RESEARCH ARTICLE

Optimization control of river pollution treatment process based on improved genetic algorithm

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River pollution has always been a major challenge in global environmental protection. With the acceleration of industrialization and rapid population growth, industrial wastewater, agricultural discharges, and domestic sewage continue to flow into rivers, triggering serious water pollution problems. The current river pollution treatment methods can alleviate the pollution problem to a certain extent, but still face inefficient treatment, expensive cost, and secondary pollution. Therefore, this study proposed an improved model that combined genetic algorithm, particle swarm optimization algorithm, and long short-term neural network. The genetic algorithm was applied to optimize processing parameters, improve processing efficiency, and reduce cost. The long and short-term memory network algorithm was used to predict and simulate changes in pollutants during different treatment stages, thereby optimizing the entire treatment process. The cyber physical system was used to ensure real-time data collection and accurate processing operations. The results showed that the absolute error of the improved genetic algorithm was as low as 0.05%. The difference between the highest and lowest error values of the model was 18.30%, and the relative error variation differed by 24.23%. By applying the proposed model, the river pollution treatment effect was improved with stronger treatment ability. In the pollutant change monitoring indicators, the conformity was 98.3% for oxygen demand, 97.5% for potassium permanganate, and 98.2% for ammonia nitrogen. The proposed model could improve the river pollution treatment system and analyze the river pollution treatment data with more comprehensive and better data signals being systematically analyzed and processed to improve pollution treatment efficiency. After adding the improved genetic algorithm, the river pollution treatment had been effectively optimized and controlled, which provided better research value for this field.

Keywords: river pollution; pollution treatment; genetic algorithm; particle swarm optimization; processing effect.

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Introduction

With the rapid development of industrialization and urbanization, river pollution has become a serious problem in globalization. Rivers, as an important component of natural ecosystems, not only play a crucial role in providing water resources, but also serve as important protected areas for biodiversity [1]. Due to industrial wastewater discharge, untreated urban domestic sewage discharge, and agricultural non-point source pollution, river pollution is becoming increasingly serious, which not only threatens the ecological safety of water environment, but also poses a serious threat to human life and public health [2]. Among many strategies for controlling river pollution, the optimization and control of the pollution treatment process is particularly important. Traditional river pollution treatment methods often focus on post treatment, lacking efficient prevention and real-time control mechanisms. In addition, due to the complexity of river pollution treatment processes, traditional methods have many limitations in resource allocation, treatment efficiency, and cost control [3]. Therefore, exploring an efficient, economical, and sustainable optimization strategy for river pollution treatment is crucial. Genetic algorithm (GA), as an efficient global optimization method, has been widely applied in multiple fields [4]. As one of the most important freshwater resources on earth, rivers play an irreplaceable role in maintaining ecological balance, ensuring human life, and promoting economic development. Vara *et al*. investigated the impact of human micro pollutants on freshwater ecosystems and the relationship between micro pollutants and the genetic structure of aquatic organisms. Genetic markers were used to analyze the genetic structure of naked cheeked toads. Their sensitivity and bioaccumulation to the common insecticide imidacloprid were analyzed. The results indicated that the sensitivity of arthropods to micro pollutants depended on the pollution degree, but long-term exposure might increase its sensitivity [5]. He *et al*. proposed a lake basin water quality management system based on the response relationship between river and lake water quality to address the mismatched water quality objectives. The results showed that the system could effectively identify key pollution sources in lake basins, and accurately locate key points for water quality improvement and pollution control [6]. Huang proposed a dynamic multi game model to explore the relationship between the river basin environmental governance effectiveness and upstream-downstream cooperation and found that, although pollution reduction cooperation could improve the environment, it might not necessarily increase social welfare. The ecological compensation mechanism must meet the conditions to be effective. Consumer preferences and other parameters had a significant impact on decision-making [7]. Cheng *et al*. proposed a new action framework based on incentive mechanisms to improve the environmental governance effectiveness in river basins and improve cross administrative governance mechanisms. The results demonstrated that horizontal cost sharing contracts could effectively improve the local cooperation in environmental governance. Under certain conditions, downstream cost sharing contracts could achieve a win-win situation between environmental governance and government governance, which provided a new research direction for the government to establish a reasonable pollution management cooperation mechanism and promote sustainable development of river basins [8].

The improved GA can not only improve prediction accuracy and precision, but also achieve good research results in different fields. Djekidel *et al*. proposed a three-dimensional quasi-static model of the electric field generated by high-voltage overhead power lines. The charge simulation method combined intelligent optimization algorithms such as particle swarm optimization (PSO), GA, and grey wolf optimizer to calculate the optimal parameter values. The results indicated that the grey wolf optimizer was more effective than other algorithms [9]. Yang *et al*. proposed an improved method combining adaptive GA and Back Propagation Neural Network (BPNN) to solve insurance fraud and improve the performance of BPNN. This method overcame the drawbacks of BPNN such as easily falling into local minima, slow convergence speed, and strong sample dependence by optimizing the initial weights of BPNN. The results showed that the improved GA was more advanced than traditional GA in convergence speed and prediction accuracy [10]. Kumar *et al*. proposed a prediction model based on random forest and GA to better determine the dosage of coagulants in water treatment processes. This model could actively determine the dosage of coagulants based on the characteristic changes of raw water, without the need for expensive chemical reagents. The method could quickly respond to changes in water quality and showed that the model performed well in simulating the dosage of coagulants in water treatment plants [11].

In the current research on GA, most of the studies mainly use GA to analyze the data and improve the performance, which is of great significance for improving the river pollution control system. However, for the river pollution treatment process, there are problems such as low efficiency and high processing costs of river data processing, as well as a lack of real-time dynamic control ability for complex pollution factors. This study used a teleological approach combining GA, PSO, and long and short-term memory network (LSTM) to optimize the river pollution treatment system. The proposed new model aimed to improve the control accuracy and efficiency of the river pollution treatment process, reduce the operation cost, and improve the system ability to adapt to complex pollution conditions, which would not only effectively optimize and adjust parameters, but also provide more accurate analysis and prediction of data in the river pollution control, thereby optimizing the entire control process. It would also provide a more efficient and economical solution for river pollution treatment. By integrating the advanced computational model, it could not only enhance the scientific and practicality of river pollution treatment technology, but also positively influence other related research in the field of environmental sciences, promoting environmental protection and sustainable economic development.

Materials and methods

Analysis of river pollution treatment process

The pollution treatment of rivers can be divided into three stages. The first stage is a physical process that involves removing a large amount of solid pollutants from rivers. The second stage is biochemical treatment that removes organic pollutants and colloids from river pollution [12]. The third stage is advanced treatment that mainly involves denitrification, dephosphorization, and disinfection of the river polluted wastewater from the previous stage. Biochemical treatment is the most important, which can solve most of the pollutants in river pollution. The Cyber Physical System (CPS) is usually used to control the biochemical treatment process. In the CPS, because the system needs to carry out monitoring, controlling, and other operations, the network structure needs to be added to the whole system [13]. The treatment process of river polluted wastewater mainly involves controlling the treatment process such as the parameters and data of the reactor and other systems of the current process flow to optimize and improve the treatment process of river polluted wastewater. During the whole treatment process, the CPS is the main system to control the operation of various reactors [14]. The process flow of river data processing mainly includes anaerobic, anoxic, and aerobic reactors. The parameters and data of each reactor are controlled by the modules of the CPS application layer unit. Therefore, how to improve the efficiency and effectiveness of existing river pollution treatment processes mainly depends on the application layer of the CPS. Since the data and parameters of river sewage treatment are recorded by operators, there are many uncertain factors in the data. Therefore, to improve the data accuracy in the current pollution treatment process, a new data pre-processing process was designed when optimizing the model data acquisition process [15]. In the data collection for river pollution treatment, the PLC controller was used to return the data collected by the server. The data flow mainly used the perception module TCP to return the data. After that, the server received the data, and then sent the data. Finally, the data and parameter information of the river pollution treatment system were obtained (Figure 1)

Analysis and model construction of river sewage treatment process based on improved GA

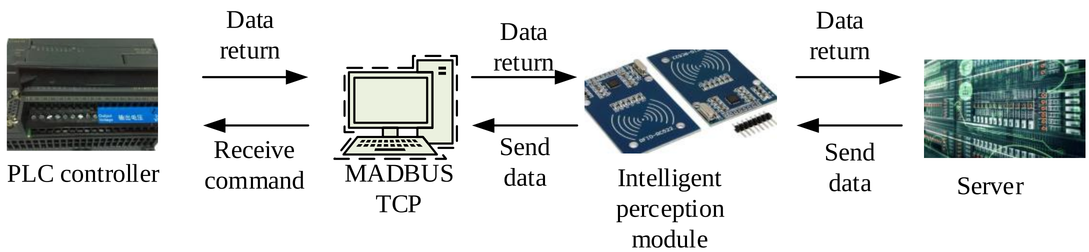

Figure 1. Data collection process.

In river sewage treatment, there are non-linear and time-varying relationships between biochemical reactions of different pollutants, reactor treatment data, and variables. The traditional CPS cannot meet the current more accurate data processing process. Therefore, the data processing process and reactor response process should be re-optimized and controlled in river pollution [16]. Deep learning is a feature expression learning model, which can analyze the highly nonlinear data of river sewage treatment process and was used to optimize the model. GA shows excellent data processing effect in processing nonlinear data and multi-objective optimization. However, the traditional GA has some disadvantages such as poor local search ability, reduced search ability after evolution, and easy to converge, which makes the traditional GA unable to better process reactor data. To solve the convergence and search ability of traditional GA, PSO and LSTM were introduced to improve the traditional GA. LSTM can maintain data information for a long time with better data dependence ability, which is more flexible in data processing than other models. PSO is simpler and more efficient with strong data adaptability and without gradient calculation, which greatly improves the data processing ability. The improved GA algorithm first needed to obtain river pollution treatment data. The obtained data was initialized to get the particle swarm, and the fitness was calculated and divided. Then the fitness particle swarm and population variation were calculated to get the new particle swarm. The individual and global extremum were updated, while the position and speed of the particles were also updated. The maximum number of iteration or the minimum limit of global extremum were then judged. If the result reached one of them, the data would be regarded as the input of the training set. Otherwise, fitness would be re-calculated. The training set was parameterized to determine whether the current parameter was a complex number, and the loss function was calculated through LSTM. If the loss function is less than the set error, the parameter size was updated to determine whether the parameter was a complex number. Both data that were less than the set error or not a complex number were output (Figure 2). The improved GA not only had the global search ability, but also could solve the easily occurring local extremum. When calculating fitness, the loss function of the current river pollution treatment data should be calculated to judge and optimize the algorithm parameters as shown in equation (1) [17].

$$Loss = \frac{1}{M}\sum_{m=1}^{M}(y_{verify} - y_{pre})^2 \tag{1}$$

where $Loss$ was the loss function of the model. y_{verify}, y_{pre} were the real value and output value of the model data at a certain time. M was the number of data. The size of the loss function calculated by PSO was shown in equation (2).

$$Loss_{pso} = Loss \tag{2}$$

where $Loss_{pso}$ was the loss function size of the PSO. The loss function value of the GA was shown in equation (3) [18].

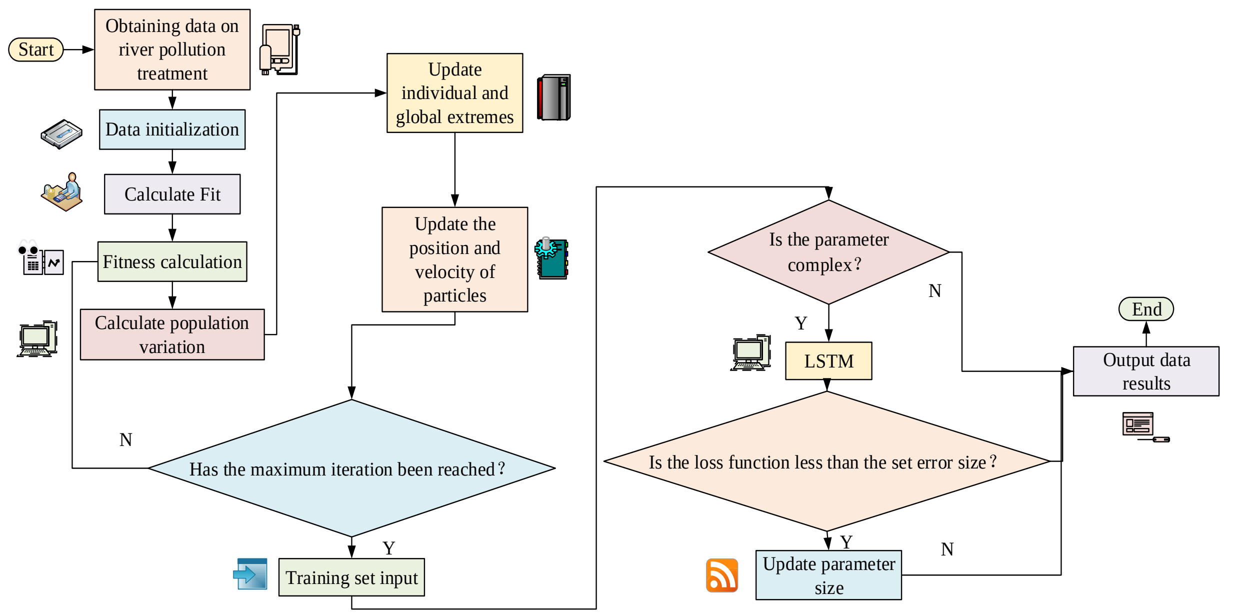

Figure 2. Schematic diagram of the improved GA flow.

$$Loss_{ga} = 1/(1-Loss) \quad (3)$$

where $Loss_{ga}$ was the loss function value of GA. The parameter calculation included the position vector, velocity vector, and optimal position in the current space. The position vector was expressed as equation (4).

$$\vec{x}_i = (x_{i1}, x_{i2}, \ldots, x_{i6}) \quad (4)$$

where $\vec{x}_i$ was the vector size of the position. $x_{i1}, x_{i2}, \ldots, x_{i6}$ represented the position coordinates of different parameters. The velocity vector of the model was shown in equation (5).

$$\vec{v}_i = (v_{i1}, v_{i2}, \ldots, v_{i6}) \quad (5)$$

where $\vec{v}_i$ was the speed vector size of the current model. $v_{i1}, v_{i2}, \ldots, v_{i6}$ was the speed information of different parameters. The optimal position of the model was shown in equation (6) [19].

$$\vec{p}_i = (p_{i1}, p_{i2}, \ldots, p_{i6}) \quad (6)$$

where $\vec{p}_i$ was the vector size of the optimal position. $p_{i1}, p_{i2}, \ldots, p_{i6}$ was the optimal position of different parameters. The optimal position of the model was shown in equation (7).

$$\vec{p}_{gbest} = (p_{gbest1}, p_{gbest2}, \ldots, p_{gbest6}) \quad (7)$$

where $\vec{p}_{gbest}$ was the optimal position vector size sought by the current model. $p_{gbest1}, p_{gbest2}, \ldots, p_{gbest6}$ was the optimal position information of different parameters. The speed update obtained at this time was as follows.

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 rand()(p_{id} - x_{id}^{k}) + c_2 rand()(p_{gbest} - x_{id}^{k}) \quad (8)$$

where wv_{id}^{k} was the affirmation of the current particle to own state. $c_1 rand()(p_{id} - x_{id}^{k})$ was the experience of the current particle. $c_2 rand()(p_{gbest} - x_{id}^{k})$ was the update speed of

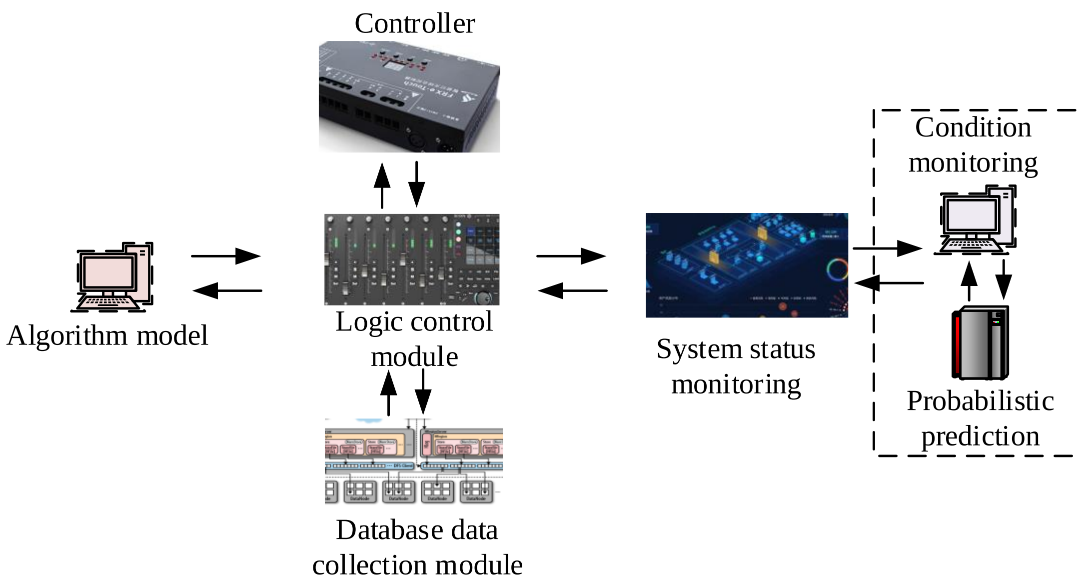

Figure 3. System modules for river pollution treatment.

the particle. w was the weight factor. c_2, c_1 were acceleration factors. $rand()$ was the randomly generated constant value in 0-1. v_{id}^{k+1} was the size after speed update. The updated particle position was than as equation (9).

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \quad (9)$$

where x_{id}^{k+1} was the updated location information. x_{id}^{k} was the current position information. To avoid convergence of the model, the inertia weight of the model was calculated below [20].

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{itera_{\max}} * itera_{current} \quad (10)$$

where $itera_{\max}$ was the maximum number of iteration steps of the current model. $itera_{current}$ was the iterations of the current model. $w_{\max}, w_{\min}$ represented the maximum and minimum values of the weight, respectively. The weight decreased with the increase of iterations. In the selection of model fitness, the loss function was selected through equation (2) to find the optimal population individual. When the number of chromosomes was M_c, the chromosome crossing of the model was equation (11).

$$M_c = M * p_c \quad (11)$$

where M was the chromosome. p_c was the gene crossover operator. The variation operation of the model was shown in equation (12) [21].

$$M_m = M * l * p_m \quad (12)$$

where M was to the number of populations. l was the coding length of the gene. p_m was the probability of chromosome variation. The system module of river pollution treatment was then built (Figure 3). The complete system module included controller, algorithm module, database data acquisition module, system state monitoring, and the most important logic control module. The system module mainly analyzed and controlled the river pollution process to optimize the river pollution treatment. The control core was the data processing and optimization process of the algorithm module.

Data resource

The data used in the study was from the Chinese National Surface Water Quality Automatic Monitoring Data Website (http://106.37.208.243:8068/GJZ/Business/Publish/Main.html), which updated the water quality data of the operating national automatic water quality monitoring station in real time with an update frequency of every 4 hours. The data was collected from 03:00 on August 15, 2023 to 19:00 on January 25, 2024 with 1,000 water quality data being collected. The population distribution on both sides of the river was dense, making it a conventional urban river. The water quality of this section of the river was complex, which was subject to various interventions. Two datasets were used for this study, which represented data from two sections of the river. River section 1 referred dataset 1 that flew through the main city and was relatively affected by the city. River section 2 was dataset 2 that flew through the urban edge area and was less affected by the city. Both datasets contained 2,000 pieces of river data information.

Computer hardware and software

The computational system used for this study was a 4 Cores CPU with the RAM of 32 GB and 200 GB disk volume. The initial learning rate of the algorithm was set to 0.02, while the weight value was set to 0.0005. Visual Studio (Microsoft, Redmond, WA, USA), Eclipse (https://www.eclipse.org/), IntelliJ IDEA (JetBrains, Prague, Czech Republic), and Xcode (Apple, Cupertino, CA, USA).

Model training and validation

To prove the feasibility and effectiveness of the designed method, river pollution treatment data in a sewage treatment plant was simulated. The data parameters of the reactor in the current sewage treatment plant were selected for optimization analysis, which included oxidation-reduction potential (ORP) with a time step of 20, an optimizer of adam, a batch size of 100, a model neuron count of 160, and dropout of 0.5. The dissolved oxygen (DO) value was set as a time step of 40, an optimizer of adam, a batch size of 150, a model neuron count of 200, and a discard rate of 0.5%. The setting parameters in ORP and DO were specific parameter values that the model needed to set during training. ORP represented the redox values in river water quality changes, while DO represented the dissolved oxygen content of water in river pollution. The LSTM model was used as the main model for data processing when verifying the performance effect of the model. Ablation experiments were conducted by comparing different traditional models including autoregressive model (AR), moving average (MA), and geographic information system (GIS) to analyze the advanced performance of the proposed model. Further, the GA-LSTM, PSO-LSTM, LSTM, and the improved GA used in the study were tested for error comparison. The evaluation index included absolute error (AE) and relative error (RE).

Results and discussion

Comparison with different models

The results showed that AE and RE of the improved GA were the lowest among the four tested models with the lowest AE of 0.05% and the lowest RE of 0.13% (Table 1). The maximum error value appeared in the LSTM with the maximum AE of 18.35%, and the maximum RE of 24.36%. The differences of AE and RE between the two models were 18.30% and 24.23%, respectively, which indicated that the improved GA had better model effect in data analysis and processing. The pollution indicators before and after using the improved GA were compared and demonstrated that the DO decreased faster after applying the model, and the maximum deviation reached about 2 ppm (Figure 4a). The pH reached neutrality faster, and the maximum difference in pH was 0.4 (Figure 4b). The decline curve of potassium permanganate after adding the model was relatively fast with a maximum difference of 1 mg/L (Figure 4c). The nitrogen ammonia also decreased faster after adding the model with the maximum difference of 0.2 mg/L (Figure 4d).

Table 1. Comparison of test errors for four algorithms.

Number	GA-LSTM		PSO-LSTM		LSTM		Improved GA	
	AE (%)	RE (%)	AE (%)	RE (%)	AE (%)	RE (%)	AE (%)	RE (%)
1	5.32	6.67	5.26	6.67	18.24	23.56	1.21	1.25
2	5.26	5.36	5.36	6.95	18.35	24.36	1.95	1.54
3	5.16	6.35	5.48	3.48	16.35	20.64	0.51	0.21
4	3.54	4.21	2.65	1.36	13.51	15.34	0.12	0.31
5	3.65	3.95	2.31	1.24	13.62	15.36	0.12	0.31
6	2.64	2.54	2.15	1.45	10.35	11.65	0.09	0.21
7	2.36	2.35	2.64	1.65	10.23	11.21	0.08	0.23
8	2.36	2.64	1.32	0.95	5.36	11.21	0.07	0.22
9	1.24	1.12	1.24	0.95	3.25	8.25	0.05	0.13
10	1.11	1.12	1.32	0.85	3.12	8.15	0.06	0.11

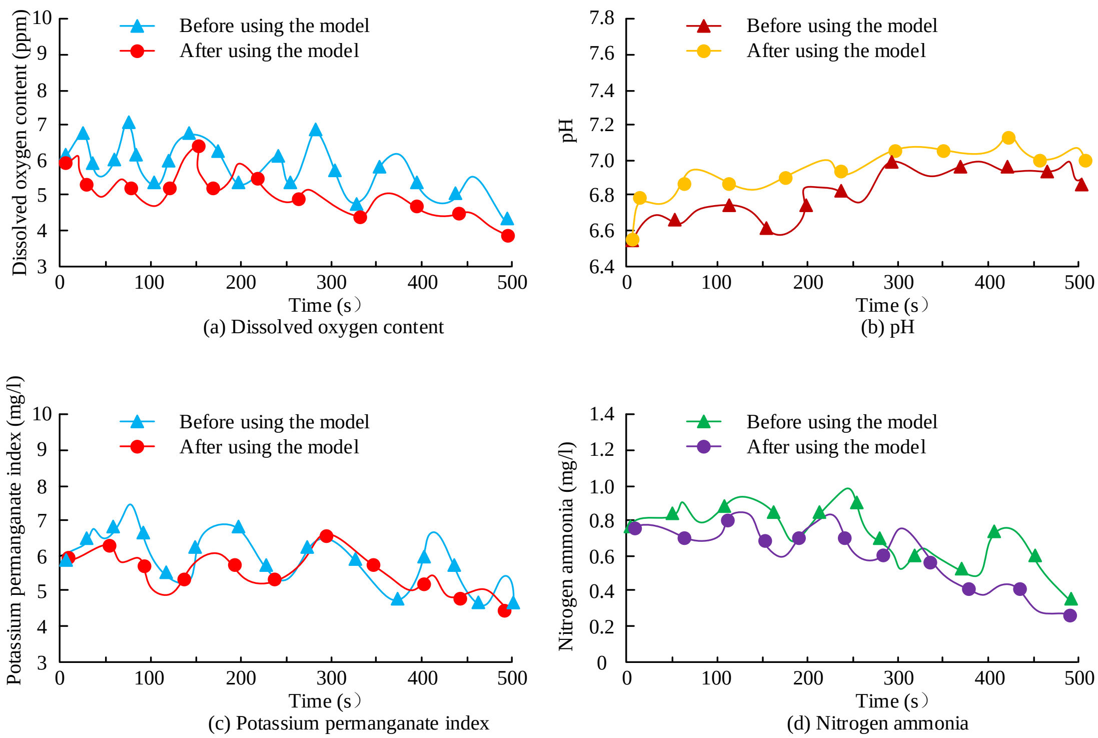

Figure 4. Comparison of different pollutant indicators before and after using the model.

From the comparison of four indexes, the results showed that the improved system could enhance the treatment efficiency of current pollutants. The average AE reflected the comparison relationship between the true value and the monitoring value. If the error value was small, the data would be better. The average AE of the four models was then compared. The results showed that the average AE curve of the designed method was the lowest, while the error curve of other algorithms fluctuated up and down (Figure 5), which indicated that the data detection effect of other algorithms was poor when processing the data. The data monitoring effect of the designed model was better than others with the average error of LSTM of 6.23%, and the average value of improved GA of 2.03%, which was 4.20% lower. To test the pollutant prediction effect

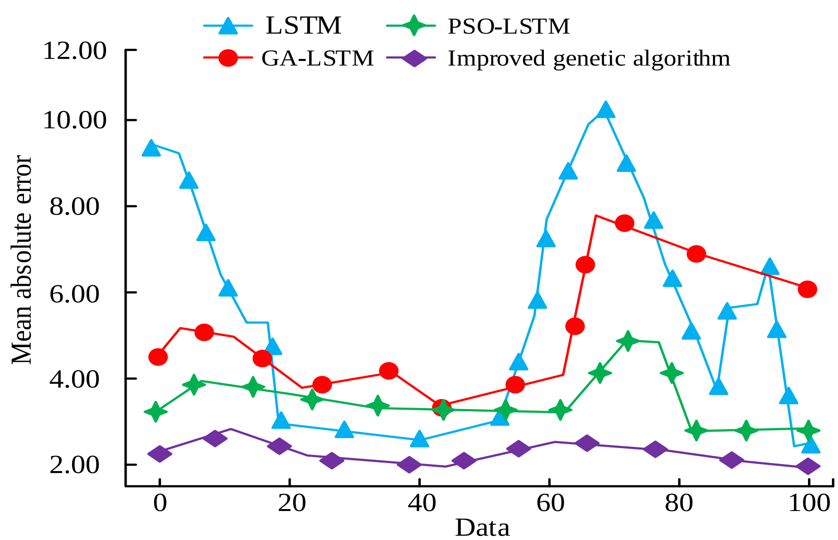

Figure 5. Comparison of average absolute error of four models.

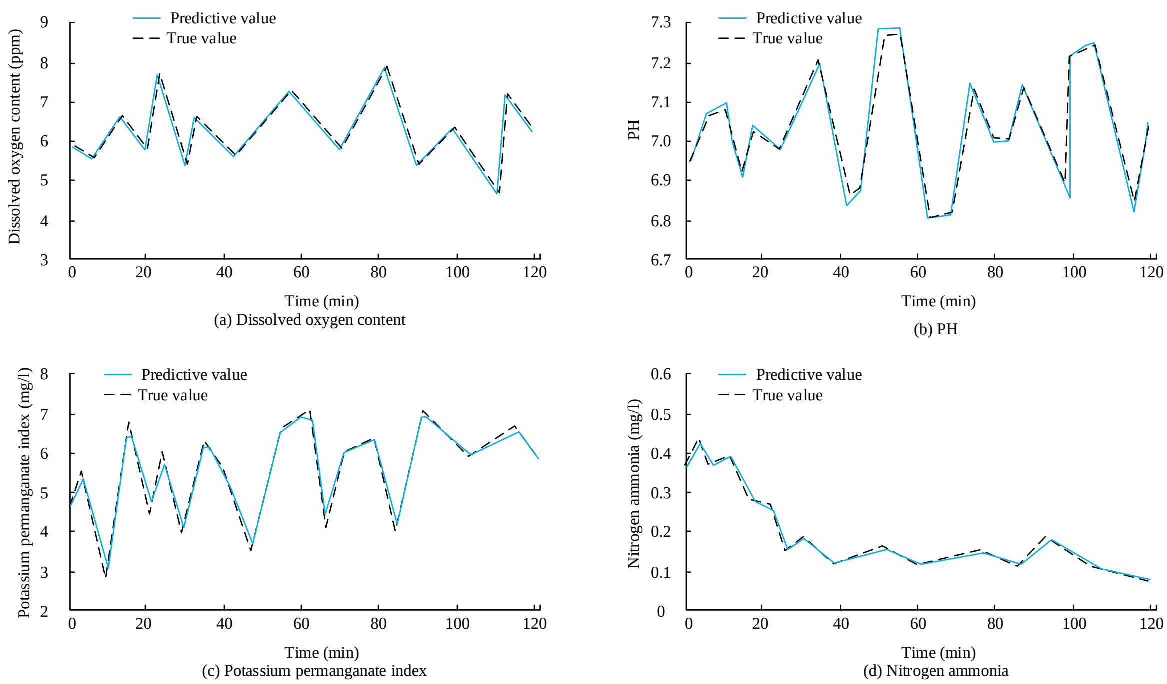

Figure 6. Comparison of model data testing.

after adding the improved algorithm, the pollutant treatment results obtained from the model simulation were compared with the real data. The results demonstrated that, in the comparison of four pollutant indexes, the real value and predicted value change curves of the improved GA were consistent (Figure 6), which indicated that, after adding the improved model, the prediction of pollutant changes was almost consistent. Among them, the pH value prediction showed significant consistency of 92.3%. The other three pollutants were 98.3% for oxygen demand, 97.5% for potassium permanganate, and 98.2% for ammonia nitrogen, respectively.

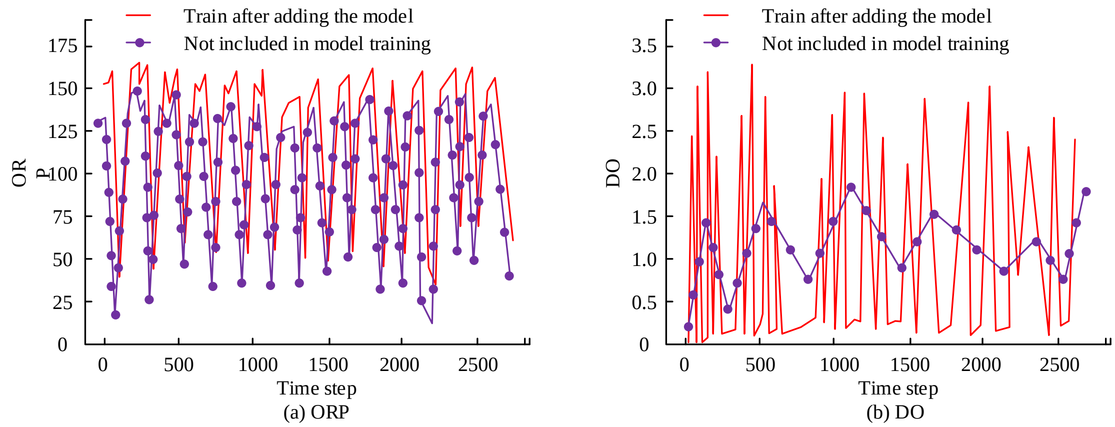

Figure 7. Numerical changes of two pollutants after model training.

Table 2. Comparison of error and accuracy in data processing of four models.

Dataset	Models	MSE	RMSE	MAE	MAPE	Accuracy (%)
Dataset 1	AR	3.24	13.56	10.25	11.32	88.35
	MA	2.25	15.96	11.64	12.32	86.07
	GIS	4.23	14.62	10.35	12.54	87.62
	Improved GA	1.23	9.56	8.64	9.62	92.35
Dataset 2	AR	3.54	14.20	11.32	12.57	89.24
	MA	4.65	13.24	11.65	11.68	91.20
	GIS	5.36	12.34	11.75	12.68	90.35
	Improved GA	2.15	8.36	7.57	9.56	94.35

Notes: MSE: the mean square error. RMSE: the root mean square error. MAE: the average absolute error. MAPE: the average absolute percentage error.

Model training and testing

The dataset was divided into training and testing datasets on average. After setting the different detection parameters for pollutants, the model data training of pollutants showed fluctuations. After adding the new system model for data training, the change was consistent with the initial change, but the difference was that the data for both pollutants showed a downward trend, which indicated that data training on pollutants could improve the entire process and efficiency of pollutant treatment and reduce river pollution (Figure 7).

Comparison to traditional treatment methods

The comparison results between the proposed method and traditional treatment methods including AR, MA, and GIS showed that the designed model demonstrated lower error values. The improved GA in both datasets showed better accuracy changes with the highest accuracy in dataset 2 of 94.35%, which was 5.11% higher than the lowest model in the same dataset (Table 2). The results showed that the model used in the study had better river pollution treatment effect and optimization control ability.

A new improved model based on GA was proposed to address the poor control effectiveness and incomplete technology in current river pollution treatment processes. The new model integrated PSO and LSTM into the GA, enhancing data monitoring and control of pollution treatment processes in the system, and improving the effectiveness and efficiency of river pollution treatment. After adding the model, the treatment effect of river pollution was better, and the treatment ability was stronger.

Compared with traditional algorithms, the research method had the highest accuracy among the tested algorithms. The pollution treatment process of the system was more efficient and fast after adding the model. However, there were still some shortcomings for this study, which included that the pollutants tested in the study did not include insoluble pollutants. In addition, more other models should be compared with the proposed model. Further research should train more models for comparative analysis.

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