Analysis on the investment efficiency of industrial pollution control based on Markov and DEA model

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Abstract. Taking the investment amount of industrial "three wastes" pollution control in 2000-2016 as an input indicator, the investment amount predicted by the grey residual GM (1, 1) Markov model is compared with the actual value in 2014-2016 to verify the feasibility and accuracy of the model. Sulphur dioxide removal, smoke (powder) dust removal, industrial wastewater discharge standards and solid waste comprehensive utilization are used as output indicators. The DEA-BCC model is used to calculate the input efficiency of industrial pollution control from 2000 to 2016, and the main factors restricting the effect of pollution control are analyzed, and the forecast model is used to provide basis for improving the input efficiency. The results show that the average comprehensive efficiency of industrial pollution control input from 2000 to 2016 was 0.887. Overall, the comprehensive efficiency is relatively low. The fluctuation of input efficiency fluctuated greatly and is not stable enough. There are only 6 years in DEA effective state. The unstable investment scale, the lack of rational allocation of resources, the shortage of talents and governance technologies and the low level of supervision are the key factors affecting the efficiency of industrial pollution treatment.

1. Introduction
Since the reform and opening up, extensive economic development mode and the reason of poor environmental protection consciousness, a large amount of wastes are generated and serious environmental pollution is caused. The contradiction between economic development and environmental protection became apparent. As our country enters the new normal of economy, environmental issues are getting more and more attention in macro situations such as slowing economic growth, continuous optimization of economic structure, and driving to innovation driven development. In recent years, the state has increased investment intensity in environmental governance and investment in industrial sources has increased year by year, but the efficiency of industrial pollution control has been low. Therefore, it is of great significance to improve the efficiency of industrial pollution control, to improve pollution control measures, to ease the contradiction between resource environment and economic development, and to realize the transformation of China's economy into an intensive economy.

International scholars have put forward that environmental protection has a great positive effect on economic development. Such as economist Grossman and Krueger (1995) proposed the Environmental Kuznets Curve (EKC), think environmental quality degradation as per capita income
increased at first, when the per capita income rose to a certain range, and with the increase of per capita income and environmental quality improved [1]. Brock and Scott (2004) introduced the pollution factor and environmental quality into the endogenous growth model, and found that the growth of green investment could not only improve environmental quality but also promote sustainable economic development [2]. Sk Mandal (2010) and so on analyzed the impact of carbon dioxide emissions from industrial pollution on environmental benefits, using DEA model and the directional distance function (DDF) to analyze the relationship between beneficial output and harmful output in environmental benefits [3].

Domestic scholars choose different input-output indicators to construct the evaluation index system of environmental governance investment efficiency, and to analyze the problem of low efficiency of environmental governance investment. Yin Yicheng and Liu Yunguo (2015) use data envelopment analysis (DEA) [6] model to decompose the comprehensive technical efficiency of pollution control into pure technical efficiency and scale efficiency, analyzing the restrictive factors influencing the pollution control effect, the results show that the annual average comprehensive technical efficiency, pure technical efficiency and scale efficiency of industrial wastewater treatment are the highest, followed by waste gas, solid waste is the lowest, showing obvious imbalance [5]. Nie Hualin and Chen Shaoqian (2010) calculated the static efficiency and inter-period dynamic efficiency of industrial pollution control in 11 western provinces (autonomous regions and municipalities directly under the central government) from 2001 to 2008 by DEA method and Malmquist productivity index [6]. Yuan Huaping (2016) through the construction of DEA - CCR model, the investment efficiency of industrial pollution control in various regions of China from 2005 to 2010 was analyzed by DEA window. The results show that there are still ‘high investment, low efficiency’ other problems in most regions of China's industrial pollution control investment, and the regional differences in investment efficiency are expanding [7].

The innovation of this paper is to combine the annual investment of industrial pollution control predicted by the grey residual GM (1, 1) Markov model [8-9] with DEA - BCC [10] model to optimize the investment efficiency. The method has the advantages that firstly, the annual investment amount in the short term in the future can be predicted accurately, and then the reasons of low comprehensive efficiency of investment are analyzed through the DEA - BCC model to facilitate the rational allocation of these investments, so that the efficiency of resource use is increased, the relevant government departments are helped to better use the investment funds for pollution control, and the effect of pollution control is improved.

2. Construction of the predictive model
Grey Model recorded as GM. The solution of the differential equation is obtained by generating a series of sequences using the original data. The original grey model is the GM (1, 1), which is a one-order variable model. The modeling process of GM (1, 1) is as follows:

Set the original non-minus number as $X^{(0)}=\{x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\}$; $X^{(1)}$ is an additive sequence of $X^{(0)}$ (recorded as1-AGO) [9], $X^{(1)}=\{x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)\}$, $x^{(1)}(i) = \sum_{j=1}^{k} x^{(0)}(i-j)$, $k = 2, 3, ..., n$; $i=1, 2, ..., n$.

$Z^{(1)}$ is adjacent to the mean sequence, $Z^{(1)}=\{z^{(1)}(1), z^{(1)}(2), ..., z^{(1)}(n)\}$, $Z^{(0)}=0.5(x^{(1)}(k)+x^{(1)}(k-1))$, $k=2,3, ..., n$. The first order differential equation of GM (1, 1) is performed on the accumulated data.

The corresponding whitening differential equation is

$$dx^{(1)}(t)/dt+ax^{(1)}(t)=b$$

The ‘a’ is called the development grey number, reflects the growth rate of $X^{(0)}$ sequence; The ‘b’ is called the endogenous control grey number, reflecting the relationship between the data. Result $x^{(1)}(t)$ (It also called the time response function) is

$$(x^{(0)}(1)-b/a)*e^{-at}+ b/a$$

The least square method can be used to calculate the grey parameters (T represents the transpose matrix, the same below):

$$[a, b]^T=(B^TB)^{-1}B^TY$$
The result \( X(1)(k+1) \) is
\[
Y = [x(0)(2), x(0)(3), ..., x(0)(n)]^T \tag{5}
\]
The GM (1, 1) is
\[
X(0)(k+1) = X(1)(k+1) - X(1)(k) = (1-e^{ak})(x(0)(1)-b/a)e^{-ak}, k = 1, 2, ..., n \tag{6}
\]

2.1. Construction of grey residual GM (1, 1) Markov model

If only the grey GM (1, 1) model \( X(0)(k+1) \) is used may result in insufficient prediction accuracy, so the model needs to be corrected. The residual GM (1, 1) model is constructed according to the residual between the predicted value and the actual value of GM (1, 1) model. The derivation process is the same as the grey GM(1,1) model: if \( Q(0)1={Q(0)1(2),Q(0)1(3),...,Q(0)1(n)} \), the residual GM(1,1) model \( Q(0)(k+1) \) can be obtained, and the grey residual GM(1,1) model \( X(0)(k+1) \) with higher prediction accuracy can be obtained by combining the two models.

\[
Q(0)(k+1)=Q(1)(k+1)-Q(1)(k) = (1-e^{ak})(Q(0)(1)-b/a)e^{-ak}, k = 2, 3, ..., n \tag{7}
\]
\[
X(0)(k+1)=X(0)(k+1)±Q(0)(k+1)=(1-e^{ak})(x(0)(1)-b/a)e^{-ak}±(1-e^{ak})(Q(0)(1)-b/a)e^{-ak} \tag{8}
\]

\( k = 2, 3, ..., n \). And the ‘±’ for each residual correction value should be the same as the symbol number of the corresponding value in \( Q(0)1 \).

The grey predictive model is mainly used for predicting problems with short time and low volatility, but it has poor fitting degree to data with large random volatility. Markov prediction is a stochastic process with Markov property (It's also called Non-Hysteresis). The Markov feature description process is as follows: \( T_k \) as the present moment, so \( T_1, T_2, ..., T_{k-1} \) is the past moment, and \( T_{k+1} \) represents the future. That is, under the condition that the past moments \( X(T_1) = x_1,...,X(T_{k-1}) = x_{k-1} \), and the present moment \( X(T_k)=x_k \), the Process state probabilistic property at the time greater than \( T_k \) is related to the state at \( T_k \) has nothing to do with the Process status before \( T_k \) moment. In other words, under the condition of known "present", "future" and "past" are independent of each other \textsuperscript{[9]}. Therefore, combining the GM (1, 1) prediction with Markov prediction can improve the prediction accuracy of the random fluctuation data.

The prediction process is based on the transfer probability between states to predict the future development of the system, which can reflect the degree of influence of random factors and be suitable for the prediction of stochastic volatility. This paper improves on the basis of the grey GM (1, 1) model to obtain the grey residual GM (1, 1) Markov model, which can further improve the prediction accuracy. The build process is as follows:

1. State division. State 1 is a positive sign for the residual and state 2 is a negative sign for the residual.
2. Determine the state transfer matrix. The solution of state transfer probability matrix is as follows:

\[
P_{ij}=N_{ij}(x)/N \tag{10}
\]
\[
P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}
\]  
(11)

(3). Determine the initial state vector. \( S_0 = [S_{01}, S_{02}] \), \( S_{01} \) represents the probability of initial state 1, and \( S_{02} \) represents the probability of initial state 2.

(4). Solving k-phase state transfer probability.

\[ S_k = S_0^* P^k \]  
\( k = 1, 2, ..., n \). Take the maximum probability state for each \( S_k \) period.

(5). The predictive model is obtained. The probability state \( S_k \) is determined, then the corresponding residual value symbol is taken. The grey residual GM (1,1) Markov model \( X^{00}(k+1) \) can be obtained.

3. Case analysis

In this paper, the total investment data of industrial pollution control from 2000 to 2016 (compiled from the China Statistical Yearbook) are calculated by MATLAB R2014. The grey GM (1, 1) model is constructed based on the data from 2000 to 2013, and predicted value from 2014 to 2016 is obtained. It is found that the accuracy is not high enough compared with the actual value. After modifying the model, the grey residual GM (1, 1) Markov model is obtained, and the more accurate industrial pollution control investment value from 2014 to 2016 can be obtained. The unit of investment in this section is ‘billion Yuan’.

3.1. Parameter solution of the model

The grey prediction GM (1, 1) model is obtained by modeling the data from 2000 to 2016 and equations (4), (5), (6) and (7) as follows,

\[ X^{00}(k+1) = (1 - e^{-0.0768}) (342.2693) e^{0.0768 k} = 25.3022 e^{0.0768 k}, \]  
\( k = 1, 2, ..., n \).  
(13)

Grey parameter matrix \([a, b]^T = [-0.0768, 24.4831]^T\). Thus, the predicted values from 2014 to 2016 can be obtained. As shown in table 1, the average accuracy of the last three years data predicted by using the grey GM (1, 1) model is less than 90 %, so it is necessary to construct the grey residual GM (1,1) Markov model.

Table 1. Actual value and grey GM (1, 1) predictive value error table.

| Year | Actual value | Predictive value | Relative error | Average error |
|------|--------------|------------------|---------------|--------------|
| 2014 | 99.7651      | 74.1502          | 25.68%        |              |
| 2015 | 77.3682      | 80.0693          | -3.49%        | 11.58%       |
| 2016 | 81.9004      | 86.461           | -5.57%        |              |

Through the data in table 2 and equation (8) residual value prediction model is obtained as follows:

\[ Q^{00}(k+1) = 1.7550 e^{-0.0024 k} \]  
\( k = 2, 3, ..., n \)  
(14)

Finally, the grey residual GM (1, 1) Markov model is obtained by equation (9),

\[ X^{00}(k+1) = 36.1313 e^{-0.0679 k} + 1.7550 e^{-0.0024 k} \]  
\( k = 2, 3, ..., n \)  
(15)

The grey parameter of the residual sequence is \([aQ, bQ]^T = [-0.0024, 1.7697]^T\). The ‘±’ of equation (15) needs to be determined by the state transition probability matrix hereinafter.

Table 2. Residual sequence table.

| Years | Residual | Q^{00} | Z_{0}^{r}\rangle |
|-------|----------|--------|------------------|
| 2000  | \      | \      | \                |
| 2001  | -9.8692  | 9.8692 | \                |
| 2002  | -10.6664 | 20.5356| 15.2024          |
| 2003  | -9.6753  | 30.211 | 25.3733          |
| 2004  | -3.5907  | 33.8016| 32.0063          |
| 2005  | 8.6717   | 42.4733| 38.1375          |
| 2006  | 8.2822   | 50.7555| 46.6144          |
\[ Q^{(3)} \] represents a cumulative sequence of residuals. \( Z^{(1)}_Q \) represents a sequence of mean values for adjacent two values.

### 3.2. Establishment of state transition probability matrix and revise predictive value

As can be seen from the residual values in table 2 from 2000 to 2013, the residual values appear positive signs 5 times and negative signs 8 times. One step from positive sign transfer to positive sign appeared 3 times, from positive sign one step transfer to minus sign appeared 1 times. From minus sign one step transfer to plus sign appeared 6 times, minus sign one step transfer to minus sign appeared 2 times. Accord to that ergodicity principle of Markov chain, two states of Markov of residual values can be reached and aperiodic, so the chain is irreducible ergodic Markov chain [9]. The probability of state transition can be derive from equation (11) as

\[
P = \begin{bmatrix} \frac{3}{4}, & \frac{1}{4} \\ \frac{3}{4}, & \frac{1}{4} \end{bmatrix}
\]

The last year of data that was simulated was a positive sign in 2013, so the initial state vector is \( S_0 = [1, 0] \). Through the formula (12), the residual state vectors of 2014 - 2016 can be obtained as follows:

\[
S_1 = \begin{bmatrix} \frac{3}{4}, & \frac{1}{4} \end{bmatrix}, \quad S_2 = \begin{bmatrix} \frac{3}{4}, & \frac{1}{4} \end{bmatrix}, \quad S_3 = \begin{bmatrix} \frac{3}{4}, & \frac{1}{4} \end{bmatrix}
\]

Table 3. Comparison of relative errors between predicted values of two models.

| Year | Actual value | GM(1,1) predicted value | Relative error | Residual analog value | Final predicted value | Corrected relative error |
|------|--------------|-------------------------|----------------|----------------------|-----------------------|-------------------------|
| 2014 | 99.7651      | 74.1502                 | 25.68%         | 17.3317              | 91.4819               | 8.30%                   |
| 2015 | 77.3682      | 80.0693                 | -3.49%         | 18.6368              | 80.0693               | -3.49%                  |
| 2016 | 81.9004      | 86.461                  | -5.57%         | 20.0401              | 86.461                | -5.57%                  |

From table 3, it can be seen that the investment predicted by a single GM (1, 1) model has a large relative error in 2014 and a small relative error in the next two years, so only the predicted value in 2014 needs to be corrected. \( S_1 = \begin{bmatrix} 3/4, & 1/4 \end{bmatrix} \), the 2014 residual value sign is positive. After the revision, the average accuracy of the forecast values from 2014 to 2016 increase to 94.2126%.

Figure 1. Industrial pollution control investment actual value and predicted value.

Figure 1 shows that the grey GM (1, 1) model shows the long-term increasing trend of industrial pollution control investment, but does not highlight the specific fluctuations. However, the grey
residual GM (1, 1) Markov prediction model not only accurately shows the long-term increasing trend, but also the specific fluctuations are consistent, and the accuracy is much higher than the single grey GM (1, 1) model. The results show that fitting degree of the grey residual GM (1, 1) Markov prediction model is higher, and the effect is better.

High precision industrial pollution control input prediction value can provide a good scientific basis and theoretical basis for the relevant government departments to improve the rational allocation of industrial pollution control investment resources and use efficiency in the future. It can be combined with the DEA model below, for example, when it was found that the governance investment in previous years was insufficient or redundant, it could increase or reduce the investment in specific amounts of funds and equipment in future years according to the predicted value, so as to increase the scale efficiency and achieve better investment results.

4. DEA - BCC model
DEA model can effectively evaluate the investment efficiency of industrial pollution control by determining reasonable input and output terms, and does not need specific functional relationship. In this paper, the DEA-BCC model is used to calculate the comprehensive technical efficiency (Crste), pure technical efficiency (Vrste) and scale efficiency (Scale). Wherein the comprehensive technical efficiency is equal to the product of pure technical efficiency and scale efficiency. Crste is the comprehensive measurement and evaluation of the decision-making unit's resource allocation ability and resource utilization efficiency. Vrste refers to whether input can be effectively used to maximize output or minimize input, which is influenced by production technology level, management level and institutional constraints. Scale efficiency represents whether the proportion of input-output is appropriate, the higher the value represents the more appropriate proportion of scale$^4$.

4.1. Evaluation index system construction and data selection
Following the principles of scientific data and availability, this paper constructs the evaluation index system of industrial pollution control investment efficiency as shown in table 3. According to the annual China Statistical Yearbook, the data values of the indicators for the year 2000 - 2016 are obtained. Due to the lack of data on the total amount of industrial waste gas removal from 2011 to 2016, the investment efficiency of the national treatment of industrial waste gas in these years is not analyzed and evaluated.

| NO | Input index         | Unit        | NO | Output index                 | Unit          |
|----|---------------------|-------------|----|-----------------------------|---------------|
| 1  | Industrial wastewater treatment investment | ten thousand Yuan | 1  | Industrial standard wastewater discharge | ten thousand tons |
| 2  | Investment in treatment of industrial solid waste | ten thousand Yuan | 2  | Investment in treatment of industrial solid waste | ten thousand tons |
| 3  | Investment in industrial waste gas control | ten thousand Yuan | 3  | Total amount of industrial sulphur dioxide and smoke (powder) dust removal | ten thousand tons |

Table 4. National industrial pollution control investment efficiency evaluation index.

| Firm | Crste | Vrste | Scale | Scale revenue | Slack variable |
|------|-------|-------|-------|---------------|----------------|
| 1    | 0.998 | 1     | 0.998 | Irs           | 0              |
| 2    | 1     | 1     | 1     | -             | 0              |
| 3    | 1     | 1     | 1     | -             | 0              |
| 4    | 0.972 | 0.972 | 1     | -             | not 0          |
| 5    | 0.819 | 0.9   | 0.91  | Drs           | not 0          |
| 6    | 0.698 | 0.922 | 0.757 | Drs           | not 0          |

Table 5. National industrial pollution control investment efficiency.
Table 5 is compiled from the evaluation index data through the DEAP 2.1. Firm 1 - 11 indicates the investment efficiency of industrial “three wastes” pollution control from 2000 to 2011, and Firm 12 - 17 indicates the investment efficiency of industrial “two wastes” pollution control after removing various indexes of industrial waste gas control from 2012 to 2016. The Irs represents increasing returns to scale; Drs represents diminishing returns on scale; The ‘-‘represents scale income unchanged. Slack variable represents the slack variable and mean represents the average of the efficiencies.

4.2. Results analysis
The criterion for judging whether DEA is effective is that if only the comprehensive efficiency value is 1, the decision-making unit is weak DEA effective; If the comprehensive efficiency value is 1 and the slack variable is 0, the decision unit is DEA efficient; Otherwise, if the comprehensive efficiency value is less than 1, the DEA is invalid [11].

From the data calculated in table 4, it can be seen that the average comprehensive efficiency of the 17 years from 2000 to 2016 is 0.887, and the overall comprehensive efficiency is relatively low. Among them, there are 6 years where Crste is 1 and the slack variable is equal to 0, which are 2001, 2002, 2010, 2013, 2014 and 2016, indicating that the input-output of industrial pollution control in these 6 years is DEA effective state. The results show that the existing technology is fully used to improve the efficiency of industrial pollution control in these six years, and the investment scale is appropriate, and there are no problems such as redundant investment and insufficient output. In the remaining 11 years, the comprehensive efficiency values are all less than 1, and their industrial pollution control input and output are in a DEA ineffective state. In these 11 years, the integrated efficiency value reached 0.85 or above only in 2000, 2003, and 2015. It can be seen that the industrial pollution control input-output efficiency has been general since 2000.

In these 17 years, the year when the scale efficiency was less than 0.900 was only 2005, with a value of 0.757. The average scale efficiency of 17 years is 0.976, Relatively speaking, the scale efficiency is still relatively high, but it is still slightly insufficient; Since 2000, the average technical efficiency of is 0.908, which does not meet expectations, indicating that the overall management experience and technology utilization and other aspects are the shortcomings. It can be seen that the main reason for the low input-output efficiency of industrial pollution control comes from comprehensive technical efficiency, pure technical efficiency and scale efficiency in turn. Therefore, based on the efficiency of these three aspects, the corresponding effective measures can be taken to improve the input-output efficiency of the overall industrial pollution control.

5. Conclusion
To realize the healthy and sustainable development of the environment, it is necessary to optimize the efficiency of industrial pollution control and broaden the way of environmental protection. The paper draws the following conclusions and recommendations from the input and output data of industrial
pollution control from 2000 to 2016, combined with the grey residual GM (1, 1) Markov and DEA-BCC model.

(1). Industrial pollution control resource allocation capacity is insufficient and use efficiency is low. This may be due to factors such as inadequate strategic planning, inadequate institutional guarantees, weak foundations, etc. No strict industrial pollution control investment approval procedures have been established to ensure the appropriate allocation and use of relevant governance resources. Therefore, through the improvement of relevant industrial pollution investment strategic planning and systems, and through the use of predictive values of industrial pollution investment to rationally allocate the use of related governance resources, it is possible to increase the overall technical efficiency of industrial pollution control investment and ensure that the comprehensive technical efficiency is in an effective state.

(2). The investment scale of industrial pollution control is not stable. It may be related to the government's insufficient attention to industrial pollution treatment and the lack of investment awareness. The investment intensity of industrial pollution control and its effect are easily affected by all kinds of external factors. Unstable investment scale cannot achieve higher returns on scale and reduce investment efficiency. Therefore, increasing the government's emphasis on industrial pollution control and financial input and increasing the scale of investment can make up for the lack of scale efficiency and ensure the stability of scale revenue.

(3). The technical ability of industrial pollution control is not high. Due to the lack of funds, the pollution control facilities in some enterprises are backward, the technical content is low, and the treatment effect is poor. It also leads to a lack of high-level professionals and low level of scientific research. The management facilities and process quality lack high-level technical guidance in design, research, development, manufacturing, management, etc. It is difficult to meet the national standards, and the effect of pollution treatment is often lower than it should be. Therefore, we should focus on scientific and technological innovation and the development of related technology research and development, management, marketing and other senior professionals, provide technical and personnel support for enterprises to improve pollution control capabilities, and promote the transformation and practical application of relevant scientific research results. Thus, the deficiency of pure technical efficiency is improved.

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