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# Prediction of water quality class based on an ELM optimized by a MFOA

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**Abstract.** As an extreme learning machine easily runs into local optimization and is slow in convergence, a MFOA-ELM-based water quality evaluation model was proposed so as to enhance the prediction accuracy and applicability of water quality evaluation model. In order to prevent the FOA from running into local optimization, the correction factor was introduced into FOA to put forward a MFOA. High-precision water quality prediction and evaluation can be realized by optimizing the weight and threshold of ELM with MFOA under the condition of optimal parameters. Water quality monitoring data of Chao Lake between 2010 and 2015 were selected as objects of research. The water quality of Chao Lake was predicted and evaluated based on the research on the parameter change trends of different water qualities. Through the comparison of 3 water evaluation and prediction methods, namely, MFOA-ELM, FOA-ELM and PSO-ELM, it is found that the prediction accuracy of MFOA-ELM reaches up to 98.36 %, which is higher than the prediction accuracies of PSO-ELM and FOA-ELM. Thus, it shows that MFOA-ELM is more accurate and applicable in evaluating and predicting water quality, verifying the validity and reliability of MFOA-ELM. Meanwhile, compared with other algorithms, MFOA-ELM is faster in convergence and better in effect.

**Key words.** FOA, ELM, water quality evaluation, particle swarm optimization, correction factor, convergence rate.

## 1. Introduction

Water quality evaluation and prediction aim to correctly reflect the quality and pollution of water environment through the water quality evaluation, predict the future development tendency of water environment quality, and provide a basis and method for scientific decision-making of management, protection and governance of water environment. At present, water prediction methods mainly consist of grey prediction method [1], artificial neural network [2] and support vector machine (SVM) [3] etc. Although a satisfactory result can be obtained through water prediction based on the grey theory, this prediction method is low in prediction accuracy and not suitable for long-term prediction [4–5]. To increase the prediction accuracy of

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water quality, reference [6] and reference [7] respectively proposed a water quality prediction model based on weighted array, exponential smoothing and GM (1,1) model combination. Although this method can increase the prediction accuracy to a certain extent, it fails to fundamentally solve the problem of prediction error. In order to enhance the accuracy of water quality evaluation, reference [8] proposed a water quality evaluation model based on grey renewal GM(1,1) model. The experimental result shows that the prediction accuracy of this method is superior to that of a traditional GM(1,1) model. Based on the accurate non-linear mapping capability and generalization ability of BP neural network, reference [9] proposed a water quality prediction model based on BP neural network. The experimental result shows that the method is high in accuracy and generalization ability. As the small sample data of BP neural network is low in prediction accuracy and easily runs into local optimization, reference [10] proposed a water quality prediction model based the improved BP neural network, increasing the prediction accuracy. In consideration of the disadvantages of BP neural network such as local optimization and slow convergence, references [11–12] established a water quality prediction model based on GA-BP neural network by optimizing the weight, threshold and network structure of BP neural network with GA; through the optimization with GA, both its prediction accuracy and the stability in its prediction result can be enhanced. As the single SVM prediction model is low in prediction accuracy and slow in speed, reference extracted the characteristic information of water quality data via the wavelet analysis and proposed a water quality prediction model based on wavelet transformation and SVR. Reference proposed a water quality parameter prediction model based on improved weighted SVM, largely increasing the prediction accuracy. According to small samples and time series data of jump water quality, reference proposed a water quality prediction model based on ELPM data preprocessing and PSO algorithm optimizing the parameters of least square VSM.

FOA (Fruit Fly Optimization Algorithm), which is a swarm intelligence algorithm proposed by simulating the fruit fly's forging behavior, has the advantages such as few control parameters and fast convergence. At present, it is found that there is no article concerning the application of FOA in water evaluation. In consideration of the disadvantages of a traditional water quality evaluation model such as low prediction accuracy and poor adaptability, a ELM optimized by MFOA (Modified Fruit Fly Optimization Algorithm) is proposed here to evaluate water quality. The research result shows that MFOA has obvious advantages in both the optimization effect and computing speed so it has a satisfactory effect.

## 2. MFOA

### *2.1. FOA*

The flow of FOA is shown below:

Step 1. Initialize the algorithm parameters and set the population size and maximum numbers of iterations to be popsize and iteration respectively; set the initial positions of fruit flies to be $X_{\text{begin}}$ and $Y_{\text{begin}}$.

Step 2. Find out the optimizing directions of individual fruit fly and calculate the distance according to the formulas

$$x_i = X_{\mathrm{begin}} + \mathrm{Value} \times \mathrm{rand}\,, \tag{1}$$

$$y_i = Y_{\mathrm{begin}} + \mathrm{Value} \times \mathrm{rand}\,. \tag{2}$$

In the formulas above, $x_i$ and $y_i$ refer to positions of individual fruit flies. Quantity Value refers to the scouting distance of fruit fly.

Step 3. Calculate the distance $d_i$ between the individual fruit fly and the original point and smell concentration $s_i$ of individual fruit fly according to the formulas

$$d_i = \sqrt{x_i^2 + y_i^2}\,, \tag{3}$$

$$s_i = \frac{1}{d_i}\,. \tag{4}$$

Step 4. Calculate the decision function of smell concentration and obtain the smell concentration of current position of individual fruit fly in the form

$$\mathrm{Smell}_i = \mathrm{Function}(s_i)\,. \tag{5}$$

Step 5. Search for the best smell concentration $\mathrm{Smell}_{\mathrm{b}}$ and best positions given by $x_{\mathrm{b}}$ and $y_{\mathrm{b}}$ among the fruit fly population.

### *2.2. MFOA*

According to formula (3) and formula (4), it can be seen that the decision value of smell concentration $s_i$ gets very small after calculating the reciprocal in formula (4). Then, if smell concentration $s_i$ is used as the decision function, FOA will run into local optimum, causing the problem of "prematurity".

To prevent FOA algorithm from running into local optimum, a MFOA (Modified Fruit Fly Optimization Algorithm) was proposed by introducing the correction factor $\beta$ into the basic FOA. Its modified formulas are shown below.

$$d_i = \sqrt{x_i^2 + y_i^2}\,, \tag{6}$$

$$s_{Mi} = \frac{1}{d_i} + \beta\,. \tag{7}$$

In the formulas above, $s_{Mi}$ refers to the smell decision function of MFOA. Now

$$\beta = \begin{cases} g \times d_i, \\ K \times X_{\mathrm{axis}} \text{ or } K \times Y_{\mathrm{axis}}, \end{cases} \tag{8}$$

where $g$ obeys uniform distribution and $K$ refers to a constant.

## 3. ELM (extreme learning machine)

For $N$ different samples

$$(\boldsymbol{x}_i, \boldsymbol{t}_i), \quad \boldsymbol{x}_i = [x_{i1}, x_{i2}, ..., x_{in}]^{\mathrm{T}} \in R^n \text{ and } \boldsymbol{t}_i = [t_{i1}, t_{i2}, ..., t_{im}]^{\mathrm{T}} \in R^m$$

a unified model of SLFN with the number of nodes in a hidden layer of $\tilde{N}$ and the excitation function of $g(x)$ is shown below:

$$\sum_{i=1}^{\tilde{N}} \boldsymbol{\beta}_i g_i(\boldsymbol{x}_j) = \sum_{i=1}^{\tilde{N}} \boldsymbol{\beta}_i g(\boldsymbol{a}_i \cdot \boldsymbol{x}_j + b_i) = \boldsymbol{t}_j, \quad j = 1, \cdots, N\,. \tag{9}$$

In the formula above, $\boldsymbol{a}_i = [a_{i1}, a_{i2}, \cdots, a_{in}]^{\mathrm{T}}$ refers to input weight connecting the $i$th hidden layer node, $b_i$ refers to the bias of $i$th hidden layer node, $\boldsymbol{\beta}_i = [\beta_{i1}, \beta_{i2}, \cdots, \beta_{im}]^{\mathrm{T}}$ refers to the output weight of $i$th hidden layer node, and $\boldsymbol{a}_i \cdot \boldsymbol{x}_j$ refers to the inner product of $\boldsymbol{a}_i$ and $\boldsymbol{x}_j$.

Let $E(\mathbf{W})$ refers to the sum of squared error between the expected value and actual value. The problem solved is to find out the optimal weight $\mathbf{W}(\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{\beta})$ to minimize the cost function $E(\mathbf{W})$. Its mathematical model can be expressed as

$$\begin{aligned} &\underset{\mathbf{W}=(\boldsymbol{a},\boldsymbol{b},\boldsymbol{\beta})}{\operatorname{argmin}} \; E(\mathbf{W}) = \underset{\mathbf{W}=(\mathrm{a},\mathrm{b},\beta)}{\operatorname{argmin}} \; ||\boldsymbol{\varepsilon}||^2, \\ &s.t. \; \textstyle\sum_{i=1}^{\tilde{N}} \boldsymbol{\beta}_i g(\boldsymbol{a}_i \cdot \boldsymbol{x}_j + b_i) - \boldsymbol{t}_j = \boldsymbol{\varepsilon}_j, \quad j = 1, \cdots, N. \end{aligned} \tag{10}$$

$\boldsymbol{\varepsilon}_j = [\varepsilon_{j1}, \varepsilon_{j2}, ..., \varepsilon_{jm}]$ refers to the error of $j$th sample. The schematic diagram of ELM is depicted in Fig. 1.

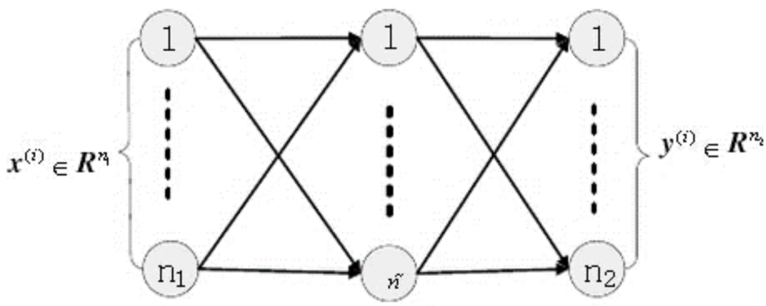


Fig. 1. Schematic diagram of ELM

## 4. Water quality prediction with the ELM optimized by MFOA

### 4.1. Water quality evaluation indexes

Water quality evaluation is to calculate and determine the water quality class of water sample through a certain mathematical model based on water quality evaluation criteria and all index values of water sample. As there are abundant indexes of water quality analysis, this paper uses ammonia nitrogen, dissolved oxygen, chemical oxygen demand, permanganate index, total phosphorus and total nitrogen as water evaluation indexes in combination with the quality standards for surface water environment; their corresponding water quality classes are shown in Table 1:

Table 1. Water quality classes and content standards

| Type | Type 1 | Type 2 | Type 3 | Type 4 | Type 5 |
|---|---|---|---|---|---|
| Ammonia nitrogen (mg/l) $<$ | 0.15 | 0.50 | 1.0 | 1.5 | 2.0 |
| Dissolved oxygen (mg/l) $>$ | 7.5 | 6.0 | 5.0 | 3.0 | 2.0 |
| Chemical oxygen demand (mg/l) $<$ | 15 | 15 | 20 | 30 | 40 |
| Permanganate index (mg/l) $<$ | 2.0 | 4.0 | 6.0 | 10 | 15 |
| Total phosphorus (mg/l) $<$ | 0.02 | 0.10 | 0.20 | 0.30 | 0.40 |
| Total nitrogen (mg/l) $<$ | 0.20 | 0.50 | 1.0 | 1.5 | 2.0 |

### 4.2. Fitness function

On the premise of guarantee the minimum prediction errors in water quality classes, the MFOA is used to optimize the weight and threshold of ELM. Since the weight and threshold among the parameters of ELA need to be optimized, its fitness function is

$$\text{Minimize Fitness}(w_{ij}, b_j) = \sum_{i=1}^{m} (o_i^k - d_i^k)\,. \tag{11}$$

In the formula, $d_i^k$ and $o_i^k$, respectively, refer to the input and output of ELM; $w_{ij}$ and $b_j$, respectively, refer to the weight and threshold of ELM.

### 4.3. Algorithm steps

The algorithm flow of water quality prediction with the ELM optimized by MFOA is shown below.

Step 1. Normalize water quality sample data and establish training samples and test samples.

Step 2. Set the population size and maximum number of iterations of MFOA to be popsize and iteration, respectively.

Step 3. Input the established training samples into the ELM. Calculate the fitness function value of individual fruit fly according to the objective function formula (11).

Search for the positions and optimal values of individual fruit fly and global optimal fruit fly.

Step 4. Update the speed and position of fruit fly.

## 5. Experimental analysis

### 5.1. Data source

Water samples from the Chao Lake were collected as objects of water quality evaluation. The sampling water intakes were the Nanfei River lake inlet, Pai River lake inlet and Chao Lake dam entrance; the longitudes and latitudes of sampling points are shown in Table 2. The water quality sampling time of Chao Lake was between 2010 and 2015. The sampling frequency was once every quarter. The changing trend of all indexes of water samples are shown in the Figs. 2, and 3.

Table 2. Longitudes and latitudes of sampling points

| No. | Sampling point | Longitude | Latitude |
|---|---|---|---|
| 1# | Nanfei River lake inlet | $117°24'40''$ | $31°42'15''$ |
| 2# | Pai River lake inlet | $117°18'15''$ | $31°41'30''$ |
| 3# | Chao Lake dam entrance | $117°51'46''$ | $31°34'18''$ |

### 5.2. Empirical results

In order to verify the validity and reliability of algorithm proposed in this paper, the water quality data of three sampling points in the Chao Lake between 2010 and 2015 were used as objects of research. The parameters of MFOA are set below: the population size is 20, the maximum number of iterations is 100, the maximum number of iterations of ELM is 100, the target error is 0.001, the number of internuncial neurons is 20. The water quality prediction result with MFOA-ELM is shown in Fig. 4. The water quality class evaluation results of MFOA-ELM, FOA-ELM and PSO-ELM are shown in Table 3 and Table 4.

According to the water quality class prediction results of MFOA-ELM, FOA-ELM and PSO-ELM in Table 3 and Table 4, it can be seen that the prediction results of MFOA-ELM and PSO-ELM and better than that of FOA-ELM, and the water quality evaluation result and misjudgment rate of MFOA-ELM are the best, thus verifying the superiority and reliability of MFOA-ELM.

### 5.3. Comparison of convergence rates of different algorithms

In order to compare the convergence rates of ELMs optimized by MFOA, FOA, PSO and GA [10], these algorithms were randomly operated for 4 times and the comparison of their convergence results are shown in Figs. 5 and 6. Compared with

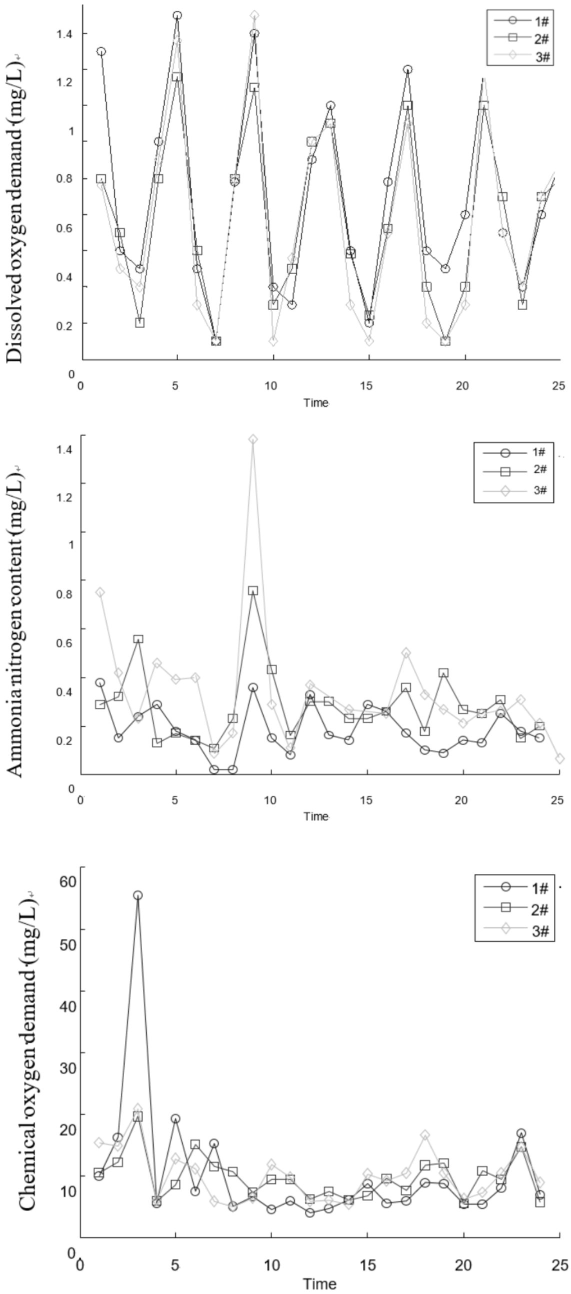


Fig. 2. Dissolved oxygen content, ammonia nitrogen content and chemical oxygen demand

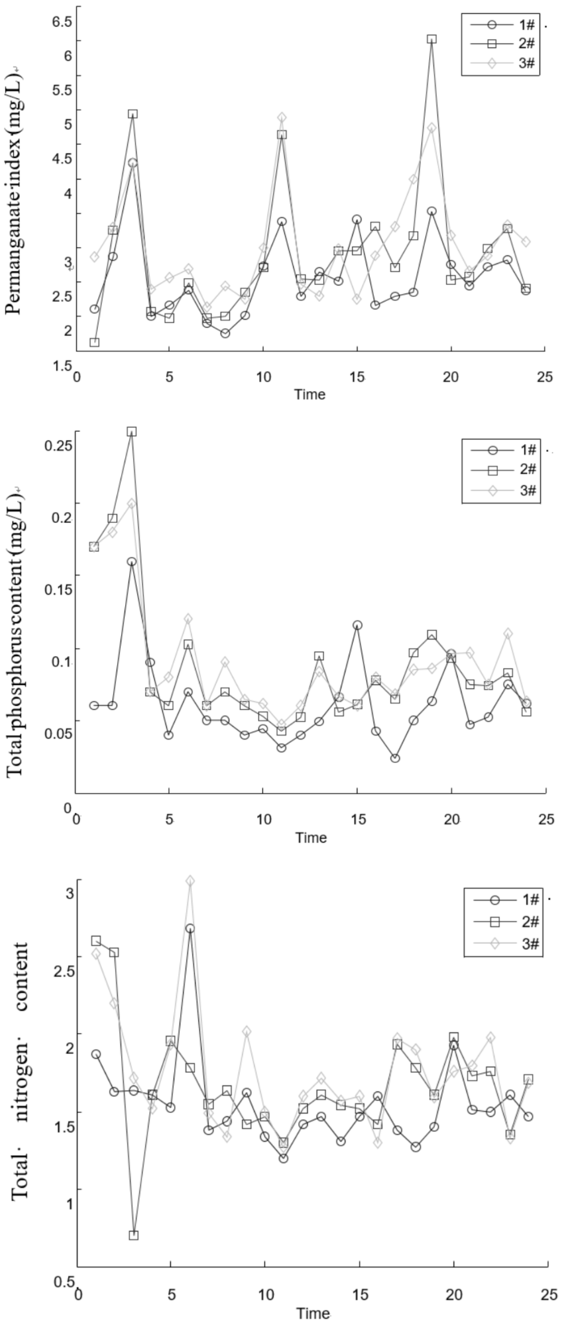


Fig. 3. Permanganate index content, total phosphorus content and total nitrogen content

FOA, PSO and GA, MFOA is faster in convergence.

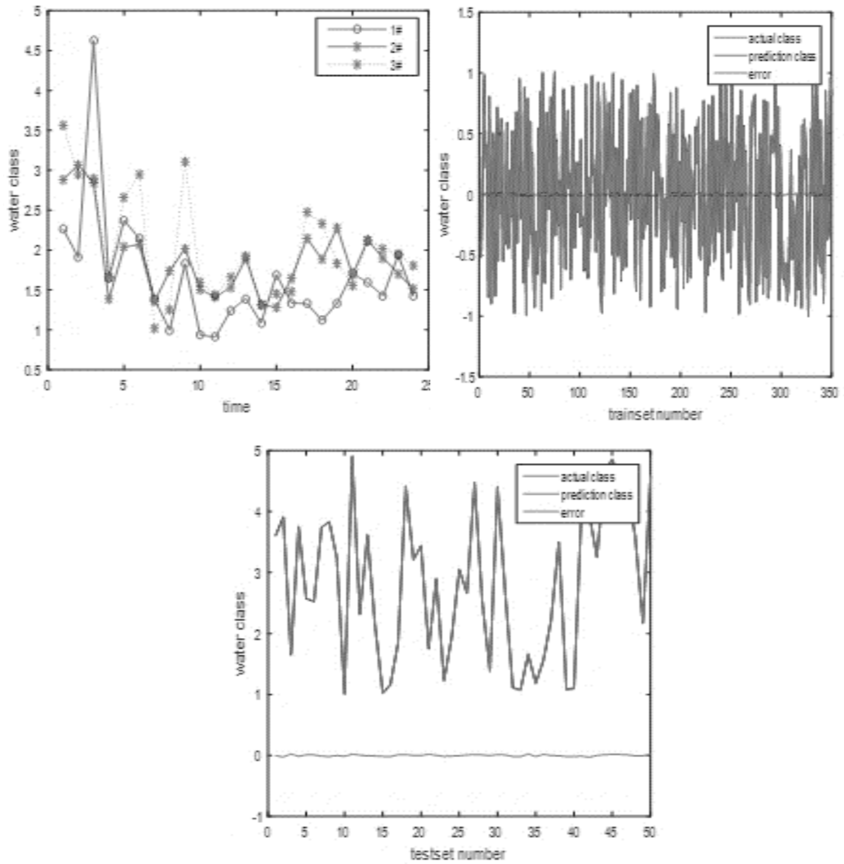


Fig. 4. Water quality prediction result: up left–prediction result, up right–training result, bottom–test result

Table 3. Water quality class prediction results of ELMs optimized by MFOA, FOA and PSO

| Method | Time (s) | Grade 1 | Grade 2 | Grade 3 | Grade 4 |
|---|---|---|---|---|---|
| MFOA_ELM | 40.0672 | 100.00% | 99.35% | 96.12% | 99.56% |
| FOA_ELM | 89.5534 | 98.54% | 90.65% | 58.33% | 76.74% |
| PSO_ELM | 0.8036 | 98.67% | 96.12% | 98.52% | 90.43% |
| PSO | | | | | |
| Method | Time (s) | Class 1 | Class 2 | Class 3 | Class 4 |
| MFOA_ELM | 40.0672 | 100.00% | 99.35% | 96.12% | 99.56% |
| FOA_ELM | 89.5534 | 98.54% | 90.65% | 58.33% | 76.74% |
| PSO_ELM | 0.8036 | 98.67% | 96.12% | 98.52% | 90.43% |

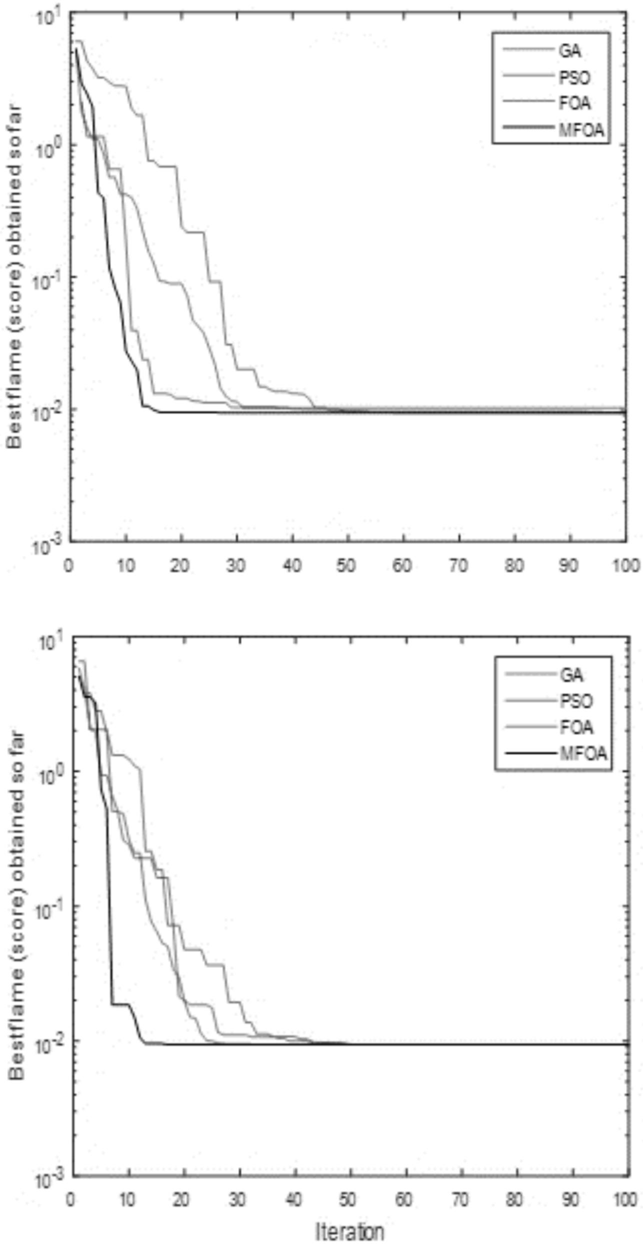


Fig. 5. Comparison of convergence rates: up–first time, bottom–second time

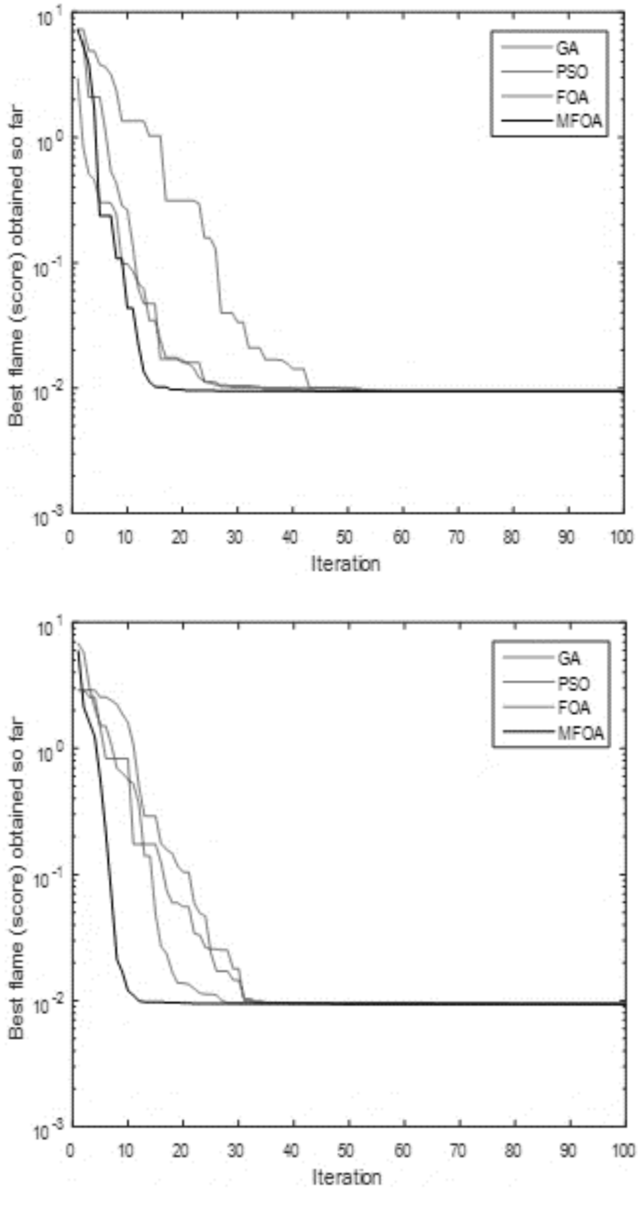


Fig. 6. Comparison of convergence rates: up–third time, bottom–fourth time

## 6. Conclusion

In consideration of the disadvantages of a traditional water quality prediction and evaluation model such as low prediction accuracy and poor adaptability, an ELM optimized by a MFOA was proposed to establish a water quality evaluation model. Through the comparison of 3 water quality evaluation and prediction methods, namely, MFOA-ELM, FOA-ELM and PSO-ELM, it is found that the prediction accuracy of MFOA-ELM reaches up to 98.36 %, which is higher than those of PSO-ELM and FOA-ELM. Thus, this indicates that water quality evaluation and prediction with the MFOA-ELM is higher in accuracy and adaptability, thus verifying the validity and reliability of MFOA-ELM. Meanwhile, compared with other algorithms, MFOA-ELM has a higher convergence rate and a better effect.

Table 4. Water quality class prediction results of ELMs optimized by MFOA, FOA and PSO

| Method | Class | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| MFOA-ELM | 1 | 100.00% | 0.00% | 0.00% | 0.00% |
| | 2 | 0.65% | 99.35% | 0.00% | 0.00% |
| | 3 | 0.00% | 3.00% | 95.00% | 2.00% |
| | 4 | 0.00% | 0.00% | 0.65% | 99.35% |
| FOA-ELM | 1 | 98.65% | 1.35% | 0.00% | 0.00% |
| | 3 | 0.00% | 0.67% | 24.00% | 75.33% |
| | 3 | 0.00% | 3.00% | 95.00% | 2.00% |
| | 4 | 0.00% | 0.67% | 58.00% | 41.33% |
| PSO-ELM | 1 | 98.67% | 0.00% | 1.33% | 0.00% |
| | 2 | 0.00% | 96.00% | 3.67% | 0.33% |
| | 3 | 0.00% | 2.00% | 96.67% | 1.33% |
| | 4 | 0.00% | 1.00% | 8.33% | 90.67% |

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