A study on environmental governance in China based on GA-BP neural network and TOPSIS method

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ABSTRACT

Regarding the construction of a mathematical model between air quality index (AQI) and different pollutant concentrations, firstly, a genetic algorithm was used to optimize the BP neural network model with PM2.5, PM10, SO_2, CO, NO_2 and O_3 as the main air pollutants, and then the air pollution in Beijing from 2015 to 2021 was used as the validation object, and it was found that the fitted R-squared on the basis of 20% test set is greater than 0.95 or above, and finally the Spearman correlation model is used to analyze the main pollutants associated with AQI index to provide solutions for the subsequent treatment of air pollution.

Regarding the construction of a comprehensive water quality evaluation model, firstly, the weight integration method based on the moment estimation theory was used to assign subjective and objective weights to the indicators, and dissolved oxygen, temperature, turbidity, ammonia nitrogen, permanganate index and hydrogen ion concentration index were used as indicators for evaluating water quality, and then the optimal weights of each indicator were derived as 7.766%, 9.509%, 37.962%, 19.666%, 17.726% and 7.7371%, and finally the comprehensive evaluation of water quality in each city was carried out by TOPSIS method.

Regarding the construction of urban noise pollution monitoring network, firstly, a genetic algorithm based on Gaussian kernel support vector machine was used to optimize the model, and Guangzhou was used as the validation object to solve the Gaussian response surface with the building density as the noise index, and the optimal number of monitoring points of 10 was obtained by using genetic algorithm for optimization.

Keywords: Genetic algorithm; BP neural network; Spearman correlation; Theory of moment estimation; TOPSIS; Gaussian kernel support vector machine

1 INTRODUCTION

In recent years, as the economy and population continue to grow, China has faced serious environmental problems such as air and water environmental pollution and urban noise pollution. In order to better understand these problems, three questions are posed in this paper, and they are explored in depth. First, we established a mathematical model between air quality index (AQI) and different pollutant concentrations, used genetic algorithm to optimize the BP neural network model, and developed corresponding measures based on the correlation analysis of relevant pollutants to finally rank the 10 cities with the best air quality in China. Next, we established a comprehensive evaluation system of water environment quality and ranked the 10 cities with the best water environment in China by weight integration method and TOPSIS comprehensive evaluation method. Finally, we took Guangzhou as an example and used Gaussian kernel support vector machine to fit the response surface, and optimized the number and location of monitoring points by genetic algorithm to minimize the number of monitoring points to ensure the accuracy and comprehensiveness of the monitoring results. Through these studies, we hope to provide some useful information and suggestions for improving environmental problems in China.

2 RELEATED WORK

The problems that need to be addressed in this paper are as follows:

Based on the data collected by the team, establish a mathematical model between the air quality index (AIQ) and the concentration of different pollutants to better understand the air quality situation; based on the above findings, take corresponding measures to improve the air quality; list the 10 cities with the best air quality condition in the country.

Establish a comprehensive evaluation system of water environment quality to reflect the pollution level and treatment effect of water environment; list the 10 cities with the best water environment in China.

Based on the selected cities, consider the accuracy and comprehensiveness of the detection results, and optimize the detection network of urban noise pollution with the goal of minimizing the number of monitoring points.

In addition, we need to collect the data from the national statistical yearbook, such as air pollution data and water quality data of each city.

3 MODEL ESTABLISHMENT AND SOLUTION

3.1 Problem 1 modeling

Since there is a large correlation between AQI and different pollutant concentrations, and also a large nonlinearity, traditional prediction models such as multiple linear regression are not good at mining the relationship between AQI and pollutant concentrations, while machine learning BP neural network fitting models are not only good at mining the nonlinear relationship between variables but also can better handle a large number of data samples. In addition, genetic algorithm is the most effective optimization algorithm in today's intelligent optimization algorithm, and the combination of genetic algorithm and BP neural network can further optimize the BP neural network.

Therefore, in this paper, we use BP neural network model to fit AQI and pollutant concentration for prediction, and combine genetic algorithm to optimize the fitting error and construct genetic algorithm optimized BP neural network model (GA-BP neural network) Finally, for taking corresponding measures to improve air quality problem we can first calculate the correlation size of each pollutant concentration to AQI and then intervene in a targeted way. important pollutant concentration to effectively reduce the AQI value.

3.2 Genetic algorithm optimization of BP neural network model

(1) Genetic Algorithm

Genetic algorithm (GA) is derived from Darwin's theory of evolution of life (reproduction, mating and mutation). In GA, the optimal solution is obtained by the reproduction and evolution of the population.

In GA, there are three types of genetic operators: selection, crossover and mutation.

a) Selection. Selecting certain data among a portion of regular data as the next set of data is the selection operator. Commonly used selection operators include: roulette wheel method, tournament method, etc. In this paper, we use the roulette wheel method:

$$f_i = \frac{k}{F_i} \tag{1}$$

$$p_i = \frac{f_i}{\sum_{i=1}^{N} f_i} \tag{2}$$

Where F_i denotes the fitness value of an individual i, p_i denotes the selection probability of i, k is the coefficient; N is the number of individuals in the population .

b) Crossover. The crossover operator simulates the genetic recombination process in order to transfer the current best genes to the next population and obtain new individuals. The specific steps of the crossover operator are as follows:

Step1: Random selection of objects;

Step2: According to the selected object length, randomly select the intersection position.

Step3: Define the crossover probability $P_c(0 < P_c \leqslant 1)$, run the crossover operator and change the genes. The intersection of the k chromosome a_k and chromosome one a_{kl} at the j position is as follows:

$$\begin{cases} a_{ki} = a_{ki}(1-b) + a_{lj}b \\ a_{li} = a_{li}(1-b) + a_{kj}b \end{cases} \tag{3}$$

Where b is a random number in the interval 0-1.

c)Mutation. This operator simulates the phenomenon of gene mutation in biology, and new individuals are obtained according to the probability of mutation (mutation probability). The individual that carries out the mutation is the j gene of the i individual a_{ij} and the mutation is performed as follows:

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{max}) \times f(g) \\ a_{ij} + (a_{min} - a_{ij}) \times f(g) \end{cases} \tag{4}$$

where: the maximum value of gene a_{ij} is a_{max}; the minimum value of gene a_{ij} is a_{min}; $f(g) = r_2(1 - g/G_{\max})^2$; the random number is r_2; g is the current iteration number; G_{max} is the maximum evolution number; r is the random number between [0,1] [1].

(2) GA-BP neural network prediction model

BP neural networks have been quite influential; In areas such as pattern recognition and signal processing, however there is still a challenge on the way of attacking the design network, namely the determination of the structure. This paper takes the condition that the genetic algorithm can reach a specific value to find the global optimal solution, which in turn is used to optimize the connection weights and thresholds of the neural network, and then in taking the boost [2].

3.1.2 Spearman Correlation Model

The Spearman rank correlation coefficient [3] is used to measure the correlation between two variables and is usually used to measure non-linear relationships. It is based on the ranking position of each variable in the sample rather than a specific numerical magnitude [4] .

The formula for Spearman's rank correlation coefficient is expressed as follows:

$$P = 1 - \frac{6\sum d^2{}_i}{n(n^2 - 1)} \tag{5}$$

The Spearman's rank correlation coefficient takes values between [-1,1], where -1 indicates a perfectly negative correlation, 0 indicates no correlation, and 1 indicates a perfectly positive correlation. Unlike the Pearson correlation coefficient, the Spearman rank correlation coefficient can be used to measure the correlation between any two variables, both linear and nonlinear, and does not require the relationship between the two variables to be linear.

3.2 Problem 1 model solving

Before solving, we need to review the relevant literature to determine what are the main pollutants that affect AQI. By reviewing the relevant literature, we choose PM2.5, PM10, SO2, CO, NO2 and O3 as the main air pollutants in this paper. In order to demonstrate the feasibility of our AQI model, the daily AQI values and the concentrations of each pollutant in Beijing from 2015 to 2021 were collected and obtained from the public data of the National Environment Bureau.

3.2.1 GA-BP neural network model solving

(1) Data pre-processing

First, the analysis of data related to air quality and pollutant concentrations in Beijing from the National Environment Agency (NEA) public data shows that there are no missing values.

Second, the original data need to be normalized before fitting the BP neural network. Normalization can make the data have zero mean and unit variance, which is convenient for neural network learning; while inverse normalization converts the normalized data back to the original scale, which is convenient for practical application.

The relevant standardized formula is as follows:

$$\hat{x} = \frac{x - \mu}{\sigma} \tag{6}$$

Where $\hat{x}$ is the standardized data, x is the original data, μ is the mean of the original data, and σ is the standard deviation of the original data.

Inverse normalization equation:

$$x = \hat{x}\sigma + \mu \tag{7}$$

Finally, we need to set the parameters related to the GA-BP neural network, which are set as follows:

Table 1: GA-BP neural network parameter settings

Initializing the population	Number of iterations	Crossover probability	Mutation probability
10	50	0.4	0.15
Number of neural network iterations	Number of hidden layers	Learning Rate	Training target value
200	10	0.1	0.00001

Meanwhile, in order to evaluate the fitting effect of GA-BP neural network, the root mean square error is used in this paper as an evaluation of the reasonableness and accuracy of the model.

Root mean square error:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{8}$$

(2) GA-BP neural network solution results

First, the first 80% of Beijing 2015~2021 is selected as the training set and the last 20% as the test set, and the results are solved using MATLAB software as follows:

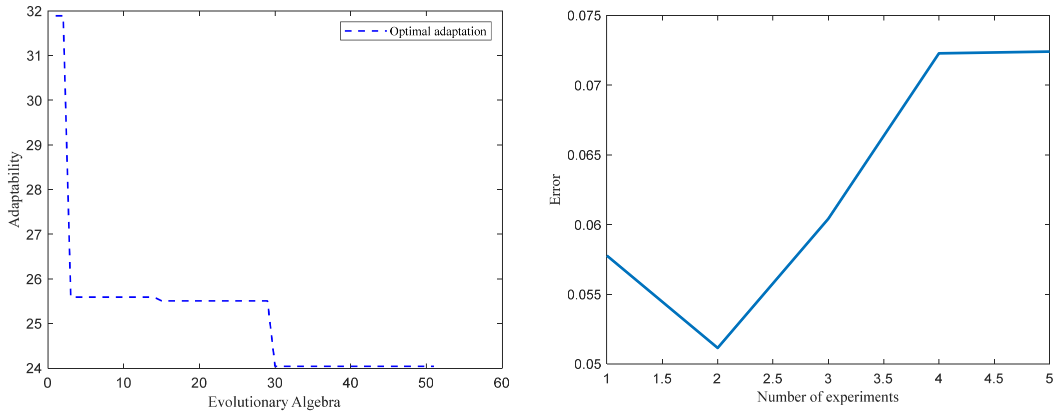

Figure 1: GA-BP neural network error drop curve

From the left side of Figure 1, it can be seen that the fitting error of the BP neural network after combining the genetic algorithm decreases significantly and reaches the optimal value at the 30th iteration; on the right side of Figure 2, it can be seen that the relative root mean square error of the GA-BP neural network decreases significantly after 5 iterations of training.

Finally, we obtain the fitting results for the test set of GA-BP neural network:

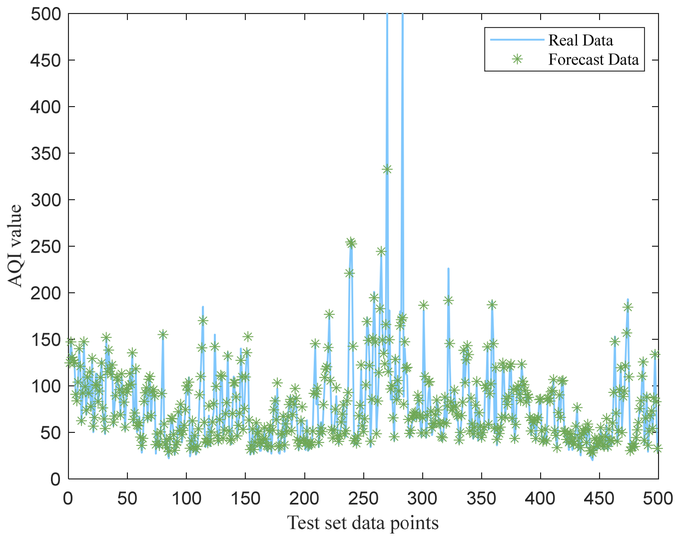

Figure 2: GA-BP neural network test set fitting results

From Figure 2, it can be seen that the root mean square error of the GA-BP neural network test set is 13.8635, which is a small error and high model accuracy. Besides, the GA-BP neural network regression R-square is greater than 0.95 on both the training and test sets.

3.2.2 Air Quality Improvement Measures

Firstly, we performed Spearman correlation analysis between the concentration of each pollutant and AQI values from 2015 to 2021 in Beijing, and solved the results using MATLAB as follows:

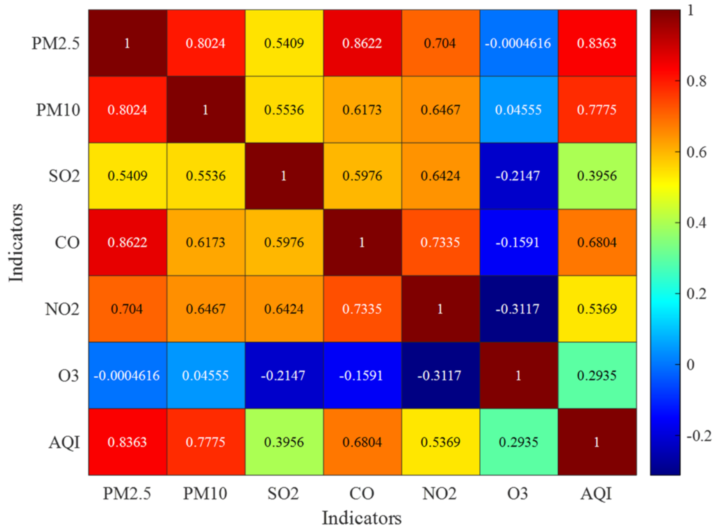

Figure 3: Heat map of Spearman's correlation coefficient

From Figure 3, we can see that PM2.5, PM10, and CO have a strong correlation to AQI, so in the treatment of Beijing air pollution, we can first target the above pollutants with a strong correlation.

Next for air quality improvement measures, we can improve from reducing industrial production of air pollution, in order to introduce the results of the above Spielman correlation analysis, we can establish the relative degree of intervention of the relevant pollutants equation, assuming that the environmental sector requires the development of relevant industrial pollution emissions policy is expected in the future AQI need to be reduced by 10%, which corresponds down to the concentration of each pollutant to reduce emissions The equation related to the strength of the policy is then.

$$\Phi_i = \omega_i \times 10\% \tag{9}$$

$$w_i = \frac{\alpha_i}{\sum_{i=1}^{n} \alpha_i} \tag{10}$$

Where α_i is the Spearman correlation coefficient for each pollutant concentration, w_i is the intensity of the policy intervention pollutant, and Φ_i is the expected reduction in each pollutant concentration requirement. The results were calculated as follows:

Table 2: Beijing Air Pollutant Intervention Program

Contaminants	PM2.5	PM10	CO
Intervention intensity	0.365	0.339	0.297
Projected reduction	3.65%	3.39%	2.97%

To verify the feasibility of our air quality treatment measures, we use Beijing November 2021 as the validation dataset and compare the post-intervention AQI values with the pre-intervention AQI values.

Using the above established Beijing air quality GA-BP neural network model to predict the AQI values after the intervention pollutant treatment, the results are as follows:

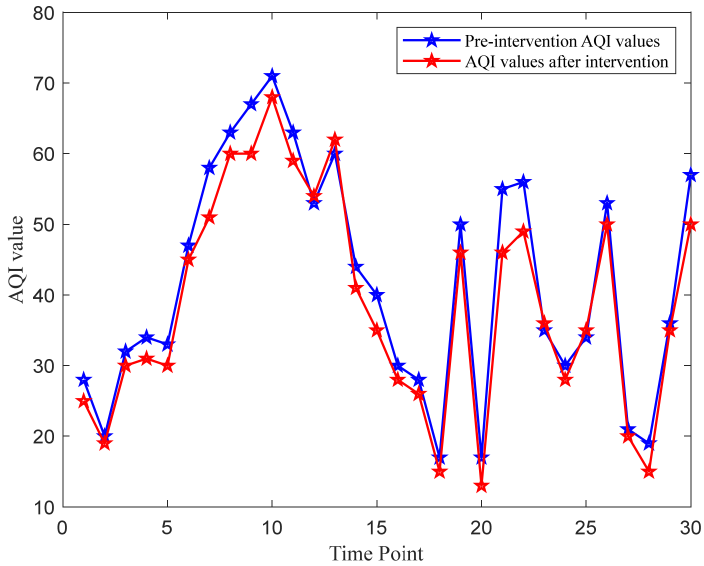

Figure 4: AQI curve with and without pollutant intervention in November 2021

From Figure 4, it can be seen that the AQI values decreased after the relevant policy interventions for pollutants PM2.5, PM10 and CO, indicating that our intervention model is reasonable and effective.

3.2.3 National air quality ranking by city

In order to evaluate the ranking of the air quality of each city in the country, we can predict the AQI values based on the GA-BP neural network model mentioned above. Specifically, we can start from November 30, 2021 for each city in the country and predict the AQI values of each city in the next 10 days backward, and rank each city by the magnitude of the AQI prediction.

Before that we need to collect the daily pollutant concentrations and AQI values of each city in the country according to the public data of the National Environment Bureau, and use MATLAB to solve to get the top 10 cities in the country in terms of air quality:

Table 3: Predicted AQI values for the top 10 cities with the best air quality in China

City \ day	1	2	3	4	5	6	7	8	9	10	Average value	Ranking
Yushu Prefecture	37	36	36	35	33	32	33	27	46	32	34.7	1
Chamdo	34	35	35	37	36	39	35	33	34	31	34.9	2
Linzhi City	30	31	36	37	41	38	38	36	33	30	35.0	3
Qujing City	38	28	26	38	40	38	31	34	35	43	35.1	4
Lhasa	39	42	43	39	36	39	39	40	36	39	39.2	5
Lijiang City	42	39	43	41	44	42	45	44	40	39	41.9	6
Shigatse	46	50	46	44	44	44	45	40	41	44	44.4	7
Haibei Prefecture	46	45	47	43	41	43	45	47	47	41	44.5	8
Ahri area	52	49	50	49	49	48	45	46	48	50	48.6	9
Nagchu City	47	52	47	49	46	50	59	49	64	59	52.2	10

3.3 Problem 2 Modeling

First of all, in order to build a comprehensive evaluation model of water environment quality, we can use the superiority and inferiority solution method - TOPSIS objective comprehensive evaluation method, and for how to determine the weight of indicators, we use the weight integration method based on the moment estimation theory, that is, the subjective and objective weights are integrated to assign weights to indicators, specifically we Specifically, we can assign weights from subjective weighting: hierarchical analysis and sequential relationship method; objective weighting: entropy weighting and coefficient of variation method, using the moment estimation theory for comprehensive weighting.

3.3.1 Integrated assignment method based on moment estimation theory

(1) Hierarchical analysis method

The Analysis Hierarchy Process (AHP), which divides the human thinking process into goal, criterion and solution levels and analyzes them with the help of mathematical models, is a practical decision analysis method that effectively combines qualitative judgment and quantitative calculation for decision makers. The following are the core formulas of hierarchical analysis assignment [5]:

$$W_i = \frac{(\Pi_{j=1}^{n} a_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n} (\Pi_j^{n} a_{ij})^{\frac{1}{n}}}, ij = 12kn \tag{11}$$

Where a_{ij} is the expert score of the judgment matrix.

(2) Sequential relationship method

The sequential relationship method is a comprehensive analysis method used to solve complex problems by representing the relationship between factors in a problem as a directed graph and giving the order of priority among the factors to arrive at a final decision [6].

1)To give a guideline for the comparison of relative importance between two adjacent indicators: let the ratio of the relative importance of the expert's evaluation indicators X_{k-1} and X_k about the evaluation object X_{k-1}/X_k be assigned as follows:

$$r_k = \frac{w_{k-1}}{w_k} (k = n, n-1, \ldots, 2) \tag{12}$$

Where, n is the total number of evaluation indicators of product quality.

2) Calculation of indicator weights w_k : Assuming that experts give r_k rational assignments, the

$$w_n = (1 + \sum_{k=2}^{n} \prod_{i=k}^{n})^{-1} \tag{13}$$

$$w_{k-1} = r_k w_k (k = n, n-1, \ldots, 2) \tag{14}$$

3) The final set of weights is obtained as

$$w_k = (w_1, w_2, \ldots, w_n)^T \tag{15}$$

(3) Entropy method

Entropy is a concept in information theory, which is a measure of uncertainty. The greater the amount of information, the smaller the uncertainty, the smaller the entropy; the smaller the amount of information, the greater the uncertainty, and the greater the entropy [7].

The following is the core formula for the entropy method of empowerment:

1) Calculate the weight of the j indicator.

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij}), j = 1, \ldots, m \tag{16}$$

where $k = 1/\ln(n) > 0$ satisfies $e_j \geqslant 0$

2) Calculate the information entropy redundancy.

$$d_j = 1 - e_j, j = 1, \ldots, m \tag{17}$$

3) Calculate the weight of each indicator

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, j = 1, \ldots, m \tag{18}$$

(4) Coefficient of variation method

For the application of the coefficient of variation method, the actual values of each variable should first be standardized for data processing, and then a weighted average method should be used to determine the overall rating of the potpourri after baking, and the coefficient of variation for each indicator should be calculated as follows [8]:

$$V_i = \frac{\sigma_i}{X_i} \tag{19}$$

Where V_i denotes the coefficient of variation of the indicator i; σ_i denotes the standard deviation of the indicator i; X_i denotes the arithmetic mean of the indicator i.

The weights of each variable are calculated by the following formula:

$$w_i = \frac{V_i}{\sum_{i=1}^{n} V_i} \tag{20}$$

(5) Moment estimation theory weight integration method

In order to reflect both subjectivity and objectivity of decision making in the evaluation system, the subjective and objective weights are linearly combined and the optimal weights are calculated. The set of subjective weights for each indicator determined by each subjective weighting principle can be obtained by having l subjective weighting methods to assign weights to malpractice evaluation indicators [9] .

$$W_s = \{ w_{ij} \mid 1 \leqslant s \leqslant l, 1 \leqslant j \leqslant m \} \tag{21}$$

Among them, $\forall s, \sum_{j=1}^{m} w_{ij}, w_{ij} > 0$

The objective weighting method of $q - l$ was used to assign weights to the evaluation indicators, and the set of objective weights obtained

$$W_b = \{ w_{bj} \mid l+1 \leqslant b \leqslant q, 1 \leqslant j \leqslant m \} \tag{22}$$

Among them, $\forall b, \sum w_{bj} = 1, w_{ij} > 0$.

Calculate the relative importance coefficients of the subjective and objective weights ξ and ψ , then the optimization model for integrating the portfolio weights:

$$\min H(w_j) = \xi \sum_{s=1}^{l} (w_j - w_{sj})^2 + \psi \sum_{b=1}^{l} (w_j - w_{bj})^2 \tag{23}$$

Where $0 \leqslant w_j \leqslant 1, 1 \leqslant j \leqslant m$.

q For each evaluation index, the expectation values of w_{sj} and w_{bj} are according to the basic idea of moment estimation theory.

$$\begin{cases} E(w_{sj}) = \dfrac{\sum_{s=1}^{l} w_{sj}}{l} \\ E(w_{bj}) = \dfrac{\sum_{b=1}^{l} w_{sj}}{q-1} \end{cases} \tag{24}$$

Using equation (23), the importance coefficients of the subjective and objective weights of each indicator $m\xi_j$ and ψ_j can be calculated as

$$\begin{cases} \xi_j = \dfrac{E(w_{sj})}{E(w_{sj}) + E(w_{bj})} \\ \psi_j = \dfrac{E(w_{bj})}{E(w_{sj}) + E(w_{bj})} \end{cases} \tag{25}$$

For the evaluation indicator in the multi-indicator decision matrix [10], it can be regarded as taking m samples from each of the 2 aggregates, and using the same basic idea of moment estimation theory, we can obtain

$$\begin{cases} \xi = \dfrac{\sum_{j=1}^{m} \xi_j}{\sum_{j=1}^{m} \xi_j + \sum_{j=1}^{m} \psi_j} = \dfrac{\sum_{j=1}^{m} \xi_j}{m} \\ \psi = \dfrac{\sum_{j=1}^{m} \psi_j}{\sum_{j=1}^{m} \xi_j + \sum_{j=1}^{m} \psi_j} = \dfrac{\sum_{j=1}^{m} \psi_j}{m} \end{cases} \tag{26}$$

For each evaluation indicator $d_j (1 \leqslant j \leqslant m)$,the smaller the better, for which the optimization model shown in equation (26) can be transformed into

$$min\, H = \{H(w_1), H(w_2), \cdot\cdot, H(w_m)\} \tag{27}$$

$$s.t.\{ \begin{matrix} \sum_{j=1}^{m} w_j = 1 \\ 0 \leqslant w_j \leqslant 1, 1 \leqslant j \leqslant m \end{matrix} \tag{28}$$

In order to solve equation (27,28), a linear weighting method with equal weights is used to transform the multi-objective optimization model into a single-objective optimization model.

$$min\, H(w_j) = \sum_{j=1}^{m} \xi \sum_{s=1}^{l} (w_j - w_{sj})^2 + \sum_{j=1}^{m} \psi \sum_{b=1}^{l} (w_j - w_{bj})^2 \tag{29}$$

$$s.t.\{ \begin{matrix} \sum_{j=1}^{m} w_j = 1 \\ 0 \leqslant w_j \leqslant 1, 1 \leqslant j \leqslant m \end{matrix} \tag{30}$$

3.2.2 TOPSIS comprehensive evaluation model

Let the multi-attribute decision sample set be $D = \{d_1, d_2, \cdots, d_n\}$ and the attribute variable that measures the merit of a sample be $x_1, x_2, \cdots, x_n$, when the vector consisting of n attribute values for each sample $d_i (i = 1, 2, \cdots, n)$ in the sample set D is $[a_{i1}, \cdots, a_{in}]$, which acts as a point in the n dimensional space that uniquely characterizes the sample d_i [11].

The specific algorithm is shown here:

Step1: Construction of weighted normative matrix $C = (c_{ij})_{m\times n}$.

Step2: Determine the positive ideal solution c_j^* and the negative ideal solution c_j^0.

$$c_j^* = \begin{cases} max_i\ c_{ij}, jisabenefit - typeattribute, \\ min_i\ c_{ij}, jisacost - typeattribute, \end{cases} \quad j = 1,2,\cdots,n \tag{31}$$

$$c_j^* = \begin{cases} min_i\ c_{ij}, jisabenefit - typeattribute, \\ max_i\ c_{ij}, jisacost - typeattribute, \end{cases} \quad j = 1,2,\cdots,n \tag{32}$$

Step3: Calculate the distance from each sample to the positive ideal solution s_i^* and the negative ideal solution distance s_i^0.

$$s_i^* = \sqrt{\sum_{j=1}^{n}(c_{ij} - c_j^*)^2}, i = 1,2,\cdots,m \tag{33}$$

$$s_i{}^0 = \sqrt{\sum_{j=1}^{n}(c_{ij} - c_j^0)^2}, i = 1,2,\cdots,m \tag{34}$$

Step4: Calculate the queuing index value (i.e., the composite evaluation index) for each sample.

$$f_i^* = \frac{s_i^0}{s_i{}^0 + s_i{}^*}, i = 1,2,\cdots,m \tag{35}$$

3.4 Problem 2 model solving

Before the comprehensive evaluation, we need to determine the indicators to evaluate the good or bad water quality, by reviewing the relevant literature, this paper determines the following indicators as water quality evaluation indicators, and distinguish which indicators belong to positive indicators, which belong to negative indicators, and which belong to interval-type indicators.

Dissolved oxygen: the greater the dissolved oxygen value, the better the water body. That is, it is a positive indicator, and the optimal interval should be in the higher range.

Temperature: High water temperature will affect the river ecology, i.e., it is a negative indicator, and the optimal interval should be in the lower range.

Turbidity: the smaller the turbidity value, the better the water body. That is, the negative indicator, the optimal interval should be in the lower range.

Ammonia nitrogen and permanganate index: both indicators reflect the degree of pollution of the water body, that is, negative indicators, the optimal interval should be in the lower range.

Hydrogen ion concentration index: This index is related to the acidity and alkalinity of water, usually between 6~8 is neutral, that is, the interval type index, the optimal interval should be within this range.

Secondly, we collected and obtained the data of the above-mentioned relevant indicators for December 2021 for cities across the country through the water monitoring data of cities (including county-level cities) publicly available from the National Environment Agency.

Finally, MATLAB and SPSSPRO were used to solve the above established comprehensive water quality evaluation model.

3.4.1 Data pre-processing

First, we analyze the collected water quality-related indicators of the cities in December 2021 whether there are missing, using EXCEL screening found that 249 cities (including county-level cities) have missing indicators, so we need to exclude these cities with missing indicators, after the exclusion of a total of 1742 cities we will be the remaining cities as the evaluation object.

Secondly, since our selected water quality evaluation indicators have three attributes (positive, negative and interval) therefore we need to normalize the corresponding indicators, the normalization formula is as follows:

Positive type indicators:

$$b_{ij} = \frac{a_{ij}}{a_j{}^{max}} \tag{36}$$

Negative type indicators:

$$b_{ij} = 1 - a_{ij}/a_j{}^{max} \tag{37}$$

Interval-type indicators:

$$b_{ij} = \begin{cases} 1 - (a_j^0 - a_{ij})/(a_j{}^0 - a_j{}'), if\ a_j{}' \leqslant a_{ij} < a_j{}^0 \\ 1 \qquad\qquad\qquad\qquad\quad , if\ a_j{}^0 \leqslant a_{ij} < a_j{}^* \\ 1 - (a_j^0 - a_{ij})/(a_j{}^0 - a_j{}'), if\ a_j{}' \leqslant a_{ij} < a_j{}'' \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad\qquad , else \end{cases} \tag{38}$$

where the given optimal attribute interval is $[a_j{}^0, a_j{}^*]$, $a_j{}'$ is the lower intolerable limit, and $a_j{}''$ is the upper intolerable limit.

3.4.2 Weight integration solution based on moment estimation theory

Assignment of objective weights using SPSSPRO:

Table 4: Entropy weighting results

Indicators	Information entropy value e	Information utility value d	Weighting(%)
Turbidity	1	0	0.612
Ammonia nitrogen	1	0	0.78
Permanganate index	0.998	0.002	7.196
Dissolved oxygen	0.995	0.005	19.661
Hydrogen ion concentration index	0.994	0.006	25.764
Temperature	0.989	0.011	45.987

Table 5: Weighting results of the coefficient of variation method

Indicators	Average value	Standard deviation	CV factor	Weighting(%)
Hydrogen ion concentration index	7.866	0.465	0.059	0.93
Dissolved oxygen	9.998	1.889	0.189	2.974
Temperature	11.358	5.303	0.467	7.347
Permanganate index	2.68	1.72	0.642	10.101
Ammonia nitrogen	0.168	0.281	1.675	26.352
Turbidity	36.422	121.045	3.323	52.297

For the subjective weighting method, this paper refers to the weighting sizes recognized by international experts, combines the above objective weighting results, and uses MATLAB software to solve the moment estimation theoretical weighting integration model to obtain the final index weight sizes:

Table 6: Optimal weights based on moment estimation theory

Indicators	Hierarchical analysis method	Sequential relationship method	Entropy method	Coefficient of variation method	Optimal weighting(%)
Turbidity	25.3	24.1	0.612	52.297	37.962
Ammonia nitrogen	12.3	13.2	0.78	26.352	19.666
Permanganate index	23.1	25.1	7.196	10.101	17.726
Dissolved oxygen	15.6	12.4	19.661	2.974	7.766
Hydrogen ion concentration index	13.2	13.6	25.764	0.93	7.371
Temperature	10.5	11.6	45.987	7.347	9.509

We also obtain the relative importance coefficients of the subjective and objective weights: $\xi = 0.5084, \psi = 0.4916$.

3.4.3 TOPSIS comprehensive evaluation of water quality by city

SPSSPRO is used to combine the optimal weights obtained from the above solution to obtain a comprehensive water quality score for each city in China, and the top 10 cities in terms of water quality are selected for display in this paper:

Table 7: Water quality ranking of the top ten cities

City	Positive ideal solution distance (D+)	Negative ideal distance (D-)	Overall Score	Water Quality Ranking
Jilin	0.1442	0.9199	0.8645	1
Mudanjiang City	0.1468	0.9274	0.8633	2
Benxi	0.1606	0.9407	0.8541	3
Ili Kazakh Autonomous Prefecture	0.1618	0.9317	0.8520	4
Tieling City	0.1629	0.9259	0.8504	5
Yingkou	0.1672	0.9333	0.8481	6
Yanbian Korean Autonomous Prefecture	0.1662	0.9173	0.8466	7
Qiqihar	0.1660	0.9154	0.8465	8
Yanbian Korean Autonomous Prefecture	0.1668	0.9184	0.8463	9
Hulunbuir City	0.1691	0.9228	0.8451	10

In order to reflect the effect of water environment management, we need to integrate the size of the weight of each indicator and the number of urban water quality monitoring points, through the national environmental department to provide the distribution of water quality monitoring points in cities across the country:

Figure 5: Distribution of water quality monitoring points by city in 2021

As can be seen from Figure 5, water quality monitoring points mainly show an uneven distribution of dense in the east and sparse in the west, dense in the south and sparse in the north, combined with the above-mentioned determination of the weight of each indicator, so we can develop relevant measures to improve the quality of the water environment, increase the number of water quality monitoring points in the western region of China, and develop relevant policies to reduce the main indicators affecting water quality: turbidity, ammonia nitrogen and high manganese index.

Suppose, the relevant authorities have formulated a relevant policy for the above description, requiring a 10% improvement in water quality in the western region, then we can build a relevant model specific to the changes in the relevant indicators, as follows:

$$\phi_i = \varpi_i \times 10\% \tag{39}$$

$$\varpi_i = \frac{\mu_i \times 50\%}{\sum_{i=1}^{n} \mu_i} + \frac{50}{n}\% \tag{40}$$

Where μ_i is the weight of turbidity, ammonia nitrogen and permafrost index, ϖ_i is the weight of policy intervention for turbidity, ammonia nitrogen and permafrost index, ϕ_i is the degree of change under policy intervention for turbidity, ammonia nitrogen and permafrost index, in the above equation we have assumed 50% weight for each of the indicator impact and monitoring points, so they are equally divided and the corresponding results are calculated:

Table 8: Indicator weights

Indicators	Turbidity	Ammonia nitrogen	Permanganate index
Intervention weights	50.38%	26.10%	23.52%
Degree of reduction in intervention changes	5.04%	2.61%	2.35%

Finally, SPSSPRO was used to solve for the top ten cities' score indices for water quality after policy interventions:

Table 9: Combined scores of the top 10 cities for water quality after policy intervention

City	Positive ideal solution distance (D+)	Negative ideal distance (D-)	Overall Score	Water Quality Ranking
Jilin	0.1514	0.8739	0.9077	1
Mudanjiang City	0.1542	0.8810	0.9065	2
Benxi	0.1687	0.8937	0.8969	3
Ili Kazakh Autonomous Prefecture	0.1699	0.8851	0.8946	4
Tieling City	0.1710	0.8796	0.8929	5
Yingkou	0.1756	0.8866	0.8905	6
Yanbian Korean Autonomous Prefecture	0.1746	0.8715	0.8889	7
Qiqihar	0.1743	0.8696	0.8888	8
Yanbian Korean Autonomous Prefecture	0.1752	0.8725	0.8886	9
Hulunbuir City	0.1776	0.8766	0.8874	10

The above table shows that the urban water quality after the policy intervention has improved significantly compared to that before the intervention.

3.5 Problem 3 Modeling

Because of the increase of traffic density and building density, these factors will affect the degree of urban noise pollution, so this paper may use the building density as a quantitative indicator of noise pollution, firstly, we use Gaussian kernel support vector regression to fit the building density and monitoring points, the reason why this paper uses Gaussian kernel support vector machine regression model is because the model is excellent for nonlinear fitting; then we use Then, a genetic algorithm is used to solve the minimum number of monitoring point coordinates; finally, the distance constraint of the relevant monitoring points is added to ensure the accuracy and comprehensiveness of the monitoring results at the same time.

3.5.1 Gaussian kernel support vector machine

Gaussian kernel support vector machine regression (SVR): used to fit the response surface to building density and monitoring points [12].

$$min_{\omega,b,\epsilon} \frac{1}{2} \parallel \omega \parallel^2 + C \sum_{i=1}^{m} (\epsilon_i + \xi_i) \tag{41}$$

$$s.t. \begin{cases} y_i - \omega^T \phi(x_i) - b \leqslant \epsilon_i, i = 1, \ldots, m \\ \omega^T \phi(x_i) + b - y_i \leqslant \xi_i, i = 1, \ldots, m \\ \epsilon_i, \xi_i \geqslant 0, i = 1, \ldots, m \end{cases} \tag{42}$$

where w denotes the weight coefficients of the decision function, $\phi(x)$ denotes the nonlinear mapping function that maps the input x to a high-dimensional feature space, b is the bias top, ϵ_i and ξ_i denote the relaxation variables, and C denotes the regularization parameters. The goal of the model is to find a hyperplane that minimizes the training error and the regularization term to separate the training data from the predicted data.

Usually, to evaluate the accuracy of the model fit, the R-squared is used to evaluate the goodness of the model:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y_i} - y_i)^2}{\sum_{i=1}^{n}(\hat{y_i} - \bar{y})^2} \tag{43}$$

Where, n denotes the sample size and $\overline{y}$ denotes the mean of the observations.

3.5.2 Monitoring point accuracy and comprehensiveness modeling

In order to ensure the accuracy and comprehensiveness of the monitoring results, we can take the distance from the monitoring point as the constraint, and the specific model principle is as follows:

1)The distance between adjacent monitoring points should not be too close. Let the minimum distance threshold be $d_{\min}$, then:

$$\| x_i - x_j \| \geqslant d_{min}, \forall i \neq j \tag{44}$$

2)Ensure that the monitoring points are distributed within the specified extent of the city. Assume that the horizontal extent of the city is $[x_{\min}, x_{\max}]$ and the vertical extent is $[y_{\min}, y_{\max}]$, then

$$x_{min} \leqslant x_i \leqslant x_{max}, y_{min} \leqslant y_i \leqslant y_{max}, \forall i \neq j \tag{45}$$

3)Ensure that there is at least one monitoring point within each region. Divide the city into n regions and assume that the horizontal extent of the k region is $[x_{\min}^{(k)}, x_{\max}^{(k)}]$ and the vertical extent is $[y_{\min}^{(k)}, y_{\max}^{(k)}]$, then

$$\sum_{i=1}^{n}(x_i \in [x_{min}, x_{max}] \cap y_i \in [y_{min}, y_{max}]) \geqslant 1 \tag{46}$$

3.6 Problem 3 model solving

Firstly, we choose Guangzhou as the object of study for this problem, Secondly, we take different areas of Guangzhou as the arrangement area of monitoring points, collect building density data and latitude and longitude of all areas of Guangzhou, and finally get the collection results through Baidu search engine as follows:

Table 10: Floor area and latitude and longitude of Guangzhou area

Region	Minimum building density	Maximum building density	Dimensionality	Longitude
Baiyun District	10.00%	25.00%	23.16	113.27
Conghua District	5.00%	10.00%	23.55	113.59
Panyu District	10.00%	25.00%	22.94	113.38
Haizhu District	20.00%	35.00%	23.09	113.26
Huadu District	5.00%	15.00%	23.40	113.22
Huangpu District	15.00%	30.00%	23.18	113.48
Nansha District	5.00%	15.00%	22.80	113.53
Tianhe District	20.00%	40.00%	23.12	113.36
Yuexiu District	25.00%	45.00%	23.13	113.27

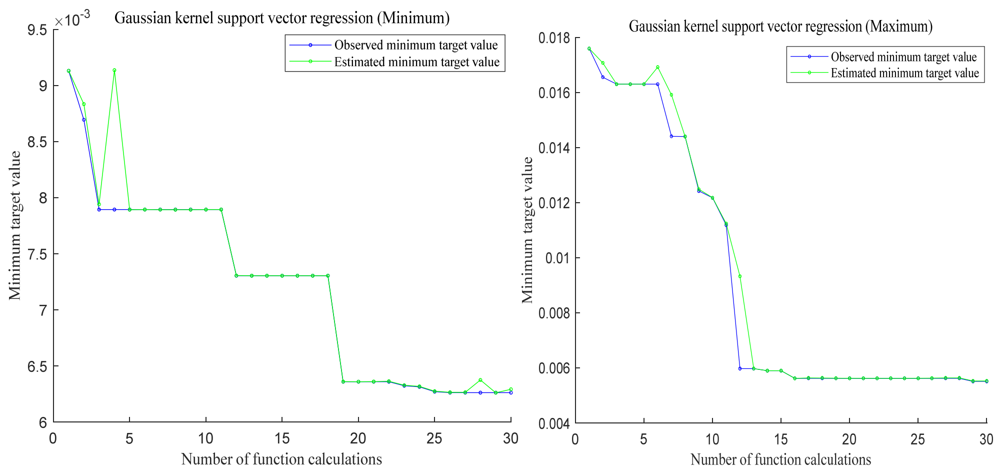

Figure 6: Gaussian kernel vector regression results for monitoring points and floor area

According to Figure 6, it can be seen that the Gaussian kernel vector fit R-squared values are all greater than 0.8, which indicates that the model fit is excellent.

Visual analysis of initial monitoring points:

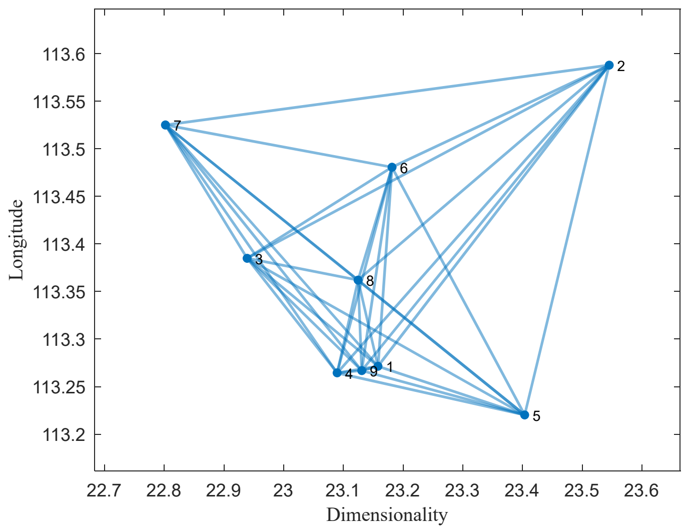

Figure 7: Initial detection network

Finally, the minimum monitoring points are solved using genetic algorithm with the minimum distance of monitoring points and the maximum range that can be monitored by a single monitoring point as constraints, and the above-mentioned model of accuracy and comprehensiveness of monitoring points as the basis for judging the feasibility of monitoring points, and the results are solved as follows:

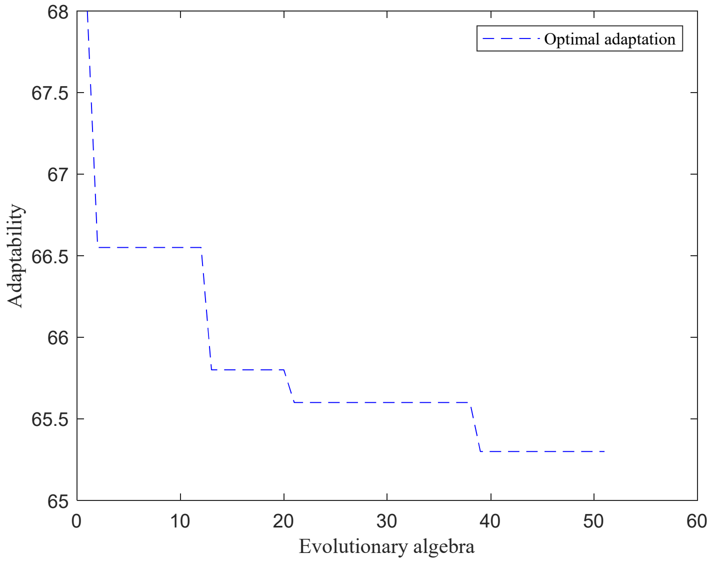

Figure 8: Genetic algorithm error adaptation curve

As can be seen from Figure 8, the optimization error of monitoring points using genetic algorithm significantly decreases with the increase of the number of iterations, which indicates that the genetic algorithm is effective in processing.

Table 11: Genetic algorithm to solve the optimal monitoring points

	Optimal monitoring points at minimum building density		Optimal monitoring points at maximum building density	
Serial number	Dimensionality	Longitude	Dimensionality	Longitude
1	40.000	113.25	40.000	113.392
2	107.083	113.224	107.083	113.449
3	22.968	113.516	22.89	113.416
4	22.858	113.58	22.887	113.361
5	23.345	113.237	22.849	113.414
6	22.914	113.245	23.15	113.281
7	22.875	113.236	23.342	113.448
8	23.176	113.263	23.088	113.388
9	23.391	113.33	23.145	113.232
10	23.263	113.561	23.252	113.524
11	23.228	113.319	22.893	113.265
12	23.339	113.485	22.917	113.536

According to the accuracy and comprehensiveness requirements of the monitoring points established above, the limited range of monitoring points is set to the latitude and longitude range of the Guangzhou border, i.e., dimension 23.150 and longitude 113.851, and the monitoring points that do not meet the above requirements can be eliminated according to the limited conditions, which are the monitoring points under the minimum building density The minimum number of monitoring points after elimination is 10, and the optimal monitoring network under each building density after elimination is obtained (see Figure 9)

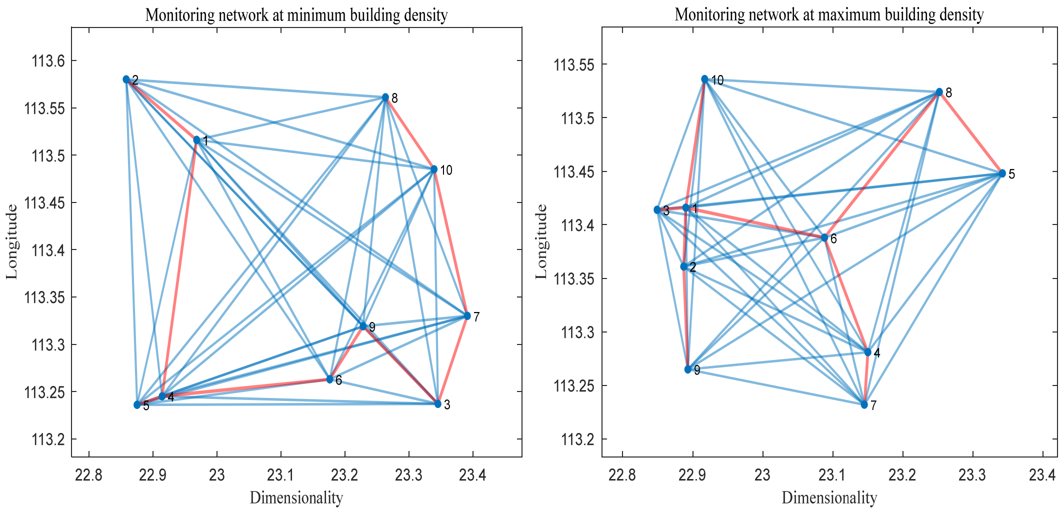

Figure 9: Optimal monitoring network for each building density

In order to integrate the optimal monitoring network at each building density, we take the average of the optimal monitoring points at each building density as the final monitoring network:

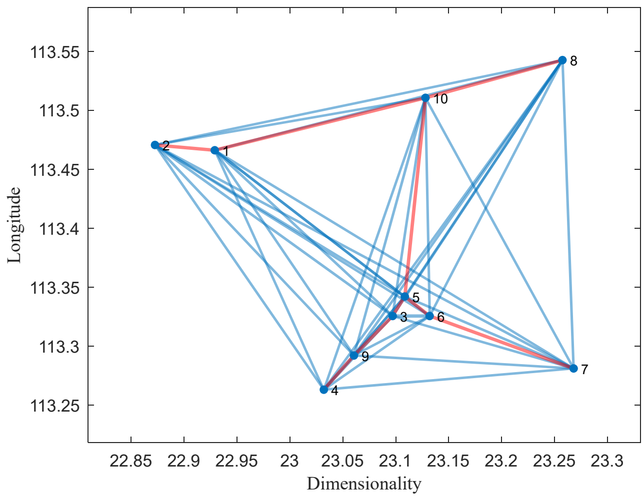

Figure 10 Optimal monitoring network under synthesis

4 CONCLUSION

Based on the research on environmental governance in China in this paper, the following conclusions are drawn:

1) The GA-BP neural network model is used to fit the air pollutant concentration to the air quality index (AQI value), and Beijing is used as an example, and it is found that the fitting effect is excellent, the fitted R-square is greater than 0.95 or more, and the root mean square error of the test set is small, which indicates the superiority of the GA-BP neural network model in studying the relationship between the air quality index and air pollutants.

2) The TOPSIS integrated evaluation method based on the moment estimation theory is used to comprehensively evaluate the water quality situation in each city. The weight integration method based on the moment estimation theory can avoid the one-sidedness of the weights and has some innovative points.

3) Using genetic algorithm to optimize the Gaussian kernel support vector machine model for urban noise pollution monitoring points and taking Guangzhou as an example, it is found that the fitted R-squared using Gaussian kernel support vector regression model is greater than 0.85 or more, which indicates a good fitting effect, and the genetic algorithm is used to optimize the minimum number of monitoring points to get the optimal number of monitoring points and monitoring point coordinates.

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