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Retraction

Retracted: Application of Artificial Intelligence in the Process of Ecological Water Environment Governance and Its Impact on Economic Growth

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] Y. Wei, "Application of Artificial Intelligence in the Process of Ecological Water Environment Governance and Its Impact on Economic Growth," *Mathematical Problems in Engineering*, vol. 2021, Article ID 9967531, 9 pages, 2021.

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Research Article

Application of Artificial Intelligence in the Process of Ecological Water Environment Governance and Its Impact on Economic Growth

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With the increasing pollution of the ecological water environment, the treatment of the ecological water environment has become the focus of everyone's attention. At present, there are many research results on water environment governance, but the effect is not ideal. In order to effectively control the ecological water environment and promote sustainable economic growth, this research combines artificial intelligence algorithms and applies them to the governance process to explore its application effects and its impact on economic growth. First, the environmental sensor of the corresponding module is designed according to the water environment factor, and the data of dissolved oxygen content, water temperature, turbidity, temperature and humidity, and smoke concentration in the water environment are collected. Then the dynamic time-varying exponential smoothing prediction method is used to predict water quality, and a water quality prediction model is established. Then use support vector machine (SVM) to train the collected data samples, use the decision tree-based SVM classification method to classify the data samples, establish a water quality evaluation model, and use particle swarm optimization algorithm to optimize the evaluation model. Put the sensors and predictive evaluation models established in this research design into the governance of a certain river reach, and collect relevant data from 7 : 00 to 18 : 00 on October 11, 2019. And predict and evaluate its water quality. The experimental results show that the average absolute error of predicting dissolved oxygen content is 0.97%, and the average absolute error of predicting phosphorus content is 2.27%. This shows that the application of artificial intelligence algorithms in the process of ecological water environmental governance can effectively help collect effective information and make more accurate predictions and evaluations of water quality, thereby improving governance efficiency and promoting sustainable economic growth.

1. Introduction

1.1. Background Significance. With the rapid development of industry, a large amount of industrial sewage and domestic wastewater has caused serious pollution to the water environment, and the originally scarce water resources are facing severe tests [1]. The effects of some current water environment treatment projects and sewage treatment facilities are not satisfactory, which not only are unfavorable to the sustainable development of the environment and economy but also bring serious hidden dangers to the lives and health of residents [2]. Therefore, the use of artificial intelligence algorithms to monitor ecological water environment-related data and propose scientific processing methods is of great significance for improving the efficiency of water environment governance.

1.2. Related Work. As the treatment of water environmental pollution is becoming more and more important, research teams at home and abroad have carried out research and discussion on it, and there are many achievements. According to the characteristics of PPP project of urban water environment treatment [3], an *X* established the basic standard and demonstration standard, formed the government compensation mode of PPP project of urban water environment treatment, considered the economic benefits of urban water environment treatment, and used game theory method to solve the incentive coefficient [4]. Although his research is targeted, the source of his experimental data is unknown. Chen et al. proposed a feasible method of using SO_2 (sulfite) to catalyze the oxidation of wastewater to improve the removal rate of pollutants in the water environment [5]. Their research and experimental steps are too complex, and it is very difficult to repeat the operation. Muerdter et al. introduced the influence of plants on pollutant removal performance and mechanism, including the impact on total suspended solids, nitrogen, phosphorus, toxic metals, hydrocarbons, pathogens, and emerging pollutants in urban rainwater [6]. Although their research analyzed the impact of plants on water pollution, they did not propose direct treatment methods. Hashimoto et al. studied the application of a new slurry type titanium dioxide (TiO_2) photocatalyst in the degradation of pesticides in water, aiming to reduce the pollution of pesticide use on rural domestic water [7]. Their experimental procedures are little confused, leading to the increase of experimental time and cost.

1.3. Innovative Points in This Paper. In order to improve the efficiency of ecological water environment governance, improve the status quo of ecological water environment, and promote green growth of the economy, this paper conducts in-depth research. The innovations are as follows: (1) According to the selected water environment factors, a series of sensors with perfect functions are designed to collect the timely data of dissolved oxygen content, water temperature, turbidity, temperature and humidity, and smoke concentration in the water environment. (2) The water quality prediction model is established by using the dynamic time-varying index smoothing prediction method, which can effectively predict the water quality and put forward the corresponding treatment scheme as soon as possible. (3) The support vector machine (SVM) and SVM classification method based on decision tree are used to train and classify the data samples. The water quality evaluation model is established after the optimization of particle swarm optimization algorithm, which can accurately classify the water quality.

2. Artificial Intelligence and Ecological Water Environment Governance

2.1. Artificial Intelligence Algorithm

2.1.1. Genetic Algorithm. Genetic algorithm imitates the natural evolution process to find the optimal solution and applies the principle of Darwinian evolution theory [8]. Before the calculation of the genetic algorithm, we need to do some preparatory work [9]. Firstly, the decision variables are coded, and the completeness, soundness, and non-redundancy of the coding should be paid attention to [10, 11]. Then the fitness function is set to judge the quality of individuals in the population. The fitness needs to be transformed into selection probability in a certain way, and most of them are positive numbers. When the population is set, the range of possible solutions of the model should be roughly estimated to be as close as possible to the optimal solution. When generating a certain number of individuals, excellent individuals must be added to the initial population.

After the maximum iteration number, selection probability, crossover probability, and mutation probability are set in advance, the iterative calculation can be started [12]. Firstly, the operators are selected randomly according to the probability to retain the excellent genes. Then the crossover operation is carried out. After pairing the chromosomes selected in the previous step, a segment of genes at the same position on the chromosome is randomly selected and exchanged to improve the searchability of genetic algorithm. In order to obtain new high-quality genes that cannot be obtained by cross operation, maintain population diversity, and prevent local optimum, it is necessary to select gene segments randomly for mutation. In order to maintain the size of the population, retain the optimal individuals of the original population, and prevent the loss of good individuals, it is necessary to add insertion operator after each iteration. Finally, the operation is stopped when the maximum number of iterations is satisfied or the ideal solution is reached.

Genetic algorithm (GA) searches the global optimal solution in the form of string set, which has a strong ability of optimization. GA evaluates individuals according to fitness function, which is not limited by specific objective function, and its application space is greatly expanded. GA uses probability transition rules to know the search direction and has the ability of self-organization, self-adaptive, and self-learning, so it is very practical.

2.1.2. Simulated Annealing Algorithm. The simulated annealing algorithm simulates the physical process of the solid in the molten state from gradually cooling to crystallization and uses random simulated solid annealing to solve the problem [13]. In the simulation process, the control of algorithm progress depends on the cooling schedule [14]. Under certain control parameters, the algorithm slowly cools down to zero, and the global optimal solution is obtained.

In the simulated annealing algorithm, the initial state should be selected as the current initial solution and the initial temperature should be set. After initializing the parameters, the next adjacent state is generated to judge whether the adjacent state is accepted or not and whether the balance point is reached. If not, it is necessary to return to generate the adjacent state until the balance is reached. Determine whether the termination conditions are met. If the requirements are not met, select a new temperature to generate the adjacent state, and the operation can be terminated if the termination conditions are met [15].

The simulated annealing algorithm can accept the deteriorating solution to a certain extent and accept the trial points that make the objective function value worse. The simulated annealing algorithm uses implicit parallelism algorithm, which is suitable for searching complex regions [16]. Only using the value of the objective function for optimization calculation can avoid the limitation of continuous differentiability. The ability of global optimization can be greatly improved by setting the definition domain arbitrarily.

2.1.3. Particle Swarm Optimization Algorithm. The particle swarm optimization algorithm is based on the foraging behavior of birds [17]. The flight space of birds is the search space of the problem. Each bird is an individual, and it is converted into particles whose weight is ignored to represent the feasible solution of the problem. The optimization process is similar to the population foraging process, and the most abundant food found is the optimal solution [18].

When the particle swarm optimization algorithm is used, first set the population size, search dimension, maximum iteration times, algorithm accuracy requirements, search range, and speed range [19]. The initial population and initial velocity are generated in the feasible region, the number of iterations is set, and the vector of the first iteration is determined according to the fitness value of different individuals in the population. If the current iteration times meet the preset accuracy requirements, the operation will be terminated.

As a swarm intelligence algorithm, particle swarm optimization algorithm has the flexibility to adapt to the changing system environment at any time [20]. It will not affect the robustness of the whole problem solution because of the failure of an individual. The increase of the number of individuals will not lead to the scalability of a large amount of communication overhead, and the implementation of individual execution time is relatively short [21, 22].

2.2. Ecological Water Environment Treatment Methods

2.2.1. Basic Principles of Ecological Water Environment Treatment. At present, the treatment technology for ecological water environment mainly includes three aspects: controlling external pollution sources, controlling and changing environmental conditions, and controlling abnormal growth of algae [23]. The control of external pollution sources can reduce the content of phosphorus by reforming the sewage pipe network, dephosphorization, and denitrification treatment of sewage and also can carry out dredging, nutrient passivation, sedimentation flocculation, and adjusting the ratio of nitrogen and phosphorus of lake water. In order to control and change the environmental conditions, the nutrient content in water can be reduced by introducing clean water, and the growth and accumulation of algae will be destroyed by using the flowing water. In order to control the abnormal growth of algae, chemical killing and flocculant can be used, and manual harvesting can also be used to remove the algae.

When carrying out ecological restoration of water environment, it is necessary to understand that ecological restoration is the restoration of biodiversity, ecosystem structure, and function, which is obviously different from bioremediation [24]. Ecological restoration focuses on the restoration of the whole ecosystem, while bioremediation focuses on the use of aquatic organisms to reduce pollutants in water. The ecological restoration of water environment needs to repair the water environment and the self-recovery ability of the ecosystem, which must be realized by restoring or constructing submerged plant communities [25].

The key to water eutrophication restoration is to control phytoplankton and enhance water permeability. According to the classical biological regulation theory, increasing the number of carnivorous fish can form a balance in the aquatic ecological environment, thus enhancing the water permeability. In particular, macrocladoceran zooplankton can directly control the number of phytoplankton and create favorable environmental conditions for the restoration of submerged macrophytes.

According to the theory of steady-state transition of phreatic lakes, there are two kinds of states that can be transformed into each other, the turbid water state dominated by phytoplankton and the clear water state dominated by submerged macrophytes. Under the condition of changing environment, eutrophic muddy water can be restored to clear water state [26]. And the fundamental way to control eutrophication and purify water quality is to restore a complete water ecosystem with submerged plant community as the core.

2.2.2. New Measures for Ecological Water Environment Control. Domestication of algae eating insects: excessive discharge of nitrogen and phosphorus will continue to increase the number of algae in the water, and the proliferation and growth of algae will damage the original ecosystem and the self-purification capacity of water body. In the short term, the technology of domesticating algae eating insects can be used to phagocytize the excessive algae in water body and improve the transparency of water body. Algae eater is a large cladocera zooplankton; after artificial domestication, it will feed on algae and rotten debris in the water [27]. To use this technology, different treatment methods should be adopted in three periods. Firstly, the domesticated algae eating insects should be used to devour the algae in the water body, reduce the turbidity of the water body, promote the growth of submerged plant communities, and form a new ecological balance. After that, submerged plant communities were constructed to oxidize and decompose suspended solids into minerals. The increase in oxygen content can also promote the reproduction of bottom microorganisms. Finally, in the long run, the ecosystem composed of submerged plants can promote the deposition of phosphorus in the water, eliminate the excess nutrients in the water body, and cultivate appropriate amount of underwater acoustic animals which can transform the nutrition of water body into edible animal protein, making the water quality cleaner.

In order to construct underwater forest, a healthy aquatic ecosystem with submerged plants as the core must be established. Submerged plants are the basis for the maintenance of water biodiversity and have important environmental value and strong water purification function. First of all, aquatic plants can remove a large number of nitrogen and phosphorus substances in the water area and improve the self-purification ability of water area [28]. In addition, submerged plants can create living environment for other aquatic plants, so the rational utilization and protection of submerged plant resources is an important node to ensure the ecological balance of aquatic plants. The main environmental factors affecting submerged macrophytes include light intensity, nutrient content, water sediment, suspended solids, and water environment temperature [29].

Microporous aeration technology: sufficient dissolved oxygen is needed for the survival of microorganisms. The microorganisms mentioned here are mainly aerobic microorganisms. Aeration can effectively improve the dissolved oxygen in the water, oxidize the organic matter in the water with oxygen, then convert it into inorganic matter, improve the aerobic environment of the water area, restore the original microbial community, and change the original water environment through mechanical functions such as collision and mixing, so as to make the oxygen distribution uniform in the water area and reduce the occurrence of water pollution.

2.3. Environmental Sensors

2.3.1. Sensor Data Acquisition Strategy. When the wireless sensor monitors the environmental data, the interval time of data collection is always the same, because this method is very simple. It only needs to set a fixed time interval in the sensor terminal node. In this way, the data will be collected every other period of time and finally transmitted to the server [31]. However, this method does not consider that the speed of data change is different at different times. If the data are collected only in the same time interval, the average information of data will be reduced. Moreover, the length of interval time will directly affect the acquisition results: being too short will lead to data redundancy, and being too long will lead to information loss. Therefore, when using sensors to monitor the environment, we must design a reasonable data acquisition strategy to effectively collect key information and reduce the number of sensor data acquisition and transmission.

Adaptive frequency conversion data acquisition strategy plays an important role in environmental monitoring, and the change of collected data can be roughly estimated by judging the change trend of data. Based on the univariate linear regression model, the data acquisition interval can be adjusted adaptively [32]. However, the efficiency of the strategy for data acquisition is not high, and the algorithm is complex and time-consuming.

Data acquisition based on data correlation is a method for continuous and long-term data acquisition. The data collected by sensors arranged in the environment are correlated. In a short time, the data collected by the same sensor are correlated in time, and the data collected by adjacent sensors at the same time are also spatially correlated. Among the existing sensor data collection methods based on data correlation, some of them cannot flexibly expand the scale of wireless sensor networks. In addition, because the method is relatively simple, the amount of data collection and transmission is still too large to greatly reduce the data load of wireless sensor networks [33]. Therefore, the sensor data acquisition based on data correlation needs to design a distributed data acquisition method consistent with the reasonable and effective data correlation model, so as to ensure the quality of collected data and reduce the energy consumption of sensor nodes as much as possible [34]. Finally, it meets the requirements of flexible adaptability and excellent scalability.

2.3.2. Selection of Water Environmental Factors. In the detection of water environment, the water environmental factors that need to be detected are clearly specified in relevant laws and regulations, which are mainly divided into underwater environmental factors and aquatic environmental factors.

Underwater environmental factors include dissolved oxygen, water temperature, pH, and turbidity [35]. Dissolved oxygen is the content of oxygen dissolved in water in molecular state. The content of dissolved oxygen in water is related to many factors. It not only provides the necessary oxygen for fish and microorganisms to survive but also is the detection parameter of water environmental quality. Water temperature can affect most of the chemical and physical properties of water, which is an important indicator of water quality. pH affects not only the growth of organisms in water but also the chemical and biological reactions in water. Turbidity is used to indicate the degree of turbidity in water environment. It is a measure of the scattering and absorption capacity of water to light. It is related to the quantity, size, and refractive index of particles in water.

The water environment does not only refer to the water area, and the aquatic environmental factors may also have a great impact on the water environment. Therefore, when testing the water environment, the influence of the water environment factors on the aquatic environment must be considered, such as smoke concentration, temperature and humidity, and light [36]. Smoke is one of the standards to detect air pollution, which is harmful to human health and the survival of animals and plants. The change of water temperature has a direct impact on water temperature, and the change of surface water temperature will delay the change of air temperature. The change speed of the water temperature is slower than that of the air, and the temperature difference between the surface water temperature and the deep-water temperature becomes larger when the temperature changes violently. Most aquatic organisms are variable temperature organisms, which are sensitive to the changes in external temperature and water temperature. If the temperature difference changes greatly, it will have a great impact on the thermophilic organisms and the quality of the water environment. In daily life, if the humidity in the air is too high, the bacteria are easy to reproduce, especially in the places close to the water environment, and the quality of the water environment will decline. Therefore, the collection of humidity factors is particularly important. There are two main types of oxygen in water, one is dissolved oxygen in the air of water, and the other is dissolved oxygen in water after photosynthesis of aquatic plants. In order to supplement the dissolved oxygen content in water, aquatic plants need sufficient light for photosynthesis, so illumination is also one of the important factors [37].

3. Experiments on Intelligent Algorithm Model of Ecological Water Environment Management

3.1. Sensor Module Design. In this study, the dissolved oxygen sensor with a coated electrode was used to collect the dissolved oxygen data. The potential difference between the anode and cathode of the sensor produces a reduction reaction, which is directly proportional to the concentration of dissolved oxygen. Because the output current of the dissolved oxygen sensor is very small, it is necessary to use operational amplifier circuit and use core processing module for data conversion.

The water temperature sensor used in this study is a stainless steel packaged digital sensor, which adopts a unique single bus data structure and has the advantages of small size, high sensitivity, and high anti-interference ability. The working power supply voltage of the sensor is about 5 V, and the temperature range that can be measured is −15°C~110°C. Put the probe part of the sensor into the water directly; the sensor can directly transmit the digital signal to the core MCU.

In this study, TS type turbidity sensor is used to collect turbidity data, and the light penetration is calculated by refraction of transistor and optical diode to a specific wavelength, so as to detect turbidity in water environment, and then the output current signal is converted into voltage signal. The working voltage of the sensor is about 5 V and the working current is less than 25 mA. It has the advantages of small volume and low price.

In this study, MQ-2 smoke sensor is used to collect smoke concentration data. Different concentrations and different types of gases have their corresponding resistance values. The change of conductivity is converted into the change of voltage so that the smoke concentration and voltage change show a linear relationship. The module has the advantages of high stability, high sensitivity, and wide detection range.

In this study, the composite digital sensor with professional temperature and humidity sensing technology is selected to collect the temperature and humidity data, which can accurately calibrate the data and ensure the reliability and stability of the sensor at a high level. The temperature measurement range is −5~45°C, the accuracy error is about 2°C, the humidity measurement range is 15~95% RH, and the accuracy error is about 3%.

3.2. Establishment of Water Quality Prediction Model. In this study, the dynamic time-varying exponential smoothing prediction method is used to predict the water quality. The exponential smoothing method overcomes the problem of insufficient prediction space, makes up for the shortcomings of incomplete consideration of data, fully considers the impact of data development trend on future data changes, and realizes the prediction in an average way. The basic formula of exponential smoothing method is

$$G_t = \beta Q_t + (1-\beta)G_{t-1} = G_{t-1} + \beta\left(Qt - G_{t-1}\right), \quad t = 1, 2, \ldots, n. \tag{1}$$

Among them, G_t, G_{t-1} are the exponential smoothing average at time t and time $t-1$, respectively, Q_t is the measured value in time t, β is the smoothing coefficient, and the range is between [1, 2].

The exponential smoothing method can be classified according to the smoothing times. In this study, the quadratic exponential smoothing method is used, which is suitable for the series with parabolic linear trend. The smoothing value formula and prediction formula are shown in formulae (2) and (3), respectively:

$$\begin{cases} G_t^{(1)} = \beta x_t + (1-\beta)G_{t-1}^{(1)}, \\ G_t^{(2)} = \beta G_t^{(1)} + (1-\beta)G_{t-1}^{(2)}, \end{cases} \tag{2}$$

$$\widehat{x}_{t+T} = d_t + e_t \cdot T + f_t \cdot T^2. \tag{3}$$

Among them, $G_t^{(1)}, G_{t-1}^{(1)}, G_t^{(2)}, G_{t-1}^{(2)}$ are the first exponential smoothing average of t period and $t-1$ period and the second exponential smoothing average of t period and $t-1$ period; $\widehat{x}_{t+T}$ is the prediction value of $t+T$ period; β is the smoothing coefficient; d_t, e_t, f_t are the parameters of related model.

When using the exponential smoothing method, attention should be paid to the determination of initial value and smoothing coefficient, which have great influence on the accuracy of prediction. The common method is to take the measured value of the first phase as the initial value, and the value range of smoothing coefficient is 0.3~0.5.

3.3. Establishment of Water Quality Evaluation Model. At present, the water quality evaluation methods include comprehensive pollution index method, Ross water quality index method, and brown water quality index method. With the wide application of artificial intelligence algorithm, water quality evaluation model also presents diversification. In this study, SVM is used to train data samples, and SVM classification method based on decision tree is used to classify data samples. The optimal classification discriminant function of the training set is shown in formula (4):

$$g(x) = \operatorname{sgn}\left[\sum_{i-1}^{i} r_i m_i\left(x_i, x_j\right) + n\right], \tag{4}$$

where m_i is the Lagrange multiplier, x_i is the sample vector, r_i is the classification identifier, and n is the classification threshold.

The particle swarm optimization algorithm is used to optimize the parameters of SVM, and the optimization process is shown in Figure 1.

As shown in Figure 1, the initial population and initial speed are generated in the feasible region, the number of

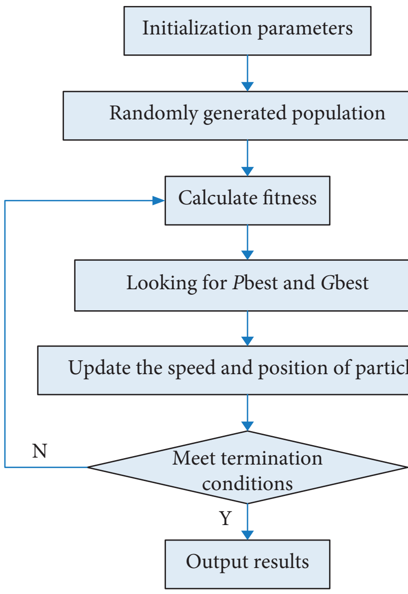

FIGURE 1: Flowchart of particle swarm optimization algorithm.

iterations is set, and the first iteration vector is determined according to the fitness values of different individuals in the population. Update the speed of the individual and the optimal position in the global history, and terminate the operation if the current iteration number reaches the preset accuracy requirement.

4. Discussion on the Application of Intelligent Algorithms and Its Impact on Economic Growth

4.1. Sensor Data Acquisition Results. The sensor designed in this study is used to collect the data of dissolved oxygen, water temperature, turbidity, temperature and humidity, and smoke concentration in a river section. The collection period is from 7 : 00 to 18 : 00 on October 11, 2019, and the data are recorded every 1 h.

As shown in Table 1, during the period from 7 : 00 to 18 : 00 on October 11, 2019, the changes of dissolved oxygen content, water temperature, turbidity and temperature, and humidity of the reach are not particularly obvious, and the change of smoke concentration is more obvious. With the change of the ambient temperature, the water temperature will also change accordingly. The ambient temperature reaches the highest value of 17.2°C at 13 : 00, while the water temperature reaches the maximum of 15.7°C at 18 : 00. The content of dissolved oxygen showed a U-shaped trend, and the content was the lowest at noon. Turbidity and humidity were the lowest at 13 : 00 noon. The smoke concentration fluctuated and peaked at 9 : 00, 13 : 00, and 18 : 00, which may be due to the increase of the number of vehicles in the morning and evening peak, and the automobile exhaust aggravates the environmental pollution, which makes the current smoke concentration increase.

4.2. Application and Analysis of Water Quality Prediction and Evaluation Model

4.2.1. Water Quality Prediction Results. The water quality samples of the river section from October 11 to 20, 2019, are collected, the data are calculated by quadratic exponential smoothing, and the smoothing coefficient is 0.5. The dynamic time-varying exponential smoothing prediction model was used to predict the dissolved oxygen content of the reach from October 21 to 30, and the results were compared with the actual detection results. The results are as follows.

As shown in Figure 2, the residual errors of the dynamic time-varying exponential smoothing prediction model are 0.18, −0.21, 0.171, −0.11, −0.15, 0.241, 0.123, −0.18, 0.214, and 0.187, respectively, with an average absolute error of 0.97%. In order to further verify the prediction ability of the model, the phosphorus content of the same water sample was predicted. The results are as follows.

As shown in Figure 3, the residual errors of the dynamic time-varying exponential smoothing prediction model are 0.0021, −0.0051, 0.019, 0.001, 0.012, 0.0098, 0.0123, −0.0087, 0.0107, and 0.0109, respectively, with an average absolute error of 2.27%. Although there are some unavoidable errors, the model still has high prediction ability, which can provide scientific data for the treatment of water environment.

4.2.2. Water Quality Assessment Results. Using the water quality evaluation model established in this study, the above water quality parameters and the results based on dynamic time-varying index smoothing prediction are normalized, and then the parameters are optimized by particle swarm optimization algorithm. The results are as follows.

As shown in Figure 4, the water quality can be divided into five categories through the water quality evaluation model, and there is no phenomenon of misclassification and leakage. Moreover, the classification speed is very fast, and the training time is also a lot. After the classification, the decision function can be obtained by training, and the water quality of the samples can be corresponding to the corresponding water quality categories.

4.3. Impact on Economic Growth. Ecological water environment and economic growth are complementary. Relying on the economic growth of the secondary industry will bring irreversible pollution to the water environment. While developing the economy, we must pay attention to environmental protection. The scientific treatment method of water environment based on artificial intelligence can effectively improve treatment efficiency [38]. In a short period of time, the polluted water environment will be treated to prevent water environment pollution that has not yet appeared but may occur and promote sound and rapid economic development while protecting the water environment.

Table 1: Measured data of sensors.

Time	DO mg/l	Water T °C	Turbidity %	T °C	Humidity %	Smoke C ppm
7 : 00	9.3	14.8	3.7	15.7	41.2	229
8 : 00	9.2	14.8	3.8	15.9	41.0	301
9 : 00	9.0	14.9	3.7	16	39.8	318
10 : 00	9.0	15.3	3.4	16.3	39.9	268
11 : 00	8.9	15.4	3.3	16.8	38.6	254
12 : 00	8.9	15.5	3.5	17	37.9	281
13 : 00	8.9	15.6	3.2	17.2	37.1	305
14 : 00	9.0	15.5	3.4	17.2	38.5	299
15 : 00	9.1	15.3	3.5	16.9	38.2	264
16 : 00	9.1	15.3	3.6	16.6	38.9	237
17 : 00	9.0	15.6	3.6	16.8	39.3	223
18 : 00	9.2	15.7	3.5	16.9	40.2	314

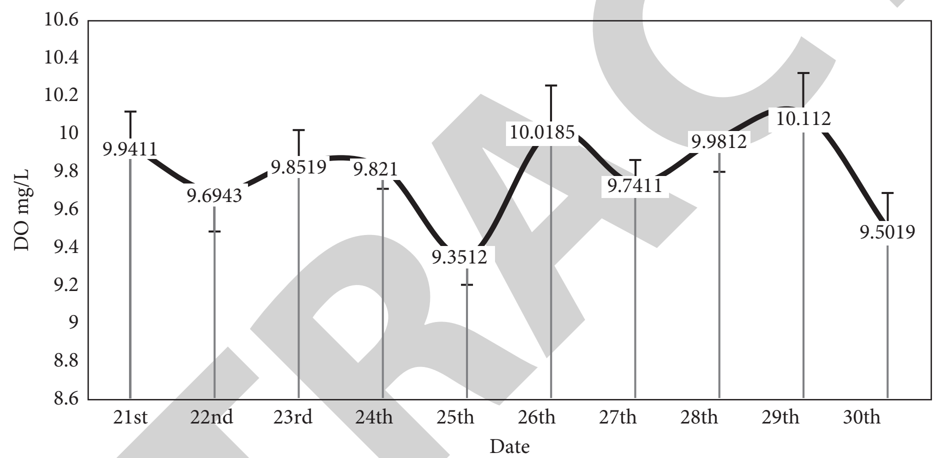

Figure 2: Prediction results of dissolved oxygen content.

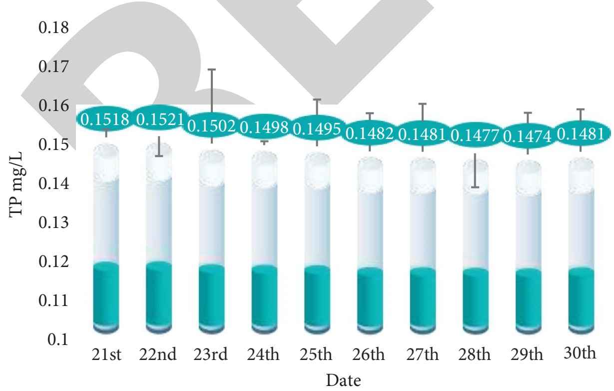

Figure 3: Prediction results of phosphorus content.

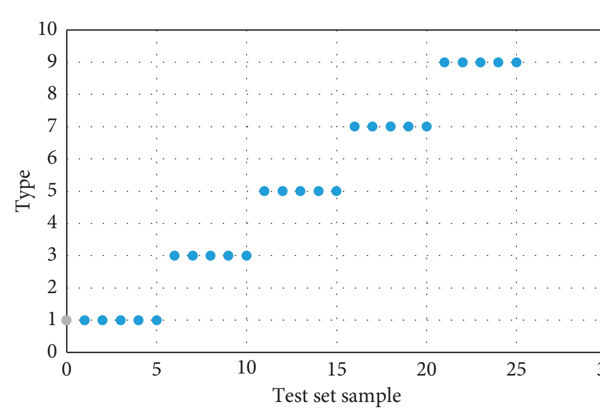

Figure 4: Classification of water quality samples.

5. Conclusions

The task of ecological water environment management cannot be completed overnight. It needs to be carried out from three aspects: controlling external pollution sources, controlling and changing environmental conditions, and controlling the abnormal growth of algae. In the treatment process, the collection and analysis of water environment factor data are directly related to the treatment effect. Timely and accurate data help to make reasonable and scientific decisions.

The sensor designed in this study can collect effective information and provide timely feedback, providing scientific data for water quality prediction models and water quality evaluation models. Accurately predict and evaluate water environment-related data to make scientific decisions, improve water environment management efficiency, and save manpower and material resources.

Due to the limited time and knowledge, the design of water environment sensor in this study is too simple to consider the problem of energy consumption and damage in the process of using. When establishing the prediction model, this study only predicted the content of dissolved oxygen and phosphorus in the water, but the composition of the elements in the water is complex, and it is not enough to predict these two alone. In the next step of the research work, we will predict as many water quality indicators as possible.

Data Availability

The data underlying the results presented in the study are available within the manuscript.

Conflicts of Interest

The author declares no conflicts of interest.

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