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Computer-Aided Design AND APPLICATIONS

Adaptive Water Environment Optimization Strategy Based on Reinforcement Learning

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Abstract. The main goal of this study is to combine computer-aided design (CAD) and reinforcement learning (RL) technologies to develop an adaptive water environment optimization strategy to cope with the increasingly severe water resource challenges. In this article, an intelligent decision-making system is constructed according to the actual water environment. The system can automatically adjust management strategies to maximize water quality improvement and ecosystem protection while minimizing management costs. To assess the strategy's efficacy, a range of simulation experiments have been devised to mimic its performance across varied water environmental conditions. The results show that the adaptive water environment optimization strategy is superior to the traditional management method in many key indicators, which significantly improves the efficiency and effect of water environment management. In addition, the strategy shows good adaptability and robustness and can maintain stable performance under complex and changeable water environment conditions. This study not only provides new theoretical and methodological support for the field of water environment optimization, but also points out the direction for future related research. It is expected that this strategy will play a greater role in practical application and contribute to the sustainable utilization and management of water resources.

Keywords: Computer-Aided Design; Reinforcement Learning; Deep Deterministic Policy Gradient; Water Environment Optimization
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1 INTRODUCTION

As industrialization and urbanization have progressed rapidly, water environmental issues have gained increasing prominence, posing a pressing global challenge. As an important water resource area in China, the rational allocation and management of water resources in the Han River Basin are crucial for ensuring sustainable ecological, economic, and social development within the basin. With the continuous progress of technology, advanced technologies such as computer-aided design and reinforcement learning have provided new solutions for water resources and environmental allocation. Deng et al. [1] explored the combination of computer-aided design and reinforcement learning to achieve multi-objective optimization of water resources and environmental allocation in the Han River Basin and analyzed its potential and challenges in practical applications. Reinforcement Learning (RL) is a machine learning technique that learns the optimal decision strategy through the interaction between intelligent agents and the environment. In the allocation of water resources and environment, RL can use historical data and simulation results to autonomously learn and adjust water resource allocation strategies in order to achieve comprehensive optimization of multiple goals (such as water supply security, ecological environment protection, economic benefits, etc.). The optimization of the water environment not only pertains to ecological balance and the conservation of biodiversity but also has a direct bearing on the economic growth and standard of living of human society.

With the growth of global trade and increasingly busy port activities, water resource scheduling in port environments is facing increasing challenges. Fang et al. [2] explored how these two technologies can be combined to achieve more efficient and intelligent water resource scheduling. Through CAD technology, an accurate port water environment model can be established to simulate changes in factors such as water flow, tides, and water quality. These models can provide decision support for water resource scheduling, help managers better understand and predict water environment conditions, and thus develop more reasonable water resource scheduling plans. Reinforcement learning is an adaptive machine-learning technique that interacts with the environment to learn how to make the best decisions. In water resource scheduling, reinforcement learning algorithms can dynamically adjust scheduling strategies based on real-time water environment data to cope with various uncertainties and changes. This adaptive feature gives reinforcement learning unique advantages in optimizing water resource scheduling. Reinforcement learning is a machine learning technique that learns the optimal decision strategy through the interaction between intelligent agents and the environment. In water supply management, reinforcement learning can be applied to predict water supply demand, optimize water resource allocation, and develop emergency response strategies. Through continuous trial and error and adjustment, reinforcement learning can help decision-makers quickly adapt to the dynamic changes of the water supply system and effectively respond to emergencies such as water supply interruptions. In order to more effectively address the impact of water supply interruption on the water economy, we will combine reinforcement learning with multiregional input-output optimization models. Specifically, we will apply reinforcement learning algorithms to the optimization process of the model, learning the optimal resource allocation plan through the interaction between the agent and the environment. In each simulation, the model will make decisions based on the current water supply and economic situation, adjust the allocation and use strategies of water resources, and maximize the economic benefits of each region [3]. Nevertheless, conventional methods of water environment management often hinge on empirical assessments and manual interventions, rendering them ill-suited to handle the intricate and dynamic nature of real-world scenarios. Consequently, the quest for a water environment management approach that can adapt flexibly and optimize efficiently holds paramount significance.

With the acceleration of urbanization, the complexity of water distribution systems is increasing, which poses higher requirements for the operational efficiency and stability of water pumps. Traditional water pump control methods are often based on fixed rules and thresholds, making it difficult to achieve real-time and dynamic optimization. In recent years, the successful application of Deep Reinforcement Learning (DRL) in the field of control has provided new ideas for real-time optimization of water pumps. Hajgató et al. [4] explored the application of DRL in real-time optimization of water pumps in water distribution systems. In water distribution systems, the real-time optimization problem of water pumps can be modelled as a Markov Decision Process (MDP). Through the DRL algorithm, agents can learn the optimal decision strategy to maximize cumulative rewards. In order to verify the effectiveness of DRL in the real-time optimization of water pumps, we conducted experimental verification. The experimental results show that compared with traditional control methods, DRL can achieve higher pump efficiency and stability. In addition, DRL can adaptively handle the dynamic changes of the water distribution system and is highly robust. In recent years, the swift advancement of cutting-edge technologies, namely CAD and RL, has paved the way for novel approaches in water environment optimization. Decentralized technology is gradually receiving attention in the field of underwater resource control. Compared with traditional centralized methods, decentralized methods can better adapt to the dynamic changes of underwater environments and improve the robustness and scalability of the system. Meanwhile, reinforcement learning, as an adaptive decision-making method, has also shown great potential in underwater resource control. By interacting with the environment and learning the optimal decision strategy, reinforcement learning can make underwater resource control systems more intelligent and efficient. Traditional underwater resource control methods often rely on centralized decision-making systems, but these methods often exhibit low efficiency and poor adaptability when facing complex and ever-changing underwater environments and uneven resource distribution. To overcome these limitations, Han et al. [5] proposed a decentralized reinforcement learning-based underwater resource control method aimed at achieving sustainable underwater resource management through energy harvesting. Dynamic water resource planning, aimed at making timely decisions based on the constantly changing supply and demand of water resources, has become a research hotspot in the field of water resource management. In this process, computer-aided design (CAD) serves as a powerful tool that not only helps engineers and decision-makers quickly build and optimize water resource system models but also plays a crucial role in dealing with uncertainty. Herman et al. [6] reviewed the application of CAD in dynamic water resource planning and looked forward to its future development direction. CAD software provides a rich graphic library and modelling tools, allowing engineers to quickly construct three-dimensional models of water resource systems. These models can accurately reflect the distribution, flow, and consumption of water resources, providing support for subsequent decision-making. Based on the established model, CAD can conduct simulation analysis and predict the changes in water resources under different management strategies. Meanwhile, through built-in optimization algorithms, CAD can help decision-makers find the optimal management strategy and achieve maximum utilization of water resources.

With the rapid development of technology, intelligent and adaptive technologies are gradually being applied in various fields, especially in environmental protection and resource management. As an indispensable part of the ecosystem, the management and optimization of the water environment are of great significance for maintaining ecological balance and sustainable human development. Hoang et al. [7] explored how to use intelligent adaptive systems to form adaptive water environment optimization and adjustment management in order to achieve more efficient and accurate water resource management. Traditional management methods often rely on manual monitoring and empirical judgment, which is not only inefficient but also difficult to cope with complex and changing water environment conditions. For example, sudden changes in water quality, sudden pollution incidents, etc., require quick and accurate responses and adjustments. Therefore, forming a water environment management system that can adapt to changes and respond quickly is an important challenge currently faced. As an important means of achieving real-time monitoring, the accuracy and stability of water quality sensors are crucial. However, due to the complexity and variability of water quality parameters, traditional water quality sensor models often find it difficult to accurately describe the relationship between water quality parameters and sensor outputs. Therefore, Huang and Yang [8] proposed a water quality sensor model based on the radial basis function (RBF) neural network optimization method to improve the accuracy and stability of water quality monitoring. In order to construct a water quality sensor model based on the RBF neural network, a large amount of water quality parameter data, including temperature, pH value, dissolved oxygen, etc., was first collected. Then, use these data to train an RBF neural network model and establish a mapping relationship between water quality parameters and sensor outputs. During the training process, the optimization of the model is achieved by adjusting parameters such as the center, width, and output weights of the RBF neural network. The experimental results show that compared with traditional water quality sensor models, the water quality sensor model based on the RBF neural network has higher accuracy and stability. At the same time, the model can also adaptively handle changes in water quality parameters and has strong robustness. CAD leverages the robust computational power and data processing capabilities of computers to model and analyze water environment systems precisely and efficiently. Conversely, RL emerges as a machine learning technique that learns optimal decision-making strategies through environmental interaction, making it highly apt for addressing optimization challenges in intricate dynamic systems. Against this backdrop, this study aims to integrate CAD and RL technologies to forge an adaptive water environment optimization strategy tailored to overcome the contemporary challenges confronting water environment management.

This study is of great significance for improving water environment management and promoting sustainable development. Firstly, by introducing CAD and RL technology, accurate modelling and efficient optimization of water environment systems can be realized, and the scientific and effective management of the water environment can be improved. Secondly, the adaptive water environment optimization strategy can be dynamically adjusted according to the actual situation to better adapt to the complex and changeable water environment, thus improving management efficiency and effectiveness. Finally, this study can also provide a reference for the optimal management of other similar complex systems and promote theoretical development and practical application in related fields.

The originality of this article is primarily evident in the following areas:

Methods Integration and Innovation: In this article, CAD technology and RL algorithm are combined and applied to the field of water environment optimization. This interdisciplinary integration provides a new perspective and tool for solving complex water environment problems.

Adaptive strategy design: An adaptive water environment optimization strategy is designed, which can make intelligent decisions according to the actual water environment. This adaptive feature enables the strategy to respond flexibly to the changes in the water environment and improve the management efficiency and effect.

Multi-index evaluation system: In the simulation experiment, a multi-index evaluation system is adopted to comprehensively evaluate the performance of the strategy. This comprehensive evaluation method can more accurately reflect the comprehensive performance of the strategy in terms of water quality improvement, ecosystem protection, and management cost.

Integrating theoretical concepts with practical applications: This article not only delves into the theoretical design and implementation procedures of an adaptive water environment optimization strategy but also corroborates its efficacy through rigorous simulation experiments. This hybrid approach, which seamlessly blends theory and practice, serves as a formidable foundation for further advancements in the domain of water environment optimization.

Initially, the article presents the research background and objectives, followed by a comprehensive elucidation of the design and implementation process of the adaptive water environment optimization strategy. This encompasses a thorough examination of the strategy's central tenets, technical nuances, and innovative elements. Subsequently, the strategy's effectiveness is substantiated through meticulous simulation experiments, accompanied by an in-depth analysis and discussion of the experimental outcomes. In conclusion, the study's key discoveries and contributions are concisely summarized, along with a forward-looking perspective on potential future research avenues.

2 RELATED WORK

With the increasing awareness of environmental protection, wastewater treatment has become a highly concerned research field. Dissolved air flotation (DAF), a commonly used wastewater treatment technology, can effectively remove suspended particles in Water and improve water quality. However, traditional DAF process control methods often rely on experience and practice, lacking intelligence and adaptability. In order to optimize the DAF process and improve particle removal efficiency, Jelodar et al. [9] explored how to combine reinforcement learning (RL) technology to develop environmental optimization strategies. Dissolved air flotation is a water treatment technology based on the adhesion between bubbles and suspended particles. By injecting tiny bubbles into wastewater, the bubbles adhere to the particles and rise to the Water's surface, thereby achieving particle removal. However, the DAF process is influenced by various factors, such as bubble size, distribution, wastewater flow rate, etc., and changes in these factors may lead to unstable particle removal efficiency. By adjusting the frequency and position of bubble release, bubbles can more effectively adhere to suspended particles and improve particle removal efficiency. Dynamically adjust the wastewater flow rate based on environmental conditions and particle removal efficiency to balance the relationship between particle removal efficiency and energy consumption.

Traditional methods for controlling water environment ecosystems are often based on experience and rules, lacking adaptability and flexibility. In recent years, researchers have begun to attempt to apply deep reinforcement learning to water environment ecosystem control in order to achieve intelligent perception and decision optimization of water environment status. Deep reinforcement learning combines the representation learning ability of deep learning with the decision optimization ability of reinforcement learning and can handle complex nonlinear problems and uncertainties, providing new solutions for water environment ecosystem control. Li et al. [10] explored how to use deep reinforcement learning technology to transform ecosystem control of the water environment to achieve optimization and Sustainability of the water environment. The environmental model defines state space and action space. The state space can include water quality indicators of the water environment, the number of biological populations, and so on. The action space can include adjusting water resource allocation, implementing ecological restoration measures, etc. Traditional water resource management methods mainly rely on empirical rules and static models, which are difficult to adapt to dynamic changes in water resource demand and supply. To overcome these limitations, Liu et al. [11] conducted water resource management optimization based on deep reinforcement learning, aiming to achieve more efficient water resource allocation through adaptive learning and decision-making. Deep reinforcement learning combines the representation learning ability of deep learning with the decision-making ability of reinforcement learning, enabling it to handle complex and uncertain water resource management problems. By constructing a deep neural network to approximate the water resource management strategy and utilizing reinforcement learning algorithms to optimize the strategy, DRL can learn the optimal management decisions under various water resource conditions. In reservoir scheduling, DRL can learn how to optimize the allocation of reservoir water storage under different inflow conditions in order to maximize water supply efficiency and reduce flood risk. In irrigation management, DRL can optimize irrigation strategies based on the water demand of farmland and climate prediction in order to improve crop yield and water resource utilization efficiency.

The comprehensive water environment policy is a policy system that covers multiple aspects, such as water resource management, water ecological protection, and water pollution control. By formulating and implementing these policies, it is possible to effectively promote the rational utilization of water resources and the protection of the ecological environment. Introducing comprehensive water environment policies in urban water resource management can ensure the fairness and Sustainability of water resource allocation, providing strong guarantees for the sustainable development of cities. It is particularly important to introduce comprehensive water environment policies and combine reinforcement learning technology for dynamic simulation and optimized configuration in order to achieve efficient utilization of water resources and protection of the ecological environment. Mou et al. [12] explored how to combine comprehensive water environment policies with reinforcement learning to achieve a dynamic simulation of the optimal allocation of urban water resources. It utilizes reinforcement learning technology to establish a model for urban water resource management. This model can learn the optimal water resource allocation strategy based on historical and real-time data. Urban water resources and environmental management are facing unprecedented challenges. Among them, Sponge City, as a new urban construction concept, aims to achieve effective management and utilization of urban rainwater by simulating the natural water cycle process. However, in the practical application process, the construction and management of sponge cities still face many challenges, such as water resource shortage, water environment pollution, urban flood disasters, etc. Therefore, Qi et al. [13] proposed addressing these challenges through natural-based solutions to achieve sustainable development of water resources and the environment in sponge cities. Nature-based solutions (NBS) refer to methods that utilize the functions and processes of natural ecosystems to address environmental issues. In the construction of sponge cities, natural solutions emphasize the natural accumulation, infiltration, and purification of rainwater by protecting and restoring natural ecosystems such as wetlands, green spaces, forests, etc. This solution not only helps to alleviate urban flooding disasters but also improves the urban ecological environment and enhances the efficiency of water resource utilization.

Traditional water flow control methods often rely on fixed rules and preset thresholds, making it difficult to cope with complex and ever-changing network environments and user needs. In recent years, the rise of Deep Reinforcement Learning (DRL) has provided new solutions for Water flow control. By combining the representation learning ability of deep learning with the decision-making ability of reinforcement learning, DRL can adaptively learn and optimize water flow control strategies. However, the training process of DRL usually requires a large number of samples and time, which is a huge challenge in practical applications. In order to accelerate the DRL training process, the Multi Environment Method is widely used to improve training efficiency. Rabault and Kuhnle [14] explored how to accelerate deep reinforcement learning strategies for water flow control through multiple environmental methods. DRL can learn effective water flow control rules from a large number of samples, thereby achieving adaptive management of network traffic. However, due to the complexity and uncertainty of the network environment, the training process of DRL usually requires a large number of samples and time, which limits its promotion in practical applications. With the acceleration of global climate change and urbanization, water resource management and Sustainability have become increasingly important. Traditional water management methods are struggling in the face of complex and ever-changing water environments and growing water demands. Therefore, we need to leverage advanced technologies and methods, such as reinforcement learning, to build an intelligent water management system to achieve sustainable utilization of water resources. Ramos et al. [15] explored how reinforcement learning can be applied to future sustainable water networks to achieve intelligent water management. The future sustainable water network environment is a complex system that involves multiple aspects, such as water supply, drainage, sewage treatment, etc. After establishing the model, it is necessary to use reinforcement learning algorithms to learn and optimize water management strategies. By interacting with the environment, algorithms can gradually learn the best water management strategies to achieve sustainable utilization of water resources. Compared with traditional water management methods, intelligent water management systems based on reinforcement learning can significantly improve the efficiency of water resource utilization, reduce energy consumption, and reduce waste. At the same time, the system can better respond to various emergencies and changes, ensuring a stable supply of water resources.

The quality of surface water is receiving increasing attention. Accurately assessing and managing surface water quality is crucial for protecting the ecological environment and human health. Traditional surface water quality assessment methods are usually based on chemical analysis and statistical models, but these methods are often time-consuming, costly, and difficult to handle complex nonlinear relationships. Therefore, developing an efficient and accurate surface water quality modelling method is of great significance. Shah et al. [16] proposed a method for modelling surface water quality using an adaptive neuro-fuzzy inference system (ANFIS) assisted by input optimization. Adaptive Neural Fuzzy Inference System (ANFIS) is a system that combines neural networks and fuzzy logic with self-learning, adaptive, and nonlinear mapping capabilities. ANFIS models complex systems by constructing fuzzy inference rules that map input data to output data. Compared with traditional fuzzy reasoning systems, ANFIS has stronger adaptability and generalization ability. It analyzed the correlation between various water quality indicators and selected the indicators that have a significant impact on surface water quality as inputs for the ANFIS model. Further optimize the input space through dimensionality reduction techniques such as principal component analysis, genetic algorithms, etc., reduce the complexity of the model, and improve its generalization ability. With the continuous growth of human demand for water resources and the increasingly serious problem of water scarcity, the joint utilization of surface water and groundwater has become an important way to solve water resource problems. Multi-objective simulation and optimization modelling at the watershed scale are of great significance for rational planning and management of water resources. Song et al. [17] explored a watershed scale multi-objective simulation optimization modelling method for the combined utilization of surface water and groundwater environments and analyzed its application prospects in water resource management and planning. Multi-objective simulation and optimization modelling at the watershed scale is a method based on mathematical models, optimization algorithms, and geographic information systems to simulate and optimize the joint utilization of surface water and groundwater in the watershed. Based on the characteristics of the watershed and the demand for water resource utilization, select an appropriate mathematical model for construction. At the same time, combining geographic information system (GIS) technology simulates the spatial distribution and dynamic changes of surface water and groundwater in the watershed.

Underwater wireless sensor networks (UWSN) have broad application prospects in marine environmental monitoring, underwater resource exploration, and military applications. However, due to the complexity and uncertainty of underwater environments, UWSN faces serious communication challenges. The problems of multipath propagation, channel attenuation, and time-varying characteristics make underwater wireless communication particularly difficult. To overcome these issues, Valerio et al. [18] proposed a multipath adaptive routing algorithm for underwater wireless sensor networks based on channel-aware reinforcement learning (CA-RL). It utilizes channel state information collected by underwater sensor nodes (such as signal strength, noise level, etc.) to evaluate the communication quality of each channel in real-time. The simulation experiment results show that the CA-RL-MR algorithm outperforms the traditional UWSN routing algorithm in terms of performance. Urban sewage treatment plants are playing an increasingly important role in maintaining water environment quality and ecological balance. However, due to the complex biochemical reactions and variable environmental factors involved in urban sewage treatment, its control and management face enormous challenges. In order to improve the efficiency and stability of sewage treatment, Wang et al. [19] proposed an intelligent critical control method based on Water environment-driven iterative adaptation. The traditional control methods for urban sewage treatment plants mainly rely on experience and fixed parameter adjustments, making it difficult to cope with complex and variable water quality conditions and operating environments. In recent years, with the development of intelligent control technology, some researchers have begun to attempt to apply intelligent algorithms, such as fuzzy control, neural networks, etc., to sewage treatment control. However, these methods often lack adaptive capabilities and iterative optimization mechanisms, making it difficult to achieve optimal control results. Based on the prediction results of the dynamic water quality model, use reinforcement learning algorithms to learn and adjust control strategies online. By interacting with the environment, the algorithm can gradually learn the optimal control strategy to achieve stability and optimization of the sewage treatment process.

3 RESEARCH FRAMEWORK AND RESEARCH METHODS

As an advanced technical tool, CAD has experienced continuous development and deepening in the field of water environment optimization. The early research mainly focused on the design and planning of water conservancy projects using CAD technology, such as reservoirs, rivers, and irrigation systems. These investigations significantly enhance the precision and productivity of engineering design by leveraging the efficient modelling and visualization capabilities of CAD software. As computer technology continues to advance, the utilization of CAD in optimizing the water environment has progressively extended to encompass a broader array of domains. Currently, the utilization of CAD in the optimization of the water environment has yielded impressive outcomes. However, there are still some challenges and problems, such as the complexity and large amount of calculation required for the model and the difficulty in obtaining and updating data. Therefore, future research needs to explore the potential of CAD technology in water environment optimization further in order to better cope with these challenges and problems.

RL is a machine learning method to learn the optimal decision strategy by interacting with the environment. In recent years, with the rapid development of artificial intelligence technology, the application of RL in water environment management has attracted more and more attention. This method makes use of the intelligent decision-making ability of the RL algorithm and realizes the automatic optimization and control of water environment parameters by learning and training the water environment system. The results show that this method can achieve a good control effect under actual water environment conditions and effectively improve the quality and stability of the water environment. These studies learn and optimize management strategies by constructing the RL model in a simulated environment or real environment so as to achieve better management effects.

The application of RL in water environment management shows some potential advantages. First of all, the RL algorithm can adaptively learn and adjust management strategies to cope with the complex and changeable water environment. Secondly, the RL algorithm can constantly improve and optimize strategies through interaction with the environment and has the ability to self-learning and self-adaptation. Finally, the RL algorithm can also deal with the problems of high dimension and continuous state space, which is suitable for solving some water environment management problems that are difficult to deal with by traditional methods. However, the application of RL in water environment management also faces some challenges and limitations. For example, the training process of the RL algorithm needs a lot of data and computing resources, and there may be problems such as model mismatch and insufficient generalization ability in practical application. Therefore, future research needs to explore and improve the application of the RL algorithm in water environment management further to improve its applicability and reliability.

Adaptive optimization strategy is an optimization method that can be dynamically adjusted according to the actual situation and has a wide application prospect. In the field of water environment optimization, research on adaptive optimization strategies has also made some progress. Some research is devoted to developing water environment management methods based on adaptive optimization strategies. These methods can achieve better management effects by monitoring the water environment in real time and dynamically adjusting the management strategy according to the preset optimization objectives. Generally speaking, research on adaptive optimization strategies in the field of water environment optimization has achieved certain results. However, there are still some challenges and problems to be solved. For example, how to design and implement an efficient adaptive optimization algorithm, how to deal with uncertainty and robustness, etc. Therefore, future research needs to explore the application potential and challenges of adaptive optimization strategy in water environment optimization further. The objective of this research is to construct a water environment model utilizing CAD technology, enabling the simulation and forecasting of water environment trends. Additionally, an optimization strategy model is developed using the RL algorithm, aimed at learning and identifying the most effective water environment management approach. In order to achieve this goal, this section constructs a comprehensive research framework, which includes several key elements, such as system architecture, algorithm selection, and design principles, which will be explained in detail below.

3.1 System Architecture and Design Principles

In terms of system architecture, this study adopts the idea of modular design and divides the whole water environment optimization system into several independent and interrelated modules. Each module is responsible for completing specific functional tasks, such as data preprocessing, model building, and strategy learning. Through modular design, not only can the maintainability and expansibility of the system be improved, but parallel computing and distributed processing can also be realized, thus improving computational efficiency.

In terms of design principles, this study follows the principles of scientificity, practicality, and innovation. The scientific principle requires that the research process follow the basic laws and methodology of natural science to ensure the reliability and accuracy of the research results. Practical principles require that the research results must have certain practical application value, which can solve practical problems or improve existing technologies. The principle of innovation requires that the research process must have innovative thinking and methods, which can promote the development and progress of related fields.

3.2 Algorithm Selection

In the aspect of algorithm selection, this study deeply analyzes the characteristics and requirements of water environment optimization and, based on these considerations, chooses the DDPG (Deep Deterministic Policy Gradient) algorithm. DDPG is an RL algorithm that combines deep learning and deterministic strategy gradient. This algorithm is particularly effective in dealing with the problem of continuous action space and can directly output deterministic actions without generating the probability of each action and then selecting the action with the highest probability like other algorithms. Water environment optimization usually involves multiple complex dynamic variables and continuous action space, which requires the algorithm to learn efficiently and make accurate decisions. The DDPG algorithm is designed for this kind of problem, combining the powerful perception ability of deep learning with the decision-making advantage of a deterministic strategy gradient.

The water environment is modelled by CAD software, and its physical properties, such as velocity, temperature, and pollutant concentration, are described by partial differential equations. For example, the Navier-Stokes equation in fluid dynamics is used to describe the motion of fluid:

$$\frac{\partial u}{\partial t} + u \cdot \nabla u = -\frac{1}{\rho} \nabla p + v \nabla^2 u + f \tag{1}$$

Where u are the flow rate, p pressure, ρ fluid density, v and kinematic viscosity, and f is the external force?

For pollutant diffusion, convection-diffusion equation can be used to describe:

$$\frac{\partial c}{\partial t} + \nabla \cdot cu = D \nabla^2 c \tag{2}$$

Where c is the pollutant concentration and D is the diffusion coefficient.

State space consists of key indicators of the water environment, such as measured values of flow velocity, temperature, and pollutant concentration, and external conditions (such as weather and season) that may affect the water environment. The state vector is expressed as:

$$s = \left[s_1, s_2, s_3, \ldots, s_n\right]^T \tag{3}$$

Where s_i is the i state variable and n is the number of state variables. The action space consists of adjustable water environment management strategies, such as the switch of the water pump and the opening of the valve. The motion vector is expressed as:

$$a = \left[a_1, a_2, a_3, \ldots, a_m\right]^T \tag{4}$$

Among them a_i is the i action variable, and m is the number of action variables. The reward function is designed according to the quality of the water environment and management cost:

$$r = -\sum_{i=1}^{n} w_i \left|s_i - s_i^{target}\right| - \sum_{j=1}^{m} c_j \left|a_j\right| \tag{5}$$

Where w_i and c_j are weights and s_i^{target} the target value of state variables.

In the DDPG algorithm, two distinct neural networks are employed: the actor-network and the Critic network. The Actor network has the task of generating a deterministic action based on the prevailing state, whereas the Critic network assesses the anticipated reward associated with executing an action in the current state. Both networks use deep learning technology, which can automatically extract the characteristics of the state and deal with the high-dimensional state space. The model structure is shown in Figure 1.

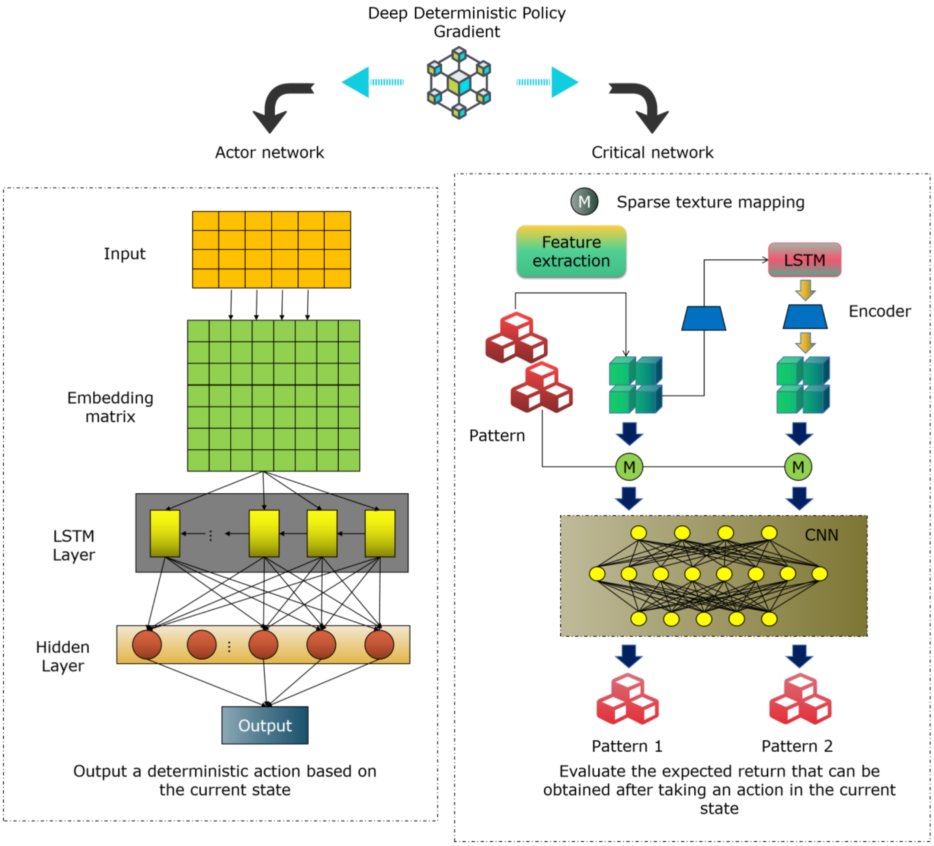


Figure 1: Model structure diagram.

In addition, DDPG also draws lessons from the experience playback and target network in the DQN (Deep Q-Network) algorithm. Experience playback can improve the utilization rate and stability of data. By storing experience in the playback buffer and randomly selecting a batch of experiences for training, the correlation between data can be broken, and the learning process can be stabilized. The target network can stabilize the learning process and avoid oscillation in the training process. DDPG uses the target network to calculate the target Q value, which remains unchanged during the training process, thus stabilizing the learning process. However, the standard DDPG algorithm may face the problems of slow convergence and insufficient stability in some cases. In order to overcome these challenges, this study has made a series of improvements and optimizations to the algorithm. For example, by introducing an experience playback mechanism, the algorithm can make more effective use of historical data and improve learning efficiency and stability. In addition, the target network technology can further stabilize the learning process and avoid excessive oscillation in the learning process. These improvement measures ensure the performance and reliability of the algorithm in solving water environment optimization problems.

In order to achieve the research goal and verify the effectiveness of the proposed strategy, a series of simulation experiments were designed to verify the performance of the proposed strategy according to the actual water environment and optimization requirements. The experimental design will include the simulation of the water environment in different scenarios, the setting of optimization objectives and the configuration of experimental parameters. Through reasonable experimental design, the objectivity and comparability of experimental results can be ensured. The parameter configuration is shown in Table 1.

Parameter dimension	*Parameter name*	*Description of parameter*	*Set value*
Initial condition	Water velocity	Initial flow velocity in the simulated area	0.5 m/s
	Water quality index	Initial pollutant concentration	100 mg/L
	Water temperature	Simulation area initial water temperature	20 ℃
Boundary conditions	Influx	Upstream water flow into the simulation area	500 m³/day
	Discharge	Water quantity flowing out of the simulation area downstream.	450 m³/day
	Pollutant input	Pollutant input from external pollution sources to the simulation area	20 kg/day
Management objective	Water-quality standards	Expected water quality standard	50 mg/L
	Ecosystem protection index	Target index for maintaining ecosystem stability and diversity	Ecosystem stability index ≥0.8
	Management cost limitation	Acceptable maximum management cost	10,000 yuan/month

Table 1: Parameter configuration.

4 DEVELOPMENT OF ADAPTIVE WATER ENVIRONMENT OPTIMIZATION STRATEGY

4.1 Strategy Design

The design of an adaptive water environment optimization strategy aims to build an intelligent system that can adaptively adjust the management strategy according to the actual water environment. The core idea of this strategy is to use CAD to model and combine the RL algorithm accurately to realize adaptive decision-making and efficient optimization of the water environment. In order to evaluate the quality of the water environment, this article introduces pollutant removal efficiency as a key index. This index quantifies the percentage of pollutants removed by management strategies and provides us with a standard to measure the optimization effect. The calculation formula is as follows:

$$\eta = \frac{C_{in} - C_{out}}{C_{in}} \times 100\% \tag{6}$$

Where C_{in} is the pollutant concentration at the water inlet, and C_{out} is the pollutant concentration at the water outlet?

In the implementation details of strategy design, firstly, the accurate model of the water environment system is established by CAD technology, including the flow dynamics model, water quality model, and ecosystem model. These models can simulate and predict the changing trend of the water environment and provide data support for subsequent optimization decisions. Then, based on these models, the appropriate RL algorithm is designed, and the optimal management strategy is found through the interactive learning between the agent and the environment. In the process of strategy design, attention should be paid to the dynamics, complexity and uncertainty of the water environment system to ensure the robustness and adaptability of the designed strategy.

In the process of RL, the Bellman equation is used to describe the recursive relationship of the state-value function or action-value function. By iteratively updating these value functions, we can learn an optimization strategy, which can choose the optimal management action according to the current state of the water environment. Bellman equation is as follows:

$$V\ s\ = E\left[R_{t=1}+\gamma V\ S_{t=1}\ \middle|S_t=s\right] \tag{7}$$

or

$$Q\ s,a\ = E\left[R_{t=1}+\gamma \max_{a'} A\ S_{t+1},a'\ \middle|S_t=s,A_t=a\right] \tag{8}$$

Where $V\ s$ is a state value function, $Q\ s,a$ is an action-value function, E represents expectation, and S_{t+1} and A_{t+1} are the next state and action respectively.

By training the RL model, an adaptive optimization strategy can be obtained, which can select the optimal management action according to the current state of the water environment. The optimization strategy can be expressed as:

$$\pi : a \mapsto a \tag{9}$$

Where π is a policy function that maps states to actions?

The key technical innovations of strategy design are mainly reflected in the following aspects: first, the precise modelling and intelligent decision-making of the water environment system are realized by combining CAD technology with RL algorithm; Secondly, an adaptive RL algorithm is designed, which can be dynamically adjusted according to the actual water environment, thus improving the adaptability and effect of the management strategy. Thirdly, the effectiveness of the strategy is verified by simulation experiments, which provides strong support for practical application.

4.2 Technical Realization

In the development process of adaptive water environment optimization strategy, technical realization is a crucial link. Firstly, this article constructs a comprehensive water environment model, which integrates many key elements such as water flow dynamics, water quality changes, and ecosystem response. This model adopts advanced numerical simulation technology, which can accurately simulate the complex interaction and dynamic change process in a real water environment. Leveraging historical and real-time datasets, the model has the capability to promptly update its state and prognosticate forthcoming alterations in the water environment. Subsequently, an adaptive optimization strategy for the water environment is devised, grounded in the DDPG-RL algorithm. In strategizing, the article delineates well-defined state, action, and reward spaces. The state space encompasses pivotal parameters from the water environment model, such as water quality indices and flow velocities, among others. The action space aligns with potential management interventions like modifying water flows and adjusting pollutant discharges. The reward function, tailored to align with management objectives and the model's outputs, aims to optimize water quality enhancements and ecological preservation.

For technical implementation, a deep learning architecture is employed to formulate and refine the DDPG model. Initially, the article outlines the neural network's structure, encompassing input, hidden, and output layers, alongside the choice of activation functions and optimization techniques. Subsequently, the model undergoes training using historical and simulated datasets, enabling it to grasp the most effective management approach through iterative adjustments of the neural network's weights and biases. During training, experience replay and target network techniques are incorporated to stabilize learning and expedite convergence.

5 SIMULATION EXPERIMENT AND ANALYSIS

Simulation experiments have been devised in this segment to validate the efficacy of the water environment model and the adaptive optimization strategy. These experiments replicate the essential features of an actual water environment, encompassing water flow patterns, water quality fluctuations, and ecological responses. For model confirmation, a combination of cross-validation and comparative experiments is employed to ascertain the model's precision and usefulness. Figure 2 illustrates the ROC curve comparison, offering a visual representation of the model's performance.

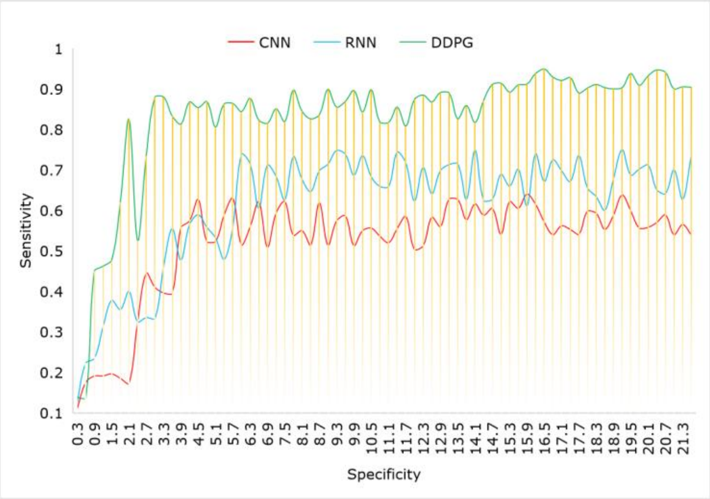


Figure 2: Comparison of model ROC curves.

The performance of this model's ROC curve is notably superior. Additionally, Figure 3 presents the MSE (Mean Square Error) associated with the model.

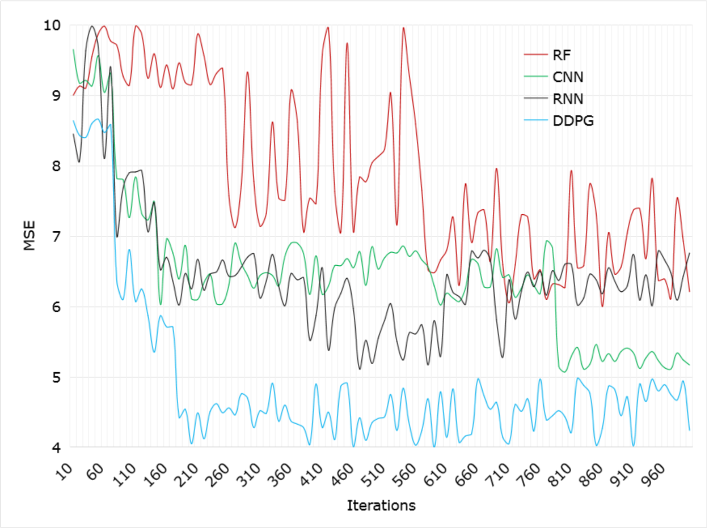


Figure 3: Model MSE.

The accuracy of the model is shown in Figure 4.

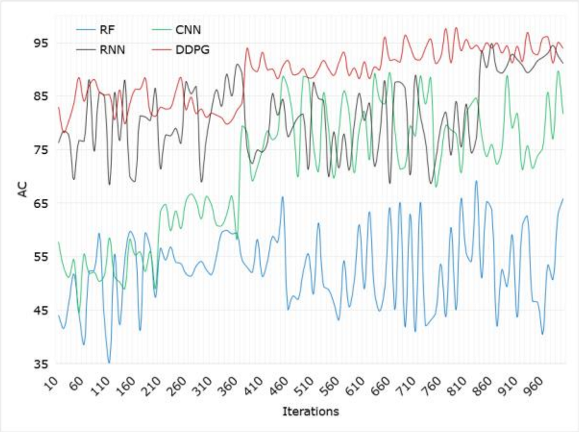


Figure 4: Accuracy of the model.

Upon analyzing the aforementioned outcomes, it becomes evident that the model's ROC curve exhibits strong performance. This indicates that the model is capable of accurately distinguishing between positive and negative samples across varying classification thresholds. Furthermore, the low MSE observed in this model underscores its proficiency in predicting continuous values or executing regression tasks, as the disparity between the predicted results and the actual values remains minimal. Furthermore, the accuracy of this model is high, which means that the model has achieved good results in classification tasks and can accurately classify samples into the correct categories.

In order to show the effect of the strategy more intuitively, the water environment is displayed visually by using CAD tools (as shown in Figure 5).

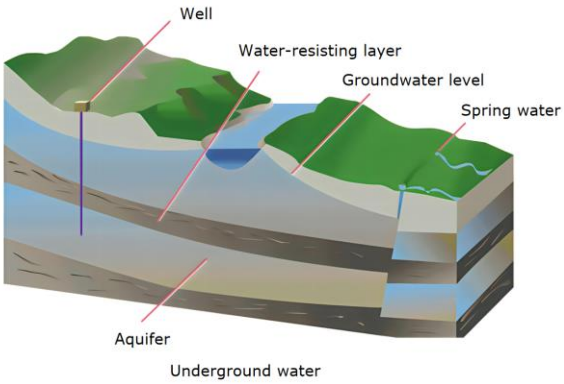
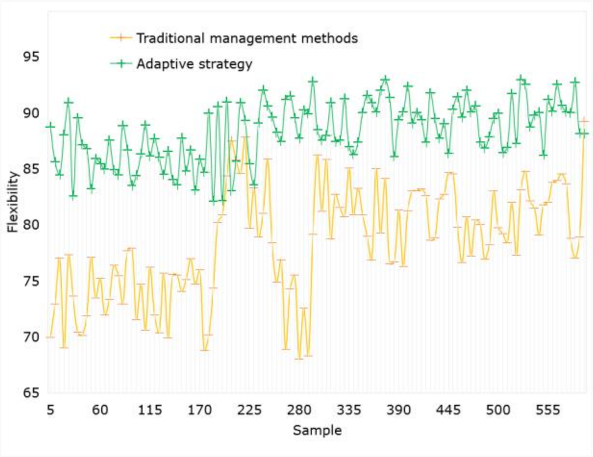


Figure 5: Visual display of the water environment.

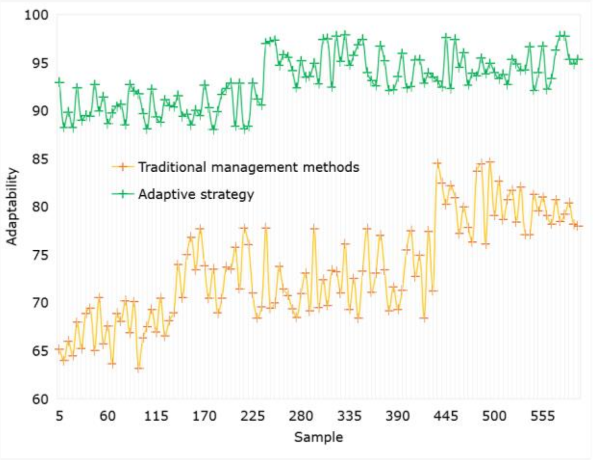
On the evaluation standard, a multi-index evaluation system is adopted, including the degree of water quality improvement, ecosystem health, management cost and so on. These indicators can fully reflect the comprehensive performance of the strategy in water environment optimization. Table 2 shows the performance of the adaptive water environment optimization strategy in multiple scenarios.

Evaluation index	*Performance of adaptive water environment optimization strategy*	*Specific situation*
Water quality improvement	Remarkable results	The concentration of pollutants is reduced by 30%, and the diffusion range is reduced by 50%
Ecosystem protection	Good effect	Ecosystem stability increased by 20%, and species diversity increased by 15%.
Handling cost	Significantly reduced	Manpower input is reduced by 25%, and resource waste is reduced by 30%.

Table 2: Effectiveness demonstration of adaptive water environment optimization strategy.



(A) Flexibility



(B) Adaptability

Figure 6: Method comparison.

The results in the table show that the adaptive water environment optimization strategy has good performance in many scenarios. Specifically, the strategy has achieved remarkable results in improving water quality, effectively reducing the concentration and diffusion range of pollutants. In the aspect of ecosystem protection, the strategy maintains the stability and diversity of the ecosystem by rationally allocating water resources. In terms of management cost, the strategy reduces unnecessary waste and manpower input through intelligent decisions.

In the comparative analysis, this article also compares the adaptive strategy with the traditional management method. The comparison results of different methods are shown in Figure 6.

The results show that the adaptive strategy has higher flexibility and adaptability in dealing with complex and changeable water environments. In addition, in terms of convergence, the RL algorithm can quickly converge to a better solution in the training process, which shows that the strategy has good learning ability and robustness (Figure 7).

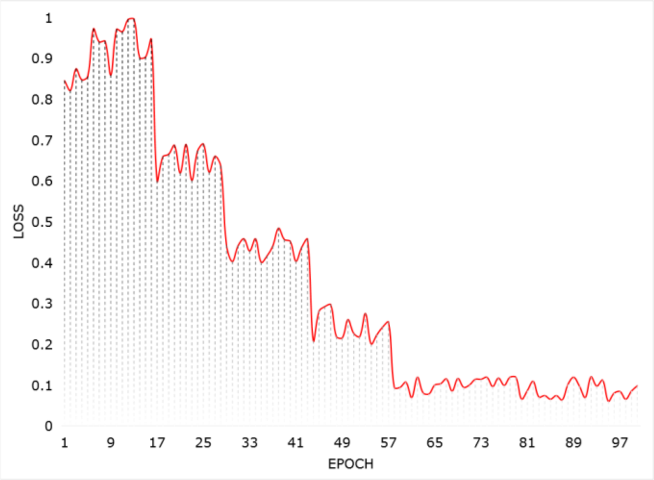


Figure 7: Convergence of RL algorithm.

Through the in-depth analysis of the experimental results, this article finds that the effectiveness of the adaptive water environment optimization strategy mainly benefits from the following aspects: first, the strategy makes full use of the accurate modelling ability of CAD tools and provides accurate environmental information for RL algorithm; Second, the strategy adopts adaptive RL algorithm, which can be dynamically adjusted and optimized according to the actual water environment; Third, the multi-index evaluation system can fully reflect the comprehensive performance of the strategy and provide a strong basis for the adjustment and improvement of the strategy.

6 CONCLUSION AND PROSPECT

In this study, an adaptive water environment optimization strategy was successfully developed by combining CAD and RL technology. This strategy can make intelligent decisions according to the actual water environment, effectively improve water quality, protect ecosystems, and reduce management costs. The results show that the strategy has good performance and adaptability in different scenarios. The main innovation of this study is to combine the accurate modelling ability of CAD with the adaptive decision-making ability of RL, which provides a new idea for solving the complex water environment optimization problem.

This article reiterates the importance and practicability of adaptive water environment optimization strategy, which can provide scientific and intelligent decision support for water environment management and help to improve the utilization efficiency and management level of water resources. Furthermore, this strategy has a broad application prospect and can be applied to other similar environmental optimization problems.

This study has important theoretical and practical contributions to the field of water environment optimization. Firstly, by introducing CAD and RL technology, the method system of water environment optimization is enriched, and the optimization effect and decision-making level are improved. Secondly, this study provides a new intelligent solution for water environment management, which is helpful in promoting the development of water environment management in a more scientific and efficient direction. Finally, this study provides useful enlightenment and reference for future related research and promotes the further development of this field.

Although some achievements have been made in this study, some problems and shortcomings have also been exposed during the experiment. For example, in some extreme cases, the policy may have performance degradation or failure. In addition, the RL algorithm consumes a lot of training time and computing resources, which may limit the promotion of the strategy in practical application. Aiming at these problems, this article puts forward the following suggestions: First, further optimize the performance and stability of the RL algorithm; The second is to explore more efficient data processing and model simplification methods to reduce the calculation cost; The third is to strengthen the docking with the actual water environment management needs to improve the practicability and pertinence of the strategy.

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