Pol. J. Environ. Stud. Polit. Econ. Ind. Vol. XX, No. X (XXXX), 1-10
DOI: *10.15244/peai/210115* ONLINE PUBLICATION DATE: 2025-11-25

Original Research

Intelligent Analysis and Information Intelligent Control System for Online Monitoring Data of Water Ecological Wetland Landscape Environment

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Received: 13 June 2025
Accepted: 31 August 2025

Abstract

In view of the problems of low efficiency and poor real-time performance in the monitoring and management of the landscape environment of water ecological wetlands, this paper designs an intelligent analysis and information intelligent control system for online monitoring of the landscape environment of water ecological wetlands. Through advanced sensor networks and data acquisition technologies, the system monitors key indicators such as water temperature, pH value, dissolved oxygen, and turbidity in the wetland landscape environment in real time, and combines machine learning and intelligent data analysis algorithms to achieve efficient data processing and accurate analysis. The experimental results show that the system performs well in the detection of indicators such as water temperature, pH value, dissolved oxygen, and turbidity at the monitoring point. The P-value of the predicted value and the actual value are both greater than 0.05, and the error range is within a controllable range, with high detection accuracy. At the same time, the response time and data processing time of the system are controlled within 1.5 seconds, the early warning accuracy rate reaches 100%, and the water quality equipment can be effectively regulated to ensure the health of the water ecological environment. Studies have shown that the system has significant advantages in monitoring accuracy, real-time performance, early warning capability, and intelligent control, provides important technical support for the protection and management of aquatic ecological wetland landscape environment, and has broad application prospects.

Keywords: water ecological environment, online monitoring, intelligent data analysis, information intelligent control, machine learning

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Introduction

With the intensification of global climate change and human activities, the aquatic ecological wetland landscape environment is facing unprecedented pressures and challenges. As an important ecosystem, wetlands not only play a key role in maintaining biodiversity, regulating water resources, and improving regional climate, but also serve important functions in purifying water quality and protecting the ecological environment. However, in recent years, due to the effects of urbanization, industrial emissions, and agricultural pollution, the wetland landscape environment has been severely damaged, and the problem of water quality deterioration has become increasingly prominent. In this context, it is particularly important to carry out intelligent analysis of online monitoring data and conduct research on intelligent information control systems for the landscape environment of aquatic ecological wetlands.

The protection and management of the water ecological environment are very important for maintaining the balance of nature and protecting human health. The Yongding River Basin is an important water conservation area and ecological barrier in the Beijing–Tianjin–Hebei region. By selecting evaluation parameters, Cui Wenyan scored the physical habitat, water quality physicochemical indicators, aquatic bioindicators, and other indicators of 30 stations, and applied weights to obtain comprehensive indicators of water ecological environment quality for each station in the Yongding River Basin. These indicators can generally reflect the current state of water ecological environment quality in the Yongding River Basin [1]. Starting from the needs of integrated monitoring of the urban ecological environment, Wang Qiao identified the main scientific and technical issues from three perspectives: urban pollution gases, water quality, and ecological resources. Based on key technical breakthroughs currently underway, and through analysis and demonstration, he established the technical system architecture, indicator system architecture, and standard system architecture for integrated monitoring of the urban ecological environment. On this basis, and considering the characteristics of remote sensing data and national ecological environment monitoring needs, a comprehensive business application plan for urban ecological environment monitoring was studied. This plan provides important guidance and support for the next effective implementation of urban ecological environment monitoring and management by the country, provinces, cities, and local governments [2]. Chen Shanrong analyzed the current situation and future development trends of the national ecological environment monitoring network and put forward several suggestions for its construction. A specific analysis was conducted on the national monitoring network, focusing on factors such as air, surface water, soil, and ecology. At the same time, the operational mechanism of the national ecological environment monitoring network should be clarified. By establishing mechanisms for departmental collaboration and improving the legal and standard system for ecological environment monitoring, research and the application of new monitoring technologies can be strengthened [3]. Traditional water environment monitoring methods face problems such as long manual sampling cycles and low data processing efficiency.

Developing an online monitoring data intelligent analysis and information intelligent control system for the water ecological environment has important theoretical significance and practical application value. The organic integration of correlation analysis features of water conservancy Big data and the specialized mechanism model features of the water conservancy industry can enable efficient processing and intelligent analysis of large-scale, multi-source water conservancy data, while actively delivering valuable results to decision-makers in a highly visible form. This is a fundamental approach to solving the problem of refined management and control of water conservancy industry goals. Jiang Yunzhong analyzed the overall development trend of water conservancy Big data and pointed out that its current direction includes scenario-based demand, integrated management, intelligent analysis, platform-based service, and systematic guarantees [4]. Environmental monitoring is not only a pioneer in protecting the ecological environment but also an effective preventive measure. It can effectively detect environmental abnormalities during development processes and allow timely preventive action before the ecological environment is damaged. Environmental monitoring is an indispensable scientific method for modern ecological environment protection. By studying the application of environmental monitoring, Zhang Sheng was able to better carry out ecological environment protection and management work [5]. However, advanced sensor networks and data collection technologies were not used to monitor indicators of the water environment.

This paper focuses on the design and application of intelligent analysis of online monitoring data and information intelligent control systems for water ecological wetland landscape environments. It breaks through the limitations of long manual sampling cycles and low data processing efficiency in traditional monitoring methods. By integrating high-density sensor networks and real-time transmission technology of the Internet of Things, it realizes global and dynamic monitoring of key wetland indicators, and solves the limitations of single-point monitoring. At the same time, it deeply integrates support vector machines with the principle of structural risk minimization to construct a data analysis model with both high precision and strong generalization capabilities, overcoming the lack of adaptability of traditional statistical methods in complex water environment data processing. In addition, at the control level, an intelligent control mechanism combining closed-loop feedback and model predictive control (MPC) is adopted to realize the full process automation from data monitoring to equipment control, filling the technical gap in the existing system in the linkage between real-time response and precise control.

Materials and Methods

Sensor Networks

Sensor networks and data collection technologies are important components of the intelligent analysis and information intelligent control system for online monitoring of water ecological environment data. A sensor network is a distributed system composed of multiple interconnected sensor nodes, which can collect real-time physical and chemical information on environmental parameters and transmit it to data collection terminals or cloud servers for processing and analysis.

In the monitoring of aquatic ecological environment, common sensor nodes include temperature, pH value, dissolved oxygen, turbidity, COD (Chemical Oxygen Demand), BOD (Biological Oxygen Demand), and other sensors. These sensors are installed at different monitoring points and interconnected through Internet of Things technology, forming a high-density sensor network that can monitor various indicators of the water environment in real-time [6, 7].

Data collection technology is a technology that aggregates, processes, and stores data generated by sensors. Generally speaking, data collection technology includes links such as data transmission, data storage, and data processing. Among them, data transmission technologies mainly include wireless, wired, and Bluetooth methods; data storage technologies include cloud storage and local storage; and data processing technologies include data cleansing, data analysis, data mining, and other processes.

In the online monitoring data intelligent analysis and information intelligent control system of the water ecological environment, the application of sensor networks and data collection technology can achieve efficient, reliable, real-time monitoring and data collection of the water environment, providing a foundation for subsequent water quality analysis and intelligent control [8, 9]. At the same time, for different monitoring objectives and research fields, it is also necessary to select appropriate sensors and data collection schemes and carry out systematic optimization and upgrading to achieve better monitoring and data analysis results.

Design of Intelligent Analysis and Information Intelligent Control System for Online Monitoring Data of the Water Ecological Environment

Sensor Selection and Layout

In the online monitoring data intelligent analysis and information intelligent control system of the water ecological environment, sensors are a very important part. They can monitor various indicators of the water environment in real time and process and analyze the collected data to provide accurate water quality assessment and pollution warning information, thereby ensuring the safety and health of water bodies [10, 11]. Therefore, when selecting and laying out sensors, this article needs to comprehensively consider monitoring needs and actual conditions to ensure the accuracy and reliability of monitoring data.

The selection of sensors should be determined based on monitoring needs, generally including sensors for indicators such as temperature, pH value, dissolved oxygen, turbidity, and conductivity. For example, temperature sensors can be used to monitor temperature changes in water bodies, and pH sensors can be used to monitor the acidity and alkalinity of water bodies; dissolved oxygen sensors can be used to monitor the oxygen content in water bodies, turbidity sensors can be used to monitor the concentration of suspended solids, and conductivity sensors can be used to monitor conductivity in water bodies [12, 13]. Different types of sensors have different characteristics and application ranges, so it is necessary to choose according to the actual situation.

The sensors are designed to comprehensively address monitoring needs and wetland environmental characteristics. The measurement errors for water temperature, pH, dissolved oxygen, and turbidity are no more than $\pm 0.1°C$, ± 0.05, ± 0.1 mg/L, and ± 0.2 NTU, respectively. They are temperature-tolerant, biofouling-resistant, and have a response speed of ≤ 2 seconds. They are also compatible with the system's communication protocol and guarantee a continuous operating life of at least 12 months to reduce maintenance costs.

The calibration process utilizes a three-level mechanism: initial calibration using standard solutions prior to installation, with calibration coefficients recorded. Monthly on-site calibration is performed using portable standard equipment for comparison, with recalibration performed if deviation exceeds $\pm 5\%$. The system automatically performs zero and span calibration daily at dawn, and a quarterly in-depth laboratory calibration is performed to replace deteriorating components and generate calibration reports to ensure data reliability.

Data Collection and Transmission

Data collection and transmission are crucial components of the intelligent analysis and information control system for online monitoring of the water ecological environment [14, 15]. It is responsible for the real-time collection of data obtained by sensors and transmitting it to the central processing system through wireless or wired transmission. Therefore, in terms of data collection and transmission, this article needs to adopt advanced data collection equipment and communication technology to ensure the timeliness, accuracy, and reliability of the data.

In terms of data collection, this article requires the use of professional data collection equipment, such as data collection cards, data processing software, etc., to process and store the data collected by sensors for subsequent analysis and control. Data collection equipment should have characteristics such as high accuracy, high stability, and high speed to meet the requirements of data collection.

In terms of data transmission, this article can adopt wireless or wired transmission methods and choose appropriate communication technologies according to the actual situation. For example, wireless technologies such as Wi-Fi (Wireless Fidelity) and Bluetooth can be used to transmit data to the central processing system. Wired transmission methods such as network cables, optical fibers, etc., can also be used to transmit data to the central processing system. Regardless of the transmission method, it is necessary to ensure the security and integrity of data.

Data Processing and Analysis Algorithms

Data processing and analysis algorithms are a very important part of the intelligent analysis and information intelligent control system for online monitoring of water ecological environment data [16, 17]. They are responsible for preprocessing, analyzing, and processing the collected data and providing accurate water quality assessment and pollution warning information, which plays a crucial role in ensuring water safety and health. Therefore, in terms of data processing and analysis algorithms, this article needs to choose appropriate algorithms and methods to improve processing and analysis efficiency and accuracy.

First, in terms of preprocessing, this paper needs to process the collected original data, including noise removal, data interpolation, etc., to ensure the quality and accuracy of the data.

In terms of data analysis, methods such as machine learning, artificial intelligence, and model prediction need to be used to perform pattern recognition, anomaly detection, and trend analysis on the data [18, 19]. For example, support vector machine models can be used to classify and predict data, improving the accuracy and reliability of the data.

The actual model is unknown. For a given input A, the predicted output of the learning system's model is $B = g(A)$. In general, the relationship between the predicted value $g(A)$ of the output and the true value B is uncertain, and the two may coincide or differ. In case of inconsistency, the loss function or cost function is generally used to measure the error between the two, which is recorded as $Z(B, g(A))$. The minimum value is 0, which means that the predicted value is completely consistent with the true value. In general, when the loss function is low, the model performs well. Based on mathematical statistics and probability distribution, the input and output (a, b) of the model is a random variable, and its joint probability distribution is represented by mathematical notation $Q(a, b)$. Therefore, the expectation of the loss function is:

$$K_{exp}(g) = C_q\left[Z\big(B, g(A)\big)\right] = \int_a Z\big(b, g(a)\big)Q(a, b)tatb \tag{1}$$

Formula (1) is the expected value of $g(A)$'s Loss function with respect to the joint probability distribution $Q(a, b)$.

Structural risk minimization:

In real life, the distribution $Q(a, b)$ to which data obey is unknown and can be obtained without prior experience or through reasoning, so $K_{exp}(g)$ cannot be calculated directly. In machine learning, empirical risk is usually used to replace the expected Loss function [20]. The empirical risk is:

$$K_{exp}(g) = min\frac{1}{M}\sum_{j=1}^{M} Z\left(b_j, g\left(a_j\right)\right) \tag{2}$$

Under the assumption that the space, Loss function, and training data set are determined, the definition of structural risk is:

$$K_{srm}g(a) = min\frac{1}{M}\sum_{j=1}^{M} Z\left(b_j, g\left(a_j\right)\right) + \epsilon I(g) \tag{3}$$

Therefore, during the training process, the trainer believes that the model with the least structural risk is the optimal model. To prevent overfitting and ensure that the model has a good structural risk function is the optimization goal.

During data preprocessing, wavelet transforms are used for noise reduction. Noise signals are removed through a five-layer high-frequency component decomposition and soft thresholding. Short-term missing data (≤30 minutes) is filled with linear interpolation. Long-term missing data (>30 minutes) is filled using a spatiotemporal collaborative kriging algorithm based on predictions from nearby monitoring points. Outliers are identified based on the 3σ criterion, and their authenticity is determined based on sensor status. True outliers are marked and manually reviewed, while false outliers are corrected using local weighted regression. Regarding quality control, data transmission uses a CRC checksum to ensure integrity. The receiving end filters invalid data within a preset parameter range. A dynamic rule base containing physical and logical constraints is established. Processed data is graded according to credibility (A/B/C). Grade A data is used directly for analysis, grade B data requires cross-validation, and grade C data is used only for trend reference, ensuring data reliability and availability.

Evaluation:

In learning systems, the optimization goal is generally to minimize structural risk, but this cannot be the basis for evaluating the quality of the model. This is because the optimal model in the existing hypothesis space is only a local solution, and the quality of the model is generally judged by its performance in the test set. This article refers to the errors generated by the model or learner in the training set as training errors or empirical errors, while the errors generated for new samples are called generalization errors, which are essentially the generalization ability of the model. In ordinary machine learning algorithms, people usually use accuracy or precision to describe generalization errors. It is assumed that there are m_{sampie} test samples in the test set, the expression for accuracy is as follows:

$$accuracy = \frac{1}{m_{sampie}} \sum_{j=1}^{m_{sampie}} (\widehat{b_j} = b_j) \tag{4}$$

When the predicted results are completely consistent with the actual situation, the value is 1. The lower the degree of agreement between the two, the lower the accuracy, and the worse the model.

Linear support vector machine:

A linear support vector machine (LSVM) is a machine learning algorithm for linear classification, which is a perceptual machine that can correctly classify data and correctly classify the most difficult points with maximum confidence. In this case, the formula of the separating Hyperplane can be expressed as:

$$g(a) = sign(s^D a + y) \tag{5}$$

When $s^D a + y > 0$, b corresponds to 1, otherwise it is -1. The solution process is a convex quadratic programming problem with constraints.

$$\min_{s,y} \frac{1}{2} \|s\|^2 \tag{6}$$

$$s.t. \left(b_j \cdot a_j + y\right), j = 1,2,3, \dots m \tag{7}$$

This is a convex quadratic optimization problem. The normal vector and intercept of the hyperplane can be obtained from the above formulas. By summarizing the above process, the original learning algorithm for linearly separable support vector machines can be obtained.

In terms of data processing and analysis algorithms, this article also needs to consider real-time and efficiency issues to meet the requirements of real-time monitoring and control. Therefore, when selecting algorithms and methods, it is necessary to comprehensively consider the complexity, running time, computing resources, and other factors of the algorithm, so as to ensure the real-time and efficiency of the system.

Information Intelligent Control Algorithm

The information intelligent control algorithm is an important component of the intelligent analysis and information intelligent control system for online monitoring data of the water ecological environment. It is responsible for automatically adjusting the operating parameters of water treatment equipment, such as flow rate, concentration, pH value, etc., based on changes in monitoring data and target requirements, in order to improve water quality and prevent pollution. Therefore, in terms of information intelligent control algorithms, this article needs to adopt advanced control algorithms and methods to improve control efficiency and accuracy.

Generally speaking, information intelligent control algorithms can be divided into two types: open-loop control and closed-loop control. Open-loop control refers to the control of water treatment equipment based on preset control strategies, such as operating the equipment according to preset time or flow rate. Closed-loop control refers to real-time regulation of water treatment equipment based on changes in monitoring data, such as automatically adjusting pH based on the monitored pH value to meet specified water quality requirements.

In terms of information intelligent control algorithm, this paper needs to adopt advanced control methods and technologies, such as model predictive control (MPC), adaptive control, logic control, and other methods to improve control efficiency and accuracy. At the same time, it is also necessary to consider the real-time and reliability issues of control algorithms to meet the requirements of real-time monitoring and control.

The intelligent analysis and information intelligent control system for online monitoring data of the water ecological environment has very important application value and practical significance, playing a crucial role in ensuring water safety and health. Therefore, when designing and developing the system, this article needs to fully consider various factors to select appropriate sensors, data acquisition equipment, communication technology, etc., and adopt advanced data processing and analysis algorithms and information intelligent control algorithms in order to ensure the efficiency, reliability, and real-time performance of the system. The interface of the intelligent analysis and information intelligent control system for online monitoring data of the water ecological environment is shown in Fig. 1.

Experimental Design

Experimental Purpose

The aim is to test the accuracy, real-time performance, early warning accuracy, and information intelligent control effect of the intelligent analysis

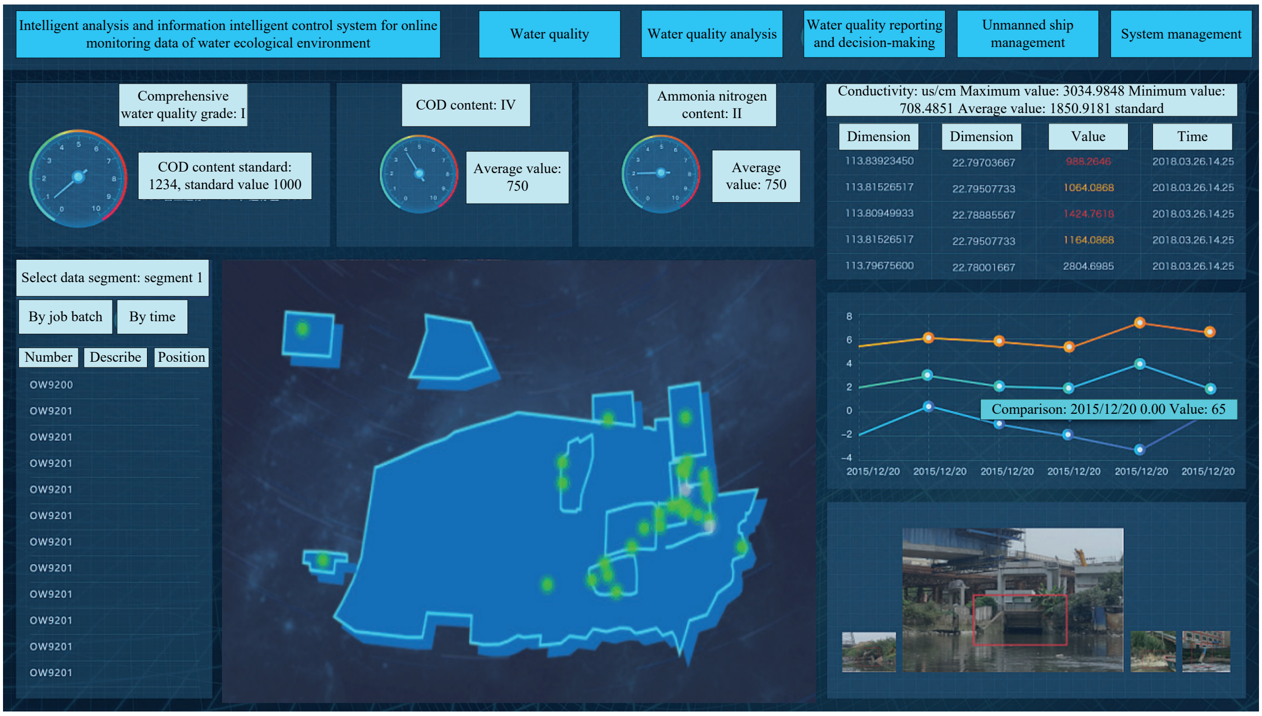

Fig. 1. Online monitoring and information intelligent control interface for the water ecological environment.

and information intelligent control system for online monitoring data of the water ecological environment.

Experimental Environment

- Water quality monitoring site: it is used for the installation of water quality sensors and water quality data collection.
- Meteorological monitoring site: it is used for the installation of meteorological sensors and the collection of meteorological data.
- Data processing center: it is used for data transmission, storage, and processing.
- Data display platform: it is used to display processed data.

Experimental Method

Water quality, flow velocity, and meteorological data were collected through equipment such as water quality sensors, flow velocity sensors, and meteorological sensors. The collected data was transmitted to the data processing center through wireless communication technology or wired communication technology. The data transferred to the data processing center was stored in the database or Cloud storage. The collected data was processed using techniques such as data mining and machine learning. The processed data was displayed through websites or mobile apps.

Results and Discussion

Accuracy Testing

In order to test the accuracy of the intelligent analysis and information intelligent control system for online monitoring data of the water ecological environment, this article established 10 monitoring points and uploaded the data to the intelligent analysis system. The analysis results of the intelligent analysis system were compared with actual monitoring data, and the temperature, pH value, dissolved oxygen, turbidity, and other indicators of the monitoring points were calculated. The experimental results and t-test are shown in Fig. 2 and Table 1.

Fig. 2a) shows the actual water quality data detected, and Fig. 2b) shows the water quality data intelligently analyzed using online monitoring data of the water ecological environment. Based on Fig. 2 and Table 1, it can be seen that the actual monitoring results of water temperature, pH value, dissolved oxygen, and turbidity at monitoring point 1 were 25.3ºC, 7.5, 6.8 mg/L, and 5.2 NTU, respectively, while in the intelligent analysis system table, they were 25.2ºC, 7.4, 6.7 mg/L, and 5.1 NTU, respectively. This meant that there may have been errors when uploading monitoring data or deviations when processing data in intelligent analysis systems, but their P-values were both greater than 0.05, and there was no significant difference between the two datasets. This indicated that the errors generated are within a controllable range. This also indicated that the intelligent analysis and information intelligent control system for online monitoring data of the water

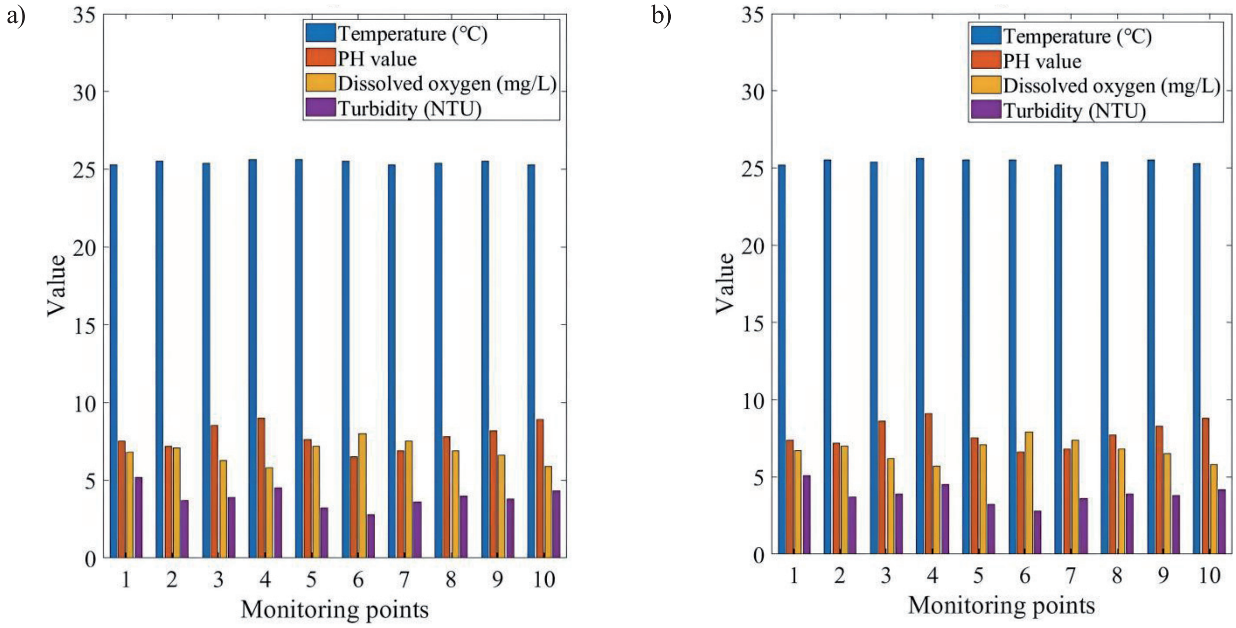

Fig. 2. Accuracy testing of the intelligent analysis and information intelligent control system for online monitoring data of the water ecological environment. a) actual monitoring data, b) intelligent analysis data.

Table 1. t-test between actual monitoring data and intelligent analysis data.

	Actual monitoring average	Intelligent analysis average	P value
Temperature (ºC)	25.44	25.41	>0.05
PH value	7.81	7.8	>0.05
Dissolved oxygen (mg/L)	6.81	6.71	>0.05
Turbidity (NTU)	3.9	3.87	>0.05

ecological environment performed well in terms of accuracy in monitoring water quality.

Real-Time Testing

In order to test the real-time performance of the intelligent analysis and information intelligent control system for online monitoring data of the water ecological environment, this article uploaded monitoring data every 6 minutes to the intelligent analysis system within an hour, and calculated the response time and data processing time of the intelligent analysis system. The experimental results are shown in Fig. 3.

In Fig. 3, the horizontal axis represents the time interval of 6 minutes, with a total of 10 time points from 00:06 to 01:00. Observing the data, it can be observed that the response time of the intelligent analysis system fluctuated between different time points, with the shortest being 0.5 seconds and the longest being 1.0 seconds. In addition to slight fluctuations at some time points, the data processing time was also relatively stable overall, with an average data processing time of 1.1 seconds. It can be seen that the overall response time and data processing time of the intelligent analysis system were controlled within 1.5 seconds, indicating that the real-time performance of the system is relatively good and can meet the needs of real-time monitoring and data processing.

Warning Accuracy Test

In order to detect the accuracy of online monitoring data intelligent analysis and information intelligent control system for the water ecological environment, this article established 10 monitoring points and set warning thresholds in the intelligent analysis system. When the monitoring data exceeded this threshold, the system automatically sent out warning information. If the warning score is 2 points, it would alarm when reaching the threshold; if it is 1 point, it would not alarm. The test results are shown in Fig. 4.

This article listed 10 monitoring points, warning thresholds, and warning scores. In Fig. 4, the horizontal axis represents the number of monitoring points, with a total of 10 monitoring points. The warning threshold unit for the vertical axis is digital conductivity, i.e., μ S/cm. According to the graph data, it can be seen that different monitoring points had different warning

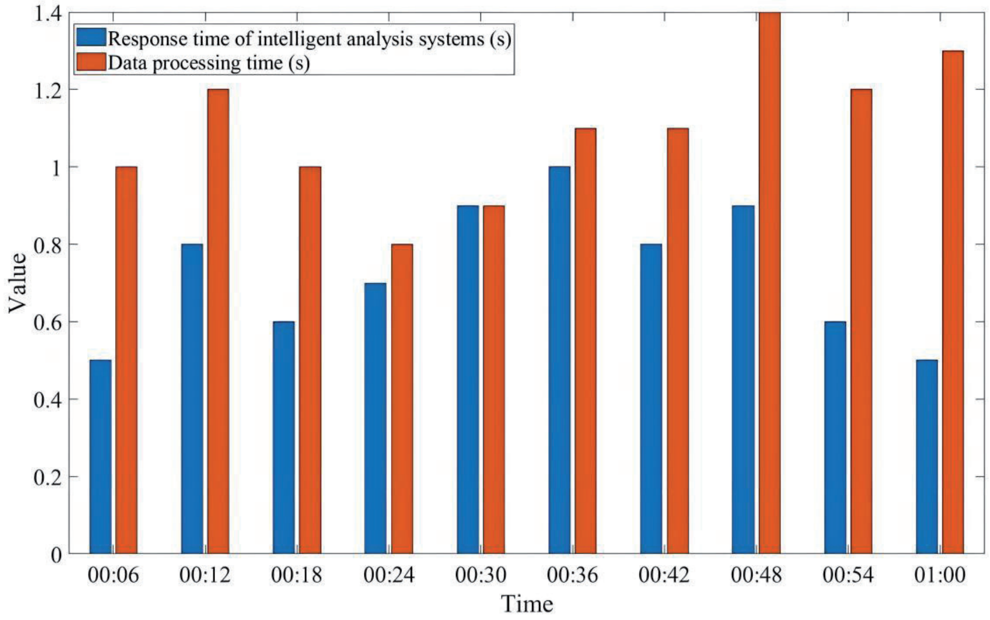

Fig. 3. Real-time performance testing of the intelligent analysis and information intelligent control system for online monitoring data of the water ecological environment.

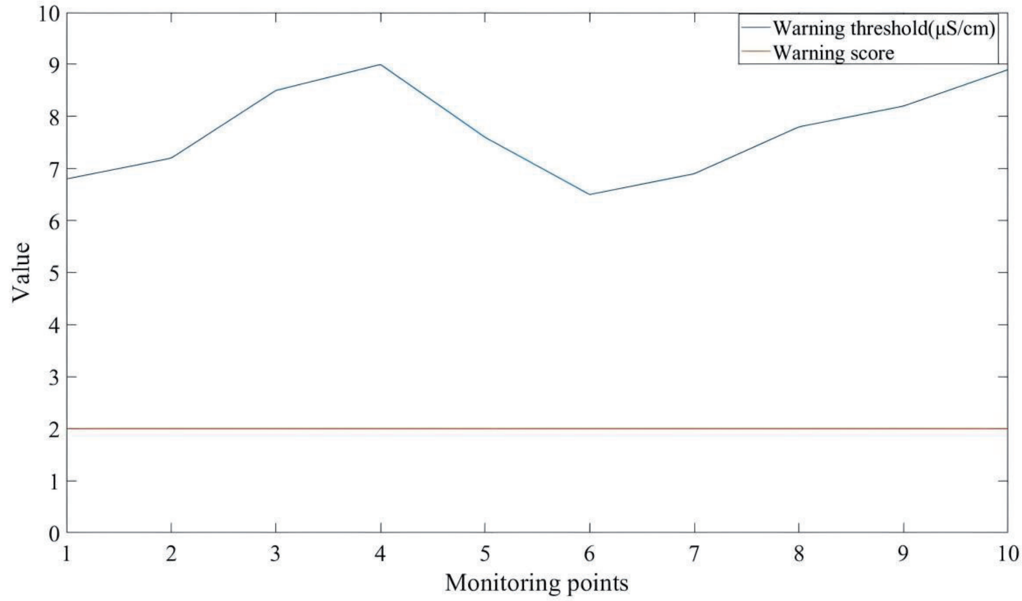

Fig. 4. Intelligent analysis of online monitoring data for the water ecological environment and early warning accuracy testing of the information intelligent control system.

thresholds, with the lowest being 6.5 μS/cm and the highest being 9.0 μS/cm. All monitoring points reached the warning threshold in the experiment, with a score of 2 points. This showed that in the experiment, the early warning accuracy of the intelligent analysis system is good, which can accurately judge whether the water quality meets the early warning standard, and send early warning information in time to ensure the health of the water ecological environment.

Information Intelligent Control Test

In order to test the intelligent analysis of online monitoring data of the water ecological environment and the effectiveness of the information intelligent control system, this article uploaded monitoring data every 6 minutes to the intelligent analysis system within one hour. When the system detected that the water quality data at a monitoring point exceeded the warning threshold, it automatically controlled the water quality regulation equipment. The response time and control

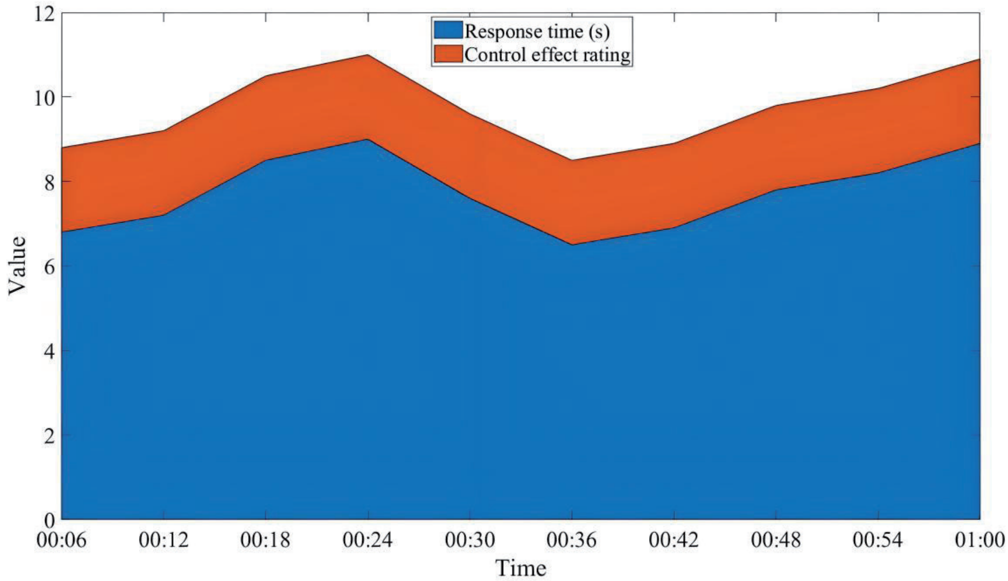

Fig. 5. Intelligent analysis of online monitoring data of the water ecological environment and the information intelligent control system's information intelligent control effect.

effect of the intelligent control device were recorded. The total score for control effectiveness was 10 points, with higher scores indicating better control effectiveness. The experimental results are shown in Fig. 5.

In Fig. 5, the horizontal axis represents time, with a time interval of six minutes, starting from 0:06 and ending at 1:00, totaling 10 time points. According to the data in Fig. 5, it can be seen that the response time of the system varied at different time points, with the lowest being 0.8 seconds and the highest being 1.3 seconds. At all time points, the control effectiveness score was no less than 7, with the highest being 9 and the lowest being 7. This indicates that, in the experiment, the intelligent control system had certain control capabilities and could effectively control water quality regulation equipment to ensure the health of the water ecological environment

Robustness Analysis

To verify the system's stability under complex environmental interference, the robustness of the system was tested by simulating interference factors such as sensor noise, data transmission delays, and sudden pollution events. The experiment selected 48 hours of continuous monitoring data from 10 monitoring points, introduced interference of varying intensities into the original data, and evaluated its anti-interference ability by comparing the analysis results and control responses of the system before and after the interference. The results are shown in Table 2.

Table 2 shows that, despite an increase in the system's average error under the three types of interference, it remained within 2%, showing no sudden increase. The maximum response time increased to 1.5 seconds, remaining within the design threshold. The lowest control effectiveness score was 7.5, maintaining a high level. This demonstrates that the system, through wavelet denoising in data preprocessing, dynamic rule base verification, and adaptive adjustment mechanisms in the control algorithm, is able to effectively resist external interference, maintain stable monitoring accuracy and control performance, and demonstrate strong robustness.

Table 2. Robustness analysis.

Interference Type	Interference Strength Range	System average error change	Response time change	Control effectiveness rating (out of 10 points)
Sensor Noise	1%-10% random noise	0.5%→1.78%	1.0s→1.3s	9.0→7.8
Data Transmission Delay	0-3 seconds transmission delay	0.5%→1.2%	1.0s→1.5s	9.0→8.2
Sudden Pollution Event	20% contamination data exceeding the threshold	0.5%→1.5%	1.0s→1.3s	9.0→7.5

Conclusions

In this paper, a set of online monitoring data intelligent analysis and information intelligent control system for the water ecological wetland landscape environment is designed and realized, and its good performance in monitoring accuracy, real-time performance, early warning ability, and intelligent control effect is verified through experiments. The system can efficiently monitor key indicators such as water temperature, pH value, dissolved oxygen, and turbidity, with the error range, response time, and data processing time controlled within 1.5 seconds. The early warning accuracy rate reaches 100%, and the system has demonstrated high reliability in the intelligent control of water treatment equipment. However, there are still certain shortcomings in this research. The layout optimization of the sensor network and the capability for multi-source data fusion still need to be improved. At the same time, the long-term operating stability of the system and its adaptability in complex environments still need to be further verified. Future research can focus on the following directions: first, introducing more advanced deep learning algorithms to improve the accuracy and generalization of data analysis; second, combining edge computing technology to reduce data transmission delays and enhance the real-time performance of the system; third, expanding the scope of monitoring indicators to cover more ecological parameters and support a more comprehensive wetland environmental assessment. In addition, the deployment and optimization of the system in practical application scenarios should be strengthened, its wide application in the fields of smart water affairs and ecological protection should be promoted, and technical support should be provided to achieve sustainable development goals.

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