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# Causality Analysis and Risk Assessment of Haze Disaster in Beijing

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**Abstract:** Due to the lack of training data and effective haze disaster prediction model, the research on causality analysis and the risk prediction of haze disaster is mainly qualitative. In order to solve this problem, a nonlinear dynamic prediction model of Beijing haze disaster was built in this study. Based on the macroscopic evaluation of multiple influencing factors of haze disaster in Beijing, a causality model and flow diagrams of the Beijing crude oil consumption system, Beijing coal consumption system, Beijing urban greening system and sulfur dioxide emission system in Hebei and Tianjin were established. The risk prediction of Beijing haze disaster was simulated at different conditions of air pollutant discharge level for the Beijing–Tianjin–Hebei region. Compared with the governance strategies of vehicle emission reduction, petrochemical production emission reduction, coal combustion emission reduction, greening and reducing dust and collaborative governance policy, the Beijing–Tianjin–Hebei cross-regional collaborative governance policy was more effective in controlling the haze disaster of Beijing. In the prediction, from 2011 to 2017, the air quality of Beijing changed from light pollution to good. By 2017, the PM2.5 of Beijing reduced to 75 $\mu g/m^3$. From 2017 to 2035, the control effect of urban haze disaster for Beijing further strengthened. By 2035, the PM2.5 of Beijing reduced to 35 $\mu g/m^3$. Finally, the PM2.5 of Beijing continued to reduce from 2035 to 2050. The speed of reduction for PM2.5 in Beijing slowed down. Meanwhile, the achievements of haze control in Beijing were consolidated. By 2050, the risk of haze disaster for Beijing was basically solved. The nonlinear dynamic prediction model in this study provides better promise toward the future control and prediction of global haze disaster under the condition of limited data.

**Keywords:** risk prediction; PM2.5; haze disaster; stochastic nonlinear dynamics; controlling strategies



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## 1. Introduction

In recent years, urban haze pollution has become more and more serious, which has increasingly affected all aspects of economic and social development. Haze dramatically reduces visibility, thus greatly affecting transportation and causing direct economic losses or personal injuries [1–4]. Haze affects the driver's visual range and the observation of road conditions, leading to serious driving safety problems [5]. In recent years, the number of traffic accidents caused by haze has increased, resulting in the increase in direct economic losses and personal injuries [6,7]. Meanwhile, haze affects the photosynthesis of plants, resulting in the decline in crop yield, which is destructive to the agricultural production [8]. Long-term haze pollution makes suspended particles block the pores of plants for gas exchange [9]. In conclusion, haze disaster brings harm to both industry development, peoples' normal lives and social production [10,11]. In order to reduce the damage of haze disasters to society, an effective risk prediction model of haze disaster is urgently needed.

The key to realizing the effective prediction of haze disaster is to clarify the causal relationship between the influencing factors of haze disaster and to establish the corresponding mechanism between each factor [12]. Moreover, the cross-regional features of haze disaster need to be considered in the prediction model [13]. While some researchers try to establish the haze risk prediction model, there is still a lack of an intuitive prediction model to reliably evaluate the effect of various governance measures to control urban haze, especially when the complex cross-regional effects are considered [11–15]. Most haze prediction models mainly focus on one administrative region, but rarely consider the interaction and game relationship of haze in multiple regions [16].

Clarifying the causal relationship between the influencing factors of haze disaster is the premise for the establishment of a haze prediction model. Researchers have studied the atmospheric haze causality of the haze system using many methods, including Granger causality analysis [17,18], convergent cross mapping [19,20] and machine learning [21,22]. The influencing factors of haze disaster include marine transport at the marine level [23,24], local and global pollution emissions [25,26] and the interaction between industrial emissions and atmospheric diffusion [27,28]. Unfortunately, these studies cannot describe the dynamic formation and evolution mechanism of cross-regional haze disaster.

In order to realize the prediction of haze disaster, incorporating the causal relationship between the influencing factors should be applied to the data analysis. A large number of researchers have studied the mathematical models of haze prediction, including nonparametric regression models [29,30], deep recurrent neural networks [31,32], inverse-matrix-free machine learning models [33], nonlinear grey models [34,35] and graphic networks [36–38]. These methods avoid the analysis of complex details and mechanisms for haze disaster. Harirchian et al. [39] developed a rapid, reliable and computationally easy method of vulnerability assessment, known as rapid visual screening (RVS). Ngo et al. [40] proposed the haziness degree evaluator model to predict haze density from a single image without reference to a corresponding haze-free image. Yuan et al. [41] adopted the Bayesian network (BN) method to measure impacts of various factors on protective behavior under smog crisis. Kumari et al. [42] used the RVS method to examine the vulnerability of buildings. Yin et al. [43] proposed a hybrid knowledge-based approach for a quantitative analysis of resilience. However, massive training data are needed to predict the trend of haze disaster. As a new natural disaster in China, the amount of related data for hazes cannot support the training. Moreover, these models lack robustness, which makes it difficult to identify the effective haze control strategy.

In this study, causal analysis and stochastic nonlinear characteristics were incorporated to construct a prediction model of the haze disaster with regional linkages. The parameters were determined from historical record data. The trend of haze disaster under different governance control policies was simulated. On this basis, the optimal pathway of evolving governance policy was identified in the complex cross-region urban haze system.

## 2. Materials and Methods

### 2.1. Analysis Model of Haze System

Urban haze is affected by many factors, whose formation mechanism needs to be analyzed from a systematic point [44]. The flowchart of this study is shown in Figure 1. In this study, the structure of haze system was defined first. Based on verification and analysis of historical data, the causal relationship of each influencing factor of haze was determined. On this basis, haze prediction model was established. According to the historical data, the parameters in the model were given initial values, which were optimized according to the simulation results of real data. Finally, the evolution trajectory of haze disaster under different governance strategies was predicted, providing policy guidance.

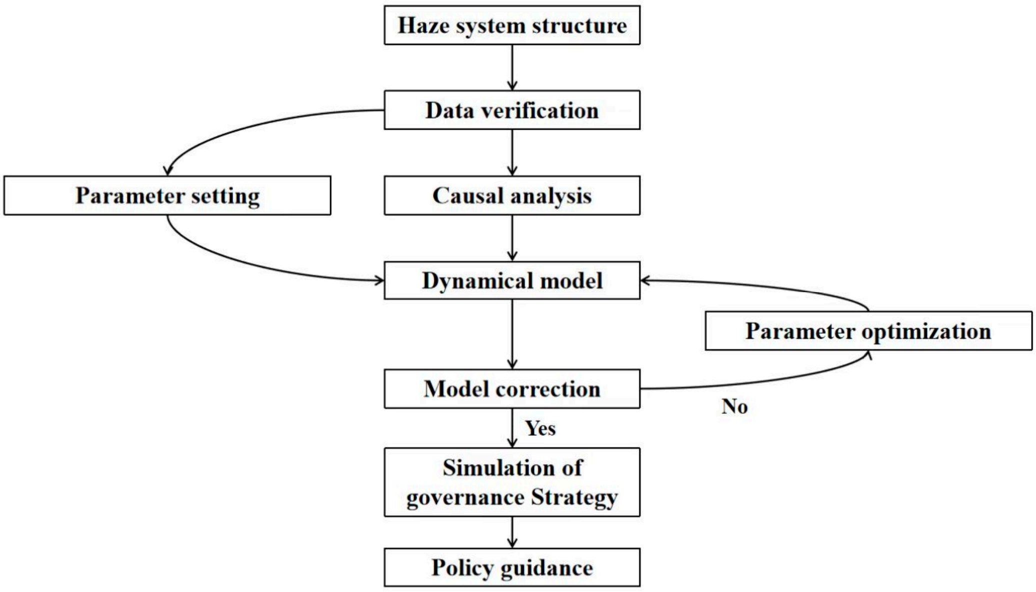



**Figure 1.** Flowchart of haze system model.

When analyzing and predicting the haze in Beijing, it is necessary to establish a cross-regional collaborative system in the whole Beijing–Tianjin–Hebei region considering the impact of geographic location and national policies. The structural framework of Beijing urban haze system is presented in Figure 2.

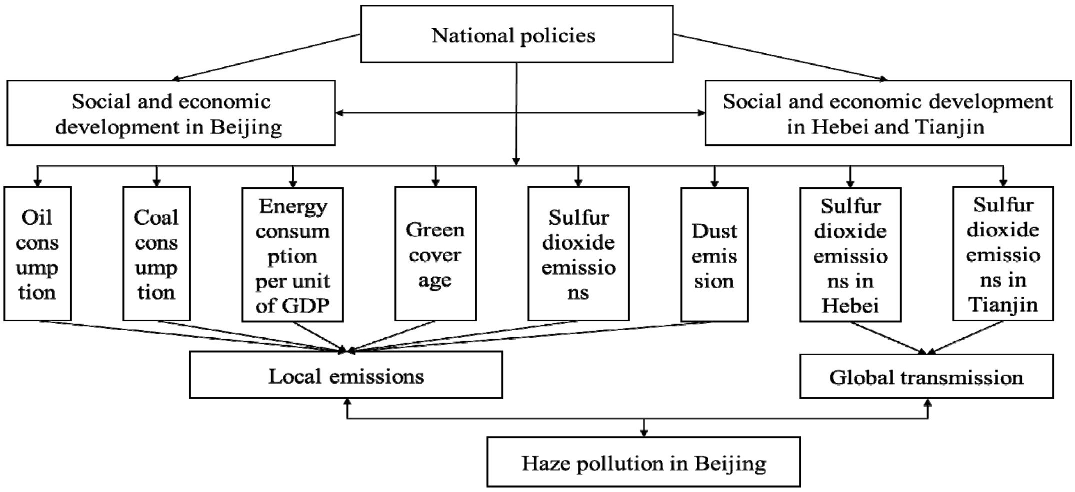
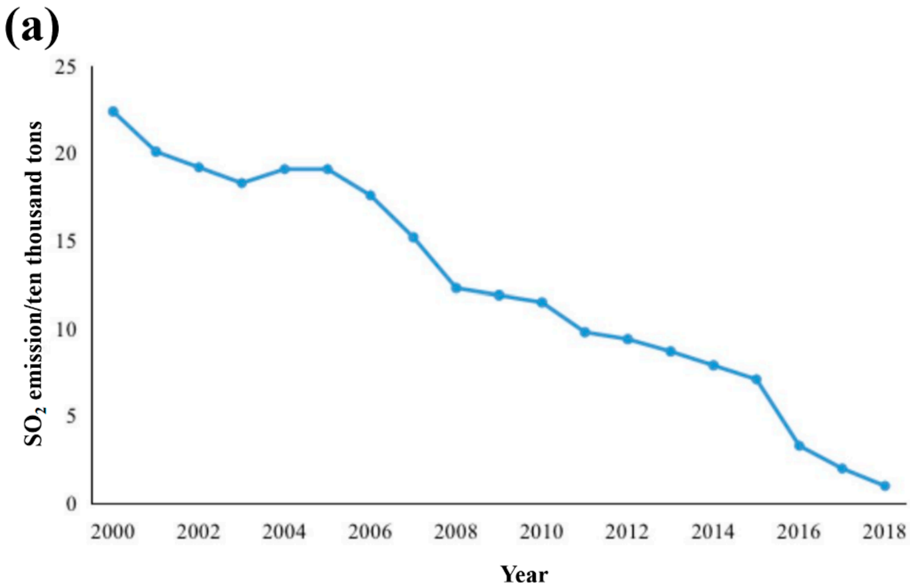



**Figure 2.** Structure of Beijing haze system.

As shown in Figure 1, the haze pollution in Beijing is mainly composed of local emissions and surrounding diffusion. Firstly, with Beijing as the core, all kinds of energy consumption in Beijing–Tianjin–Hebei region are increasing, leading to serious haze pollution. Then, under the influence of national policies, many enterprises with high pollution and high energy consumption transfer from Beijing to Hebei and Tianjin. Although this reduces the local pollutant emissions in Beijing, the pollutant emissions in Hebei and Tianjin significantly increase, and, finally, cause the accumulation and superposition of air pollutants in Beijing through the regional spread of pollutants. In addition, relevant national policies for Beijing, Hebei and Tianjin, such as industrial policies, energy policies and science and technology policies, are also important factors affecting Beijing's haze pollution.

*2.2. Causal Analysis of Influencing Factors*

The causal correlation at the macro-level is the key to analyzing the urban haze system. Based on the nonlinear with-time-lags Granger causality analysis [45,46] for Beijing haze pollution in our past studies, the causal relationship between PM2.5 and different influencing factors was tested. The inputs included PM2.5, coal consumption, crude oil consumption, unban greening rate and pollution emissions of Beijing, Tianjin and Hebei. The outputs were *p*-test values between PM2.5 and other inputs. At the significance level of 10%, Granger causality exists when *p*-test values are less than 0.1. The historical data were obtained from China Yearbook Full-text Database [47]. The pollution emission data of Beijing, Tianjin and Hebei is shown in Figure 3. The variation trends of $SO_2$ (Figure 3a) and dust emissions (Figure 3b) in Beijing were basically the same. However, the change trend of $SO_2$ emissions in Hebei and Tianjin (Figure 3c) was obviously different from Beijing (Figure 3a), which indicates the importance of cross-regional analysis of pollutant emissions. According to the result of Granger causality analysis, Beijing's crude oil consumption system, coal consumption system, unit GDP energy consumption system, urban greening system and Tianjin and Hebei's sulfur dioxide emission system could be established.



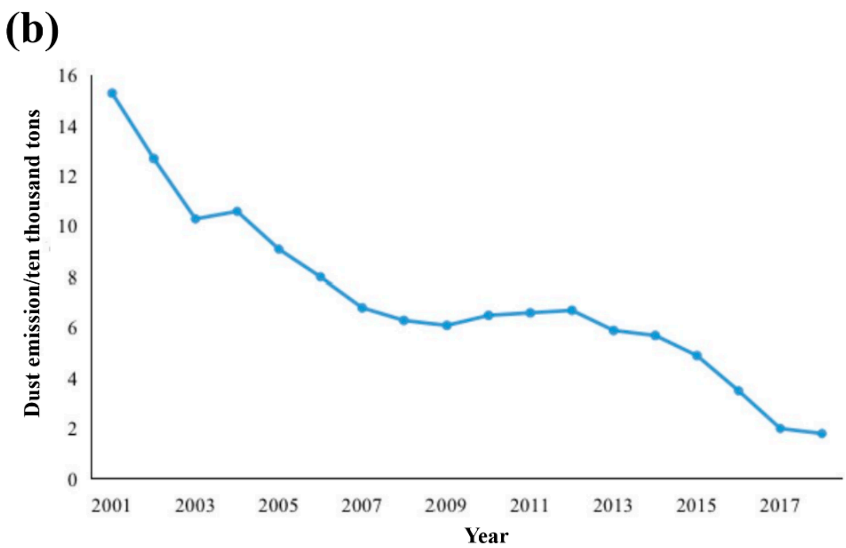




**Figure 3.** *Cont.*

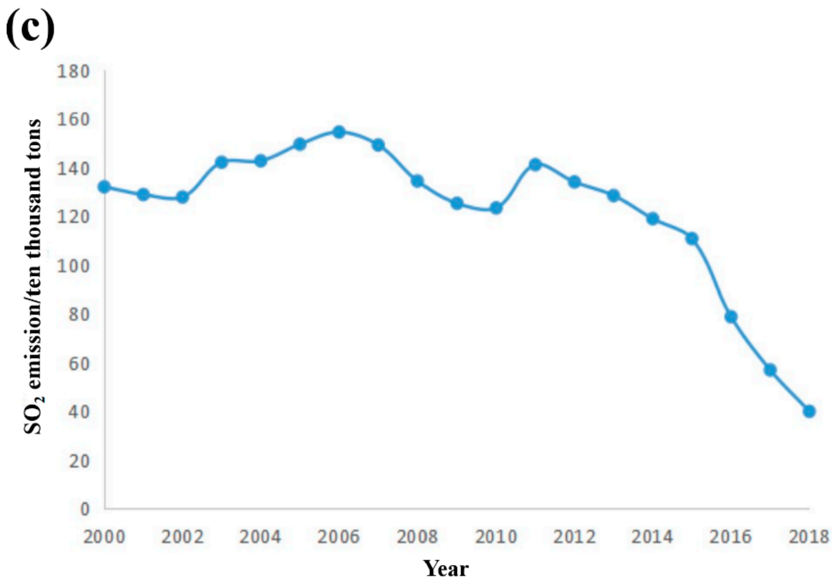



**Figure 3.** $SO_2$ (**a**) and dust emission data (**b**) of Beijing and $SO_2$ emission data of Tianjin and Hebei (**c**).

Crude oil consumption is an important source of haze pollution in Beijing and is mainly reflected in two aspects. One is the fuel consumption of urban motor vehicles, and the other is the consumption of crude oil in oil refining, petrochemical and other industries. In addition, the use of new energy vehicles and the implementation of environmental protection policies can reduce the oil consumption effectively. The corresponding causality diagram is shown in Figure 4.

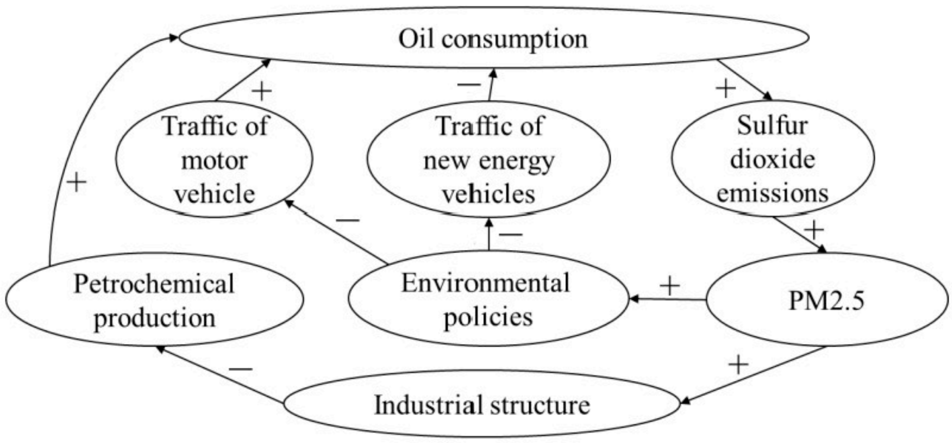



**Figure 4.** Causality diagram of Beijing crude oil consumption system.

Beijing's coal consumption mainly includes residents' coal consumption and thermal power generation consumption. In recent years, the proposal of environmental policies and the change in energy structure have significantly reduced coal consumption. The causality diagram between Beijing's coal consumption and Beijing's urban haze is shown in Figure 5.

Energy consumption per unit of GDP is the ratio of total primary energy supply to gross domestic product (GDP), which is an indicator of energy utilization efficiency. With the development of science and technology, the energy utilization rate has significantly improved, which can reduce the energy consumption effectively. The causality diagram between them is shown in Figure 6.

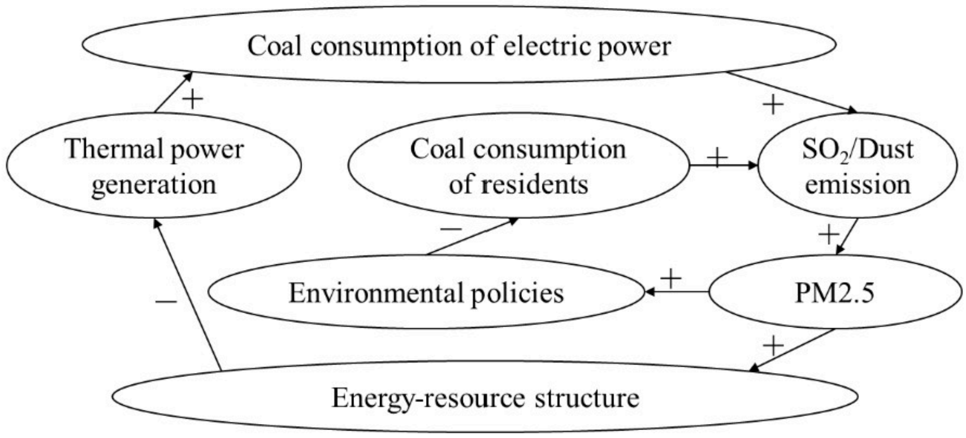



**Figure 5.** Causality diagram of Beijing coal consumption system.

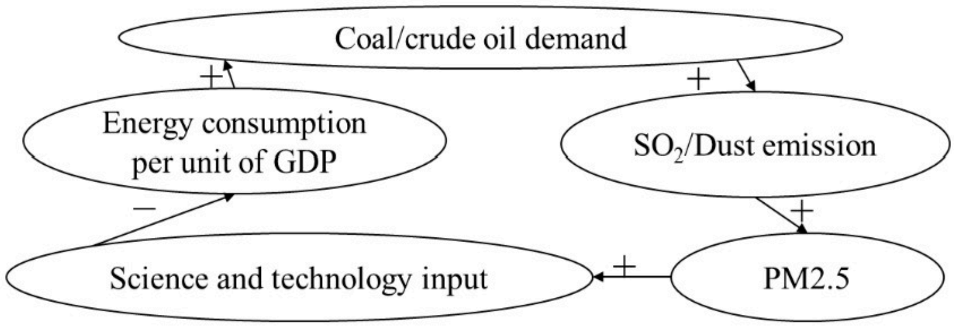



**Figure 6.** Causality diagram of Beijing energy consumption system per unit GDP.

Green coverage is the ratio of vertical projection area of various types of green space to the total urban area, and is an important indicator to measure the urban environmental quality. The improvement in urban greening rate can give full play to the important role of plants in reducing urban haze pollution. The causality diagram between urban green coverage and urban haze in Beijing is shown in Figure 7.

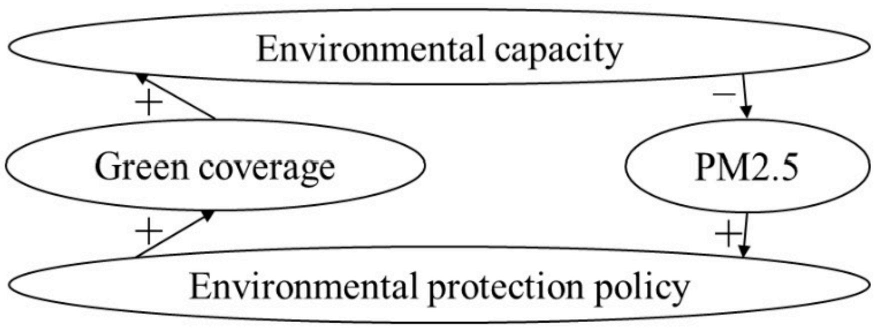



**Figure 7.** Causality diagram of Beijing urban greening system.

The haze in Beijing is affected not only by the harmful emission in the region, but also by the atmospheric circulation and the pollution emission in surrounding cities, especially Tianjin and Hebei. Similar to Beijing, the implementation of national policies and the adjustment of industrial structure have an effect on harmful emissions in Tianjin and Hebei, which indirectly affect the generation of haze in Beijing through atmospheric diffusion and other ways. The causality diagram between sulfur dioxide emissions in Hebei and Tianjin and urban haze in Beijing is shown in Figure 8.

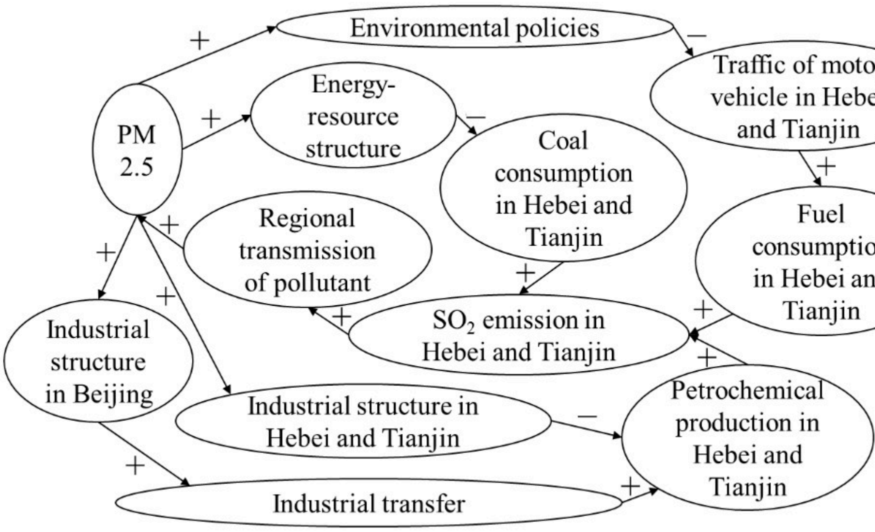



**Figure 8.** Causality diagram of sulfur dioxide emission system in Hebei and Tianjin.

Each subsystem in Figures 4–8 is combined through its logical relationship, and the Beijing urban haze system is shown in Figure 9. Figure 9 shows that the direct reason for the change in PM2.5 is the emission of pollutants. In particular, cross-regional pollutant transport also significantly affects the change in PM2.5. The accuracy of the prediction of pollutant emissions significantly affects the prediction of haze disaster.

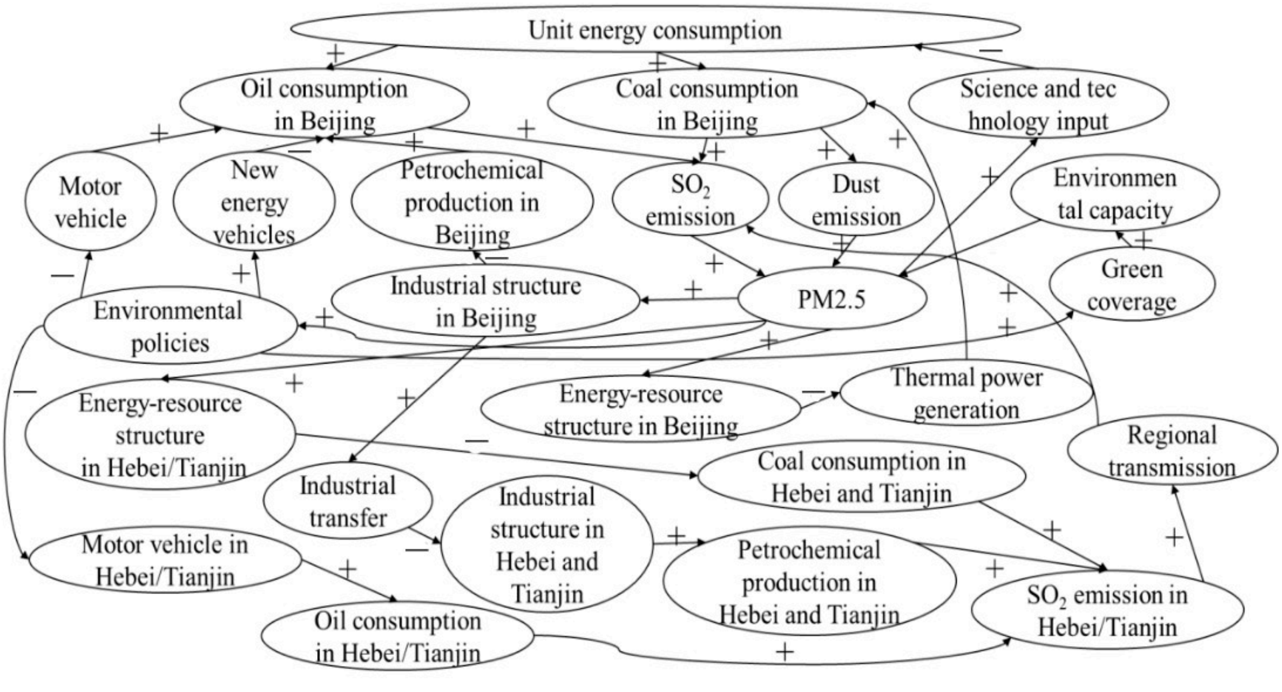



**Figure 9.** Overall causality diagram of Beijing urban haze system.

## 2.3. Nonlinear Dynamical Models

The urban haze system is a special complex system with multi-elements, multi-levels and multi-feedback with human participation. Various variables constitute multiple causal feedback loops and are self-generating within the system, which need a nonlinear model to analyze and study the interaction between the internal structure, function and behavior of the system and the feedback mechanism [41]. System dynamics is one of the important simulation methods used to study the dynamic complexity and regards the research object as a dynamic open system, which is suitable to be applied to studying the problem of macroscopic haze management [39,40]. The system dynamics model can observe the changing trend of the research system with the change in the control variable by setting and adjusting the variables, and can then obtain the sensitivity of the system to different control variables [41,42]. When conducting dynamic simulation experiments on urban haze systems, the different states and trends of the system can be obtained by changing the input parameters, and the influence mechanism of different control factors on the operation of the main system can be obtained by adjusting the control variables.

Flow level and flow rate are the main parameters in the system dynamics model, in which, flow level is an accumulation variable and flow rate is the speed that causes the change in flow level. Flow level $y(t)$ gradually accumulates on the basis of the initial value with the change in time, and the accumulation speed is affected by flow rate $x(t)$.

In a real complex system, the flow level $y(t)$ as an observable measurement will contain some observation environment errors. Generally, this observation error can be modeled as Gaussian random noise $n(t)$ with mean value of 0 and variance of $\sigma_n^2$, and its amplitude probability distribution function is as follows:

$$P\{n(t)\} = \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left[-n^2(t)/\sigma_n^2\right]$$

Generally, the observation noises at different times are independent of each other, that is, $E\{n(t) \times n(t+\tau)\} = 0$.

In the process of complex nonlinear dynamics evolution, the flow level also affects the flow rate, which is a nonlinear saturation effect. When the flow level $y(t)$ is small, the flow rate $x(t)$ may change more quickly, and when the flow level $y(t)$ exceeds a certain threshold $\gamma$, the change in flow rate $x(t)$ will slow down significantly. In order to make the simulation more consistent with the actual haze pollution system, nonlinear dynamic models were applied. The input was the flow rate $x(t)$, which represents the evolution rate of pollutant emission and haze pollution. The output was the flow level $y(t)$, which represents the level of pollutant emission and haze pollution. The model performance was validated with the actual values by simulating the results of past years.

The above nonlinear effects can be described by Sigmoid function. For the convenience of expression, the nonlinear saturation effect function was recorded as $F(x) = 1/(1+\exp(x-x_0)$, where $x_0$ represents a specific nonlinear threshold.

To sum up, the following stochastic nonlinear differential equations can be used to describe the nonlinear dynamics system composed of flow level and flow rate:

$$\begin{gathered} \frac{dy(t)}{dt} = x(t) + n(t), \\ x(t) = F(g_x(t)), \\ g_x(t) = -\sum_{j=1}^{J} \alpha_j c_j(t) + \alpha_y y(t), \end{gathered}$$

where $J$ is the number of factors that affect the flow rate change, $c_j(t)$ is the value of the $j-th$ factor, $\alpha_j$ is the correlation strength of the $j-th$ factor and the flow rate, $\alpha_y$ is the correlation strength of the flow level and the flow rate change and $g_x(t)$ is the flow rate without nonlinear saturation effect.

Taking Beijing PM2.5 as an example, the factors influencing the flow rate of PM2.5 include $SO_2$ emission reduction, dust emission reduction and concentration of Beijing PM2.5. The correlation intensity between $SO_2$ emission reduction, dust emission reduction and the flow rate of Beijing PM2.5 is $\alpha_1$ and $\alpha_2$, respectively. Through the previous qualitative analysis of the causality diagrams, a bipartite diagram of the qualitative analysis can be constructed for the flow level and flow rate pair, as shown in Figure 10.

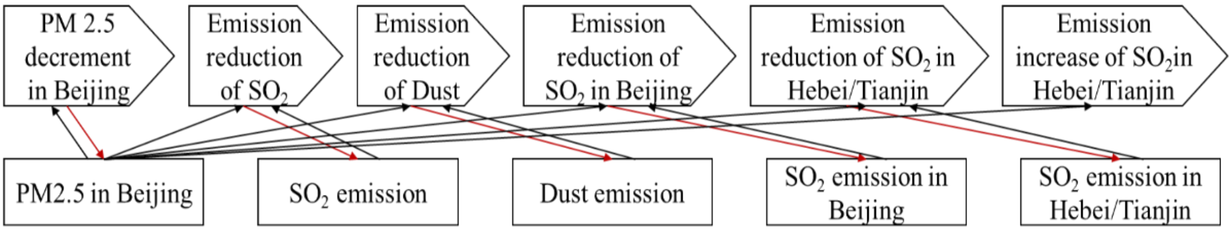



**Figure 10.** Qualitative analysis bipartite diagram for flow rate controlled by flow level.

As can be seen from Figure 10, each flow rate is controlled by at least one flow level (as black arrow), and flow level are also controlled by relevant flow rate (as red arrow). This shows that some subsystems interact with each other and form a more complex dynamic feedback system.

Based on the bipartite diagram of flow level and flow rate, the overall dynamical model flow chart of Beijing urban haze system is shown in Figure 11. The input variables were emission reduction factor of vehicle, petrochemical industry in Beijing, Tianjin and Hebei and growth factor of greening rate. The spatiotemporal resolution of the inputting variables were per year and province (city). The historical inputting variables were obtained from China Yearbook Full-text Database [47]. The future input variables were obtained from the intermediate results of simulations.

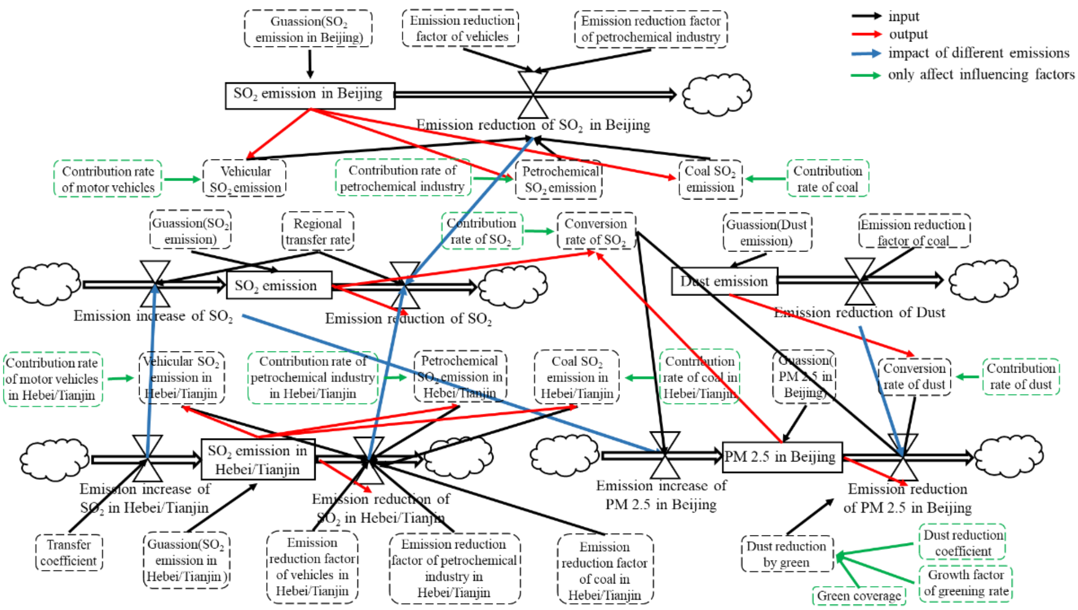



**Figure 11.** Overall dynamical model flow chart of Beijing urban haze system.

## 3. Results and Discussion

### *3.1. Comparison and Analysis of Governance Strategies*

In order to verify the performance of the haze prediction model, we analyzed the influence of macro-level factors on haze emission based on the nonlinear dynamical mechanism. The experiments took four different governance policies into account, which include vehicle exhaust emissions reduction, petrochemical production emissions reduction, coal combustion emissions reduction and greening and dust reduction. According to the simulation results, the effects of various strategies on haze formation were compared and analyzed, and feasible haze control strategies were proposed based on it.

In order to determine the parameters of the haze prediction model, such as the regional transfer rate and conversion rate of dust (Figure 11), the initial values of the parameters were set according to the Source analysis results of PM2.5 in Beijing [48] Then, the parameters were fitted and adjusted based on the historical data [49] The results of authenticity fitting are shown in Table 1. The relative error between the actual and simulation value is less than 5%, which indicates that the model fits the actual system well. The fitted parameters are shown in Table 2. On this basis, the parameterizations of emission reduction were completed for the different governance strategies, as shown in Table 3. The formula for governance strategies is the corresponding parameter combination using the manual setting.

**Table 1.** Results of authenticity fitting.

| Year | Output | Actual Value | Simulation Value | Relative Error |
|---|---|---|---|---|
| 2012 | PM2.5 | 92 | 91.23 | −0.84% |
| 2013 | PM2.5 | 89 | 87.48 | 2.24% |
| 2014 | PM2.5 | 86 | 83.50 | −2.90% |
| 2015 | PM2.5 | 81 | 79.50 | −1.85% |
| 2016 | PM2.5 | 73 | 75.61 | 3.58% |
| 2017 | PM2.5 | 68 | 66.79 | 1.78% |

**Table 2.** The parameters of Beijing urban haze system model.

| Parameter | Value |
|---|---|
| Contribution rate of $SO_2$ | 0.38 |
| Contribution rate of dust | 0.62 |
| Contribution rate of motor vehicle | 0.65 |
| Contribution rate of petrochemical industry | 0.23 |
| Contribution rate of coal | 0.12 |
| Dust reduction coefficient | 2.14 |
| Regional transfer rate | 0.03 |
| Transfer coefficient | 0.40 |
| Contribution rate of motor vehicle in Hebei/Tianjin | 0.50 |
| Contribution rate of petrochemical industry in Hebei/Tianjin | 0.23 |
| Contribution rate of coal in Hebei/Tianjin | 0.27 |

**Table 3.** The parameter combination of governance strategies.

| Governance Strategy | Emission Reduction Factor of Vehicle | Emission Reduction Factor of Petrochemical Industry | Emission Reduction Factor of Coal | Growth Factor of Greening Rate | Emission Reduction Factor of Vehicle in Hebei/Tianjin | Emission Reduction Factor of Petrochemical Industry in Hebei/Tianjin | Emission Reduction Factor of Coal in Hebei/Tianjin |
|---|---|---|---|---|---|---|---|
| Vehicle emission reduction | 0.12 | 0 | 0 | 0 | 0 | 0 | 0 |
| Petrochemical production emission | 0 | 0.12 | 0 | 0 | 0 | 0 | 0 |
| Coal combustion emission reduction | 0 | 0 | 0.16 | 0 | 0 | 0 | 0 |
| Greening and reducing dust | 0 | 0 | 0 | 0.015 | 0 | 0 | 0 |
| Collaborative governance policy | 0.12 | 0.12 | 0.16 | 0.015 | 0 | 0 | 0 |
| Cross-regional collaborative governance policy | 0.12 | 0.12 | 0.16 | 0.015 | 0.14 | 0.12 | 0.14 |

Figure 12a–d are the changes in PM2.5 in Beijing affected by the vehicle emissions reduction, petrochemical production emissions reduction, coal combustion emissions reduction and greening and dust reduction, respectively. According to Figure 12, all of these governance strategies have an effect on the haze emission in different degrees, which contributes to the downward trend of PM2.5. Under the governance strategies of vehicle emission reduction, petrochemical production emission reduction, coal combustion emission reduction and greening and reducing dust, PM2.5 in Beijing by 2050 is 70 $\mu g/m^3$, 80 $\mu g/m^3$, 62 $\mu g/m^3$ and 88 $\mu g/m^3$, respectively. Therefore, coal combustion emissions reduction is an effective way to control haze. Although the effect of coal combustion emissions reduction is better than the other three strategies, PM2.5 in Beijing is still at a high level by 2050, belonging to mild pollution. Under the governance strategy of greening and reducing dust, PM2.5 does not decrease, and even increases from 2011–2020. This implies that greening and reducing dust has hysteresis due to the growth cycle of plants.

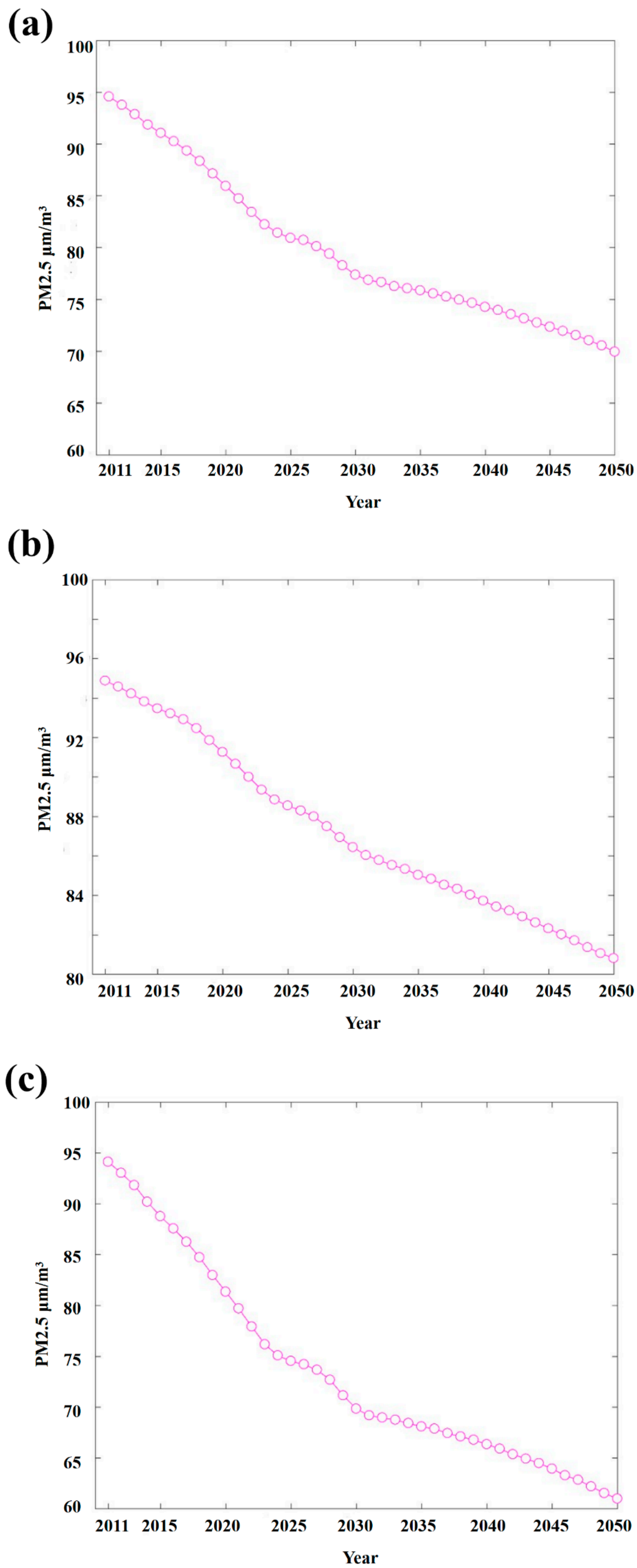



**Figure 12.** *Cont.*

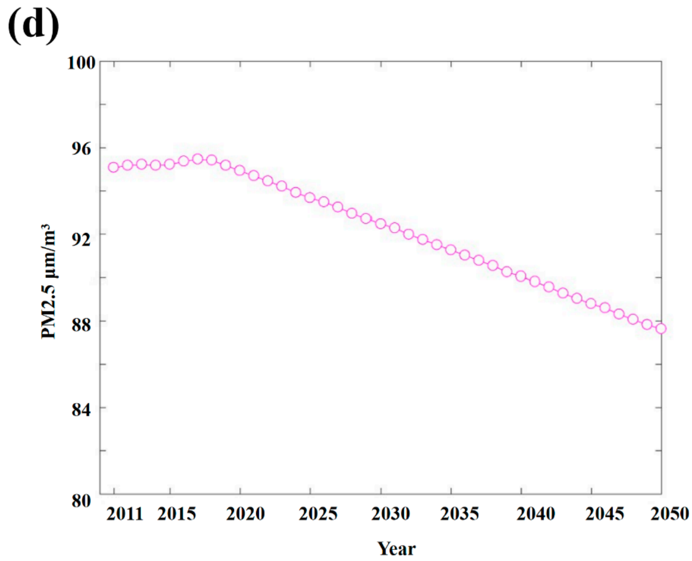



**Figure 12.** Impact of the vehicle emission reduction (**a**), petrochemical production emission reduction (**b**), coal combustion emission reduction (**c**) and greening and reducing dust (**d**) on PM2.5 in Beijing.

From the simulation results above, it can be seen that, only based on a single optimization scheme, it is difficult for the haze in Beijing to be effectively controlled. Therefore, it is necessary to optimize the combination of various governance policies to improve the governance effect.

### *3.2. Combination of Coordinated Governance Policy in Beijing*

Based on the value orientation of sustainable development, this part combines and optimizes the above-mentioned single governance policies and forms a collaborative governance policy. Through the simulation analysis of the dynamic model, we can see that the combination of governance policies reduces the haze formation significantly, and the corresponding result is shown in Figure 13. A collaborative governance policy makes various factors have an effect on the reduction in haze in Beijing at the same time, in which, the annual emission reduction in vehicle exhausts, petrochemical production, coal combustion and greening impact are 14%, 12%, 16% and 1.5%, respectively. As can be seen in Figure 14, the PM2.5 in Beijing will be lower than 75 $\mu g/m^3$ by 2023 and the air quality will change from light pollution to good. In this way, Beijing haze governance will achieve an initial effect. Furthermore, the effect of Beijing haze governance will be further consolidated in 2024–2050. By 2050, PM2.5 in Beijing will be 50 $\mu g/m^3$, which is close to the level of excellent air quality of 35 $\mu g/m^3$.

### *3.3. Combination of Cross Regional Collaborative Governance Policy*

Considering the geographical location of Beijing, Tianjin and Hebei, it is crucial to implement the cross-regional collaborative governance policy to control the haze in Beijing. Similar to Beijing, further emission reduction measures are taken for vehicle exhausts, petrochemical industry production and coal combustion in Tianjin and Hebei Province. The annual emission reduction in vehicle exhausts, petrochemical production and coal combustion in Tianjin, Hebei is 12%, 12% and 14% respectively. That is to say, in the dynamic model of the Beijing haze system, the emission reduction factor of motor vehicles, the petrochemical industry and coal combustion in Tianjin Hebei is 0.12, 0.12 and 0.14, respectively. The system simulation result is shown in Figure 14, where it can be seen that, under the combination of cross-regional collaborative governance policies of Beijing, Tianjin and Hebei, the effect of haze governance in Beijing is the best. In addition, Figure 14 shows three stages of haze control in Beijing. Firstly, from 2011 to 2017, Beijing's air quality changed from light pollution to good, and, by 2017, Beijing's PM2.5 reduced to 75 $\mu g/m^3$;

then, from 2017 to 2035, Beijing's urban haze control effect will be further strengthened, and, by 2035, Beijing's PM2.5 will be reduced to 35 μg/m$^3$; finally, from 2035 to 2050, Beijing's PM2.5 will continue to be reduced, the speed of reduction will slow down, and the achievements of haze control in Beijing will be consolidated. By 2050, the problem of haze in Beijing will be basically solved.

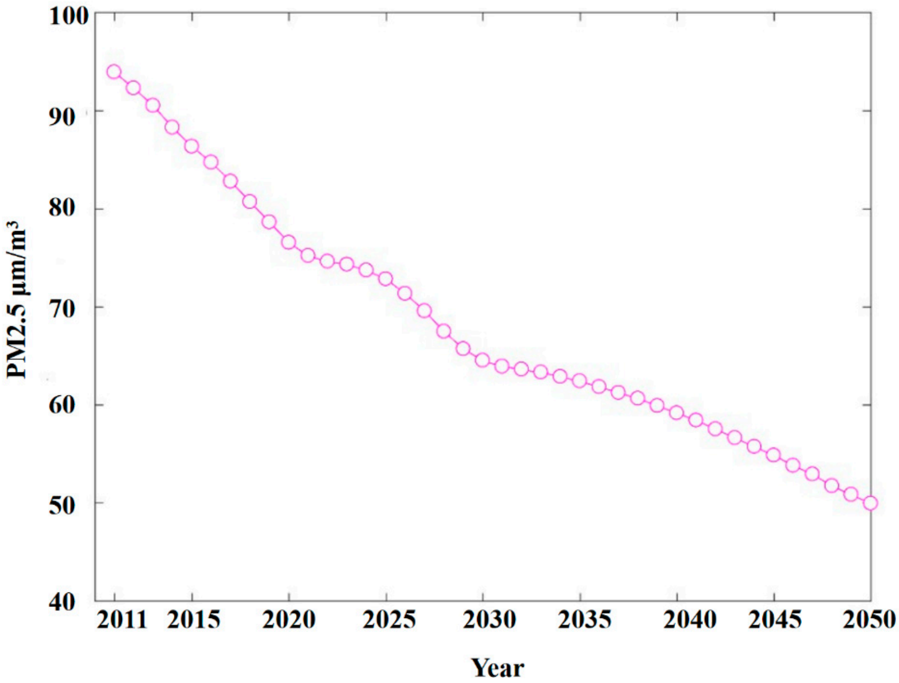



**Figure 13.** Impact of collaborative governance policy on PM2.5 in Beijing.

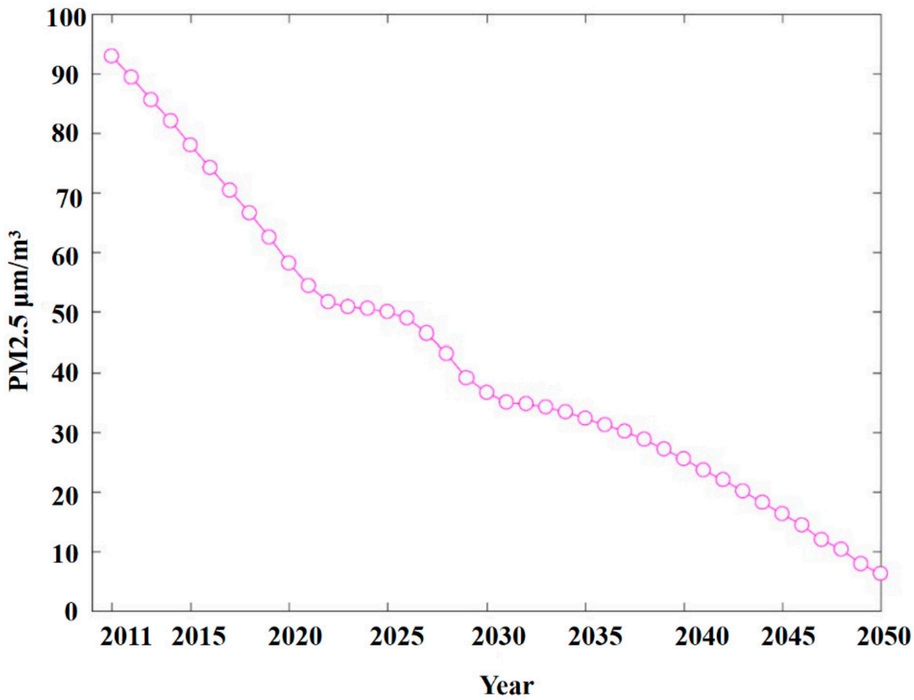



**Figure 14.** Impact of cross-regional collaborative governance policy on PM2.5 in Beijing.

In this study, a novel nonlinear dynamic haze prediction model for a complex multiple-factor and cross-regional system was established under the condition of smaller data. Different from the machine learning models, this new model incorporate the causal association and nonlinear dynamical mechanism. Therefore, it has advantages in reliably characterizing the cross-regional haze systems. Moreover, this model concentrates on long-term haze evolution under different governance control policies, which makes it easy to determine the validity of the governance policy.

### *3.4. Suggestions on Haze Controlling of Multiple Urban Regions*

The above experiments show that cross-regional joint governance is the best way to solve the haze problem in Beijing. According to the causal relationship of haze formation analyzed above, the optimization path of the regional governance policy is as follows: first, promoting public transport and new energy vehicles to reduce exhaust emissions; second, adjusting the industrial structure and developing the green economy; third, adjusting the energy structure and replacing fossil fuels, such as coal, with clean energy; fourth, improving the carrying capacity of the urban ecological environment; and, lastly, establishing a mechanism of cross-regional coordinated governance between Beijing, Tianjin and Hebei to achieve common development.

Considering the level of economic development in the Beijing, Tianjin and Hebei region, there is a big gap. It is necessary to ensure the maximization of regional interests and establish a good benefit compensation mechanism in the process of the cross-regional collaborative governance of haze reduction. To achieve effective cross-regional collaborative governance in the Beijing–Tianjin–Hebei region, the following suggestions are put forward: (1) form a strong driving force. All regions in Beijing, Tianjin and Hebei need to form a clear understanding of the urgency of haze pollution control. Local governments, enterprises and the public should actively participate in making joint efforts toward haze control; (2) build solid trust. Confidence building is the basis of dialogue and synergy and is extremely important in solving cross-region problems and conflicts of interest. All regions of Beijing, Tianjin and Hebei should be based on the common goal, that is, to eradicate haze pollution, establish firm and full trust and jointly contribute to haze control; (3) ensure good political support. In the comprehensive cooperation strategy to control cross-regional haze pollution, the political support of governments in Beijing, Tianjin and Hebei plays an important role and determines whether the cooperation policies and measures can be successfully implemented. In short, the economic development of Beijing, Tianjin and Hebei is different, and the corresponding policies for haze pollution control are also different. When formulating relevant environmental protection policies, local governments in Beijing, Tianjin and Hebei should take into account the governance measures of the region and cooperation with surrounding regions, and further promote the collaborative governance of haze pollution based on policies.

In order to realize the cross-regional collaborative governance of haze pollution in Beijing, Tianjin and Hebei, we should form multi-level, cross-regional institutional arrangements and determine accurate policy plans and detailed implementation plans, so as to ensure the efficient promotion of haze governance. In the process of haze control, we should also pay attention to the cost sharing of pollution control, eliminate the conflict of interest between regions in the process of haze control and stabilize the cooperative relationship.

## 4. Conclusions

(1) Based on the Beijing–Tianjin–Hebei region, a complex haze system was established, which not only takes several local pollution sources into account but also considers the interaction between cross-regions.

(2) The causality at the macro level and their dynamic action mechanism at the micro level were analyzed. Detailed causality diagrams and flow charts were established to show the causes and processes of haze formation, while the corresponding system dynamic model was used to learn the complex interaction mechanism between dynamic processes.

(3) The influence degree of various factors on haze formation was observed through experiments, and effective governance policies were obtained. Through an analysis and

prediction of the nonlinear dynamic haze model, we can conclude that only by cooperating with all cities in the Beijing–Tianjin–Hebei region can the haze be controlled effectively.

(4) It is necessary to improve the public's understanding of the importance of regional collaborative governance. More importantly, all regions should avoid fighting alone and transferring air pollution sources to control the haze formation. The cross-regional coordinated management of haze in Beijing–Tianjin–Hebei should serve the overall situation of the national coordinated development, and we want both economic growth and environmental improvement.

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