frontiers | Frontiers in Energy Research

TYPE Original Research
PUBLISHED 23 September 2025
DOI 10.3389/fenrg.2025.1611945

OPEN ACCESS

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RECEIVED 15 April 2025
ACCEPTED 02 September 2025
PUBLISHED 23 September 2025

CITATION
Sun Y and Wang H (2025) A collaborative analysis based on multi-objective programming method for energy consumption reduction and governance investment.
Front. Energy Res. 13:1611945.
doi: 10.3389/fenrg.2025.1611945

A collaborative analysis based on multi-objective programming method for energy consumption reduction and governance investment

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This paper delves into how to collaboratively reduce emissions of sulfur dioxide, nitrogen oxides, and carbon dioxide through rational energy consumption and governance investment strategies with limited funds. The main research contents include: employing the Granger causality test to analyze the causal relationship between air quality and pollutant emissions; using functional analysis to determine the quantitative relationship between energy consumption and the emissions of various pollutants; applying multi-objective programming method to establish an integrated model for collaborative emission reduction optimization that considers both energy consumption and governance investment, and analyzing the optimality conditions of the model; and conducting an empirical analysis of the model using Tianjin's social development data from 2005 to 2021. The optimal carbon dioxide emissions calculated by the model are significantly lower than the actual emissions, with an average optimization efficiency of 38.43%. Through reasonable energy allocation and governance investment strategies, it is possible to effectively reduce pollutant emissions while ensuring production demands. The research results of this paper provide a theoretical basis and practical guidance for formulating rational energy use and governance investment strategies.

KEYWORDS

energy consumption, governance investment, collaborative emission reduction, multi-objective programming method, optimization model

1 Introduction

In most cities, the air quality primarily depends on the levels of air pollutant concentrations. As an industrial country, the development of Chinese cities largely relies on energy-intensive secondary industries. This development pattern, while driving rapid economic growth, has also led to the massive amount of pollutant emission into the air. In particular, exhaust gases emitted from fossil fuel combustion, which cannot disperse efficiently in urban areas, pose a significant threat to air quality. To evaluate air environmental quality, China has successively implemented the Air Pollution Index (API) and the Air Quality Index (AQI). According to the calculation criteria of these two indices, sulfur dioxide (SO_2) and nitrogen oxides (NO_x) are recognized as key determinants of air quality.

Since the signing of the Kyoto Protocol, China has prioritized the reduction of green-house gases such as carbon dioxide (CO_2) in government work. In recent years, fine particulate matter (PM2.5) has increasingly garnered attention, with its harmful substances mainly originating from human activities such as energy combustion, power generation, metallurgy, petroleum, and chemical engineering. According to recent research by the Chinese Academy of Sciences (Huang et al., 2014), when considering coal burning, industrial pollution, and secondary inorganic aerosols together, emissions from fossil fuel combustion have become the primary source of PM2.5 pollution in Beijing. Furthermore, PM2.5 can also be converted from sulfur and nitrogen oxides, which are largely produced when humans burn fossil fuels (such as coal and oil) and waste.

It is evident that these severe environmental issues primarily stem from the combustion of fossil fuels to meet the demands of human social development and ensure people's living. Although people have fully recognized the severity of the problem and have actively explored and practiced various approaches, including improving combustion technology, developing new energy sources, adjusting lifestyles, and restructuring industries, it cannot be denied that fossil fuels remain the primary energy support for China's current social development. However, fossil fuels are diverse in types and vary in usage ways. Under different usage conditions, different types of energy produce varying amounts of pollutants, but there are also certain correlations among them.

Since sulfur dioxide (SO_2) in the atmosphere mainly originates from the combustion of sulfur-containing fuels such as coal and oil, with more than 90% of SO_2 emissions in China contributed by coal-fired activities (Sun, 2003). Since the 1980s, China has focused on con-trolling SO_2 emissions through various technical measures, including optimizing the coal structure, increasing the use of cleaned coal, adopting clean combustion technologies, and encouraging key emitting sectors to install flue gas desulfurization facilities. At the economic management level, measures such as shutting down small thermal power units, formulating strict emission standards for coal-fired power plants, and implementing total emission control have been adopted. Nitrogen oxides (NO_x) play a crucial role in the formation of photochemical smog and are also a major factor driving the transition of acid rain types from sulfuric acid to nitric acid in China. This is partly attributed to the late start of NO_x control efforts in China, leading to a rapid increase in nitrogen dioxide (NO_2) emissions during the "11th Five-year Plan" period. In the national "12th Five-year Plan", NO_x following SO_2 was listed as another important air pollutant subject to total emission control. Currently, China's NO_x prevention and control strategies encompass promoting low-NO_x combustion technologies, flue gas denitrification technologies, and implementing production capacity control, and so on. Furthermore, both SO_2 and NO_x are considered precursors of PM2.5. Therefore, their collaborative emission reduction holds far-reaching significance for preventing haze weather and effectively controlling PM2.5 concentrations.

Carbon dioxide (CO_2), recognized globally as a greenhouse gas, has become a top priority for governments in their efforts to mitigate climate change since the issue of global warming has become increasingly prominent. According to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), CO_2 is the most critical anthropogenic greenhouse gas, and the continuous rise of global CO_2 concentrations is mainly attributed to the extensive use of fossil fuels (IPCC, 2007). Statistical data from the International Energy Agency (IEA) also show that China's total carbon emissions surpassed those of the United States in 2007, becoming the largest contributor to global carbon emissions. In 2016, China accounted for 19.12% of the world's total carbon dioxide emissions (Quire et al., 2015). At the 2015 World Climate Conference, China submitted its nationally determined contribution report to committing to reduce carbon intensity by 60%–65% below 2005 levels by 2030. This will accelerate China's green and low-carbon transition and provide a foundation for achieving the global temperature rise control target of 2 °C. China's target of cutting carbon dioxide emissions per unit of GDP by 40%–45% from 2005 levels by 2020 was achieved ahead of schedule in 2019.

All three aforementioned gases originate from the combustion of fossil fuels. However, given the current technological limitations that prevent a complete substitution of fossil fuels, they will continue to be an important part of China's energy structure in the near future. The primary fossil fuels used in China include coal, oil, and natural gas. Although all three produce these pollutants when burned, due to differences in combustion mechanisms, there are significant variations in the emissions of these gases for the same energy output. For instance, coal, with its higher sulfur content, produces much more sulfur dioxide (SO_2) when burned compared to oil and natural gas. Oil combustion, on the other hand, generates significantly more nitrogen oxides (NO_x) than the other two fuels. Natural gas is considered a clean energy source, but its combustion produces more carbon dioxide (CO_2) than coal and oil. Additionally, different energy usage ways can also influence the proportion of gas emissions. For example, in the industrial sector, due to relatively advanced desulfurization and denitrification technologies for waste gases, the production of sulfur dioxide from coal combustion is relatively low. However, when oil is used, the higher temperatures result in higher nitrogen oxides emissions compared to other sectors.

Given these differences in energy types and usage ways, the topic of collaborative emission reduction studied in this paper focuses on how to rationally optimize the reasonable arrangement of different energies across various sectors, ensuring that production demands are met while minimizing energy consumption as much as possible. Currently, the issue of collaborative emission reduction has garnered considerable attention from some scholars. For example, Bollen et al. (2009) conducted an in-depth analysis of the co-benefits of collaborative governance for air pollution and global warming from an economic perspective. Rafaj et al. (2013) compared changes in emissions of atmospheric pollutants such as sulfur dioxide (SO_2) and nitrogen oxides (NO_x) before and after the implementation of global greenhouse gas control agreements. Their research results indicated that policy measures aimed at controlling greenhouse gas emissions have a positive impact on reducing emissions of atmospheric pollutants. Gu et al. (2016) selected three important industries in China, namely electric power, steel and cement, to analyze and calculate the SO2 emission reduction effect in the first 2 years of "11th Five-Year Plan" and "12th Five-Year Plan", as well as the synergistic effect of CO_2 emission reduction. Zhang et al. (2018) established a quantitative model for the effectiveness of energy conservation and emission reduction policies, and explored the differences in the impact of energy conservation and emission reduction policies on their effects in Beijing-Tianjin-Hebei. Wang et al. (2019) constructed an intergovernmental emission reduction evolution model to simulate the evolution process of strategy selection of independent emission reduction and cooperative emission reduction by local governments in the region, and then put forward relevant policy suggestions for improving the relationship of regional cooperation on emission reduction. Gao et al. (2021) constructed a synergistic effect evaluation method for pollutant control and greenhouse gas emission reduction, and evaluated the synergistic effect of greenhouse gas emission reduction caused by pollution control effects produced by energy structure adjustment and industrial structure adjustment in China from 2013 to 2017. Li et al. (2022) developed an evaluation model for coordinated control of PM2.5 and O3 in the Beijing-Tianjin-Hebei region, and identified the optimal project for NO_x and VOCs co-reduction that minimizes abatement costs under different air quality targets. Zhao et al. (2023) used multi-period double difference to analyze and evaluate the synergistic effect and influence mechanism of China's low-carbon city policies on CO_2 emission reduction and PM2.5 pollution control at the urban scale from 2007 to 2019.

However, most of these studies have approached the issue from an economic or technical perspective, failing to delve into the rational allocation of energy and its corresponding emission reduction benefits based on the pollution-generating characteristics of different energy sources. This paper provides an in-depth analysis of collaborative emission reduction strategies for sulfur dioxide (SO_2), nitrogen oxides (NO_x), and carbon dioxide (CO_2) based on their shared characteristics. Furthermore, as people's awareness of environmental protection continues to rise and government governance efforts intensify, effective waste gas governance mechanisms have been widely established for major industrial pollution sources in China. The implementation of these emission reduction measures often requires government investment or government-guided private investment. Therefore, formulating optimal emission reduction strategies under limited funding has become a critical issue that needs to be addressed urgently. This paper aims to explore how to balance various pollutant emissions and energy usage projects for pollution control investment on the basis of emission reduction, in order to achieve the best results in collaborative emission reduction.

2 Methods and theories

This section elucidates the application of three mathematical methods. Firstly, the Granger causality test is mentioned, which aims to explore potential causal relationships between air quality and pollutant emissions. Secondly, functional analysis techniques are employed, focusing on revealing quantitative links between energy consumption and emissions of various pollutants. Lastly, the multi-objective optimization method is introduced, which is utilized to construct a comprehensive optimization model that considers both energy consumption and governance investment, with the goal of achieving collaborative emission reduction and further facilitating extended optimization.

2.1 Granger causality test model

The Granger causality test model, an analytical tool in the field of econometrics, was established by Granger (1969), a Nobel laureate in economics. Its kernel principle can be articulated as follows: when considering the historical data of variables X and Y comprehensively, if the prediction accuracy of variable Y is significantly improved compared to predictions based solely on Y's own historical data, it indicates that variable X provides additional explanatory power for the future changes of variable Y. Therefore, we can conclude that variable X is the Granger cause of variable Y. The key step of the Granger test involve constructing a specific model (Equation 1), where u_t represents a white noise sequence, p, q are lag orders, α_i, β_j $(i = 1, \cdots, p, j = 1, \cdots, q)$ are all coefficients of the regression model (Granger, 1969).

$$Y_t = \alpha + \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{j=1}^{q} \beta_j Y_{t-j} + u_t. \tag{1}$$

This paper will utilize the econometric software Eviews7 to verify the causal relationship between pollutant emissions and air quality by using the Granger causality test method.

2.2 Functional relation among energy consumption, pollutant gas emissions, and investment

In this paper, energy refers to fossil fuels, and energy consumption involves the combustion of fossil fuels, which emits carbon dioxide (CO_2) and various atmospheric pollutants into the atmosphere, mainly including sulfur dioxide (SO_2), nitrogen oxides (NO_x), smoke and dust, carbon monoxide, hydrocarbons, and so on.

2.2.1 Relation of fossil fuel combustion and sulfur dioxide (SO_2)

Both coal and oil contain a certain percentage of sulfur, with the sulfur content of coal in China generally ranging from 0.5% to 3%, and that of oil approximately between 0.06% and 0.8%. Under normal combustion condition, the sulfur contained in the fuel is oxidized into sulfur dioxide (SO_2). Referencing the scientific method for predicting pollutant emissions outlined in the "National 12th Five-year Plan Resource (Energy) and Environmental Economic Forecast Research Report of China" (hereinafter referred to as the "Report") (Ministry of Environmental Protection of China, 2011), this study subdivides the whole society into several sectors with energy consumption, based on which it derives a functional relationship between energy consumption and sulfur dioxide (SO_2) emission, specifically expressed in Equation 2.

$$E_{SO_2} = \sum_i \sum_j 2\alpha_j \beta_j (1 - \gamma_{1i}) x_{ij}, \tag{2}$$

where, x_{ij} represents the amount of the j-th type of energy consumed by the i-th sector, α_j represents the sulfur content corresponding to the j-th type of energy, β_j represents the conversion rate of sulfur in the j-th type of energy, and γ_{1i} represents the removal rate, i.e., the desulfurization efficiency, when the i-th sector consumes energy.

2.2.2 Relation of fossil fuel combustion and nitrogen oxides (NO_x)

The generation of sulfur oxide mainly originates from the sulfur content in fuels, which is relatively straightforward. In contrast, the production of nitrogen oxides (NO_x) involves more complex factors. According to the "Report", the primary sources of nitrogen oxides (NO_x) include the oxidation reaction of nitrogen molecules in the combustion-supporting air under high-temperature conditions and the partial oxidation process of nitrogen compounds contained in fuels during burning. The functional relationship between energy consumption and nitrogen oxides (NO_x) emissions is described by Equation 3, where x_{ij} is defined as above, η_{ij} represents the nitrogen oxides emission factor corresponding to the consumption of the j-th type of energy by the i-th sector, and γ_{2i} represents the removal rate, i.e., the denitrification efficiency, when the i-th sector consumes energy (Ministry of Environmental Protection of China, 2011).

$$E_{NO_x} = \sum_i \sum_j \eta_{ij}(1-\gamma_{2i})x_{ij}. \tag{3}$$

From a mathematical perspective, Equations 2, 3 can be equivalently expressed in logarithmic form as Equation 4 (Yue, 2003), where E represents the total pollutant emissions, X represents the total energy consumption, γ represents the removal rate of pollutants, α represents the constant term, and ε represents the random error.

$$\ln E = \alpha + \ln X + \ln(1-\gamma) + \varepsilon. \tag{4}$$

2.2.3 Relation of fossil fuel combustion and carbon dioxide (CO_2)

During the combustion process of fossil fuels, their core function is to convert the energy stored within them into thermal energy through the oxidation of carbon elements, while emitting large amount of carbon dioxide (CO_2) in the process. By referring to the calculation method provided in the "Report," we can establish a functional relationship between the carbon dioxide (CO_2) emissions generated from fuel combustion and its related factors, specifically expressed in Equation 5 (Ministry of Environmental Protection of China, 2011). In this equation, x_{ij} is defined as before, c_j represents the carbon emission factor for the j-th type of energy source as given by the Intergovernmental Panel on Climate Change (IPCC), and ω_j represents the combustion loss rate for the j-th type of energy source.

$$E_{CO_2} = \sum_i \sum_j 0.98 c_j \left(1-\omega_j\right) x_{ij}. \tag{5}$$

From the aforementioned formulas for sulfur dioxide (SO_2), nitrogen oxides (NO_x), and carbon dioxide (CO_2) emissions, we can observe that although the generation mechanisms of these three gases differ, their emissions are all predominantly influenced by the total social energy consumption. More specifically, there exists a positive and linear correlation between the emissions of these three pollutants and energy consumption.

2.2.4 Relation of governance investment and gas emissions

From the emission calculation formulas for various pollutants listed earlier, we can understand that in addition to carbon dioxide (CO_2), waste gases generated from energy combustion also contain harmful substances such as sulfur dioxide (SO_2) and nitrogen oxides (NO_x). These waste gases must undergo purification processes such as desulfurization and denitrification before being emitted into the atmospheric environment. The costs required to implement these purification measures are commonly referred to as governance investments. In Equations 2–4, the efficiency of waste gas governance, namely the removal rate of each pollutant, plays a decisive role in pollution emissions. It should increase along with greater governance investments. Meanwhile, ac-cording to the law of diminishing marginal returns in economics, as the amount of investment increases, the rate of improvement in the removal rate should gradually slow down. Therefore, the functional relationship between governance investment and removal rate should conform to Equation 6; (Xu, 1999).

$$\gamma = 1 + \frac{\tilde{\alpha}}{Y} + \varepsilon. \tag{6}$$

Where, γ represents the removal efficiency of the pollutant, Y represents the funds invested in treating the pollutant, $\tilde{\alpha}$ represents the coefficient to be determined, and ε represents the random error. Substituting (Equation 6) into (Equation 4), we obtain the following (Equation 7).

$$\ln E = \alpha + \ln X + \ln\left(\frac{\tilde{\alpha}}{Y}\right) + \varepsilon. \tag{7}$$

This results in a mathematical model (Equation 8) representing the relation among the pollutant emissions, energy consumption and governance investment.

$$E = \frac{CX}{Y}. \tag{8}$$

where C is a coefficient to be determined. This equation indicates that the total emission of pollutants has a positive linear relationship with energy consumption and a negative reciprocal relationship with governance investment, which aligns with theoretical expectations.

2.3 Multi-objective optimization model for collaborative emission reduction

The concept of multi-objective optimization was initially proposed by economist Pareto in 1927. Its core lies in exploring how to find a solution within a specific decision-making space that optimizes multiple objectives that need to be considered simultaneously. These objectives often exhibit characteristics of the absence of unified criteria or measurement units and contradictory (Yue 2003). The difficulty in unified criteria refers to the lack of a common evaluation scale or unit of measurement among the objectives, while contradictory implies that in most cases, it is challenging to find a solution that simultaneously optimizes all objectives. Koopmans, 1951 introduced the concept of Pareto efficient solutions for multi-objective optimization problems. Meanwhile, Kuhn and Tucker (1950) also discussed the sufficient and necessary conditions for the existence of optimal solutions in multi-objective optimization. Johnsen (1968) published the first monograph on multi-objective optimization. Following in-depth explorations by numerous scholars during the 1970s and 1980s, the basic theoretical framework of multi-objective optimization was established and gradually developed into an independent disciplinary field.

When solving multi-objective optimization problems, it is often necessary for decision-makers to provide information on the preference relationships among the various objectives in order to evaluate the merits and demerits of different solutions. Hwang and Masud (1979) classified the solution methods for multi-objective optimization problems into three categories based on the manner of expressing preference information: prior evaluation methods, concurrent evaluation methods, and posterior evaluation methods. In recent years, concurrent and posterior evaluation methods have received increasing attention due to their flexibility and practicality. Multi-objective optimization techniques have been widely applied to numerous practical problems such as chemical production process optimization, material manufacturing process improvement, and logistics network design, demonstrating their powerful practical value.

From the above analysis of the amount of emissions for the three types of gases, this article will subsequently delve into the issue of collaborative emission reduction under different energy consumption patterns. Dividing the entire society into M different sectors, and assuming that there are N types of energy sources available for selection, we define the decision variable $x = \left(x_{ij}\right), i = 1,\cdots,M, j = 1,\cdots,N$ as the amount of the j-th type of energy consumed by the i-th sector. Let $E_i(x), i = 1,2,3$ represent the amount of emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x), and carbon dioxide (CO_2), respectively. The objective function for the collaborative emission reduction problem is set to minimize the sum of these three emissions simultaneously, and can be expressed in the form (Equation 9) (Johnsen, 1968):

$$\min \quad E(x) = \left(E_1(x), E_2(x), E_3(x)\right) \quad . \tag{9}$$

Regarding the consumption variables, they need to meet the following requirements. Firstly, energy supply must satisfy the essential needs of social development. Let $\rho_j, j = 1,\cdots,N$ represent the converting coefficient of the j-th type of energy into standard energy, and $D_i, i = 1,2,\cdots,M$ represent the total amount of demand energy for the development of the i-th sector. The mathematical representation of the energy supply condition is as (Equation 10):

$$\sum_j \rho_j x_{ij} \geq D_i, i = 1,2,\cdots,M. \tag{10}$$

On the other hand, fossil fuels are exhaustible, and their supply is limited naturally. Furthermore, the current society's capabilities of energy exploitation are also subject to various constraints. Hence, it is necessary to consider the important factor of energy limitation in our model. Let $S_j, j = 1,2,\cdots,N$ represent the supply upper limit for the j-th type of energy. The mathematical representation of the energy constraint is shown as follows:

$$\sum_i x_{ij} \leq S_j, j = 1,2,\cdots,N. \tag{11}$$

Additionally, the consumption should be nonnegative, i.e. $x_{ij} \geq 0, i = 1,2,\cdots,M, j = 1,2,\cdots,N$.

Based on the above objective function and constraint conditions, the following multi-objective optimization model is obtained (Hwang, 1979):

$$\begin{aligned} &\min \quad E(x) = \left(E_1(x), E_2(x), E_3(x)\right) \\ &s.t. \begin{cases} \sum_j \rho_j x_{ij} \geq D_i, i = 1,2,\cdots,M, \\ \sum_i x_{ij} \leq S_j, j = 1,2,\cdots,N, \\ x_{ij} \geq 0, i = 1,2,\cdots,M, j = 1,2,\cdots,N. \end{cases} \end{aligned} \quad . \tag{12}$$

Herein, the decision variables x_{ij} $(i = 1,\cdots,M, j = 1,\cdots,N)$ represent the amount of the j-th type of energy consumed by the i-th sector, $E_i(x)\,(i = 1,2,3)$ denote the emission amount of sulfur dioxide (SO_2), nitrogen oxides (NO_x), and carbon dioxide (CO_2), respectively. The three inequalities are the constraints that the decision variables must satisfy.

2.4 Analysis of optimality conditions for the model

To facilitate the analysis of the mathematical properties of model (Equation 12), we first convert it into a standard form. Let $\rho = (\rho_1, \rho_2, \cdots, \rho_N)$ and E_i represent an $N \times M$ matrix (where the i-th row are entirely 1 and the rest are 0) and $= (D_1, \cdots, D_N, -S_1, \cdots, -S_M)$, respectively, and slack variable $x^d = \left(x_1^d, \cdots, x_{M+N}^d\right)$. The constraint matrix can be written as (Equation 13) (Xu, 1999):

$$A_{(M+N)\times MN} = \begin{pmatrix} A_1 \\ \vdots \\ A_p \\ \vdots \\ A_{M+N} \end{pmatrix} = \begin{pmatrix} -\rho & \cdots & 0 \\ \vdots & \ddots & 0 \\ 0 & \cdots & -\rho \\ E_1 & \cdots & E_N \end{pmatrix}. \tag{13}$$

Then, model (Equation 12) is equivalent to the following standard form (Xu, 1999):

$$\begin{aligned} &\min \quad E(x) = \left(\frac{C_1^T x}{Y_1}, \frac{C_2^T x}{Y_2}, \frac{C_3^T x}{Y_3}\right) \\ &s.t. \begin{cases} Ax - b + x^d = 0, \\ x_{ij} \geq 0, x_p^d \geq 0, i = 1,\cdots,M, j = 1,\cdots,N, p = 1,\cdots,M+N. \end{cases} \end{aligned} \tag{14}$$

Firstly, from Lemmas 3.1 and 3.2 in (Xu, 1999), the necessary conditions for the existence of Pareto efficient solutions for the optimization problem (Equation 14) are presented.

Theorem 1: If $\bar{x}$ is a weak Pareto efficient solution of model (Equation 14), then there exist nonnegative values of $\lambda = (\lambda_1, \lambda_2, \lambda_3)$, $v = (v_1, \cdots, v_{M+N})$ and $u = (u_1, \cdots, u_{M+N})$ such that (Xu, 1999)

$$(\lambda, v) \neq 0,. \tag{15}$$

$$\sum_{k=1}^{3} \frac{\lambda_k C_k'}{Y_k} + vA = 0, \tag{16}$$

$$u_{ij} x_{ij} = 0,\ v_p x_p^d = 0,\ i = 1,\cdots,M, j = 1,\cdots,N, p = 1,\cdots,M+N. \tag{17}$$

Based on this, we can obtain the sufficient conditions for the existence of Pareto efficient solutions for model (Equation 14).

Theorem 2: Assuming that $\overline{x} \in S$ (S denotes a feasible region) is given, and there exist nonnegative values of λ and v such that Equations 15–17 hold, then $\overline{x}$ must be a weak Pareto efficient solution of model (Equation 14). Furthermore, if $\lambda > 0$, then $\overline{x}$ must be a Pareto efficient solution.

By comparing the optimality conditions of model (Equation 14) with the Kuhn-Tucker (K-T) conditions of the single-objective constrained optimization problem, it can be observed that the optimality conditions for their Pareto efficient solutions can both be regarded as adding a non-negative weight, namely λ in the theorem, to multiple objectives, thereby transforming them into the optimality conditions for the solution of a single-objective optimization problem.

Therefore, we can assign w_1, w_2, w_3 as the weight of each pollutant, $E_1^{\max}, E_2^{\max}, E_3^{\max}$ and $E_1^{\min}, E_2^{\min}, E_3^{\min}$ as the maximum and minimum emission values of each pollutant, respectively. After normalizing the three objectives and summing them up with certain weights, the problem can be transformed into a single objective expressed by (Equation 18):

$$F(x) = w_1\left(\frac{E_1(x) - E_1^{\min}}{E_1^{\max} - E_1^{\min}}\right) + w_2\left(\frac{E_2(x) - E_2^{\min}}{E_2^{\max} - E_2^{\min}}\right) + w_3\left(\frac{E_3(x) - E_3^{\min}}{E_3^{\max} - E_3^{\min}}\right). \quad (18)$$

Then, the model (Equation 12) is transformed into the following model (Equation 19) (Hwang, 1979; Xu, 199):

$$\min \quad F(x)$$
$$s.t.\begin{cases} \sum_j \rho_j x_{ij} \geq D_i, i = 1, 2, \cdots, M, \\ \sum_i x_{ij} \leq S_j, j = 1, 2, \cdots, N, \\ x_{ij} \geq 0, i = 1, 2, \cdots, M, j = 1, 2, \cdots, N. \end{cases} \quad (19)$$

3 Empirical analysis based on data in tianjin from 2005 to 2021

Tianjin, a historic industrial city, has long been dominated by coal consumption in its energy structure, leading to significant atmospheric pollution issues, particularly three major air pollutants--SO_2, NO_x and CO_2. In this empirical section, we utilize data in Tianjin spanning from 2005 to 2021 to validate our model (Equation 19).

3.1 Empirical study on granger causality test

Figure 1 presents the trend diagram of sulfur dioxide (SO_2) emissions (in $10^7 kg$) (National Bureau of Statistics of China, 2024) and the annual average concentration of sulfur dioxide (SO_2) in the air (in mg/m^3) (NBS, 2005–2021) in Tianjin from 2005 to 2021. In this figure, the line represents the total emission data over the years, while the columnar data indicates the annual average concentrations of sulfur dioxide (SO_2) in the air.

From this diagram, a certain correlation can be observed between the concentration of sulfur dioxide in the air and the emission of this pollutant. To more precisely reveal the causality between them, this paper employs a statistical method--the Granger causality test. Using the professional econometric analysis software Eviews7, we conducted a detailed Granger causality test and organized the results in Table 1.

The test results indicate that, under the condition of setting the lag term to 2, if we reject the null hypothesis that "SO2DISCHARGED is not a Granger cause of SO2INAIR," the risk of committing Type I error is relatively high, reaching 0.4741. Conversely, if we reject the alternative null hypothesis that "SO2INAIR is not a Granger cause of SO2DISCHARGED," the risk of committing Type I error is relatively low, at only 0.0243. Therefore, based on this statistical inference, we have reason to believe that sulfur dioxide emissions are a Granger cause of changes in sulfur dioxide concentrations in the air.

3.2 Actual parameters among energy consumption, polluting gas emission, and investment

3.2.1 Analysis of decision variables in the model

Based on the specific data of Tianjin, the conventional classification in the "Report" and statistical yearbooks, we have subdivided the whole society into 10 sectors, namely agriculture, power generation, heat supply, oil refining, gas manufacturing, industry, construction, transportation, commerce, and residential life. At the same time, fossil fuels are classified into 9 types: coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, and coal gas. However, if this detailed classification is adopted, the standard form of the model will contain up to 90 variables, which undoubtedly leads to an extremely large calculation burden. In view of this, we have conducted appropriate merging and simplification. Specifically, based on the actual consumption scale of different energy sources by various sectors in Tianjin, we have reclassified Tianjin into five sectors: large-scale agriculture (covering agriculture, forestry, animal husbandry, fishery, and water conservancy), industry (including power generation and heat supply), transportation, retail and accommodation, and consumption of living. Furthermore, based on the similarity of emission coefficients when these sectors consume energy, the aforementioned 9 types of energy are further summarized into 3 main types: coal, oil, and natural gas.

3.2.2 Emission parameters in the model objective

Based on the Report and statistical yearbooks, the emission coefficients (in $10^{-3}kg/kg(m^3)$) for various energy sources are summarized in Table 2.

This study has decided to adopt the pollutant emission coefficient data from Tianjin in 2012, which is supported by sufficient reason. Firstly, there is considerable difficulty in obtaining emission coefficient data for the period from 2017 to 2021. These data are often considered sensitive information by government departments and are dispersed across various departments and systems, posing significant challenges for external researchers

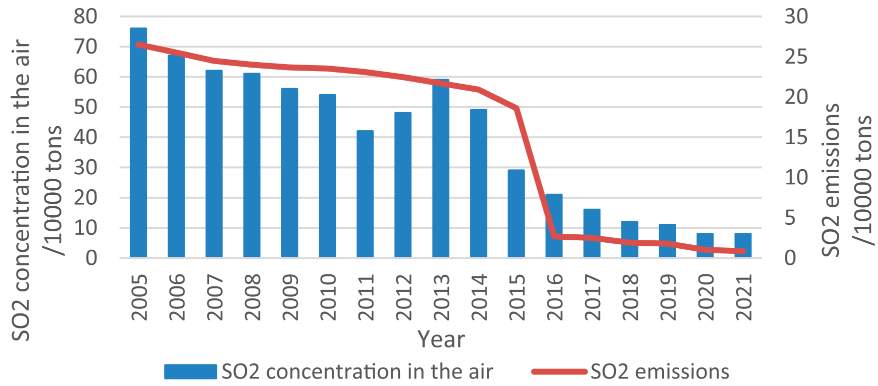

FIGURE 1
Trend diagram of sulfur dioxide emission and sulfur dioxide concentration in Tianjin.

TABLE 1 Results of granger test.

Null hypothesis	Obs	F-statistic	Prob.
SO2INAIR does not Granger Cause SO2DISCHARGED	15	5.51183	0.0243
SO2DISCHARGED does not Granger Cause SO2INAIR		0.80492	0.4741

attempting to access them. Additionally, opting to use the emission coefficient data of 2012 facilitates direct comparative analysis of the study's results with those of previous years (Meng et al., 2016), thereby enabling a more accurate assessment of the evolutionary trends in pollutant emission and governance investment over time.

As shown in Table 2, the meanings of the subscripts corresponding to parameter $C_k = \left(c_{ij}^k\right), k = 1,2,3;\ i = 1,2,\cdots,5, j = 1,2,3$ in model (Equation 14) are as follows: k represents 3 different gases, namely sulfur dioxide (SO_2), nitrogen oxides (NO_x), and carbon dioxide (CO_2); i corresponds to 5 different social sectors; j corresponds to 3 different energy sources, namely coal, oil, and natural gas. Taking c_{43}^2 as an example, it represents 1.462×10^{-3} nitrogen oxides (NO_x) is emitted by the retail and accommodation industry (product No. 4) when consuming the third energy source, natural gas, per1m^3.

3.2.3 Governance investment parameter in the model objective

Given the lack of statistical data on nitrogen oxides (NO_x) and carbon dioxide (CO_2) emissions in Tianjin prior to 2010, this study decided to utilize the aggregate data on emissions of SO_2, NO_x and CO_2 from 2011 to 2021 (China Emission Accounts and Datasets, 2023), combined with concurrent governance investment data of waste gas, to jointly create a trend diagram depicting the changes in governance investment data of waste gas versus emissions in Tianjin, as shown specifically in Figure 2.

Specifically, we selected data on the total emissions of SO_2, NO_x, and CO_2, as well as concurrent energy usage (China energy statistical yearbook, 2017–2021) and waste gas governance investment in Tianjin from 2011 to 2021, and incorporated these data into our model to estimate the model parameter C in Equation 8. However, upon observing scatter plots of the product of waste gas emissions and waste gas governance investment versus energy usage, calculated based on historical data, we noted significant deviations in the data points for 2013, 2014, 2015, and 2021. These anomalies may be attributed to numerical fluctuations caused by specific events or factors. To ensure the accuracy and rationality of the model, we decided to exclude potentially anomalous year data from the regression analysis. Therefore, we selected data from 2011, 2012, and from 2016 to 2020 as our samples and utilized the professional statistical software SPSS to conduct regression analysis, in order to accurately estimate the model parameters. The specific functional relationship obtained in Equation 8 is derived as follows:

$$E = \frac{120407.9X}{Y}. \tag{20}$$

And the regression results are shown in Table 3 below:

The regression analysis results presented in Table 3 reveal that the R-value of this model reaches 0.717, which strongly demonstrates a close and significant correlation between the model and the actual observed data. Furthermore, the R-squared value of the regression model is 0.514, indicating that the model is able to capture and explain more than half of the variability in the data, thus demonstrating the model's excellent performance in data fitting. Additionally, the significance level of variable X is 0.07, which is a statistical result that enhances our confidence in the estimation of the quantitative relationship between emissions and investments described by the above equation, suggesting that the estimation result is largely reliable.

3.2.4 Constraint parameters in the model

Based on the final consumption of 3 major energy products--coal, crude oil products, and natural gas-by various sectors in Tianjin from 2017 to 2021, as well as the coefficient for converting various energies into standard coal, this paper compiles the final consumption and the equivalent consumption in standard coal for each sector in Tianjin from 2017 to 2021. Table 4 presents the data for 2021 as an example.

TABLE 2 Pollutant emission coefficient table.

Product No.	Sectors	Type of energy	SO_2 emission coefficient $(10^7 kg)$	NO_X emission coefficient $(10^7 kg)$	CO_2 emission coefficient $(10^7 kg)$
1	Large-scale Agriculture	Coal	12	3.75	1977.90
		Oil	18	8.26	2984.75
		Gas	0	1.462	2184.03
2	Industry	Coal	8.4	8	1977.90
		Oil	12.6	8.86	2984.75
		Gas	0	2.085	2184.03
3	Transportation	Coal	12	7.5	1977.90
		Oil	9	36.25	2984.75
		Gas	0	2.085	2184.03
4	Retail and accommodation	Coal	12	3.75	1977.90
		Oil	9	5.77	2984.75
		Gas	0	1.462	2184.03
5	Consumption of living	Coal	12	1.88	1977.90
		Oil	9	16.7	2984.75
		Gas	0	0.736	2184.03

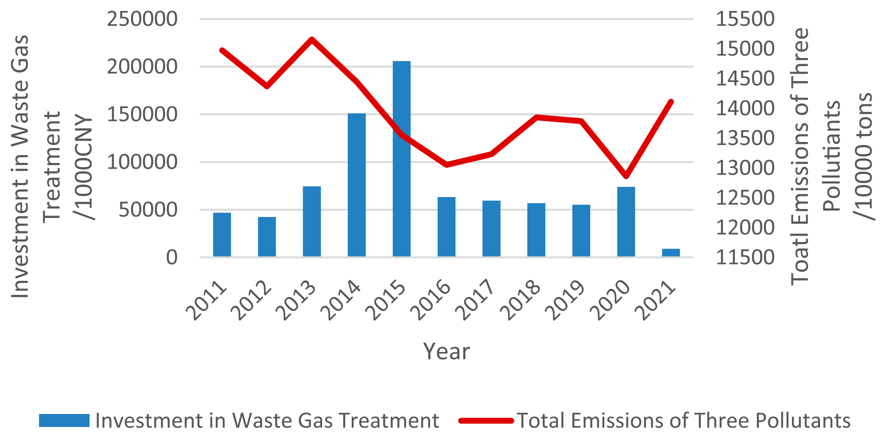

FIGURE 2
Trend diagram of waste gas governance investment versus emissions in Tianjin.

From Table 4, we can obtain the energy demand constraints in the model. Here, ρ_j represents the coefficient for converting the j-th type of energy product into standard coal, with values of 0.71 for coal, 1.47 for oil products, and 13.3 for natural gas. D_i denotes the energy demand of the i-th industry, with its value corresponding to the third column in Table 4.

Further considering the energy supply constraints of the model, since the three types of energy cannot be supplied unlimitedly and have a certain degree of complementarity under the premise of meeting energy consumption, the supply of the j-th type of energy product is set to 150% of Tianjin's consumption for that year. The reason for this setting is that if it is set too low, there will be less room for adjustment in the energy structure.

TABLE 3 Regression analysis results.

R	R square	Adjusted R square	Standard error of the estimate
0.717	0.514	0.416	80665349.76

Unstandardized coefficients			Standardized coefficients		
	B	Std. Error	Beta	t	Sig.
1 (Constant)	−146206997	402119461.1		−0.364	0.731
X	120407.939	52408.771	0.717	2.297	0.07

TABLE 4 Statistics of final energy consumption in Tianjin in 2021.

Product no.	Sectors	Standard coal D_i $\left(10^7 kg\right)$	Final consumption		
			Coal $\left(10^7 kg\right)$	Oil $\left(10^7 kg\right)$	Natural gas $\left(10^7 kg\right)$
1	Large-scale Agriculture	62.8419	5.61	40.40	0
2	Industry	1775.75	480.15	692.89	31.30
3	Transportation	432.39	0.01	258.31	3.96
4	Retail and accommodation	152.04	0	31.59	7.94
5	Consumption of living	532.90	22.00	234.09	13.02
Total		2955.92	507.77	1256.92	56.22

TABLE 5 Comparison of optimized emission with actual emission of carbon dioxide in Tianjin.

Year	Optimized emission amount $\left(10^7 kg\right)$	Actual emission amount $\left(10^7 kg\right)$	Optimization efficiency
2017	9176.7659	13215	30.56%
2018	8044.2486	13836	41.86%
2019	8444.7823	13772	38.68%
2020	7938.1368	12849	38.22%
2021	8061.2175	14101	42.83%

3.3 Analysis of the solution to the optimization model

In recent years, the focus of China's environmental protection efforts has increasingly shifted to the management of carbon dioxide (CO_2) emission. Especially during the period from 2017 to 2021, the two major goals of "Carbon Peak" and "Carbon Neutrality" were established as the country's core strategic orientations. This was followed by a series of policy releases, such as the "2023 Carbon Peak Action Plan" (State Council of China, 2021) and the "National 14th Five-Year Plan for Modern Energy System" (National Development and Reform Commission of China, 2022), which have endowed carbon dioxide governance with unprecedented policy significance and urgency. In view of this background, this paper closely examines the policy framework and established emission reduction targets, combining a meticulously constructed model to deeply analyse optimization strategies for carbon emission reduction. The aim is to provide solid theoretical support and practical guidance for the realization of the "Dual-carbon" goals.

In the specific research, based on the actual data provided in Sections 3.2.1 to 3.2.3, we substituted them into model (Equation 19) to construct a single-objective emission reduction optimization model that includes 15 non-negative decision variables and 8 linear inequality constraints. To solve this model, we fully utilized the established model parameters and efficient algorithms, with the aid of Matlab software for implementation. We present the solution process of the model in detail. Firstly, we set the weights of various pollutant emissions in the objective function of the model to $w_1 = w_2 = w_3 = 1$ and substituted the data on energy consumption by various sectors in Tianjin from 2017 to 2021 into the model. We then obtained the optimized carbon dioxide (CO_2) emission in Tianjin under the corresponding conditions of different years and compared the optimized emission with the actual emission, as shown in Table 5.

Here, this paper defines the optimization efficiency as follows:

TABLE 6 Variation of optimized carbon dioxide emissions under different weight scenarios.

Year\Weights	1:1:1	1:1:3	Relative change rate	1:1:5	Relative change rate
2017	9176.7659	9176.7612	0.00005%	9176.7564	0.00010%
2018	8044.2486	8044.2472	0.00002%	8044.2457	0.00004%
2019	8444.7823	8444.7764	0.00007%	8444.7704	0.00014%
2020	7938.1368	7938.1308	0.00008%	7938.1248	0.00015%
2021	8061.2175	8061.2155	0.00002%	8061.2134	0.00005%
Year\Weights	**1:1:1**	**1:1:7**	**Relative Change Rate**	**1:1:10**	**Relative Change Rate**
2017	9176.7659	9176.7517	0.00015%	9176.7445	0.00020%
2018	8044.2486	8044.2443	0.00005%	8044.2421	0.00010%
2019	8444.7823	8444.7643	0.00021%	8444.7553	0.00030%
2020	7938.1368	7938.1188	0.00023%	7938.1097	0.00030%
2021	8061.2175	8061.2114	0.00008%	8061.2083	0.00010%

TABLE 7 Statistics of optimized carbon dioxide emissions in Tianjin.

Year	Optimized emission amount at 1:1:1 ratio $\left(10^7 kg\right)$	Optimized emission amount at 1:1:10 ratio $\left(10^7 kg\right)$
2017	9176.7659	9176.7445
2018	8044.2486	8044.2421
2019	8444.7823	8444.7553
2020	7938.1368	7938.1097
2021	8061.2175	8061.2083

$$\text{Optimization efficiency} = \frac{\text{actual emission} - \text{optimized emission}}{\text{actual emission}} \times 100\%.$$

From the table, it can be seen that under the conditions corresponding to different years, the optimized carbon dioxide (CO_2) emission calculated by the model are generally lower than the actual emission for that year. Based on the above data and formulas, the average optimization efficiency of carbon di-oxide emissions in Tianjin from 2017 to 2021 was calculated to be 38.43%.

The following discussion focuses on the variation of optimized carbon dioxide (CO_2) emissions under different weight scenarios, specifically the results when the weight ratio of the three gases in the model is set to 1:1: a (where a = 1, 3, 5, 7, 10), as shown in Table 6.

When the weight ratio of the three gases in the model is set to 1: 1: a (where a = 3, 5, 7, 10), the optimized carbon dioxide (CO_2) emissions show minimal changes compared to when the weight ratio is set to 1:1:1. The relative change rates all fall within 0.001%. Therefore, variations in the weight a of carbon dioxide in the model within the range of 1–10 have a relatively small impact on the results.

To focus on the analysis of carbon dioxide (CO_2) emission, the weights of various pollutant emissions in the objective function of the model were adjusted to $w_1 = w_2 = 1, w_3 = 10$ The data on energy consumption by various sectors in Tianjin from 2017 to 2021 were substituted into the model to solve for the optimal carbon dioxide emission in Tianjin under the corresponding conditions of different years. These results were then compared with the optimization results obtained when the weights were $w_1 = w_2 = w_3 = 1$, as shown in Table 7.

Upon closely examining the table data, we can observe that even when the weight of carbon dioxide (CO_2) emission is substantially increased to 10 times its original value in the model, the room for improvement in the optimization results remains relatively limited. This phenomenon suggests that when the weights are set to 1:1:1, the model has already demonstrated considerable optimization efficiency.

Next, let us further analyze the investment situation corresponding to emission reduction. Firstly, when the weights are set to 1:1:1, we calculate the cumulative optimized sulfur dioxide (SO_2), nitrogen oxides (NO_x), and carbon dioxide (CO_2) emission in Tianjin from 2017 to 2021. Subsequently, we combine this cumulative value with the actual total energy consumption in Tianjin during the same period and substitute it into the function-al relationship between waste gas emissions, energy usage, and waste gas governance in-vestment mentioned in Section 3.2.3. By this step, we are able to estimate the amount of governance investment required to achieve optimized waste gas emissions at real energy consumption levels. The following Table 8 details the comparison between the optimized governance investment amount and the actual governance investment amount:

It can be observed from the table that the actual investment amount for waste gas governance in Tianjin from 2017 to 2021 was lower than the investment required to achieve optimal waste gas emission.

3.4 Test the waste gas governance investment in 2022

The collaborative emission reduction model (Equation 20) mentioned above can calculate the emission levels of waste gases and their corresponding governance investment. Below, we conduct a validation test on the emission-governance investment relationship for 2022. To ensure consistency with actual data, the waste gas emission E and total energy consumption X for 2022 are derived from regression-based predictions using historical data from previous years. We proceed with the following 3 steps.

Step 1. Prediction of emission data for three kinds of waste gases.

The trend extrapolation method is adopted below to predict the emissions of major pollutants. Based on the historical data from 2017 to 2021, a linear regression model is established.

For SO_2, the regression equation obtained is the following Equation 22:

$$E_{SO_2} = 2.8720 - 0.4200\,t \tag{21}$$

where t is the year index, $t = 1$ for 2017, $t = 2$ for 2018, …, $t = 5$ for 2021. Furthermore, the predicted emissions for 2022 are calculated as 0.3520 ten thousand tons. The goodness of fit is $R^2 = 0.9542$.

For NO_x, the regression equation obtained is the following (Equation 22):

$$E_{NO_x} = 12.3880 - 0.2800\,t, \tag{22}$$

where t is defined the same as in (Equation 21). The predicted emissions for 2022 are calculated as 10.7080 ten thousand tons. The goodness of fit is $R^2 = 0.7365$.

For CO_2, its emissions data from China energy statistical yearbook (2017–2021) are shown in Figure 3.

There are significant fluctuations. Therefore, the average value of emissions from 2017 to 2021 is considered to be used as the emissions for 2022, which is 13554.60 ten thousand tons.

Step 2. Prediction of total energy consumption.

Considering the volatility of energy consumption data, the Exponential Smoothing method is used for short-term forecasting. This method is suitable for short-term forecasting of volatile data and can assign higher weights to recent data. The calculation formula is as (Equation 23):

$$\tilde{X}_t = \alpha X_{t-1} + (1-\alpha)\tilde{X}_{t-1}, \tag{23}$$

where t is defined the same as in (Equation 21). A smoothing constant of $\alpha = 0.5$ is adopted to assign higher weights to recent data. X_t represents the total energy consumption value in the t-th year (see Table 9), and $\tilde{X}_t$ represents the predicted energy consumption value in the t-th year, and we set the following (Equation 24)

$$\tilde{X}_{2017} = X_{2017} = 3068.18. \tag{24}$$

TABLE 8 Comparison of waste gas governance investment in Tianjin.

Year	Optimized investment (10^4 Yuan)	Actual investment (10^4 Yuan)
2017	100085.5	59536
2018	117578.0	56879
2019	116869.5	55280
2020	123503.6	73987
2021	121419.5	9014

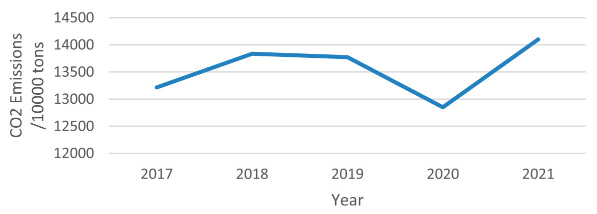

FIGURE 3
Trend diagram of carbon dioxide emissions from 2017 to 2021 in Tianjin.

TABLE 9 Annual total energy consumption from 2017 to 2021.

Year	Total energy consumption (10000 tons)
2017	3068.18
2018	2846.851
2019	2990.193
2020	2835.191
2021	2955.92

By substituting the data into the aforementioned formula, the calculated predicted value of total energy consumption for 2022 is 2930.22 ten thousand tons.

Step 3. Prediction of waste gas governance investment in 2022.

By substituting the total energy consumption in 2022 and the predicted values of the total emissions of three types of waste gases into Formula 20, the predicted value of investment in waste gas treatment in 2022 is obtained as 260.0844 million yuan. However, after consulting the National Data (National Bureau of Statistics of China, 2024), the actual value of investment in waste gas treatment in Tianjin in 2022 is 477.46 million yuan, which is higher than the predicted value. This indicates that there is still room for a decrease in the investment in waste gas treatment in 2022, or that enterprises have increased their investment in waste gas treatment due to the impact of relevant policies.

4 Discussion

The model results show that the optimized CO_2 emission amount of each year is significantly lower than the actual emission, with an average optimization efficiency of 38.43%, indicating that there is still considerable room for emission reduction in Tianjin under the current policy framework. However, the actual environmental investment amount is far below the model recommendation (for example, the actual investment in 2021 was only 7.4% of the optimized value), which directly constrains the achievement of emission reduction targets. Additionally, the sensitivity analysis of pollutant weights in the model shows that weight settings have a certain impact on the optimization results.

Based on the model results, we give the following suggestions:

1. Increase investment: It is suggested that the government should increase financial support, establish special funds for clean energy technology upgrading and "oil to gas" transformation in the transportation industry, and introduce social capital to participate in the project through PPP mode to ease the financial pressure.
2. Optimize energy structure: It is recommended to combine regional environmental carrying capacity, regularly assess and adjust weights to balance the needs of multi-pollutant co-governance. Promote the optimization of the energy structure, increase the proportion of clean energy usage, and reduce the dependence on fossil fuels. This not only helps to reduce exhaust emissions but also improves energy efficiency.
3. Improve energy efficiency: Improve energy efficiency through technological innovation and management optimization, reduce energy consumption per unit output, so as to reduce waste gas emissions.
4. Policy support: The government should introduce more incentive policies to encourage enterprises and individuals to adopt clean energy and efficient energy utilization technologies, while imposing stricter supervision and restrictions on highly polluting emission enterprises.
5. Public participation: Strengthen public education and participation, raise the awareness of the importance of waste gas treatment in the society, and encourage the public to adopt energy-saving and emission reducing lifestyles and consumption patterns.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YS: Methodology, Conceptualization, Writing – original draft, Writing – review and editing. HW: Writing – review and editing, Software, Investigation, Methodology.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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