data of 30 Chinese provinces are collected to illustrate the effectiveness of the proposed model. Results indicated that: 1) the data-driven rule-base model is able to directly forecast carbon emission trends within range from -18.54% to 19.18%; 2) by integrating regulation intensity, the predicted results of the model have smaller carbon emission tends, *e.g.*, decrease of average changing rate from 0.4100 to 0.2762; 3) by further integrating efficiency improvement, the predicted results align more with the expected objectives of policy makers, *i.e.*, the average carbon emission efficiency approximates 0.8920 and the number of provinces being effective efficiency is increased to 8. These findings also highlighted the importance of carbon emission tend forecast with environmental regulation and efficiency improvement. The proposed carbon emission trend forecast model could serve as an alternative tool for achieving dual carbon goals in the context of China.

Keyword: Data-driven rule-base; Carbon emission trend; Forecast; Environment regulation; Efficiency improvement

Acronyms	
AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
ARIMA	Autoregressive integrated moving average
BPM	Basic probability mass
BRBS	Belief rule-based system
CBRB	Cumulative belief rule-base
CBRBS	Cumulative belief rule-based system
CEAD	Carbon emission accounts & datasets
DEA	Data envelopment analysis
DMU	Decision-making unit
ELM	Extreme learning machine
ER	Evidential reasoning
FRBS	Fuzzy rule-based system
GDP	Gross domestic product
GM	Grey model
MAE	Mean absolute error
SVR	Support vector regression
CBRB-ER	Cumulative belief rule-base with environmental regulation
CBRB-EREI	Cumulative belief rule-base with environmental regulation and efficiency improvement

Symbols	
$A_{i,j}$	The jth referential value of U_i
$AR(x)$	The set of activated rules regarding input data $\boldsymbol{x}$
D	Consequent attribute
D_n	The nth consequent of D
$ER_n(\beta_n^k, w_k)$	The integrated belief degree of β_n^k and w_k
$f(\boldsymbol{x})$	The predicted output of CBRBS to reply input data x
H	The set of all evaluation grades
H_n	The nth evaluation grade
$m_{I,n}^s$	The basic probability mass of$\gamma_{I,n}^s$
$\tilde{m}_{i,H}^s$	The uncertain basic probability mass caused by belief degree
$\bar{m}_{i,H}^s$	The uncertain basic probability mass caused by weight
p_k	The activation priority of R_k
$R_{j1\cdots jM}$	The cumulative belief rule related to $RC_{j1\cdots jM}$
R_k	The kth cumulative belief rule
$RC_{j1\cdots jM}$	The rule set related to $A_{i,j1},\ldots, A_{i,jM}$
$S(U_i, x_{s,i})$	The belief distribution of U_i regarding input data $x_{s,i}$
$Sim(U_i, x_i, R_k)$	The similarity between R_k and input data x_i at U_i
U_i	The ith antecedent attribute
$u(A_{i,j})$	The utility value of $A_{i,j}$
$u(D_n)$	The utility value of D_n
w_k	The activation weight of R_k
$x_{i,j}^t$	The data of ith input indicator regarding jth DMU at tth year
$y_{r,j}^t$	The data of ith desirable-output indicator regarding jth DMU at tth year
$\hat{y}_{r,j}^t$	The adjusted data of ith desirable-output indicator regarding jth DMU at tth year
$z_{f,j}^t$	The data of ith undesirable-output indicator regarding jth DMU at tth year
$\hat{z}_{f,j}^t$	The adjusted data of ith undesirable-output indicator regarding jth DMU at tth year
$\alpha_{i,j}^k$	The belief degree assigned to $A_{i,j}$ of R_k
$\alpha_{i,j}^{j1\cdots jM}$	The belief degree assigned to $A_{i,j}$ of $R_{j1\cdots jM}$
β_n^k	The belief degree assigned to D_n of R_k
$\beta_n^{j1\cdots jM}$	The belief degree assigned to D_n of $R_{j1\cdots jM}$
β_n	The integrated belief degree of D_n
$\hat{\beta}_j^t$	The efficient degree of jth DMU at tth year
θ_k	The weight of R_k
$\theta_{j1\cdots jM}$	The weight of $R_{j1\cdots jM}$
θ_j^t	The efficiency of jth DMU at tth year
θ^s	The intensity coefficient of the sth year
$\gamma_{i,n}^s$	The belief degree of H_n at ith indicator and sth year
δ_i	The weight of U_i
$(\Delta x_s, \Delta y_s)$	The input and output data of carbon emission trends at sth year

1. Introduction

Global warming has received significant attention worldwide and also has been a primary focus of scientific community. As the most important greenhouse gas, carbon dioxide plays a crucial role in causing the global climate warming problem (Sun & Huang, 2022). Effective carbon emission reduction is becoming a critical approach to handle the problem and achieve the sustainable development of economic and ecological benefits. The worldwide actions therefore have been done in the unit of country to reduce carbon emissions in order to reach the goals of the Paris Agreement. For example, as the largest carbon-emitting country, China has set the goal of reducing carbon dioxide emissions per unit of gross domestic product (GDP) by 18% at 2025 in comparison to 2020 to achieve carbon peaking. Therefore, it is crucial to explore carbon emission changes by considering various constraints and constructing effective forecast models.

Previous studies have revealed a long-term equilibrium relationship among economic development, carbon emission, and energy consumption (Guo *et al.*, 2011; Dong *et al.*, 2021). For instance, the economic development requires a substantial amount of energy consumption, but energy consumption must promote an increase in carbon emissions. Thus, many scholars proposed environmental regulation tools in the purpose of environmental protection and carbon emission reduction, which are useful for sustainable ecological and economic development. Furthermore, to effectively control the magnitude of carbon emission growth and achieve the goal of carbon emission reduction, the input-output planning and efficiency improvement for establishing a comprehensive carbon emission management is becoming a new focus of academic researches (Ye *et al.*, 2022). However, in the most previous studies, there is still no significant breakthrough in developing a novel carbon emission forecast model, which can accurately depict the change of carbon emissions and effectively consider environmental regulation and efficiency improvement. The detailed literature reviews are provided in Section 2.1. Therefore, the following challenges must be overcome for proposing a novel carbon emission forecast model:

(1) For forecasting carbon emissions, the data-driven rule-base approaches has been demonstrated its excellent potential over other models (Ye *et al.*, 2022; Delanoe *et al.*, 2023). However, due to the dilemma that the complexity of data-driven rule-base is directly connected to the number of data, it is necessary to develop a high-efficient data-driven rule-base modeling method for carbon emission forecast because the number of carbon emission data would increase over time.

(2) The available models are mainly capable of forecasting the level of carbon emissions (Faruque *et al.*, 2022; Zhang *et al.*, 2023), which fail to intuitively reflect the trend of carbon emissions. Moreover, the modeling process of carbon emission forecast would be affected by the dimension of regional carbon emissions, leading to the loss of accuracy caused by the situation that carbon emission forecast models prefer to provide accurate prediction results on greater carbon emissions.

(3) Environmental regulation is a useful approach to enhance carbon emission management, and various influencing factors have been designed in previous studies (Hao *et al.*, 2022; Nie & Duan 2023). However, these influencing factors were typically used as a special parameter in existing carbon emission forecast models, which would be quite difficult to utilize the influencing factors of environmental regulation for proposing new carbon emission forecast model.

(4) Efficiency improvement is another useful approach to enhance carbon emission management, however, its relevant studies mainly focused on evaluating the efficiency of historical carbon emissions and rarely involved carbon emission forecast (Yang *et al.*, 2019; Zhang *et al.*, 2022). Hence, it is evident that the combination of carbon emission forecast and efficiency improvement would be more beneficial in planning the pathway of carbon emission reduction.

In order to address the above challenges, a recent and representative data-driven rule-base approach, called cumulative belief rule-based system (CBRBS) (Yang *et al.*, 2022), is introduced to develop a novel carbon emission trend forecast model. The CBRBS is composed of a cumulative belief rule-base (CBRB) and the evidential reasoning (ER)-based inference method, where the former one contains a series of input subspace-based IF-THEN rules, which can avoid an overlarge rule-base even there are a large amount of historical data; the latter one is duty for replying any given data based on the CBRB. By inheriting the advantage of CBRBS, the proposed carbon emission trend forecast model can construct a CBRB from the historical data of carbon emission changing rates for carbon emission trend forecast, as well as optimizing the CBRB by considering the influencing factors of environmental regulation and the management efficiency of carbon emissions.

According to the above discussions, the proposed carbon emission trend forecast model has following innovations:

Firstly, the changing rate of carbon emissions and CBRBS are used together to propose a carbon emission trend forecast model, indicating that the proposed model not only has a high-efficient CBRB modeling process to construct a reliable rule-base even there are a large number of carbon emission data, but also can clearly and accurately reflect the changing rates of carbon emissions without the influence of the dimension of regional carbon emissions.

Secondly, the intensity coefficient of environmental regulation is considered to improve the CBRB modeling process, where the intensity coefficient is calculated using performance-based indicators. By incorporating environmental regulation, the carbon emission trend forecast model can reflect the influence of different levels of environmental regulation on carbon emission trends and evaluate carbon emissions according to environmental and policy demands.

Thirdly, the management efficiency of carbon emissions is considered to further improve the CBRB modeling process. This improvement takes into account the optimal inputs and outputs of effective carbon emission management to predict the trend of carbon emissions. Therefore, the carbon emission trend forecast model is able to provide an effective solution for evaluating carbon emission management through efficiency improvement perspective.

To demonstrate the effectiveness of the proposed carbon emission trend forecast model, the historical carbon emission data from 30 Chinese provinces between 2004 and 2019 were collected for empirical analysis and model validation. The results showed that the data-driven rule-base approach can be effectively used for carbon emission trend forecast in accordance with environmental regulation and management efficiency. Furthermore, the comparative analysis verified the influence of efficiency improvement and environmental regulation on carbon emission trend forecast, as well as the superiority of the proposed carbon emission trend forecast model over some existing models. These findings highlighted the potential of the data-driven rule-base approach as a reliable tool for evaluating carbon emission management and forecasting carbon emission trends under different scenarios of regulatory policy and efficiency improvement.

The remainder of this paper is as follows: Section 2 reviews the previous studies on carbon emission forecast. Section 3 introduces the proposed carbon emission trend forecast model. Section 4 presents the results and discussion of carbon emission trend forecast in the context of China. Section 5 includes the conclusions and policy implications of the study.

2. Literature Review

In this section, the previous studies on carbon emission forecast are provided in Section 2.1, and the challenges to propose new carbon emission forecast model are discussed in Section 2.2.

2.1 Literature review of carbon emission forecast

Reducing carbon emissions is a primary focus of academic researches, and thus numerous studies have investigated the effectiveness of carbon emission management. These studies involved analyzing influencing factors in carbon emissions and addressing various problems associated with carbon emission management. For instance, Sun *et al*. (2020) investigated the impact of carbon dioxide emissions through an international division perspective and thus revealed a common consensus that the carbon emission management should be pay more attention at the national level, while Ge *et al*. (2023) analyzed the carbon dioxide emissions induced by the construction of hydropower infrastructure, which showed that the carbon emission management needs to be considered at the industry level. Moreover, Nie & Duan (2023) suggested that the accurate prediction of carbon dioxide emissions can serve as references for better carbon emission management. Hence, it is concluded from the above studies that the development of forecast models is a valuable research direction, and forecasting future carbon dioxide emissions has become a key issue in carbon dioxide emission management.

Previous studies on carbon emission forecast include two kinds of models (Yang *et al*., 2023). The first one is statistical models and they are mainly based on time series forecasting models, *e.g.*, grey model (GM) and autoregressive integrated moving average (ARIMA). The typical studies include: Wang and Zhang (2022) aimed to address the lack of analyzing panel data in carbon emission forecast, thus a spatial GM-based forecast model was proposed for predicting Chinese provincial carbon emission. Ning *et al*. (2021) applied ARIMA to forecast the carbon emission of Beijing, Henan, Guangdong, and Zhejiang in the period of 1997-2017 and further made feasible carbon emission reduction targets to ensure developments of those provinces. Recently, Kour (2023) studied the annual carbon emissions of South Africa from the period 1980 to 2016, thus ARIMA was used to predict the carbon dioxide emissions of South Africa during the period of 2015-2027. Li *et al*. aimed to investigated the prediction of energy-related carbon emission using the self-adaptive grey generalized Verhulst model. They indicated that the carbon emission of America, Russia, China, Japan, and India can decrease 5.7, 1.6, 7.4, 8.2, and 2.0, tons/10 thousand USD at 2025. In the aim of consider the causal relation between carbon emissions and relevant indicators, some multi-variable models were introduced to handle carbon emission forecast. For instance, Xiong *et al*. (2021) established a linear time-varying parameters discrete GM to forecast carbon emissions of Anhui province. They suggested that the multi-variable model is effective for forecasting carbon emissions in China's developing regions. Wang *et al*. (2022) proposed a grey multi-variable convolution integral model for carbon emission forecast. The comparison demonstrated that the proposed model has a high accuracy in predicting the carbon dioxide emissions of Shanxi province during 2012 to 2019. Javed and Cudjoe (2022) extended the classical GM to propose a new data-driven time-series forecast technique, where the proposed technique was confirmed its feasibility and effectiveness on the carbon emission forecast of China and India. Recently, Yin *et al*. (2023) not only developed a new multi-variable GM-based forecast model to predict the carbon dioxide emissions of China from 2011 to 2025, but also took into account the correlations between influencing factors to carbon emissions. Zhang *et al*. (2023) considered the auto-correlated relationship between carbon emissions and their influencing factor, so they proposed an integrated forecast model based on fractional accumulation GM (FAGM) to predict the carbon emissions of G20 countries in the next 10 years.

The second type of models for carbon emission forecast is AI technique-based models and these AI techniques include artificial neural network (ANN), support vector regression (SVR), and data-driven rule-base approaches, *e.g.*, fuzzy rule-base system (FRBS) and belief rule-base system (BRBS). The typical studies include Mardani *et al*. (2019), who proposed an ensemble model based on FRBS to investigate the interrelationship between renewable energy consumption, GDP, and carbon emissions. They found that renewable energy consumption can reduce carbon emissions in the context of G8+5 countries, such as Brazil, Canada, France, Germany etc. Lee *et al*. (2021) focused on evaluating the effectiveness of carbon emission reduction policies by a system dynamics-based carbon emission forecasting model. The results showed that the model can facilitate calculating effective carbon emission reduction in the three cities of Japan. Maino *et al*. (2021) developed a deep ANN-based model to forecast tank-to-wheel carbon dioxide emissions. Faruque *et al*. (2022) investigated the performance of four multivariate time series prediction model based on ANN on carbon emission forecast. The results showed that the four models have high accuracy in predicting the carbon emissions of Bangladesh. Furthermore, Ye *et al*. (2022) presented an BRBS-based model for forecasting China's carbon emissions, which utilized the management policy goal of carbon emission reduction and GM to forecast future carbon emissions. Wang *et al*. (2023) developed a multi-regional input-output model to forecast the carbon emissions of 30 provinces in China. Additionally, they used structural decomposition analysis to evaluate the influencing factor of carbon emissions. Song *et al.* (2023) proposed a spatially weighted interaction model to explore regional carbon emissions and found that optimizing carbon emission reduction task allocation is valuable. Han *et al.* (2023) studied the economy and carbon emission prediction on the objective of different countries in the world using residual neural network, where the prediction results provide suitable plans for saving energy of America, Canada, Mexico, Finland and etc. Notably, the data-driven rule-base approaches demonstrates outstanding superiority in accuracy and interpretability over other AI models. This is because rule-base approach is an advanced white-box and data-driven AI technique (Liu *et al.*, 2013), and its interpretability is critical for understanding the relationships between input variables and outcomes.

Furthermore, various influencing factors and the dynamic evolution of carbon emission change have been considered in carbon emission prediction studies. For example, Wen & Li (2020) investigated the driving forces behind industrial carbon emissions and adopted several types of energy to predict carbon emissions. Hao *et al.* (2022) afforded a general multi-factor decomposition solution for China's carbon dioxide emissions, followed by carbon emission forecast based on system dynamics model. Chen *et al.* (2022) indicated a decomposition framework for carbon emission forecast and applied driving factors to provide a reference for the basis of future 5-year plans. Recently, Nie & Duan (2023) introduced the differential term of correlation variables to consider the influence of change rate on the carbon emission forecast model. Additionally, scenario analysis and influencing factors were also considered in carbon emission forecast. Related studies include Zheng *et al.* (2020), who discussed the influence of industrial restructuring on carbon dioxide emissions at the city level based on new perspectives. Wen & Yuan (2020) achieved carbon emission forecast in several commercial departments through AI technique-based models by combining the quantitative analysis of carbon emission influencing factors. Fang *et al.* (2021) developed a forecast model based on the random forest for predicting construction-stage carbon dioxide emissions at the early design stage and used six parameters as influencing factors for carbon emission prediction. Recently, Wang *et al.* (2023) analyzed the technological, structural, and demand influencing factors on carbon emissions. They suggested the implementation of differentiated bilateral carbon emission management is necessary for government. Most of the existing studies have included relevant factors in AI technique-based carbon emission prediction models through scenario analysis and model settings.

2.2 Challenges of proposing new carbon emission forecast model

Numerous statistical models and AI technique-based models were proposed and used for carbon emission forecast in the past decade, and some of them are of great significances in achieving the management goals of carbon emissions. Among them, it needs to note that the data-driven rule-base approaches showed their potential to provide both accurate and interpretable results for carbon emission-related managers, surpassing most of existing models (Ye *et al.*, 2022). However, the following challenges still need to be overcome to improve the level of carbon emission forecast:

(1) Previous studies mainly focused on forecasting annual carbon emissions, which actually fail to reveal the interrelation of carbon emissions in adjacent years, and may also result in the accuracy loss problem because the carbon emissions have a strong regional characteristic. Moreover, the data of carbon emissions can be generated over time, which make it difficult to construct an effective rule-base because the size of the rule-base is directly connected to the number of data. Hence, the first challenge is how to propose a high-efficient rule-base modeling method for carbon emission trend forecast.

(2) Previous studies have demonstrated the importance of environmental regulation factor at carbon emission management. However, the existing environmental regulation factor was just measured using statistic indicators by weighted average, and it is only used as a specific parameter in the model to reflect the influence of management policies on carbon emission reduction. This implies that these existing factors are unique parameters for a specific model. Hence, the second challenge is how to

effectively measure environmental regulation factors and integrate them into the rule-base modeling method.

(3) Previous studies have developed various kinds of models to evaluate the efficiency of carbon emission management. However, these studies mainly focused on how to evaluate the efficiency of historical carbon emissions, which means they failed to consider the impact of efficiency on future carbon emissions reduction. Specifically, there are lack of studying the carbon emission forecast with the aim of achieving efficiency improvement. Therefore, the last challenge is how to integrate efficiency improvement into the rule-base modeling method for better carbon emission trend forecast.

From the above discussions, it is evident that the existing studies face several challenges in proposing new carbon emission trend forecast model. Hence, in this study, by taking into account environmental regulation and management efficiency of carbon emissions, an advanced data-driven rule-base approach is introduced to propose a novel carbon emission trend forecast model and its rule-base modeling method in the following sections.

3. Methods

3.1 A representative data-driven rule-base approach: CBRBS

The CBRBS is a recent representative data-driven rule-base approach and inherits the benefits of FRBS and BRBS (Yang *et al.*, 2022). Comparing to the existing data-driven rule-base approaches, the CBRBS has shown its potential in achieving high-efficient modeling and inference procedures when facing regression and classification problems. Usually, the CBRBS is composed of a CBRB and the ER-based inference method, as shown in Fig. 1, where the CBRB contains a series of input subspace-based IF-THEN rules, which provide an effective solution to avoid generating an overlarge rule-base even there are lots of historical data; the ER-based inference method can produce an output for input data by activating rules using the nearest neighbor strategy and integrating activated rules using the ER algorithm.

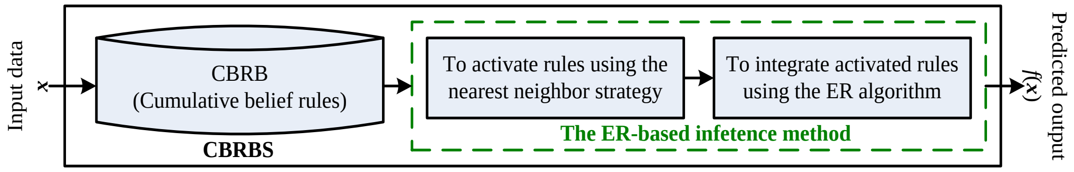

Fig. 1 Two components of CBRBS

In general, suppose that a CBRB has M antecedent attributes $\{U_i;\ i=1,\ldots,M\}$ with J_i referential values or fuzzy labels $\{A_{i,j};\ j=1,\ldots,J_i\}$ for the ith attribute and one consequent attribute D with N consequents or fuzzy labels $\{D_n;\ n=1,\ldots,N\}$. Therefore, the cumulative belief rule regarding the kth ($k=1,\ldots,L=\Pi_{i=1}^{M}J_i$) input subspace, formed by $\{A_{i,j_i};\ j_i\in\{1,\ldots,J_i\};\ i=1,\ldots,M\}$, can be written as

$$\begin{gathered} R_k : IF\ U_1\ is\ \{(A_{1,j},\alpha_{1,j}^k);\ j=1,\ldots,J_1\} \wedge \Lambda \wedge U_M\ is\ \{(A_{M,j},\alpha_{M,j}^k);\ j=1,\ldots,J_M\}, \\ THEN\ D\ is\ \{(D_n,\beta_n^k);n=1,\ldots,N\},\ with\ \theta_k\ and\ \{\delta_i;i=1,\ldots,M\} \end{gathered} \tag{1}$$

where $\alpha_{i,j}^k$ and β_n^k are the belief degree assigned to $A_{i,j}$ and D_n at R_k; θ_k is the rule weight of R_k; δ_i is the attribute weight of U_i.

After constructing a CBRB (The details can be found in Section 3.2), the ER-based inference method is performed to generate an output for replying given input data, *e.g.*, $\boldsymbol{x}=(x_i;\ i=1,\ldots,M)$, by the steps below:

***Step* 1**: To activate rules using the nearest neighbor strategy. For the input data $\boldsymbol{x}$, a set of cumulative belief rules should be activated based on the nearest neighbor strategy, denoted as $\boldsymbol{AR}(\boldsymbol{x})$, and its corresponding formula is shown as

$$\boldsymbol{AR}(\boldsymbol{x}) = \{R_k;\ p_k = \min_{R_t\in\boldsymbol{R}}\{p_t\}\} \tag{2}$$

where $\boldsymbol{R}$ denotes the set of all cumulative belief rules; p_k is the activation priority of R_k and it is calculated by

$$p_k = \max_{i=1,\ldots,M}\{|\arg\max_{j=1,\ldots,J_i}\{\alpha_{i,j}\} - j_i^k| + 1\} \tag{3}$$

where $\alpha_{i,j}$ denotes the belief degree of input data x_i assigned to $A_{i,j}$; j_i^k denotes the sequence number of A_{i,j_i} regarding the ith attributes in the kth input subspace. Next, the activation weight w_k of activated rule R_k ($R_k \in AR(\boldsymbol{x})$) is calculated by:

$$w_k = \frac{\theta_k \prod_{i=1}^{M} Sim(U_i, x_i, R_k)^{\bar{\delta}_i}}{\sum_{R_t}^{AR(x)} \theta_t \prod_{i=1}^{M} Sim(U_i, x_i, R_t)^{\bar{\delta}_i}}, \bar{\delta}_i = \frac{\delta_i}{\max_{t=1,\ldots,M}\{\delta_t\}} \tag{4}$$

where θ_k is the rule weight of R_k; δ_i is the attribute weight of U_i; $Sim(U_i, x_i, R_k)$ denotes the similarity between R_k and input data x_i at U_i and it is calculated by

$$Sim(U_i, x_i, R_k) = 1 - \sqrt{\frac{\sum_{j=1}^{J_i} (\alpha_{i,j} - \alpha_{i,j}^k)^2}{2}} \tag{5}$$

***Step* 2**: To integrate activated rules using the ER algorithm. Based on the activation weight, the activated rules in $\boldsymbol{AR}(\boldsymbol{x})$ can be integrated to obtain the integrated belief degrees by using the analytical ER algorithm:

$$\beta_n = ER_n(\beta_s^k, w_k, s = 1,\ldots,N, R_k \in AR(\boldsymbol{x})) \tag{6}$$

where Eq. (6) can be denoted below by assuming $AR(\boldsymbol{x})=\{R_k; k=1,\ldots, L\}$:

$$ER_n(\beta_s^k, w_k) = \frac{\prod_k^L (w_k\beta_n^k + 1 - w_k \sum_{s=1}^N \beta_s^k) - \prod_k^L (1 - w_k \sum_{s=1}^N \beta_s^k)}{\sum_{t=1}^N \prod_k^L (w_k\beta_t^k + 1 - w_k \sum_{s=1}^N \beta_s^k) - (N-1)\prod_k^L (1 - w_k \sum_{s=1}^N \beta_s^k) - \prod_k^L (1 - w_k)} \tag{7}$$

Next, when $u(D_n)$ is utility value of D_n and satisfies $u(D_1) \leq \ldots \leq u(D_N)$, the predicted output of CBRBS is obtained by:

$$f(\boldsymbol{x}) = \sum_{n=1}^N u(D_n)\beta_n + (1 - \sum_{n=1}^N \beta_n)\frac{u(D_1) + u(D_N)}{2} \tag{8}$$

3.2 A new carbon emission trend forecast model based on the approach

In this section, the framework of new carbon emission tread forecast model is showed in Section 3.2.1, the introduction of data-driven rule-base modeling with considering environmental regulation, efficiency improvement, and carbon emission trend are provided in Section 3.2.2 to Section 3.2.4, respectively.

3.2.1 Research framework of the new carbon emission trend forecast model

In order to illustrate how the data-driven rule-base carbon emission trend forecast model works, the research framework is provided, as shown in Fig. 2, and it includes: 1) *theoretical basis*, which is the basis of constructing a novel carbon emission trend forecast model, *e.g.*, information fusion approach, data-driven rule-base approach, and efficiency evaluation approach. 2) *data-driven rule-base modeling process*, which depicts the process of constructing the novel carbon emission trend forecast model from indicators and data; 3) *theoretical outcome*, which includes the carbon emission trend forecast model and its related environmental regulation strategy and efficiency improvement strategy.

On the basis of the research framework, a novel carbon emission trend forecast model is constructed and it can serve as a reference method for carbon emission-related researches with consideration of environmental regulation and efficiency improvement. Additionally, it should be highlighted that the proposed carbon emission trend forecast model can be regarded a generic research framework, indicating that the existing approaches regarding information fusion, data-driven rule-base, and efficiency evaluation can be potential alternatives to enrich carbon emission trend forecast models, as well as environmental regulation strategies and efficiency improvement strategies.

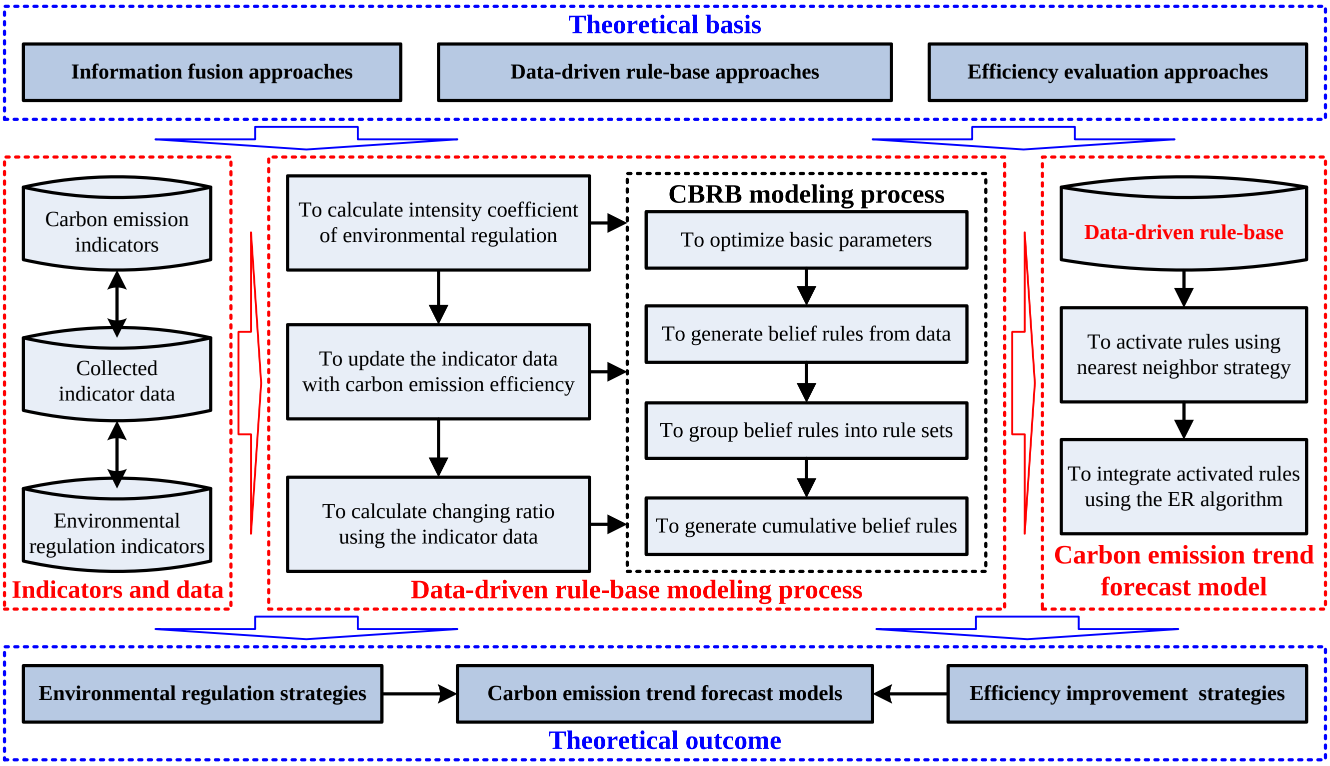

Fig. 2 Research framework

From Fig. 2, the steps of the data-driven rule-base modeling process are as follows:

***Step* 1**: To achieve the consideration of environmental regulation on CBRB modeling process. Firstly, the environmental regulation intensity coefficient should be calculated based on the data and indicators of environmental regulation. Afterwards, the environmental regulation intensity coefficients are used to optimize the basic parameters of CBRB, such as utility values of antecedent and consequent attributes, and attribute weights. The details of this step can be found in Section 3.2.2.

***Step* 2**: To achieve the consideration of efficiency improvement on CBRB modeling process. Firstly, the indicators of carbon emission should be divided into input, desirable-output and undesirable-output indicators. Afterwards, the carbon emission efficiency is calculated based on the data of carbon emissions; Finally, the efficiencies are used to update the data of desirable-output and undesirable-output indicators. The details of this step can be found in Section 3.2.3.

***Step* 3**: To achieve the consideration of carbon emission trend on CBRB modeling process. Firstly, the changing rate of carbon emissions, namely carbon emission trend data, should be calculated based on the data and indicators of carbon emissions. Afterwards, the carbon emission trend data are used for the generation of belief rules, the group of belief rules, and the generation of cumulative belief rules. The details of this step can be found in Section 3.2.4.

***Step* 4**: To predict future carbon emission trend based on the CBRB. Suppose that the carbon emission trend data of the T+1th year is $\boldsymbol{x}^{T+1}$. the carbon emission changing rate can be therefore obtained based on the steps given in Section 3.1, denoted as $f(\boldsymbol{x}^{T+1})$. Here, it worth noting that $f(\boldsymbol{x}^{T+1})<0$ means that carbon emissions present a downward trend at the T+1th year and $f(\boldsymbol{x}^{T+1})>0$ means that carbon emissions present a upward trend at the T+1th year.

3.2.2 Data-driven rule-base modeling with considering environmental regulation

This section aims to improve the CBRB modeling process using the intensity coefficient of environmental regulation. The improvement has two modules: the calculation of environmental regulation intensity coefficient from statistical indicators based on the ER approach and the integration of environmental regulation into the CBRB modeling process based on the parameter optimization, where the ER approach is a distributed information fusion framework and it has demonstrated its superiority better than weighted average (Wang *et al.*, 2021; Sachan *et al.*, 2021; Fu *et al.*, 2023); the parameter optimization makes it possible to adjust the optimal parameter values in the CBRB according to environmental regulation preference.

From the above discussion, the steps of considering environmental regulation are as follows:

***Step* 1:** To generate belief distributions from statistical indicator and data. Suppose that environmental regulation intensity coefficient is related with M statistical indicators and S years, where the data of the ith (i=1,…, M) indicator at the sth (s=1,…, S) year is denoted as x_i^s. According to the ER approach, when evaluation grades $\{H_n; n=1…, N\}$ and utilities $\{u(H_n); n=1,…, N\}$ of the ith indicator are provided, the belief distribution $S(x_i^s)=\{(H_n, \gamma_{i,n}^s); n=1,…, N\}$ can be obtained from data x_i^s.

***Step* 2**: To calculate basic probability mass (BPM) of statistical indicators for achieving environmental regulation. From ***Step* 1**, a total of $M\times S$ belief distributions $S(x_i^s)$ (i=1,…, M; s=1,…, S) are therefore obtained from data. When the set of these M statistical indicators' weight is $\{w_i; i=1,…, M\}$, the BPM of each statistical indicators can be obtained by:

$$m_{i,n}^s = m_i^s(H_n) = w_i \gamma_{i,n}^s \tag{9}$$

$$\tilde{m}_{i,H}^s = \tilde{m}_i^s(H) = w_i(1-\sum\nolimits_{n=1}^{N}\gamma_{i,n}^s) \tag{10}$$

$$\bar{m}_{i,H}^s = \bar{m}_i^s(H) = 1-w_i \tag{11}$$

where $m_{i,n}^s$ denotes the BPM of H_n on the ith indicator of environmental regulation value relative to the sth year; $\tilde{m}_{i,H}^s$ and $\bar{m}_{i,H}^s$ denote the uncertain BPM related with belief degrees and indicator weights on the ith indicator of the environmental regulation value relative to the sth year.

***Step* 3**: To integrate BPM for calculating environmental regulation intensity coefficient. According to BPM $\{m_{i,n}^s, \tilde{m}_{i,H}^s, \bar{m}_{i,H}^s; n=1,…, N\}$ (i=1,…, M; s=1,…, S) derived from ***Step* 2**, the BPM of M statistical indicators can be integrated to calculate environmental regulation intensity coefficient, where the integrated BPM is below:

$$m_n^s = K[\prod\nolimits_{i=1}^{M}(m_{i,n}^s+\tilde{m}_{i,H}^s+\bar{m}_{i,H}^s)-\prod\nolimits_{i=1}^{M}(\tilde{m}_{i,H}^s+\bar{m}_{i,H}^s)] \tag{12}$$

$$\tilde{m}_H^s = K[\prod\nolimits_{i=1}^{M}(\tilde{m}_{i,H}^s+\bar{m}_{i,H}^s)-\prod\nolimits_{i=1}^{M}\bar{m}_{i,H}^s] \tag{13}$$

$$\bar{m}_{i,H}^s = K\prod\nolimits_{i=1}^{M}\bar{m}_{i,H}^s \tag{14}$$

$$K=[\sum\nolimits_{n=1}^{N}\prod\nolimits_{j=1}^{M}(m_{i,n}^s+\tilde{m}_{i,H}^s+\bar{m}_{i,H}^s)-(N-1)\prod\nolimits_{i=1}^{M}(\tilde{m}_{i,H}^s+\bar{m}_{i,H}^s)]^{-1} \tag{15}$$

where m_n^s denotes the integrated BPM of H_n relative to the sth year, $\tilde{m}_H^s$ and $\bar{m}_H^s$ are the uncertain BPM related with belief degrees and indicator weights relative to the sth year.

***Step* 4**: To generate the data of environmental regulation intensity coefficient from integrated BPM. According to the integrated BPM $\{m_n^s, \tilde{m}_H^s, \bar{m}_H^s; n=1,…, N\}$ (s=1,…, S) of environmental regulation intensity, the integrated belief degree of environmental regulation intensity can be obtained by:

$$\gamma_n^s = \frac{m_n^s}{1-\bar{m}_H^s} \tag{16}$$

$$\gamma_H^s = \frac{\tilde{m}_H^s}{1-\bar{m}_H^s} \tag{17}$$

where γ_n^s and γ_H^s are the belief degree of H_n and uncertainty relative to the sth year. Finally, the intensity coefficient of environmental regulation can be obtained as follows:

$$\theta_s = \sum\nolimits_{n=1}^{N}\gamma_n^s u(H_n)+\gamma_H^s\frac{u(H_1)+u(H_N)}{2} \tag{18}$$

***Step* 5**: To optimize the basic parameters of CBRB by considering environmental regulation. Suppose that there are S carbon emission trend data $\{(\Delta \boldsymbol{x}_s, \Delta y_s); \Delta \boldsymbol{x}_s=(\Delta x_{s,1},…, \Delta x_{s,M}); s=1,…, S\}$ collected from the past S years. Thus, the parameter optimization model below is developed to optimize the basic parameters of the CBRB:

$$\begin{aligned}&\min \frac{\sum_{s=1}^{S} e^{\rho} \mid f(\Delta \boldsymbol{x}_s)-\Delta y_s \mid}{S}, \rho=\begin{cases}10\theta_s, if \ f(\Delta \boldsymbol{x}_s)\geq \Delta y_s \\ -10\theta_s, otherwise\end{cases}\\ &s.t.\ \ 0\leq \delta_i \leq 1; i=1,\ldots,M\\ &\quad u(A_{i,j})\leq u(A_{i,j+1}); j=1,\ldots,J_i-1; i=1,\ldots,M\\ &\quad u(A_{i,1})=\min_{s=1,\ldots,S}\{\Delta x_{s,i}\}; u(A_{i,J_i})=\max_{s=1,\ldots,S}\{\Delta x_{s,i}\}; i=1,\ldots,M\\ &\quad u(D_n)\leq u(D_{n+1}); n=1,\ldots,N-1\\ &\quad u(D_1)=\min_{s=1,\ldots,S}\{\Delta y_s\}; u(D_N)=\max_{s=1,\ldots,S}\{\Delta y_s\}\end{aligned} \tag{19}$$

where $f(\Delta \boldsymbol{x}_s)$ denotes the predicted output of the sth carbon emission trend data. Afterwards, the optimized basic parameters are used to construct CBRB according to the data-driven rule-base modeling method detailed in Section 3.2.4.

3.2.3 Data-driven rule-base modeling with considering efficiency improvement

Data envelopment analysis (DEA) model is a popular methodologies of evaluating carbon emission efficiency and it is constructed by decision-making units (DMUs) without nondimensionalization process of raw data and assigning weights for all indicators (Wu *et al.*, 2023). Thus, in carbon emission management, the DEA model serves as a bridge connecting carbon emission efficiency improvement and carbon emission trend forecast. The main process includes constructing DMUs based on input and output data of provinces, calculating efficiency for all DMUs, adjusting input and output data to achieve efficiency improvement, and using adjusted data to consider efficiency improvement in the CBRB modeling process.

From the above discussion, the steps of considering efficiency improvement are as follows:

***Step* 1**: To construct DMUs for all provinces. Suppose that there are M_1 input indicators $x^t_{i,j}$ (i=1,…, M_1; j=1,…, K; t=1,…, T), M_2 desirable-output indicators $y^t_{r,j}$ (r=1,…, M_2), and M_3 undesirable-output indicators $z^t_{f,j}$ (f=1,…, M_3) in each DMU, and there are n provinces in the past T years in carbon emission management efficiency calculation. Thus, the three types of indicators can construct n DMUs below:

$$\boldsymbol{DMU^t}=\begin{bmatrix}DMU_1^t\\ \vdots \\ DMU_K^t\end{bmatrix}=\begin{bmatrix}x_{1,1}^t & \cdots & x_{M_1,1}^t & y_{1,1}^t & \cdots & y_{M_2,1}^t & z_{1,1}^t & \cdots & z_{M_3,1}^t\\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots\\ x_{1,K}^t & \cdots & x_{M_1,K}^t & y_{1,K}^t & \cdots & y_{M_2,K}^t & z_{1,K}^t & \cdots & z_{M_3,K}^t\end{bmatrix} \tag{20}$$

where $\boldsymbol{DMU^t}$ is a DMU vector relative to the tth year; DMU^t_j is the jth DMU of the tth year.

***Step* 2**: To measure efficient degree for each province. According to the K DMUs constructed by Step 1, $\{DMU^t_j; j$=1,…, $K\}$, the efficient degree $\hat{\beta}^t_j$ of carbon emission management in the jth province relative to the tth year can be measured by the directional distance DEA model under weak disposability assumption (Emrouznejad *et al.*, 2019):

$$\begin{aligned}&\hat{\beta}_j^t = Max\ \beta_j^t\\ &s.t.\begin{cases}\sum_{k=1}^{K}\lambda_k x_{i,k}^t \leq x_{i,j}^t, i=1,\ldots,M_1\\ \sum_{k=1}^{K}\lambda_k y_{r,k}^t \geq (1+\beta_j)y_{r,j}^t, r=1,\ldots,M_2\\ \sum_{k=1}^{K}\lambda_k z_{f,k}^t = (1-\beta_j)z_{f,j}^t, f=1,\ldots,M_3\\ \lambda_k\geq 0; k=1,\ldots,K\end{cases}\end{aligned} \tag{21}$$

Next, based on the previous study of Chung *et al.* (1997), the carbon emission management efficiency of the jth province in tth year can be calculated by using the efficient degree $\hat{\beta}^t_j$:

$$\theta_j^t = \frac{1-\hat{\beta}_j^t}{1+\hat{\beta}_j^t} \tag{22}$$

***Step* 3**: To update the data of desirable-output indicators and carbon emissions. According to the K efficient degrees $\{\hat{\beta}^t_j$;

j=1…, K} relative to the tth year, the data of desirable-output indicators and carbon emissions can be adjusted by:

$$\hat{y}^t_{r,j} = (1+\hat{\beta}^t_j)y^t_{r,j}, r = 1,...,M_2 \tag{23}$$

$$\hat{z}^t_{f,j} = (1-\hat{\beta}^t_j)z^t_{f,j}, f = 1,...,M_3 \tag{24}$$

where $\hat{y}^t_{r,j}$ and $\hat{z}^t_{f,j}$ denote the adjusted data of desirable-outputs and carbon emissions relative to the jth province in tth year. According to the adjusted outputs, the n DMUs can be reconstructed by $x^t_{i,j}$, $\hat{y}^t_{r,j}$ and $\hat{z}^t_{f,j}$, and each DMU has effective efficiency that meet carbon emission management to achieve the efficiency improvement of all provinces.

***Step* 4**: To achieve efficiency improvement for CBRB modeling process. Based on Eqs. (23) and (24), the data { $x^t_{i,j}$, $\hat{y}^t_{r,j}$, $\hat{z}^t_{f,j}$; i=1,…, M_1; r=1,…, M_2; f=1,…, M_3; t=1,…, T} (i=1,…, K) can be obtained for constructing the CBRB that takes into account efficiency improvement, where $x^t_{i,j}$ and $\hat{y}^t_{r,j}$ are used as the data of antecedent attributes and $\hat{z}^t_{f,j}$ is as the data of consequent attribute according to the CBRB modeling process detailed in Section 3.2.4.

3.2.4 Data-driven rule-base modeling with considering carbon emission trend

In the aim of forecasting carbon emission trends, the carbon emission data should be transformed into carbon emission trend data. Hence, the definition of carbon emission trend data is provided as follows:

***Definition* 1**: Suppose that the carbon emission, denoted as D, is related with M environmental indicators, denoted as U_i (i=1,…, M), and their T collected input-output data are represented as {($\boldsymbol{x}_t$, y_t); $\boldsymbol{x}_t$=($x_{t,1}$,…, $x_{t,M}$); t=1,…, T}. Thus, the carbon emission trend data is defined as follows:

$$\Delta x_{t,s,i} = \frac{x_{t,i} - x_{s,i}}{x_{s,i}}, i = 1,...,M; t, s = 1,...,T \tag{25}$$

$$\Delta y_{t,s} = \frac{y_t - y_s}{y_s}; t, s = 1,...,T \tag{26}$$

For the sake of convenient narrative, the carbon emission trend data transformed from {($\boldsymbol{x}_t$, y_t); $\boldsymbol{x}_t$=($x_{t,1}$,…, $x_{t,M}$); t=1,…, T} are signed as {($\Delta\boldsymbol{x}_s$, Δy_s); $\Delta\boldsymbol{x}_s$=($\Delta x_{s,1}$,…, $\Delta x_{s,M}$); s=1,…, T×T}.

On the basis of the Definition 1, the steps of the CBRB modeling process are as follows:

***Step* 1**: To generate belief rules from carbon emission trend data. Suppose that the basic parameters, utility values {$u(A_{i,j})$; i=1,…, M; j=1,…, J_i} and {$u(D_n)$; n=1,…, N}, and attribute weights {δ_i; i=1,…, M} are provided by expert knowledge. Thus, the belief distribution $S(D, \Delta y_s)$={(D_n, β^s_n); n=1,…, N} can be generated as follows:

$$\beta^s_n = \beta(\Delta y_s, D_n) = \begin{cases} \dfrac{\Delta y_s - u(D_{n-1})}{u(D_n) - u(D_{n-1})}, & if\ u(D_{n-1}) < \Delta y_s \le u(D_n)\ and\ n > 1 \\ \dfrac{u(D_{n+1}) - \Delta y_s}{u(D_{n+1}) - u(D_n)}, & if\ u(D_n) \le \Delta y_s < u(D_{n+1})\ and\ n < N \\ 0, & otherwise \end{cases} \tag{27}$$

Similarly, the belief distribution $S(U_i, \Delta x_{s,i})$={($A_{i,j}$,$\alpha^s_{i,j}$); j=1,…, J_i} can be obtained. Finally, a total of T×T belief rules in the form of "R_s: IF $S(U_1, x_{s,1})$ ∧ …∧ $S(U_M, x_{s,M})$, THEN $S(D, y_s)$" can be obtained from carbon emission trend data.

***Step* 2**: To group belief rules into rule sets. In order to detect similar belief rules, the rule clustering is performed to group the T belief rules into multiple rule sets, where the rule clustering is as follows:

$$R_t \in \boldsymbol{RC}_{j_1 \wedge j_M}; j_i = \arg\max_{j=1,...,J_M}\{\alpha^t_{i,j}\}; t = 1,...,T; i = 1,...,M \tag{28}$$

where $\boldsymbol{RC}_{j_1 \cdots j_M}$ is the rule set related to M referential values A_{i,j_i} (j_i∈{1,…, J_i}; i=1,…, M).

***Step* 3**: To generate cumulative belief rules from rule sets. In the unit of rule sets, the all belief rules belonging to $\boldsymbol{RC}_{j_1 \cdots j_M}$

can generate a cumulative belief rule $R_{j_1\cdots j_M}$, where the belief distribution of $R_{j_1\cdots j_M}$ can be obtained by using the analytical ER algorithm as follows:

$$\alpha_{i,j}^{j_1\cdots j_M} = ER_j(\alpha_{i,p}^{k}, \bar{\theta}_k, p = 1,\dots,J_i, R_k \in \boldsymbol{RC}_{\boldsymbol{j_1\cdots j_M}}) \tag{29}$$

$$\beta_n^{j_1\cdots j_M} = ER_n(\beta_p^{k}, \bar{\theta}_k, p = 1,\dots,N, R_k \in \boldsymbol{RC}_{\boldsymbol{j_1\cdots j_M}}) \tag{30}$$

$$\theta_{j_1\cdots j_M} = \frac{|\boldsymbol{RC}_{\boldsymbol{j_1\cdots j_M}}|}{T} \tag{31}$$

where $|\boldsymbol{RC}_{j_1\cdots j_M}|$ is the number of belief rules in rule set $\boldsymbol{RC}_{j_1\cdots j_M}$; $\bar{\theta}_k$ is the normalized rule weight of the kth belief rule in $\boldsymbol{RC}_{j_1\cdots j_M}$ and it can be calculated by

$$\bar{\theta}_k = \frac{1}{|\boldsymbol{RC}_{\boldsymbol{j_1\cdots j_M}}|} \tag{32}$$

3.3 Data and indicator collection

In order to verify the effectiveness of the proposed model based on the data-driven rule-based approach, the carbon emission data and indicators of 30 Chinese provinces are collected. From the previous study on carbon emission management (Yin *et al*., 2023), it concluded that carbon emissions are usually affect by a variety of external related factors and these factors are mainly related with the indicator of economic development, population, and energy consumption (Zhang *et al*., 2011; Wang *et al*., 2015; Liu *et al*., 2022). Considering the influencing factors of carbon emissions and data availability, six indicators, including number of civilian cars, coal consumption, number of enterprises, resident population, electricity consumption, and GDP, are selected for carbon emission trend forecast. Table 1 shows the details of these six indicators, where the raw data of the six indicators are obtained from the China Statistical Yearbook from 2004 to 2019, and the data of carbon emissions are obtained from the carbon emission accounts & datasets (CEADs) (Shan *et al*., 2020; Guan *et al*., 2021). Additionally, it needs to be noted from Table 1 that the carbon emissions and its relevant indicators play different roles in CBRB and DMU, *i.e.*, GDP is used as an antecedent attribute to construct CBRB for carbon emission forecast and it is also used as a desirable output indicator to evaluate the efficiency of carbon emission management.

Table 1 Descriptions of carbon emission and its relevant indicators

Indicators	Role in CBRB	Role in DMU	Min	Max	Mean	Std. Dev
Number of civilian cars (units)	Antecedent attribute	Input indicator	10.45	2333.73	384.63	405.16
Coal consumption (10^4 ton)	Antecedent attribute	Input indicator	182.8	52331.61	12687.68	9956.68
Number of enterprises (units)	Antecedent attribute	Input indicator	335	65495	12064	13740
Resident population (10^4 person)	Antecedent attribute	Input indicator	539	12348	4470.29	2724.79
Electricity consumption (GWh)	Antecedent attribute	Input indicator	68.66	6323.35	1501.59	1199.36
GDP (10^8 yuan)	Antecedent attribute	Desirable-output indicator	443.7	99945.2	16419.81	16087.82
Carbon emissions (10^6 ton)	Consequent attribute	Undesirable-output indicator	16.5	912.20	275.67	188.44

The selection of reasonable and effective environmental regulation indicators is an important issue of concern to the academic community and government. From the previous study (Wu *et al*., 2020), there are two categories of indicators, namely, cost-based and performance-based environmental regulation indicators. Owing to the main purpose of environmental regulation that is to reduce pollutants emissions, the performance-based indicators measured by the removal, utilization, and treatment rates of different pollutants can better represent the effectiveness of government environmental regulation. Therefore, according to the existing studies (Ge and Li, 2020; Du *et al*., 2021; Liu *et al*., 2022), a total of 5 commonly used performance-based indicators are selected for measuring the environmental regulation intensity coefficient of each province. The detailed information of these indicators are showed in Table 2.

Table 2 Descriptions of environmental regulation-related indicators

Indicators	Min	Max	Mean	Std. Dev
Industrial sulfur dioxide removal rate	0.00	99.13	61.45	23.48
Industrial smoke dust removal rate	5.00	99.93	96.63	8.48
Industrial solid waste comprehensive utilization rate	6.04	100.00	78.05	14.94
Sewage treatment plants centralized treatment rate	6.04	100.00	74.52	19.15
Domestic garbage harmless treatment rate	6.01	100.00	85.90	14.72

4. Results and Discussion

4.1 Analysis of the data-driven rule-base for carbon emission trend forecast

In this section, the carbon emissions in Beijing are used as an example to illustrate the feasibility of the original CBRB modeling process on carbon emission trend forecast. According to the CBRB modeling detailed in Section 3.2.4, the changing rate of carbon emissions should be calculated firstly when the data between 2004 to 2018 are used as training data, where the corresponding data descriptions are shown in Table 3. Based on the obtained changing rate of indicators, the CBRB can be constructed when there are 5 assessment grades {Very Small, Small, Medium, Large, Very Large} for all indicators, where the initial basic parameters of the CBRB are shown in Table 4.

Table 3 Changing rate of carbon emissions and its relevant indicators

Role in CBRB	Indicators	Min	Max	Mean	Std. Dev
Antecedent attribute	Number of civilian cars	0.0000	4.6689	1.0321	0.9398
Antecedent attribute	Coal consumption	-0.9404	0.0441	-0.4219	0.2995
Antecedent attribute	Number of enterprises	0.0000	1.2858	0.3467	0.2697
Antecedent attribute	Resident population	-0.0023	0.4702	0.1801	0.1428
Antecedent attribute	Electricity consumption	0.0000	2.2360	0.6426	0.5935
Antecedent attribute	GDP	-0.5668	0.1437	-0.2635	0.2321
Consequent attribute	Carbon emissions	-0.1854	0.1918	-0.0246	0.0760

In order to guarantee the accuracy of the CBRB modeling process in forecasting carbon emission trends, the parameter optimization model is introduced to train the parameters shown in Table 3, and the relevant settings include: 1) the intensity coefficients of environmental regulation are all set as 0 to eliminate the influence of environmental regulation on carbon emission trend forecast; 2) the differential evaluation algorithm is utilized to solve the parameter optimization model showed in Eq. (19); and 3) the number of iterations and individuals are set as 100 and 40, respectively. As a consequent, Fig. 3 shows the mean absolute error (MAE) of the parameter optimization model for Beijing's carbon emission trend forecast. From Fig. 3, it can be found that the MAE of carbon emission trend forecast in Beijing is clearly decreased after 100 iterations and tends to converge, where the final MAE decreases from 0.0186 to 0.0157. Table 5 shows the trained basic parameters of the CBRB, which indicates that most of basic parameters have different values comparing to Table 4. For instance, the original attribute weights of 6 indicators are 1.0000 in Table 4, but all of them are 0.8733, 0.8777, 0.8756, 0.8768, 0.8753, and 0.8763, respectively, in Table 5.

Table 4 Initial basic parameters of CBRB for Beijing carbon emission trend forecast

Indicators	Attribute weight	*u*(Very Small)	*u*(Small)	*u*(Medium)	*u*(Large)	*u*(Very Large)
Number of civilian cars	1.0000	0.0000	1.1672	2.3345	3.5017	4.6689
Coal consumption	1.0000	-0.9404	-0.6943	-0.4482	-0.2021	0.0441
Number of enterprises	1.0000	0.0000	0.3214	0.6429	0.9643	1.2858
Resident population	1.0000	-0.0023	0.1158	0.2340	0.3521	0.4702
Electricity consumption	1.0000	0.0000	0.5590	1.1180	1.6770	2.2360
GDP	1.0000	-0.5668	-0.3892	-0.2116	-0.0340	0.1437
Carbon emissions	-	-0.1854	-0.0911	0.0032	0.0975	0.1918

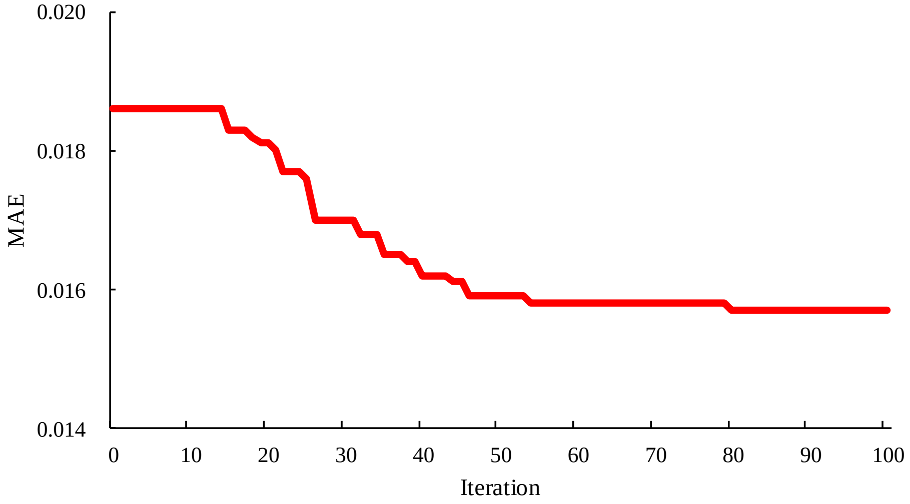

Fig. 3 MAE of the data-driven rule-base model for Beijing carbon emission trend forecast

Table 5 Trained basic parameters of CBRB for Beijing carbon emission trend forecast

Indicators	Attribute weight	*u*(Very Small)	*u*(Small)	*u*(Medium)	*u*(Large)	*u*(Very Large)
Number of civilian cars	0.8733	0.0000	0.8197	1.2389	2.7282	4.6689
Coal consumption	0.8777	-0.9404	-0.5439	-0.3141	-0.2766	0.0441
Number of enterprises	0.8756	0.0000	0.2572	0.2844	0.6563	1.2858
Resident population	0.8768	-0.0023	0.0702	0.1322	0.2379	0.4702
Electricity consumption	0.8753	0.0000	0.8727	1.2081	1.5699	2.2360
GDP	0.8763	-0.5668	-0.3935	-0.1204	-0.0420	0.1437
Carbon emissions	-	-0.1854	-0.0160	0.0368	0.1629	0.1918

Next, by applying the same CBRB modeling process on other provinces, a total of 30 CBRBs can be constructed. Fig. 4 shows the changing ratio of carbon emissions predicted by the initial and the trained 30 CBRBs. From Fig. 4, it is clear that the predicted changing ratio of the trained CBRBs is closer to the real changing ratio of carbon emissions. For example, the changing ratio of Shanxi, Inner Mongolia, Heilongjiang, Jiangsu, Ningxia, Xinjiang predicted by the initial CBRBs is lower than those by the trained CBRBs comparing to the real changing rate of carbon emissions. Additionally, Fig. 5 shows carbon emission management efficiency regarding the initial and trained CBRBs. It can be found from Fig. 5 that there is almost same efficiency for 30 provinces between the carbon emissions predicted by the initial and trained CBRBs.

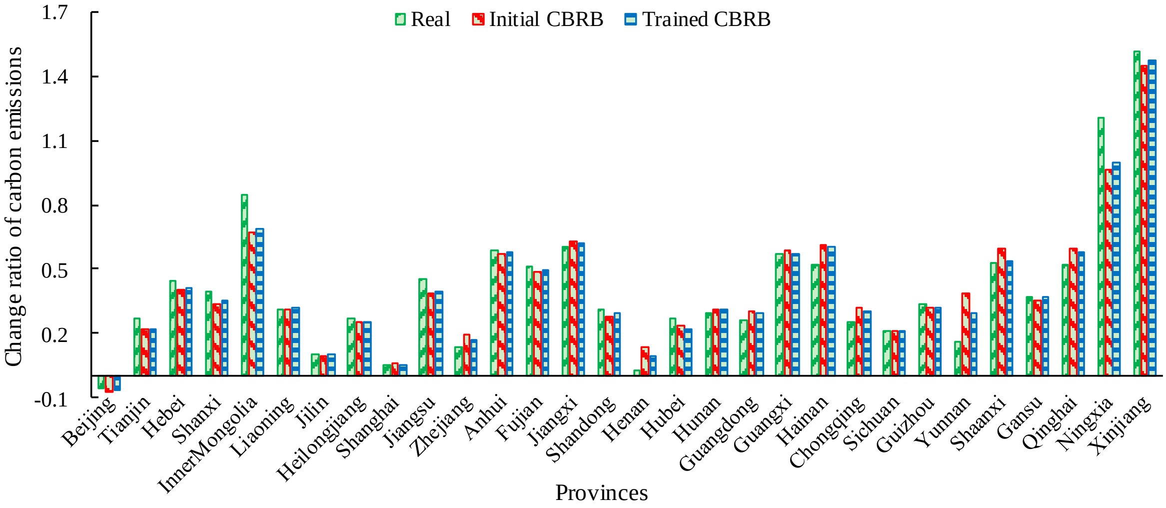

Fig. 4 Comparison of carbon emission trend forecast by initial and trained CBRBs

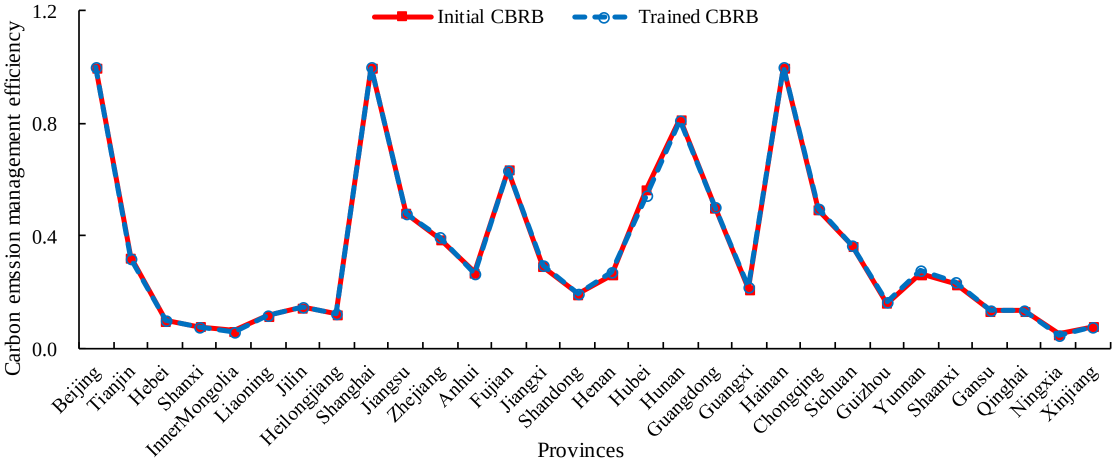

Fig. 5 Comparison of carbon emission management efficiency by initial and trained CBRBs

4.2 Analysis of environmental regulation for carbon emission trend forecast

In order to analyze the function of environmental regulation on the CBRB modeling process, the environmental regulation intensity coefficient is calculated by using the indicators shown in Table 2. For the sake of description, the original CBRB modeling process with considering environmental regulation is abbreviated as the CBRB-ER modeling process. Figs. 6 and 7 show the environmental regulation intensity coefficient and its average value for 30 Chinese provinces in 2019, respectively. It can be found from Fig. 6 that the environmental regulation intensity of Shannxi, Ningxia and Xinjiang provinces is higher than the most eastern provinces, the possible reason is that, due to the climate and terrain differences, these provinces paid more attention to the construction of green areas. At the same time, the population density is lower in Shannxi, Ningxia and Xinjiang provinces, which means that there is less destructive to environmental pollution.

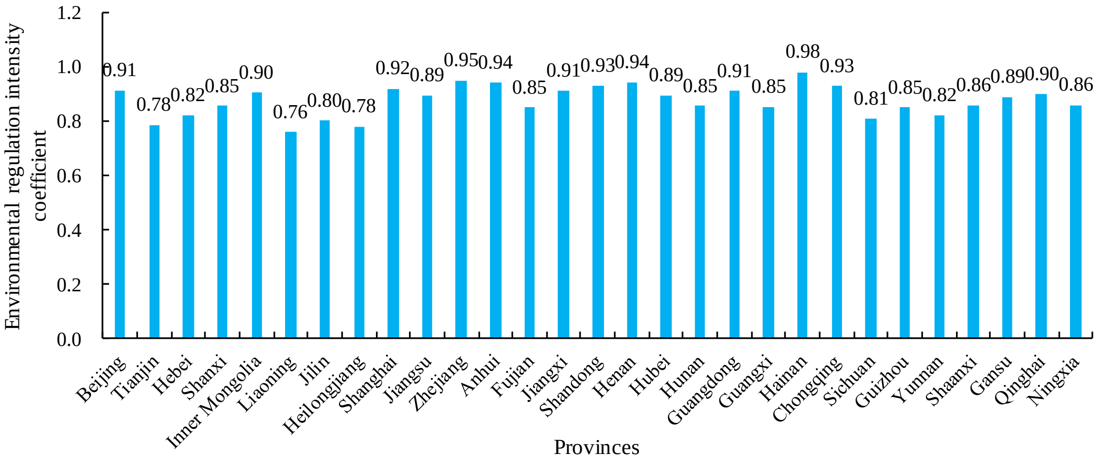

Fig. 6 Environmental regulation intensity coefficient of different provinces in 2019

From the average change of environmental regulation intensity of all provinces in Fig. 7, the overall environmental regulation intensity of 30 provinces shows an upward trend, which is consistent with the actual policy situation of China's environmental governance. Therefore, it is reasonable to calculate environmental regulation intensity through the integration of statistical indicators using the ER approach in Section 3.2.2.

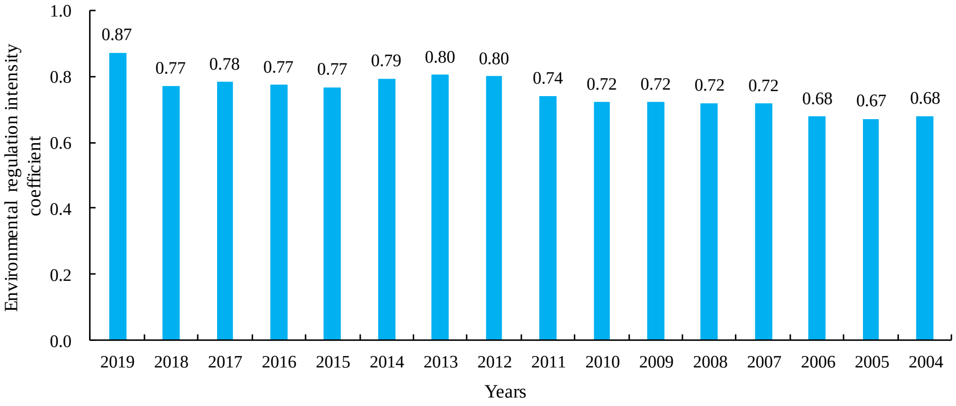

Fig. 7 Average environmental regulation intensity of all provinces from 2004 to 2019

Afterwards, by considering environmental regulation intensity coefficients, the CBRB used for the carbon emission trend forecast of 30 provinces can be updated according to Step 2 detailed in Section 3.2.2. Fig. 8 shows the comparison of carbon emission trend forecast regarding the CBRB and CBRB-ER modeling processes. Compared with the original CBRB modeling process, it is obvious that the consideration of environmental regulation is useful to reduce the changing ratio of carbon emissions for 30 provinces. This is because the environmental regulation refers to the set of rules, policies and laws that are designed to reduce carbon emissions. Therefore, the CBRB-ER modeling process clearly prefers predicting lower carbon emissions. In addition, Fig. 9 shows carbon emission management efficiency of the CBRB and CBRB-ER modeling processes. From Fig. 9, some provinces, including Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Guangxi, Chongqing, Sichuan, Yunnan, Gansu, and Qinghai, have a higher carbon emission management efficiency when taking into account environmental regulation.

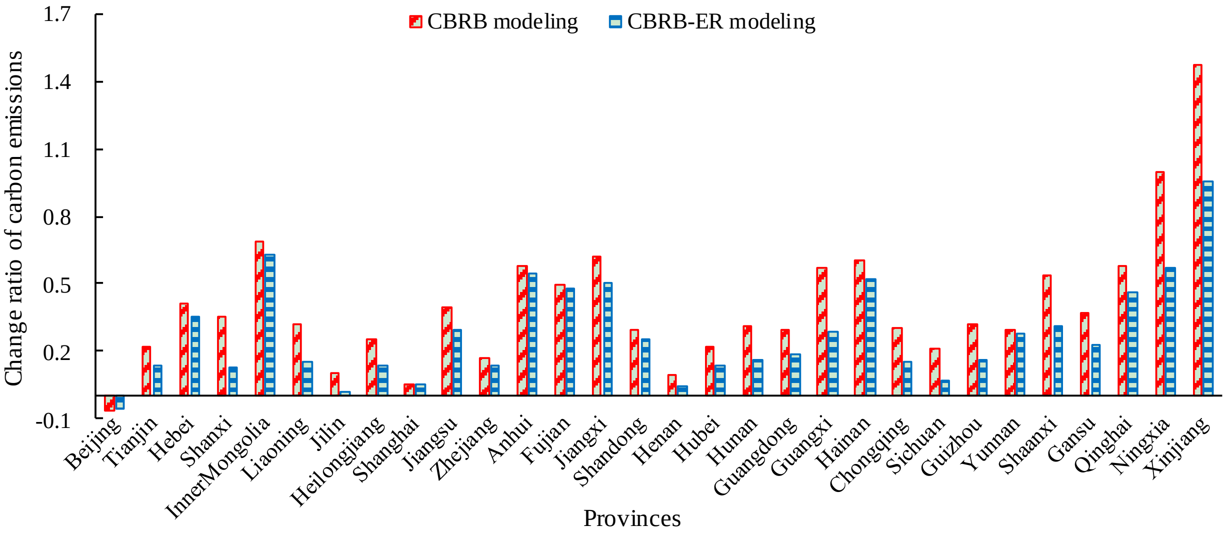

Fig. 8 Carbon emission trend forecast by considering environmental regulation

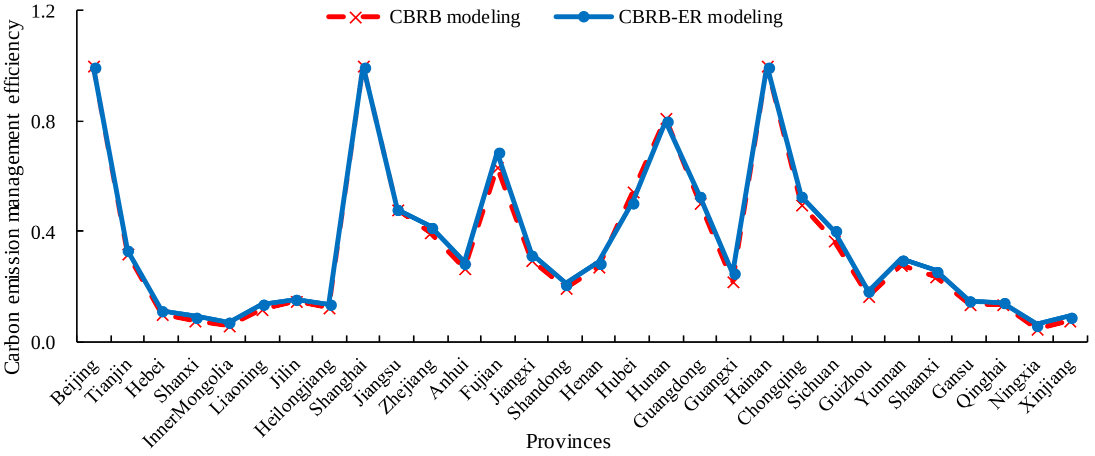

Fig. 9 Carbon emission management efficiency by considering environmental regulation

4.3 Analysis of efficiency improvement for carbon emission trend forecast

To analyze the effect of efficiency improvement on the CBRB-ER modeling process, the data of 30 provinces are used to calculate the management efficiency of carbon emissions according to the steps detailed in Section 3.2.3. In the previous studies (Yang *et al*., 2019; Zhang *et al*., 2022), the management efficiency of carbon emissions is an important standard to evaluate the effectiveness of carbon emission management, and it can optimize the inputs and outputs of carbon emission management in the aim of achieving energy conservation and emission reduction through efficiency improvement. For the sake of description, the CBRB-ER modeling process with efficiency improvement is abbreviated as the CBRB-EREI modeling process. Taking the efficiency evaluation of 30 Chinese provinces in 2020 as an example, the results are shown in Fig. 10. It can be observed that only three provinces achieve the relatively effective management of carbon emissions, while the carbon emission management efficiency of most Chinese provinces is lower than 0.5, indicating the need of further improving carbon emission efficiency. From a regional perspective, the management efficiency of carbon emissions is lower in the northwest and higher in the eastern coastal provinces, showing a certain correlation between carbon emission management efficiency and regional development level.

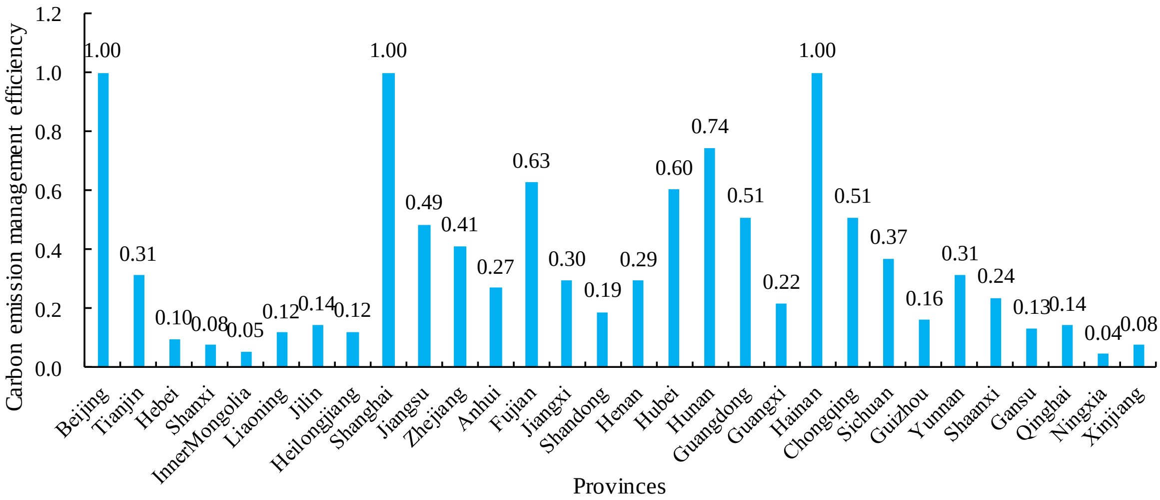

Fig. 10 Management efficiency of 30 Chinese provinces' carbon emissions in 2020

Next, based on the efficiency improvement approach given in Section 3.2.3, the new desirable-outputs and undesirable-outputs, that take into account management efficiency of carbon emissions, of 30 Chinese provinces in 2019 can be updated, as shown in Table 6. The results reveal that, in order to achieve effective carbon emission management, all provinces must increase desirable-outputs and reduce undesirable-outputs. Specifically, increasing GDP and reducing carbon emissions can effectively achieve efficiency improvement, which is also a critical problem for the developing countries who need to address and achieve carbon emission reduction and economic development. The CBRB-EREI modeling process provides an effective analysis tool and decision-making basis for solving this problem. Moreover, it is obvious from Table 6 that most of Chinese provinces have different corrected values after considering management efficiency of carbon emissions. For instance, the updated values of GDP and carbon emissions of the provinces located in Chinese eastern regions, such as Hebei, Shanxi, Jiangsu, and Zhejiang, are always higher than the provinces located in Chinese western regions. In addition, the update values of the three provinces, namely Beijing, Shanghai and Hainan, are zero because all of them actually have achieved relatively effective carbon emission management.

Table 6 Updated values of desirable-outputs and carbon emission based on management efficiency

Province name	Δy	Δz	Province name	Δy	Δz	Province name	Δy	Δz
Beijing	0	0	Zhejiang	26007	-159	Hainan	0	0
Tianjin	7377	-83	Anhui	21250	-235	Sichuan	7695	-51
Hebei	28835	-754	Fujian	9741	-64	Chongqing	21313	-145
Shanxi	14578	-486	Jiangxi	13416	-132	Guizhou	12104	-188
Inner Mongolia	15433	-712	Shandong	48080	-639	Yunnan	12118	-97
Liaoning	19639	-421	Henan	29345	-252	Gansu	15925	-183
Jilin	8759	-152	Hubei	11282	-88	Shannxi	6667	-126
Heilongjiang	10589	-217	Hunan	5868	-46	Qinghai	2205	-39
Shanghai	0	0	Guangdong	35033	-185	Ningxia	3430	-194
Jiangsu	34133	-278	Guangxi	13676	-159	Xinjiang	11696	-392

It should be noted from Table 6 that, after considering efficiency improvement, the carbon emission reduction and GDP increase in different provinces vary greatly, which is connected with development differences and natural vegetation coverage in different provinces. This regional difference also reflects the unified implementation of carbon emission governance policies in various provinces. Therefore, when predicting carbon emission trends for 30 provinces, the CBRB-EREI modeling process conducts carbon emission trend forecast through the updated carbon emissions of each province. Finally, Fig. 11 shows the predicted carbon emission changing ratios regarding the CBRB-ER and CBRB-EREI modeling process. Compared with the CBRB-ER modeling process, it can be observed that efficiency improvement further reduces the changing ratio of carbon emissions, and most of them have a negative changing ratio. For example, the carbon emissions of Beijing, Hebei, Jilin, Shandong, Guangxi, Yunnan, Gansu, Qinghai, and Xinjiang provinces have a negative changing ratio. Thus, efficiency improvement can be used as a policy tool to effectively reduce carbon emissions and achieve pollution control. Additionally, Fig. 12 shows the comparison of the carbon emission management efficiency between the CBRB-ER and CBRB-EREI modeling processes. It is evident that the CBRB-EREI modeling process can significantly improve the carbon emission management efficiency of 30 provinces, except for Beijing, Shanghai, and Hainan provinces, as these three provinces have achieved relatively effective efficiency when using the CBRB-ER modeling process to predict carbon emission trends.

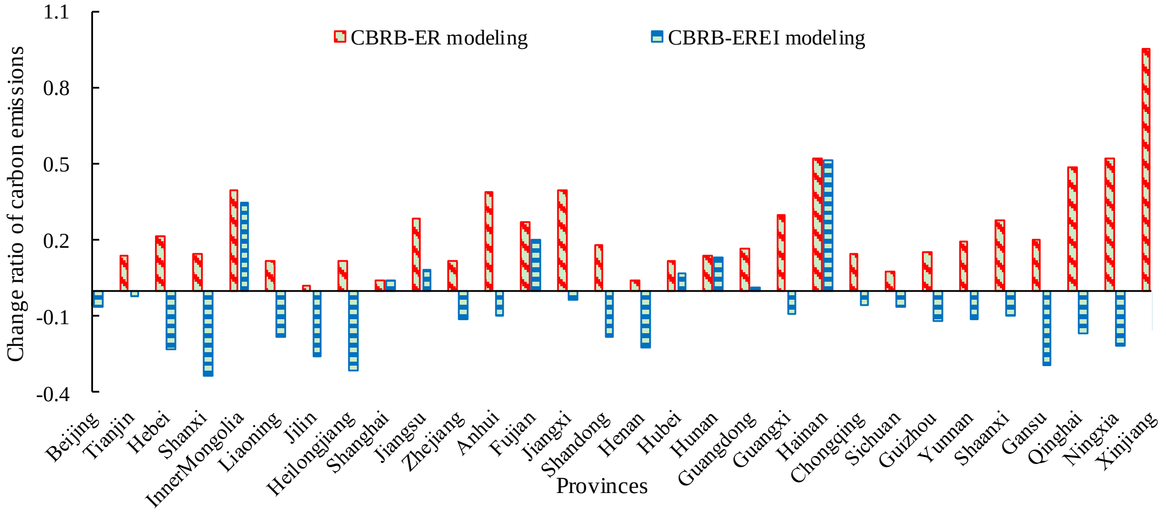

Fig. 11 Carbon emission trend forecast by considering environmental regulation and efficiency improvement

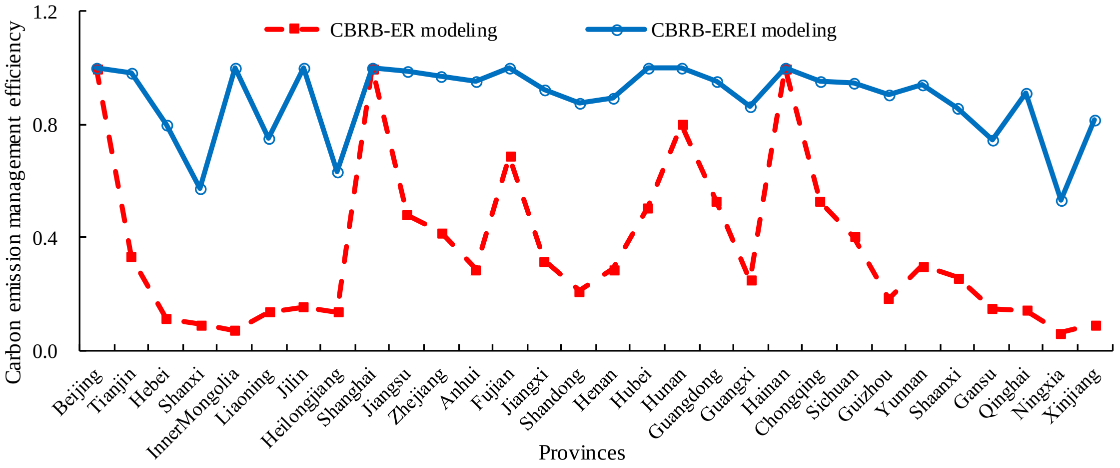

Fig. 12 Carbon emission management efficiency by considering environmental regulation and efficiency improvement

4.4 Comparative analysis of some existing carbon emission forecast models

In order to verify the effectiveness of the proposed model for carbon emission trend forecast, the carbon emissions are considered to discuss the influence of efficiency improvement and environmental regulation and the superiority of the proposed carbon emission trend forecast model, and the corresponding results are shown in Figs. 13 to 14 and Tables 7 to 8. Noting that 1) the all models used in this section are constructed by the carbon emission data between 2004 to 2018 and aim to predict the carbon emissions of 2019; 2) carbon emissions are calculated using carbon emission changing ratio, *i.e.*, the carbon emissions at the *T*th year is 100 and the predicted changing ratio between the *T*th and *T*+1th years is 10%, thus the predicted carbon emissions at the *T*+1th year is 100×(1+10%)=110; 3) six criteria are used to evaluate the performance of the models and they are: a) *average efficiency*, which means the average efficiency of carbon emission management for 30 provinces; b) *number of effective provinces*, which means number of provinces being effective efficiency; c) *average changing rate*, which means average changing rate of carbon emissions for 30 provinces; d) *number of negative provinces*, which means number of provinces being negative changing rate; e) *mean* (α=95%), which means 95% confidence intervals for the parameters estimation on the mean; and f) *standard deviation* (α=95%), which means 95% confidence intervals for the parameters estimation on the standard deviation.

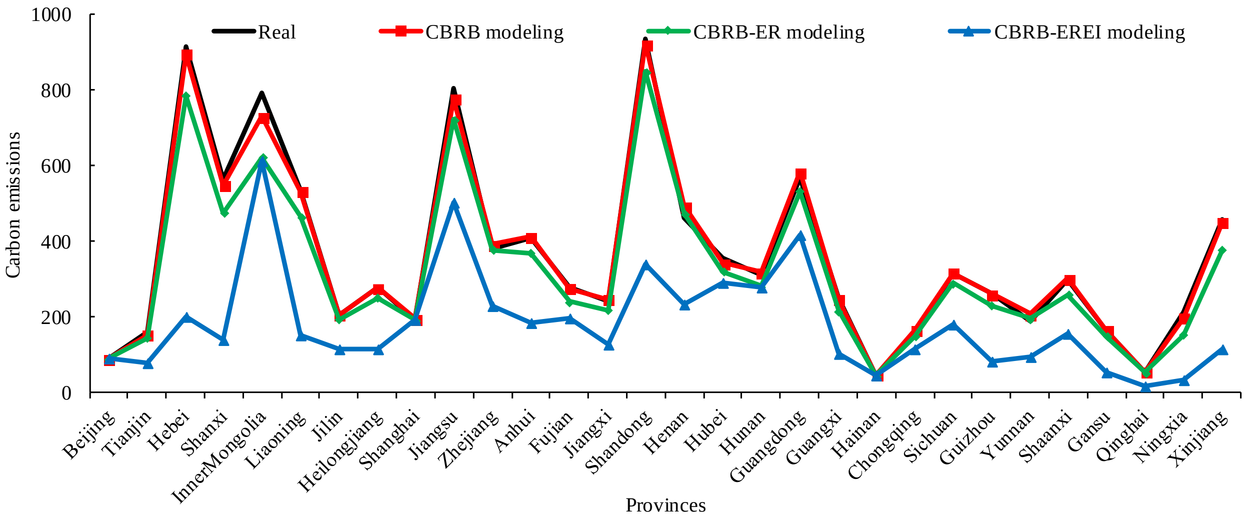

Fig. 13 Graphical analysis of CBRB modeling for carbon emission prediction

Table 7 Statistic analysis of CBRB modeling for carbon emission prediction

	Real	CBRB modeling	CBRB-ER modeling	CBRB-EREI modeling
Average efficiency	0.3517	0.3489	0.3608	0.8920
No. of effective provinces	3	3	3	8
Average changing rate	0.4100	0.4037	0.2762	-0.0677
No. of negative provinces	1	1	1	22
Mean (α=95%)	[271, 453]	[272, 447]	[244, 402]	[130, 233]
Standard deviation (α=95%)	[194, 727]	[187, 316]	[168, 283]	[110, 185]

From Fig. 13, it can be seen that the primary CBRB modeling has similar results to real carbon emissions of 30 provinces, where only one province has negative changing ratio and three provinces have effective efficiency. However, the carbon emissions predicted by CBRB-ER and CBRB-EREI modeling are different in most provinces, indicating that it is of important practical significance to consider environmental regulation and efficiency improvement in carbon emission management to reduce carbon emissions, where the real carbon emissions have the maximum values, but they are gradually changed into smaller values after considering environmental regulation and further considering efficiency improvement. Looking at Table 7, the CBRB modeling has the maximum average changing ratio and minimum efficiency, indicating that the 30 provinces has a continuous mass of carbon emissions. However, after considering environmental regulation and efficiency improvement, the carbon emissions in most provinces show a decreasing trend and the management efficiency in most provinces show an increasing trend, indicating that both of environmental regulation and efficiency improvement play key roles in reducing carbon emissions, which can be further confirmed by the results that there are 21 provinces being negative changing ratios and 6 provinces being effective efficiencies for the CBRB-EREI modeling, as well as the results of 95% confidence intervals for the parameters estimation on the mean and standard deviation, where the upper value of CBRB-EREI modeling is smaller than the lower value of the other three modeling.

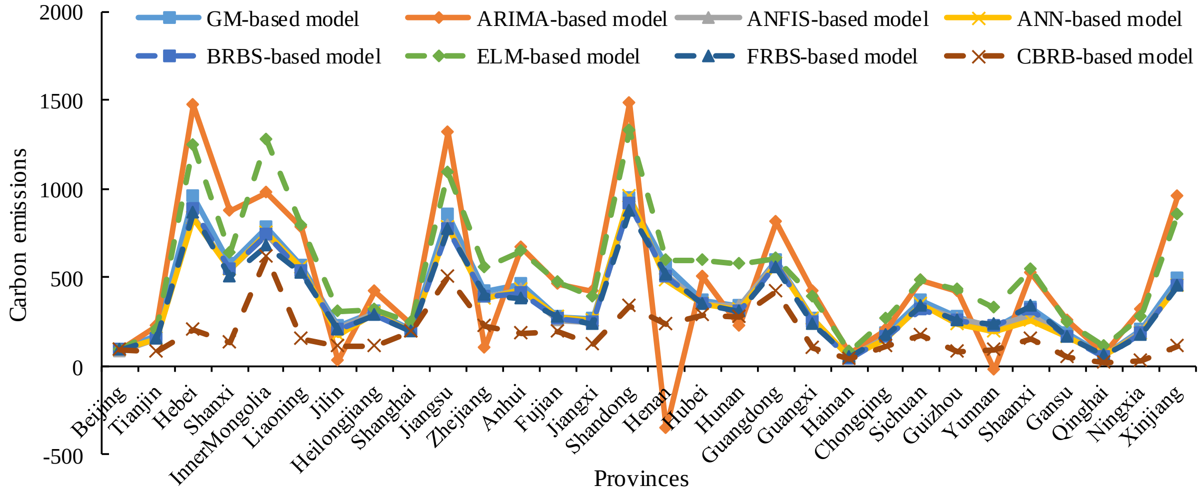

Fig. 14 Graphical results of eight models for carbon emission forecast

Table 8 Statistic results of eight models for carbon emission forecast

	Statistical models		AI-based models					This paper
	GM	ARIMA	ANN	ELM	FRBS	ANFIS	BRBS	CBRB
Average efficiency	0.3405	0.3585	0.3466	0.3316	0.3418	0.3448	0.3465	0.8920
No. of effective provinces	3	5	3	4	3	3	3	8
Average changing rate	0.5279	0.9187	0.3956	0.9945	0.3907	0.4442	0.3889	-0.0677
No. of negative provinces	1	6	1	1	1	1	1	22
Mean (α=95%)	[294, 480]	[316, 647]	[270, 447]	[407, 662]	[272, 439]	[277, 450]	[273, 448]	[130, 233]
Standard deviation (α=95%)	[197, 334]	[353, 596]	[189, 319]	[272, 460]	[178, 300]	[185, 312]	[186, 315]	[110, 185]

From Fig. 14 and Table 8, it can be found that, compared with existing models, including GM (Wang *et al.*, 2022), ARIMA (Kour, 2023), BRBS (Wang *et al.*, 2020), FRBS (Yang *et al.*, 2021), ANN (Wen & Yuan, 2020), ELM (Yang *et al.*, 2023), and ANFIS (Delanoe *et al.*, 2023), the predicted carbon emissions of the CBRB-based model are smaller than these existing models for 30 provinces, *i.e.*, the predicted carbon emissions of the ELM-based and ARIMA-based models have the maximum values in almost all provinces, while the predicted carbon emissions of the FRBS-based, BRBS-based, ANN-based, and ANFIS-based models are smaller than those of the ELM-based and ARIMA-based models but are larger than those of the CBRB-based model. Table 8 further confirms that the superiority of the CBRB-based model, which has maximum average efficiency and minimum average changing ratio. More importantly, from the results of the CBRB-based model, there are 22 provinces being negative changing ratio, 8 provinces being effective efficiency, minimum mean and standard deviation under 95% confidence intervals for the parameters estimation, which are significantly better than other existing models. All in all, it can be concluded from the comparative results that the CBRB-based model makes it easier for carbon emission prediction to take into account efficiency improvement and environmental regulation.

4.5 Policy implications

On the basis of carbon emission trend forecast for 30 Chinese provinces using the proposed data-driven rule-base model, the following policy suggestions are made for better carbon emission management:

(1) All provinces should prioritize investing in scientific forecasts to achieve the maximum benefits of carbon emission

reduction. This includes establishing an integrated regulatory system for the fine-grained, digitized, and standardized carbon emission management. It is advisable to prioritize digital and information-based monitoring in provinces with significant emission reduction potential. Moreover, industrial structure upgrading is encouraged through the development of new energy technologies and low-carbon industrial technologies.

(2) The management efficiency of carbon emissions is an important aspect of corporate performance regarding carbon emission reduction. For the provinces with inefficient input-output structures, they should optimize the energy and industry structure through adjusting and promoting regional autonomous technological innovation for carbon emission reduction. For the provinces with relatively reasonable input-output structures, they should maximize benefits by improving environmental protection policies and ensuring the rational utilization of emission reduction resources.

(3) The intensity of environmental regulation has a slight influence on carbon emissions, indicating that policy decisions must be made according to specific province development situation. It is not advisable to blindly increase direct environmental costs in response to environmental regulations. The steadily environmental regulatory standards should involve strengthening cleaner innovative production activities, formulating technology innovation strategies, nurturing green technology researchers, and ensuring synchrony between economic development and environmental regulatory implementation.

5. Conclusions

Forecasting carbon emissions is crucial for investigating greenhouse effect and environmental sustainable development. Focusing on this hot topic and providing a more intuitional view on future carbon emission management, this study proposed a new carbon emission trend forecast model, which not only depends on the changing rates of carbon emissions to construct a data-driven rule-base, but also embeds both environmental regulation and management efficiency into the rule-base, thereby presenting an innovative framework for carbon emission trend forecast. The main conclusions are as follows:

(1) The environmental regulation was considered to design a data-driven rule-base model in the aim of carbon emission trend forecast. Owing to this, the overall carbon emissions predicted by the proposed model have smaller trends. This suggests that the intensity coefficient of environmental regulation can have a visible influence on carbon emission control. Thus, the implementation effect of the current environmental regulation intensity needs to be considered when implementing carbon emission reduction policies for carbon emission management.

(2) The efficiency improvement was further considered to improve the carbon emission trend forecast model. As a result, the predicted carbon emissions were much lower than real values, which demonstrated that the efficiency improvement can effectively reduce carbon emissions and improve the effect of carbon emission management. Considering that the carbon emission forecast under efficiency improvement aligns with the expected objectives of policymakers, the proposed model can provide an effective reference for actual carbon emission management.

(3) The representative data-driven rule-base approach, named CBRBS, was used as the basis of the carbon emission trend forecast model and it exhibited a high superiority better than some existing statistical models and AI-based models when forecasting the carbon emissions of 30 Chinese provinces. Hence, the proposed carbon emission trend forecast model can serve as an effective tool for the implementation of long-term carbon emission reduction planning and improve the utilization of resources related to carbon reduction.

This study still has several shortcomings needed to be improved in future researches. Firstly, due to the limitations of data collection, this study only investigated the carbon emission forecast in the context of Chinese provinces. Future studies could investigate carbon emission forecast at city level and/or other countries. Secondly, this study provided comprehensive results and discussion regarding carbon emission trend forecast. However, applying carbon emission forecast to display the staircase pathway of carbon peaking is the final goal for the government sectors. Hence, it is valuable for future researches to study the forecast of carbon peaking using the proposed data-driven rule-base model with scenario analysis. Finally, the selection of indicators in this study only applied some commonly used indicators, *e.g.*, GDP, electricity consumption, and coal consumption. However, there are significant differences in selecting indicators for different stakeholders, *e.g.*, government and enterprises, more relevant indicators under the requirement of the stakeholders still need to be further investigated.

Acknowledgements

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