Hindawi
Mobile Information Systems
Volume 2022, Article ID 9981624, 12 pages
https://doi.org/10.1155/2022/9981624

Research Article

Online Learning Platform for Air Environment Detection and Career Planning Based on 5G Network

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Received 7 May 2022; Revised 12 July 2022; Accepted 18 July 2022; Published 31 August 2022

Academic Editor: Imran Shafique Ansari

With the faster and faster economic and social development, environmental problems will gradually become prominent. At the same time, mobile learning is receiving more and more attention from trainers, and mobile learning is bound to become an important and effective means for corporate training. Based on the 5G network, this paper conducts research and analysis on the air environment detection and career planning online learning platform. This article first introduces the atmospheric environment monitoring system based on 5G wireless sensor network, analyzes the gray GM(1, 1) model modeling to better predict air quality, and gives the model programming the basic idea. Gray system theory model, also known as gray model or gray dynamic model, is referred to as GM model. The most typical of them is the gray model GM(1, 1). Subsequently, the air environment quality in City A was tested and predicted, and at the same time, the overall status of the career planning of college students was analyzed and discussed. The results of the study show that, in the forecast of the air quality in City A, it is found that the air quality in City A from 2021 to 2025 is still not optimistic. Among them, the annual average value of PM10 shows a downward trend; the annual average value of SO_2 fluctuates greatly, and the annual average value of NO_2 is on the rise compared with 2020 and will reach 0.045 mg/m^3 in 2025. Therefore, City A still needs to take practical measures to control air quality. The results of the analysis of the overall status of career planning show that in the process of cultivating career planning ability and stimulating learning motivation, it is also necessary to pay attention to the cultivation of social responsibility and dedication.

1. Introduction

Environmental forecasting refers to activities that predict the impact of social and economic activities on the environment and changes in environmental quality. It is the basis of environmental decision-making and management, and an important measure to implement the principle of prevention. Environmental prediction is the use of information and observation statistics that have been obtained to estimate and infer future or unknown environmental impacts. It is the basis for the government to make major environmental protection decisions and take environmental protection management measures, and it is also the basis for the government to formulate major environmental plans. The air quality forecast is also the main part of the government's environmental protection forecast. It can forecast the future trend of air pollution in a particular area, thereby providing effective measures to improve the quality of the marine and ecological environment, so as to provide reference for national decision-making agencies in formulating air pollution prevention and control plans in the region and national economic and social development plans and basis. Based on the 5G network, this paper studies and analyzes the online learning platform for air environment detection and occupational planning, aiming to give guiding suggestions for air environment monitoring and occupational norms.

Air quality is also a major problem that interferes with the environmental protection of human habitation and investment in urban construction. As a comprehensive city with fast economic development, air quality issues have become the focus of people's concern. In-depth research and analysis of the current situation and development rules of urban air quality, as well as scientific forecasts of future changes in air quality, are of critical significance for the assessment, management, and decision-making of urban air quality.

According to the research progress at home and abroad, different scholars also have a certain degree of cooperation in 5G network, air environment monitoring, and career planning: The focus of Ho and Wang's research is to develop portable wireless environments and medical auxiliary sensing systems. It is a sensing system that combines airborne particles, temperature, humidity, and ultraviolet measurement, as well as wireless functions. It can be placed in any workplace or home environment for real-time measurement and used with the Internet of Things. It can upload data to a remote server, and it can be checked with laptops, computers, and smartphones, while enabling environmental warning indicators to protect itself [1]. In order to identify residual organic pollutants in the air and water, Chung et al. used a polyurethane foam passive air sampler to perform nontarget screening using two-dimensional gas chromatography time-of-flight mass spectrometry (GC × GC-TOFMS) at 10 locations. Most of the chemical substances classified as undetectable are not detected by nontarget screening with a detection frequency of more than 20%, and it shows that the simple equilibrium model has strong potential and can be used to exclude chemical substances that are unlikely to remain in the environment after target monitoring emissions [2]. Dimzon et al. have developed a method to determine representative precursor compounds in wastewater treatment plant (WWTP) air and water samples, including PFAI, FTI, FTO, FTAC, and FTMAC. The sampling and sample preparation steps involve the use of solid phase extraction (SPE) cartridges with HLB™ materials to enrich the analytes. Gas chromatography mass spectrometry is used to detect and quantify analytes. The results show that the positron ionization-selected ion monitoring mode (+EI-SIM) has high linearity and sensitivity [3]. Xiao et al. explained how to provide effective methods for online chemistry teaching, combined with DingTalk, WeChat, Learning@ZJU website, and other applications to build a network platform and successfully carry out courses. He also discussed his personal views on high-quality online teaching of inorganic chemistry. The study found that these students performed very well in the two exams, which confirmed that the online platform and strategies established by Xiao C are very effective for teaching and learning [4]. Frias and Martínez discussed potential conflicts between network neutrality regulations and future 5G services, especially with regard to network virtualization. And based on the objective and necessary judgment of traffic optimization, the challenge of establishing network neutrality is discussed. This proves to be complicated in a technical environment that envisages the creation and pricing of network "slices" on demand based on the quality of service (QoS) required by a particular application at any given time [5]. Vlachos et al. focused on this aspect for D2D users belonging to different tenants (virtual network operators), assuming that the future 5G wireless network is virtualized and programmable. Under the assumption of the cross-tenant coordinator, it is shown that by optimizing the resource sharing of different tenants, that is, the slicing of the underlying physical network topology, significant benefits can be achieved in terms of network performance. To this end, an overall rate optimization framework for optimal sharing of virtualized resources is proposed. Through extensive numerical investigations, the effectiveness of the proposed solution and the achievable benefits compared with traditional methods have been proved [6]. Zhang et al. first gave a comprehensive overview of the extensive research work being carried out and categorized it according to basic green trade-offs. Then, it will focus on the research progress of 4G and 5G communications, such as orthogonal frequency division multiplexing and nonorthogonal aggregation, multiple input, multiple output, and heterogeneous networks. Zhang et al. will discuss the potential challenges and impacts of basic green trade-offs in order to provide some enlightenment for the energy-saving research and design of wireless networks in the future [7]. However, these scholars did not conduct research and discussion on the online learning platform for air environment detection and career planning based on the 5G network, but only unilaterally analyzed their significance.

The innovations of this paper are as follows: (1) the atmospheric environment monitoring system of 5G wireless sensor network is introduced. (2) The gray GM(1, 1) prediction model is constructed. (3) The air quality of City A was tested and predicted. (4) The overall situation of college students' career planning was analyzed and discussed.

2. Method of Air Environment Detection and Career Planning Online Learning Platform Based on 5G Network

2.1. Atmospheric Environment Monitoring System Based on 5G Wireless Sensor Network. The structure diagram of the atmospheric environment monitoring system based on 5G wireless sensor network is shown in Figure 1. Environmental monitoring management system, also known as environmental monitoring information management system, is an information system that manages a large amount of environmental monitoring information and data storage with computer technology and database technology as the core. The environmental monitoring system can be divided into four modules according to its functions: data acquisition subsystem, data transmission subsystem, monitoring center server, and remote monitoring application [8, 9].

There are usually two interpretations of data collection: one is the process of collecting, identifying, and selecting data from data sources. The other is digitization, the recording process of electronic scanning systems, and the encoding process of content and attributes. The data collection system is mainly composed of various gas sensors, microprocessors, and Zigbee system terminal node modules composed of the Zigbee technology core board [10]. After the Zigbee technology network terminal node performs simple data processing on the collected various data information, it uses the Zigbee technology network to send the data information to the central coordinator node and then

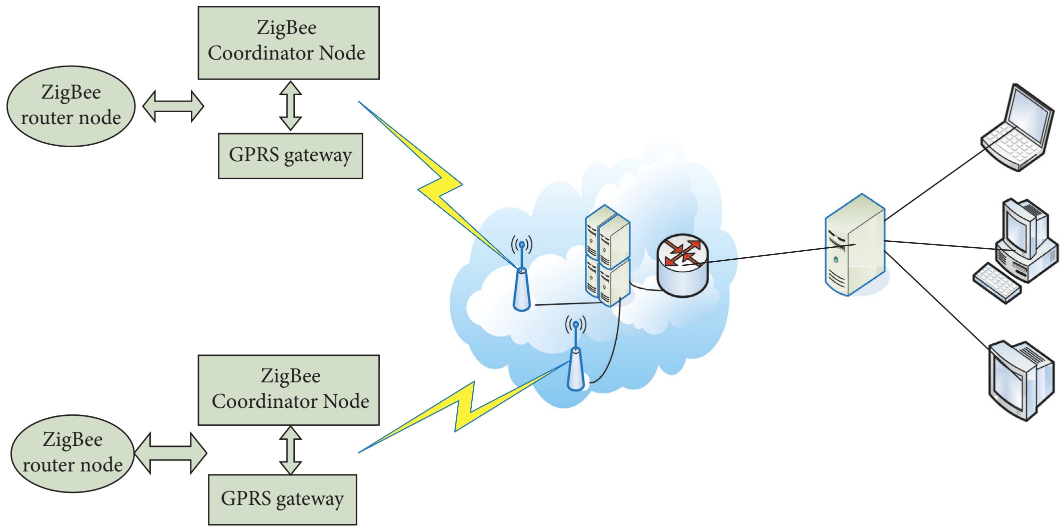

Figure 1: Block diagram of the overall system design structure.

uses the GPRS function to send the data information to the monitoring center server [11]. Zigbee technology is mainly used for data transmission between various electronic devices with short distance, low power consumption, and low transmission rate, as well as typical applications with periodic data, intermittent data, and low response time data transmission.

The monitoring center server mainly runs the middleware function designed in this article and has the role of a remote monitoring center connecting the data acquisition system and the host computer system. The monitoring center server mainly runs the middleware function designed in this article and has the role of a remote monitoring center connecting the data acquisition system and the host computer system. Register the ID number for the sensor node to facilitate the orderly management and operation of the wireless sensor node in the future [12]. The middleware part accepts the data collected from the collection system, converts the data into a suitable format, and stores it in the back-end database, allowing the monitoring center to retrieve the data from the database. Considering that in actual applications, it may be necessary to lay a large number of sensor nodes in the monitoring area for data collection, resulting in a large amount of data being collected and transmitted, causing network congestion or excessive energy consumption of sensor nodes and premature death. Therefore, a node sleep scheduling algorithm based on wireless sensor network can be designed, which can effectively alleviate network congestion and ensure the real time, stability, and validity of data. At the same time, it has a significant effect on extending the life of 5G wireless sensor networks [13]. A wireless sensor network is a distributed sensor network with sensors at the tip that can sense and inspect the outside world. A multi-hop self-organizing network is formed by wireless communication.

The user remote monitoring center allows users to register, log in, and delete operations. Figure 2 shows the environmental monitoring based on 5G network [14]. After registering personal information, the user obtains the access

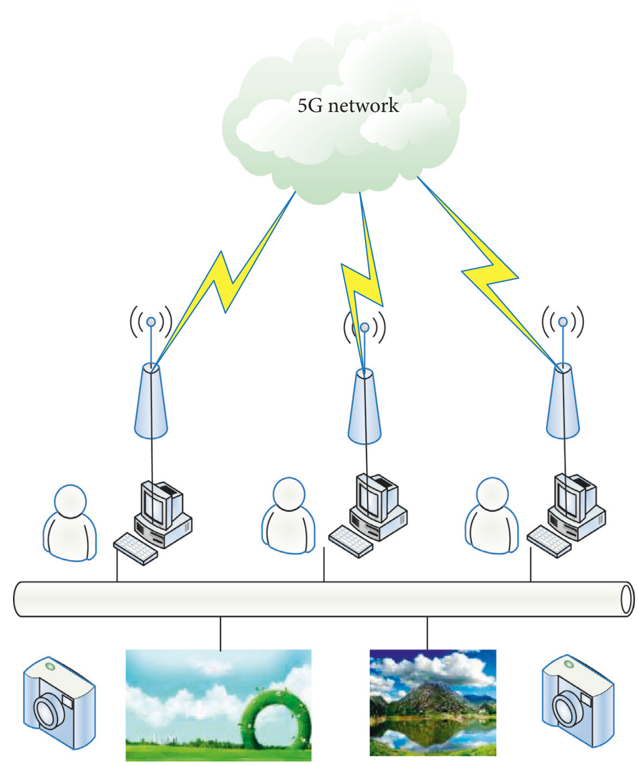

Figure 2: Environmental monitoring based on 5G network.

authority and then logs in to the host computer system monitoring center and performs corresponding queries on the data stored in the background. The user selects the corresponding time range and corresponding location according to his actual needs to query all pollutants or query the data results of one or several pollutants.

Later, the management of the user's access authority setting level will be increased. Users of different power levels will have different operating functions allowed. At the same time, the identity of the super-administrator is added to manage user information in a unified manner [15].

2.2. Gray GM(1, 1) Model Modeling. The air quality prediction model can truly reflect the distribution trend and spatial distribution characteristics of pollutants in the near-surface atmosphere and has practical scientific significance for the prediction and prevention of urban air quality. At present, there are many scientific research methods for air quality prediction. In recent years, gray systems and neural networks, which have been widely studied and applied, have also been applied to atmospheric environmental quality prediction [16]. The gray GM(1, 1) model can use less data modeling and analysis techniques, with features such as simple construction and simple calculation. Artificial neural network has strong self-organization, self-adaptability, autonomous learning, correlation, fault tolerance, and anti-interference technology capabilities. In addition, it also has high approximation capabilities for complex nonlinear functions. Gray GM(1, 1) model and artificial neural network have been widely used in air quality forecasting. The establishment of a gray system model generally has to go through five steps of thought development, factor analysis, quantification, dynamization, and optimization, so it is called five-step modeling. The gray GM(1, 1) forecasting model is mainly used for single-factor forecasting and has the advantage of better accuracy of forecasting and estimating single-number columns [17]. Among them, gray modeling is to use the original data sequence as the generating number to establish differential equations.

The modeling steps of the GM(1, 1) model are as follows:

Step 1: Quasi-smoothness test

Let $A^{(0)}$ represent the original data non-negative data sequence, where $k \geq 4$.

$$A^{(0)} = \left(a^{(0)}(1), a^{(0)}(2), \ldots, a^{(0)}(k)\right). \tag{1}$$

For $A^{(0)}$, its smooth ratio is

$$r(h) = \frac{a^{(0)}(h)}{\sum_{d=1}^{h-1} a^{(0)}(d)}, h = 2, 3, \ldots, k. \tag{2}$$

The smoothness ratio reflects the smoothness of the sequence. The smoother the data change in $A^{(0)}$, the smaller the smoothness ratio $r(h)$. When the sequence meets

$$\begin{gathered}\frac{r(h+1)}{r(h)} < 1, h = 2, 3, \cdots, k-1,\\ r(h) \in [0, \beta], h = 3, 4 \cdots, k.\end{gathered} \tag{3}$$

When $\beta < 0.5$, $A^{(0)}$ is a quasi-smooth sequence, and a GM(1,1) model can be established.

Step 2: Cumulative generation

Perform an accumulation generation on the original data sequence $A^{(0)}$ (1-AGO, AGO is the accumulation symbol), and generate a new sequence $A^{(1)}$.

$$\begin{gathered}A^{(1)} = \left(a^{(1)}(1), a^{(1)}(2), \cdots, a^{(1)}(k)\right),\\ A^{(1)}(h) = \sum_{d=1}^{h} a^{(0)}(d), h = 1, 2, \cdots, k.\end{gathered} \tag{4}$$

Step 3: Construct a series of numbers next to the mean

$$\begin{gathered}B^{(1)} = \left(b^{(1)}(2), b^{(1)}(3), \cdots, b^{(1)}(k)\right),\\ b^{(1)}(h) = \frac{1}{2}\left(a^{(1)}(h) + a^{(1)}(h-1)\right), h = 2, 3, \cdots, k.\end{gathered} \tag{5}$$

Step 4: Establish a first-order linear differential equation

Since sequence $A^{(1)}$ has an exponential growth law, a first-order linear differential equation in whitened form can be established for this sequence. It is called the whitening equation of the gray equation, also called the shadow equation, that is, the GM(1, 1) model, as shown in the following formula.

$$\frac{da^{(1)}}{dl} + ea^{(1)} = w. \tag{6}$$

In the formula, e and w are undetermined coefficients, and they are obtained by the least square method, as shown in the following formula.

$$\begin{gathered}[e, w]^L = \left(S^L S\right)^{-1} S^L m,\\ S = \begin{pmatrix} -b^{(1)}(2) & 1\\ -b^{(1)}(3) & 1\\ \vdots & \vdots\\ -b^{(1)}(k) & 1 \end{pmatrix}\\ m = \left[a^{(0)}(2), a^{(0)}(3), \cdots a^{(0)}(k)\right]^L.\end{gathered} \tag{7}$$

Substituting the obtained e and w into equation (9), the solution of the whitening equation is obtained, also called the time response function:

$$a^{(1)}(l) = \left(a^{(1)}(1) - \frac{w}{e}\right)o^{-el} + \frac{w}{e}. \tag{8}$$

Step 5: Establish a time response sequence of $a^{(1)}(h) + eb^{(1)}(h) = w$

$$\hat{a}^{(1)}(h+1) = \left(a^{(1)}(1) - \frac{w}{e}\right)o^{-eh} + \frac{w}{e}, h = 1, 2, \cdots, k. \tag{9}$$

Step 6: Accumulate and reduce to obtain the prediction model of the original sequence (0) X.

$$\hat{a}^{(0)}(h+1) = \hat{a}^{(1)}(h+1) - \hat{a}^{(1)}(h) = \left(1 - o^{e}\right)\left(a^{(0)}(1) - \frac{w}{e}\right)o^{-eh}. \tag{10}$$

Step 7: Perform a posteriori error and small error probability test

The mean of the original data series:

$$\overline{a} = \frac{1}{k}\sum_{h=1}^{k} a^{(0)}(h). \tag{11}$$

Variance:

$$S_1^2 = \frac{1}{k}\sum_{h=1}^{k}\left[a^{(0)}(h) - \overline{a}\right]^2. \tag{12}$$

Mean error:

$$\overline{o} = \frac{1}{k}\sum_{h=1}^{k} o(h) = \sum_{h=1}^{k}\left[a^{(0)}(h) - \widehat{a}^{(0)}(h)\right]. \tag{13}$$

Residual variance:

$$S_2^2\frac{1}{k}\sum_{h=1}^{k}\left[o^{(0)}(h) - \overline{o}\right]^2. \tag{14}$$

Comparison of posterior difference:

$$Q = \frac{S_2}{S_1}. \tag{15}$$

Probability of small error:

$$P = P\left\{\left|o^{(0)}(h) - \overline{o}\right| < 0.5872 S_1\right\}. \tag{16}$$

The accuracy of the model is judged by the residual error, and the smaller the Q is, the larger the P is, the better [18, 19], as shown in Table 1.

In addition, when modeling, you should pay attention to the value of e solved in step 4. The applicable conditions of the GM(1, 1) model vary with the development coefficient a and generally have the following rules, as shown in Table 2.

In the air quality forecasting work, there are often insufficient statistical data signals and large fluctuations in the numerical sequence. In the gray GM(1, 1) model, the fitting efficiency of data models with large fluctuations is usually not good, and when forecasting, only the most recent values have corresponding practical significance and forecast accuracy. The farther value can only indicate the trend of change and become the planned value. The special uncertainty mapping characteristics in the neural network also help to overcome this problem [20]. However, the artificial neural network prediction model requires a large amount of measured data to be able to track the changes in the data, so as to draw better expected conclusions. The gray GM(1, 1) model can use small sample modeling and prediction to make up for the deficiencies of the neural network prediction method [21, 22]. Figure 3 shows the basic idea of model programming. The core of gray system theory and method is gray dynamic model, which is characterized by generating function and gray differential equation.

3. The Experimental Results of the Air Environment Detection and Career Planning Online Learning Platform Based on the 5G Network

3.1. Detection and Prediction Analysis of Air Environment Quality in City A. Urban air pollution refers to the air pollution caused by the city's special underlying surface conditions and boundary layer structure and the concentration of pollution sources. The annual average values of SO_2, NO_2, and PM10 in the 2013–2020 Environmental Status Bulletin of City A are used as the main analysis objects, as shown in Figure 4. These three indicators are conventional pollutants in the ambient air quality standards, which are representative of the air quality status. Use annual average values of SO_2, NO_2, and PM10 from 2013 to 2017 as the original data to establish the IGNNM model, and predict the annual average value from 2018 to 2020 to test the accuracy of the model. At the same time, it is analyzed and compared with the gray GM(1, 1) model and the traditional GNNM model. When sulfur dioxide dissolves in water, sulfurous acid is formed. If sulfurous acid is further oxidized in the presence of PM2.5, sulfuric acid will be generated quickly and efficiently. This is one reason for concern about the environmental effects of using these fuels as energy sources.

It can be seen from the figure that the air quality in City A has been significantly improved; especially, the PM10 content has dropped significantly and occasionally fluctuates, with a decrease of 44.3%; SO_2 and NO_2 have not changed much. Among them, from 2013 to 2016, SO_2 has an increasing trend and then slowly decreased; NO_2 has been fluctuating up and down in the national secondary standards.

The annual average value of pollutants in City A from 2013 to 2017 was used as the original data series to model and predict the air quality situation from 2018 to 2020. Before using the GM(1, 1) model to predict, the quasi-smoothness test was performed on the data of Tianjin from 2013 to 2017. The smoother the original data, the more obvious the index characteristics, and the better the prediction effect of GM(1, 1). The test results are shown in Figure 5.

It can be seen from the figure that when $k \geq 3$, the annual average value of PM10 meets the quasi-smoothness test, and $P(k) < 0.5$; when $k > 3$, the annual average values of SO_2 and NO_2 also meet the quasi-smoothness test, so the original data can be used for modeling.

It can be seen from Figure 6 that the gray GM(1, 1) prediction model has a large relative simulation error when fitting the annual mean value of PM10 from 2013 to 2017. The model only reflects the development trend of the data. The forecast error for 2018~2020 is up to 23.66%, which is not credible in the forecast work. The traditional GNNM model has an ideal data fitting effect, but when using the data from 2018 to 2019 for model verification, it is found that the relative error of the traditional GNNM model reaches 13.00%, 9.38%, and 6.45%, while the relative error of the IGNNM model reaches 7.00%, 2.08%, and −2.15%,

Table 1: Gray GM(1, 1) prediction model accuracy judgment standard.

Prediction accuracy	Relative error $\overline{o}$	P	Q
Good	0.01	>0.9	<0.3
Qualified	0.05	>0.75	<0.45
Reluctantly	0.10	>0.65	<0.6
Unqualified	0.20	<0.65	>0.6

Table 2: GM(1, 1) model usage conditions.

	$\lvert e\rvert \geq 2$	$\lvert e\rvert > 1$	$0.8 < \lvert e\rvert \leq 1$	$0.5 < \lvert e\rvert \leq 0.8$	$0.3 < \lvert e\rvert \leq 0.5$	$\lvert e\rvert \leq 0.3$
Applicability	Meaningless	Not suitable for use	Residual error correction GM(1, 1) model	Use it with caution in short-term forecasts	Short-term forecasts, be used with caution in medium- and long-term forecasts	Can be used for long-term forecasting

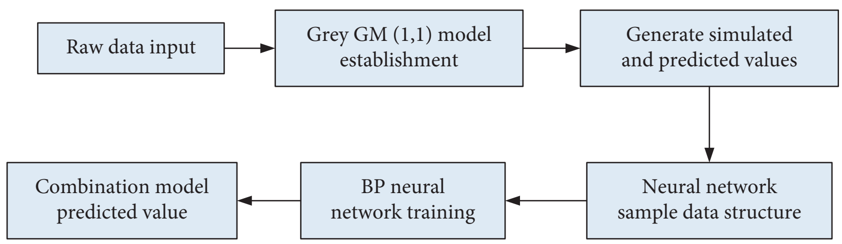

Figure 3: Programming ideas.

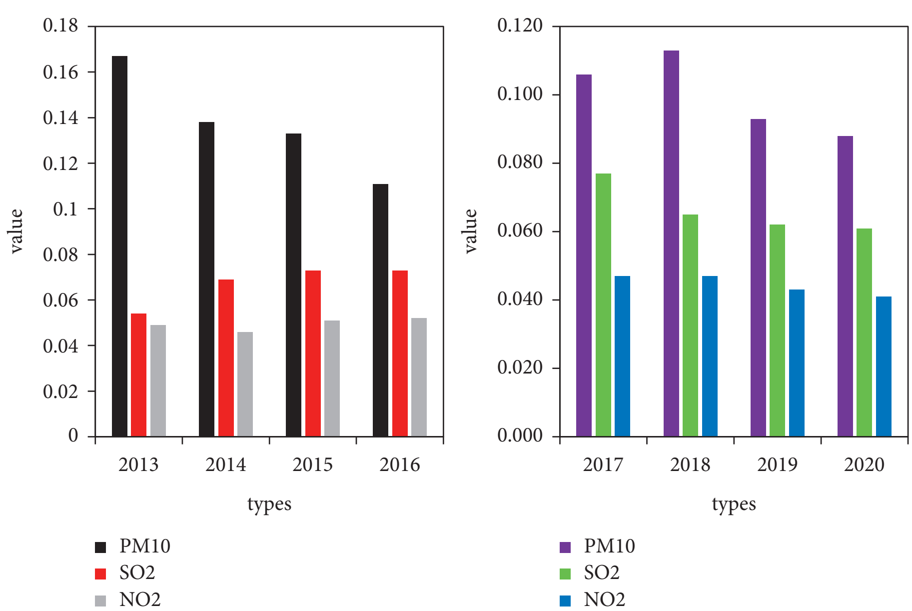

Figure 4: Air quality changes in City A.

which is significantly better than the traditional GNNM model.

It can be seen from Figure 7 that when the annual average value of SO_2 is simulated and predicted, the maximum and minimum relative errors of the GM(1, 1) model fitting are 11.69% and -3.08%, respectively. The maximum relative error of the traditional GNNM model fitting is 6.49%, while the simulation error of the IGNNM model is only 5.19%. When verifying and predicting data from 2018 to 2019, the effect is also the most ideal. However, it is worth noting that the relative errors of the three models when predicting the 2020 data are relatively large, especially the GM(1,1) model, which even reached −38.10%. The absolute value of the relative error of the traditional GNNM and IGNNM models has reached more than 10%. Analyzing the annual average value of SO_2 from 2013 to 2020, it is found that from 2017 to 2019, the annual average value of SO_2 has a slow decline stage, with a maximum decrease of 0.006 mg/m^3. From 2019

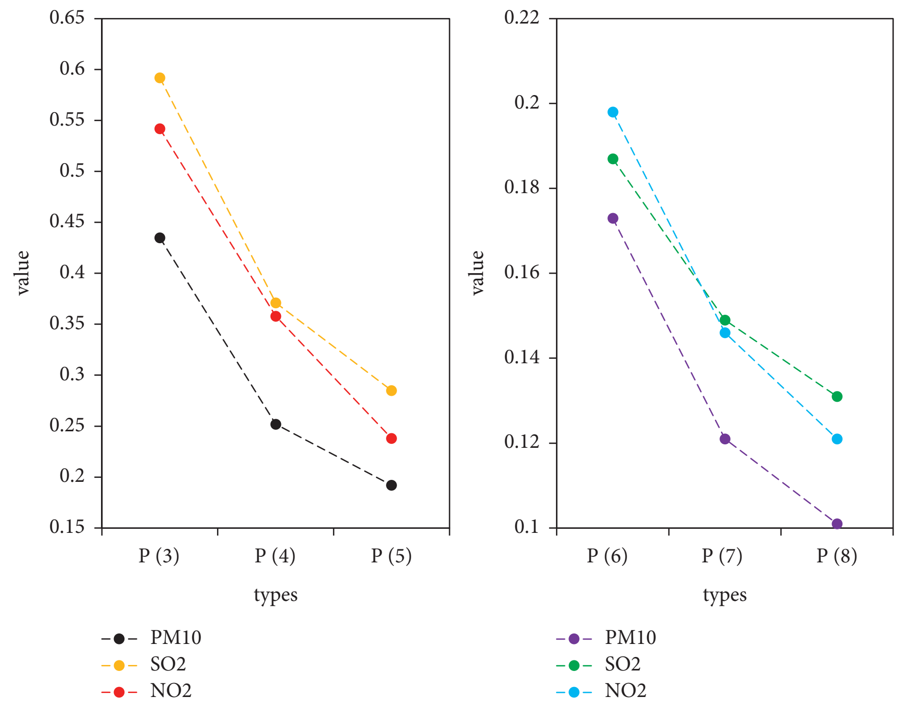

FIGURE 5: Quasi-smoothness test of annual average air quality in City A.

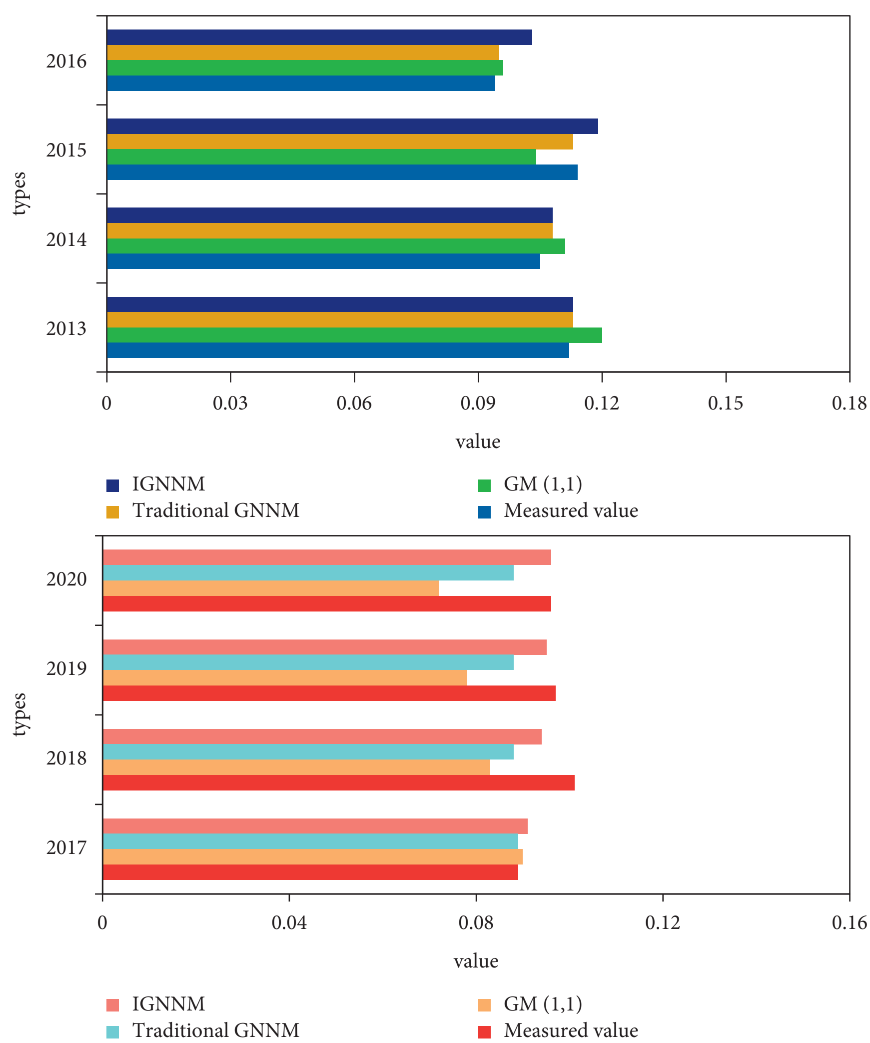

FIGURE 6: Comparison of PM_{10}'s predicted and measured values.

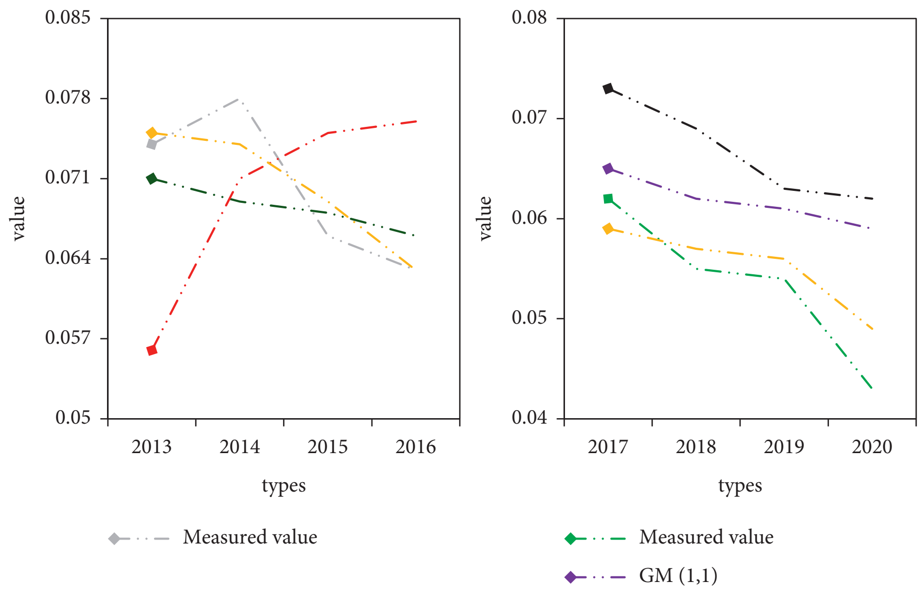

Figure 7: Comparison of predicted and measured values of SO_2.

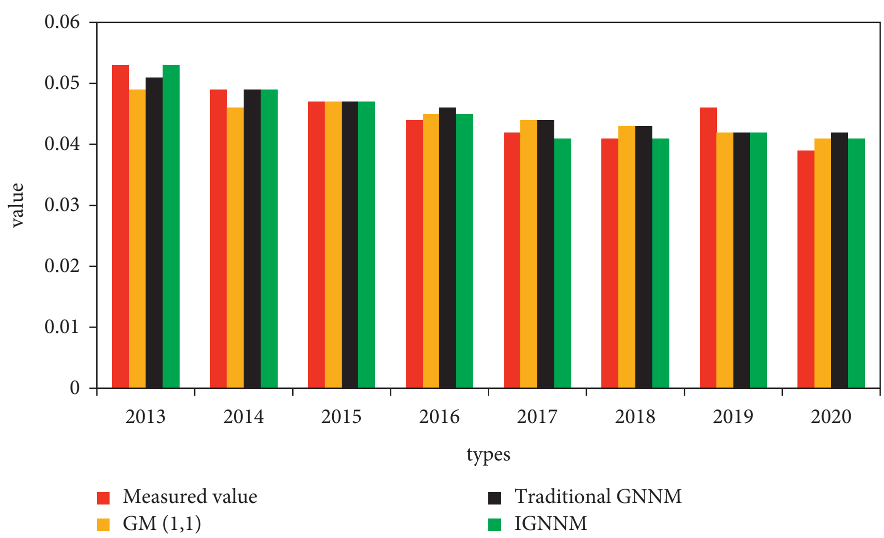

Figure 8: Comparison of predicted and measured values of SO_2.

to 2020, the drop suddenly reached 0.012 mg/m3, which was twice as high as the maximum drop. This is the reason for the large error of the prediction model.

It can be seen from Figure 8 that when the GM(1, 1) model is fitting the original NO_2 data from 2016 to 2018, except for the maximum and minimum simulation errors in 2004, which reaches 7.69%, the fitting effect is good. The relative simulation errors of the traditional GNNM model and IGNNM model are also lower than 5% and 3%, respectively. However, when verifying with data from 2018 to 2020, it is found that the prediction errors of the GM(1, 1) model and the traditional GNNM model are relatively high; especially for the prediction value in 2019, the relative errors reached 8.89% and 8.89%, respectively. Analyzing the annual average value of NO_2 from 2001 to 2011, it is found that the annual average value of NO_2 from 2013 to 2016 is in an upward phase, reaching the highest value of 0.052 mg/m^3 in 2016. However, until 2018, the annual average value of NO_2 has continued to decline, reaching 0.04 mg/m^3 in 2018. The data used for verification in 2019 suddenly jumped to 0.045 mg/m^3, and there was a relatively large fluctuation, resulting in large prediction errors of the GM(1, 1) model and the traditional GNNM prediction model. Similarly, the prediction error of the IGNNM model in 2019 is also relatively large, but compared to the GM(1, 1) model and the traditional GNNM prediction model, the simulation and prediction errors of the IGNNM model are obviously more ideal.

Through the analysis of the three prediction models, overall, the IGNNM model is more reliable in the simulation of the original data and the prediction of the future, and the prediction of the three indicators in the air

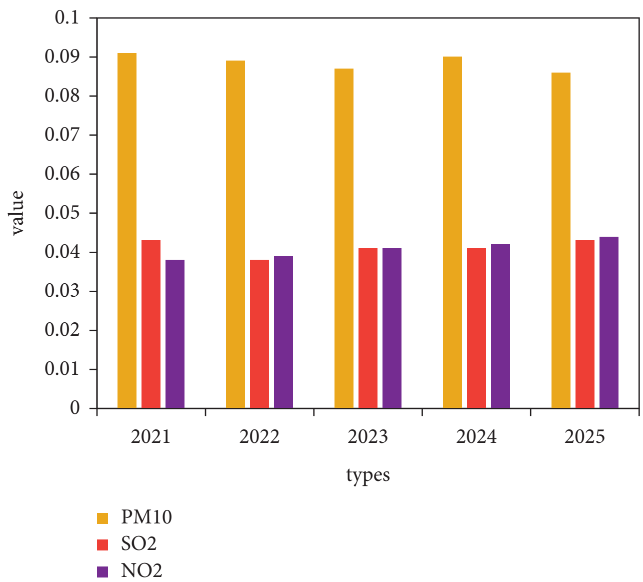

Figure 9: Air quality forecast results for City A from 2021 to 2025.

quality standard has achieved ideal results. Here, we use PM10, SO_2, and NO_2 from 2013 to 2020 as the original data, and use the IGNNM model to predict the air quality of City A from 2021 to 2015. The prediction results are shown in Figure 9.

It can be seen from the figure that the air quality in City A from 2021 to 2025 is still not optimistic. Among them, the annual average value of PM10 shows a downward trend; the annual average value of SO_2 fluctuates greatly, with an overall upward trend, but the magnitude is not large; the annual average value of NO_2 is on the rise compared with 2020 and will reach 0.045 mg/m^3 in 2025. In addition, except that SO_2 can meet the secondary standard, neither PM10 nor NO_2 can reach the secondary standard limit. Therefore, City A still needs to take practical measures to control air quality.

3.2. Overall Status Quo of College Students' Career Planning. Analyze the overall situation of college students' career planning, as shown in Table 3. After statistics, the students' self-assessment level score is an average of 31.69 points, which is higher than the average of 30 points corresponding to "conformity," indicating that the students currently have a relatively good understanding of career planning; the level of self-recognition (including interests, personality, values, and professional skills) of the trainees is divided into 26.97 points. Although they are in the second place, they are still far from reaching the "qualified" average score of 33 points, which shows that although the students have a good sense of career planning, the planned behavior is a bit messy. Finally, we can see that the average score of career exploration and decision-making in the table is not more than 30, which is lower than the average score. It shows that students "say and do nothing," lack the ability to act, and only realize its importance, but lack a decisive career line. There is also a lack of clear career goals, so no specific actions are needed. In addition, from the skewness and kurtosis indicators given in the table, it can be seen that the distribution at each level appears to be skewed to the right.

Table 4 provides descriptive statistics on the evaluation of the status quo of college students' occupational status. It can be found in the table that college students have the highest score for environmental awareness, 11.52 points. This shows that the school still has a good understanding of employment and environmental protection awareness, and it can also be that colleges or communities instill more college students in this regard. However, after excluding environmental awareness, the scores in the other two parts are not high, indicating that there are some deficiencies in both aspects of students, and students need to have a clear understanding of their own interests, personalities, and interests.

Table 5 shows the descriptive statistics of students' self-knowledge. At this level, we divide it into two sub-parts: "self-adaptation" and "desired goals." The values of self-adjustment and expected goals are generally low, indicating that students cannot determine which jobs are suitable for them during the career planning process, and there is a gap between the jobs they want to do and their personal abilities.

It can be seen from Figure 10 that the scores of these three parts are not much different. They all look like 9 to 10 points, which are not high. But in general, the scores of the interpersonal relationship part of the three levels are higher than the other two, indicating that students believe that good interpersonal relationships are important for employment and their career planning process, for example, have a good teacher-student relationship and have a good relationship with classmates and roommates. The same is true for understanding from a practical level. People who can handle interpersonal relationships will inevitably have an advantage in employment.

Career counseling is still very common in major colleges and universities, and career counseling courses have been offered in almost all universities. However, by consulting the literature on the theoretical and practical levels, it can be seen that most of the courses are only targeted at students who are close to graduation, and the courses for freshmen and other grades are very rare. The career planning work of colleges and universities has not paid attention to every group in the school. According to this survey, first, college students' career planning awareness is already at a relatively high level, and they are willing to accept relevant counseling; second, the student's school experience, especially the student counseling experience, is a key factor influencing the level of career planning. Therefore, the employment guidance center of colleges and universities should start from here, and the target of employment assistance must be changed from the senior year to cover all aspects of the entire school.

4. Discussion

Through the analysis and comparison of the prediction results and relative errors of the three prediction models, the improved gray neural network model is relatively ideal in terms of prediction accuracy and prediction effect. The

Table 3: Overall situation.

	Sample		Average value	Standard deviation	Skewness		Kurtosis	
	Efficient	Invalid	Numerical value	Numerical value	Numerical value	Standard error	Numerical value	Standard error
Status quo	3123	0	31.69	5.501	0.502	0.105	0.321	0.211
To understanding	3123	0	17.02	2.192	0.771	0.102	1.039	0.211
Explore	3120	0	26.97	5.598	0.439	0.105	0.902	0.212
Decision-making	3120	0	16.08	3.589	0.402	0.105	0.121	0.211

Table 4: Distribution characteristics of status quo assessment scores.

	Sample		Average value	Standard deviation	Skewness		Kurtosis	
	Efficient	Invalid	Numerical value	Numerical value	Numerical value	Standard error	Numerical value	Standard error
Career awakening	3123	0	10.61	2.621	0.071	0.983	−0.441	0.198
Self-awareness	3123	0	9.71	2.395	0.502	0.983	−2.51	0.198
Environmental awareness	3123	0	11.52	2.601	0.592	0.985	0.349	0.199

Table 5: Distribution characteristics of self-knowledge-level scores.

	Sample		Average value	Standard deviation	Skewness		Kurtosis	
	Efficient	Invalid	Numerical value	Numerical value	Numerical value	Standard error	Numerical value	Standard error
Self-fit	3123	0	7.98	2.231	0.801	0.102	0.581	0.211
Desired goal	3123	0	8.71	1.802	0.391	0.102	7.98	0.211

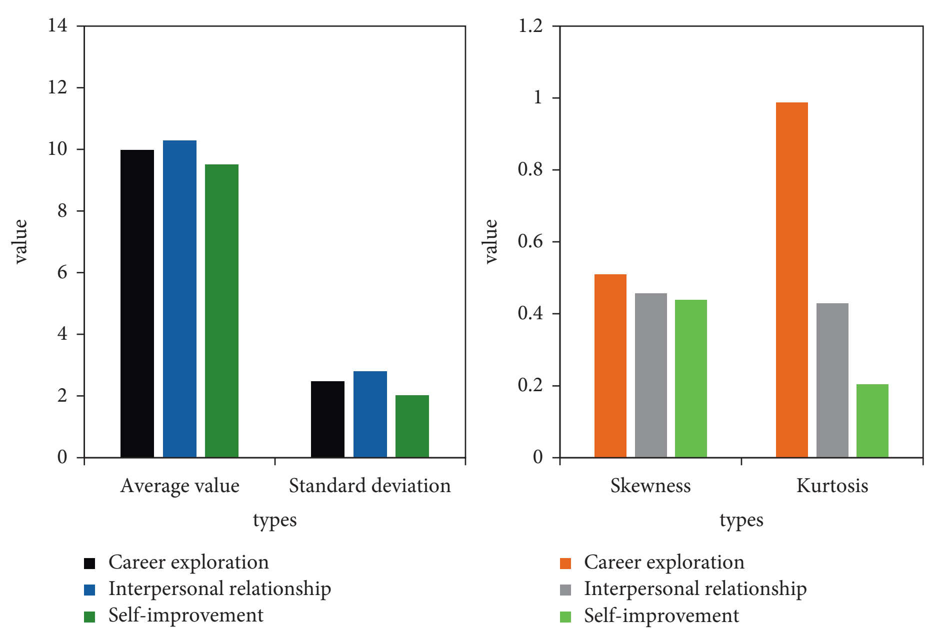

Figure 10: Distribution characteristics of career exploration level.

requirements for air quality prediction can already be met without significant changes in air quality [23, 24]. Among them, the traditional gray neural network combination model also shows better fitting accuracy. But when the model is used to predict the future air quality, the prediction effect is not reliable enough. It shows that even if a model has a high fitting accuracy, it does not mean that the future prediction value will be reliable, and the improved gray neural network combination model shows its advantages. Therefore, this model is more feasible in future air quality predictions [25].

It should be noted that the improved gray neural network combination model has a better prediction effect than the gray GM(1, 1) model and the traditional GNNM model. However, careful analysis shows that when the measured value of pollutants changes significantly, for example, the annual average value of PM10 suddenly jumped from $0.088\,mg/m^3$ to $0.1\,mg/m^3$ from 2017 to 2018; the annual average change of SO_2 from 2019 to 2020 reaches $0.012\,mg/m^3$, which is twice the previous change; after a slow decline period from 2016 to 2018, the annual average value of NO_2 suddenly increased from $0.04\,mg/m^3$ in 2018 to 0.045 mg/m3 in 2019, and then dropped to $0.038\,mg/m^3$ in 2020. These changes have caused large deviations in the prediction results of the model, which is a problem that needs to be improved urgently. The model can meet the requirements of air quality prediction when the air quality does not change much.

5. Conclusions

The career planning of college students has a significant impact on their learning motivation. Through group counseling intervention on the career planning of higher vocational students, it can promote the improvement of students' learning motivation. However, it is worth noting that career planning group counseling has different effects on different dimensions of students' learning motivation. It has a significant impact on the group orientation dimension, but has no significant impact on the social orientation dimension. Therefore, in the process of cultivating career planning ability and stimulating learning motivation, it is necessary to pay attention to the cultivation of social responsibility and dedication. Nowadays, most of the relevant functional departments of colleges and universities narrowly equate career counseling as employment guidance, that is, helping students find jobs, and they are all targeted at senior class students who are about to graduate. This conflicts with the variability of careers. Therefore, colleges and universities should update their ideas, engage in professional career planning activities throughout the campus, and provide students with practical opportunities. On another level, make full use of the power of counselors and student leaders. In the life of the university, students have little contact with the professors and more frequent contacts with the counselors, and the relationship is better. With the help of the counselors, it is easier to increase the students' enthusiasm for participation. In short, colleges and universities must change their traditional concepts, abandon the false figures of blindly brushing high employment rates, and correct their career concepts to serve students. However, due to the limitations of time and technology, we have not carried out detailed research on the construction of an online learning platform for career planning in 5G networks. We will further explore this in the future.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no potential conflicts of interest in this study.

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