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Soft Measurement of Effluent Ammonia Nitrogen Based on IABC-MFFNN

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ABSTRACT

In wastewater treatment processes (WWTPs), it is difficult to accurately measure effluent ammonia nitrogen. a soft measurement method of effluent ammonia nitrogen is proposed based on improved artificial bee colony of multi-feedback fuzzy neural network (IABC-MFFNN). Firstly, multiple feedback links are added to the fuzzy neural network (FNN). Due to existence of internal feedback and external feedback, the system can perform self-adaptive adjustments based on previous status information and output signals, which can fully reflect the dynamic information. Secondly, an improved artificial bee colony (IABC) is proposed as the parameter optimization method of the network. The multi-strategy selection mechanism was used to design different search strategies for each subgroup, and the double index dynamic subgroup mechanism was used to adjust the number of food sources for each ordinary subgroup, which improved the accuracy of the soft measurement method. Simulation experiment results show that the proposed method has higher prediction accuracy compared with other methods.

KEYWORDS

Effluent Ammonia Nitrogen; ABC; FNN; Multiple Feedback

1. INTRODUCTION

The effluent ammonia nitrogen is one of the important indexes to measure effluent quality in WWTPs. The excessive ammonia nitrogen in water is harmful to humans and aquatic organisms [1]. Therefore, the accurate detection of effluent ammonia nitrogen is of great significance. The reaction mechanism of WWTPs is complex, and it is difficult to establish an accurate prediction method. At present, the detection technology of ammonia nitrogen is mainly chemical detection technology, which is simple to operate. However, the detection instrument is expensive and collection of data takes a long time, which makes it difficult to achieve accurate detection of ammonia nitrogen [2]. Data-driven soft measurement methods can predict quickly in real time and overcome the shortcomings of chemical detection technology [3]. In recent years, data-driven methods based on neural networks have become a research hotspot in online prediction of ammonia nitrogen [4].

The soft measurement method of effluent ammonia nitrogen based on Error back propagation (BP) neural network is proposed [5], but the convergence speed of BP neural network is slow, it is easy to fall into local minimum, and the prediction accuracy is low. Qiao et al. [6] used radial basis function (RBF) network to predict effluent ammonia nitrogen, and the results showed that the method had a small prediction error. However, neural networks have black box characteristics, the internal parameters have no physical meaning, and it is difficult to find the relationship between the parameters and the output vector. FNN has clear physical meaning, which overcomes the shortcomings of neural network by combining the self-learning ability of neural network and the interpretability of fuzzy system [7]. A soft measurement method of effluent ammonia nitrogen based on adaptive second-order algorithm of FNN is proposed [8], which solved the problem that effluent ammonia nitrogen was difficult to measure in real time, but the model accuracy was poor. Based on this, the modeling error probability density function (PDF) is introduced, and a FNN based on adaptive gradient descent (GD) algorithm is designed and applied to the soft measurement of effluent ammonia nitrogen[9], which improves the accuracy of effluent ammonia nitrogen prediction. Although the above methods have achieved ideal prediction accuracy, the dynamic characteristics of the traditional feedforward network are poor due to the influence of uncertain factors in wastewater treatment and the non-stationary and dynamic time-varying environment. Therefore, it is necessary to improve the dynamic characteristics of soft measurement methods to ensure stability and reliability. Literature [10] proposed a soft measurement method based on recurrent RBF neural network to predict ammonia nitrogen, and the output layer information was fed back to the hidden layer. Compared with the soft measurement method established by RBF neural network, the performance of the neural network with feedback was improved, but its generalization ability was poor. Fei et al. [11] proposed a fuzzy double hidden layer recurrent neural network, which combined FNN and RBF neural network to improve the accuracy of nonlinear approximation, and added outer layer feedback to improve dynamic approximation capabilities. However, due to its structure is complex and the network convergence speed is slow. Therefore, it is worth exploring how to detect effluent ammonia nitrogen with high efficiency, real time and high precision.

Based on the above research, a soft measurement method of effluent ammonia nitrogen based on IABC-MFFNN is proposed. Compared with traditional neural network, the proposed neural network has a double feedback structure, which combines the output value of current time and the output value of previous time neurons, so that output of the system is smoother, dynamic characteristics and stability of the system are improved. The improved ABC algorithm is used to adjust network parameters. Through population division, multi-strategy selection and double index dynamic subgroup mechanism, different ordinary subgroups compete to produce offspring according to their indexes, and dynamically adjust the population number of each ordinary subgroup to improve the prediction accuracy of the network.

2. SOFT MEASUREMENT OF EFFLUENT AMMONIA NITROGEN BASED ON IABC-MFFNN

2.1. Overall Framework

The soft measurement method of effluent ammonia nitrogen mainly includes: auxiliary variable selection and soft measurement method establishment. The overall framework is shown in Figure 1. Based on the mechanism model analysis of wastewater treatment process, 12 auxiliary variables closely related to ammonia nitrogen were selected. Due to the measurement accuracy of instruments, human operation and other reasons, there are often abnormal data, which needs to be pre-processed [6]. The purpose is to improve the accuracy of the model, including eliminating outliers and normalization. After data preprocessing, there are still serious correlations and influences among auxiliary variables, which requires dimensionality reduction. In this paper, principal component analysis (PCA) [12] was adopted to eliminate the correlation between variables, and five auxiliary variables were finally determined: influent temperature T, aerobic terminal dissolved oxygen DO, aerobic terminal total solid suspended matter TSS, effluent pH and effluent redox potential ORP.

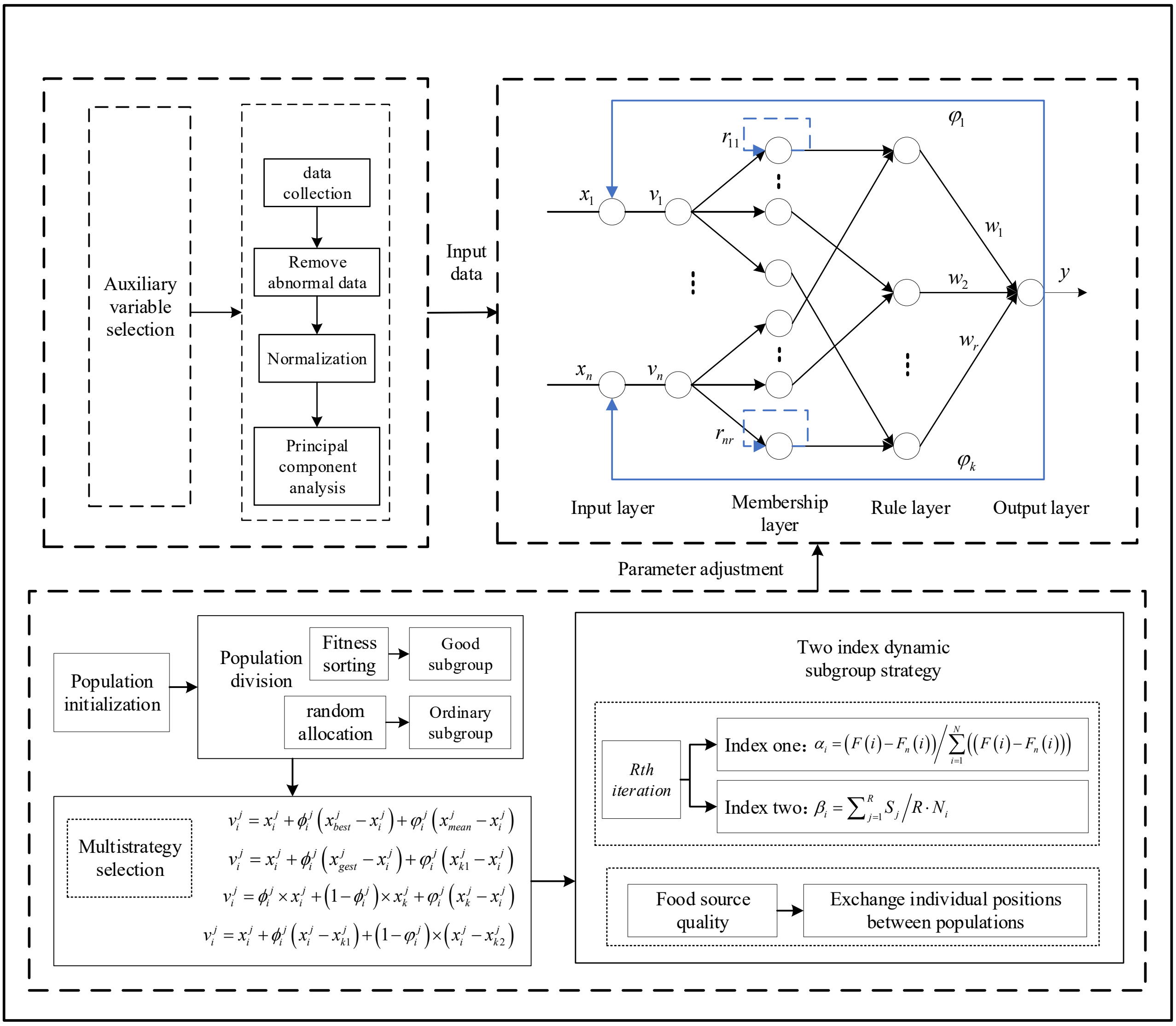

Figure 1 Overall block diagram

2.2. The establishment of soft measurement method

2.2.1. Multi-feedback FNN

Although feedforward neural network has the characteristics of simple structure and wide application range, its dynamic characteristics are poor and its stability is insufficient [13]. In view of its shortcomings, this paper proposes an internal and external double feedback structure. The double feedback combines the output value of current time and the previous time neuron, which improves stability of the system and further improves its approximation ability. The existence of internal feedback and external feedback can make the system self-adjust by combining the previous state information and output signal, making output of the system smoother and preventing sudden changes.

The structure of multi-feedback FNN is shown in Figure 2, which is divided into input layer, membership layer, rule layer and output layer[14][15].

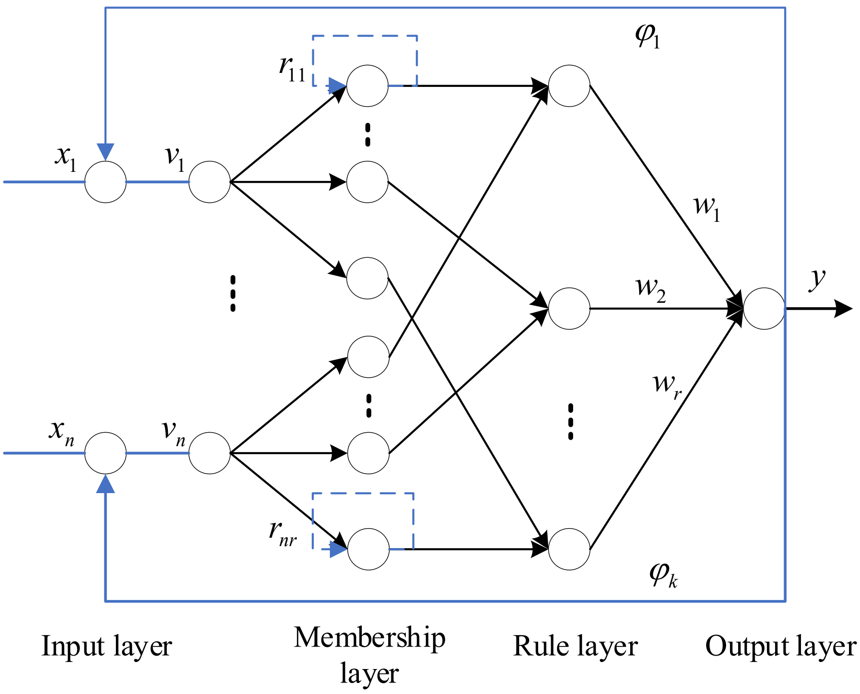

Figure 2 Multi-feedback FNN

The first layer is the input layer, which is also divided into two layers: the first and the second input layer. The first input layer is the input part of the whole neural network, which is output by combining with the feedback weight. The second input layer each neuron represents an input variable, the output of this layer is equal to the input, and there are n neurons, expressed as:

$$x(t)=\left[x_1(t),x_2(t),\cdots,x_n(t)\right]^T \tag{1}$$

$$v_i(t)=x_i(t)\cdot\varphi_{ri}\cdot y(t-1) \tag{2}$$

Where v_i is the output value of the ith node of the first input layer, y is the output value of the neural network in the last iteration process, and φ_{ri} is the external feedback weight. Because the second input layer only performs transmission and no other processing, the output of this input layer does not change [19].

The second layer is the membership layer, each input neuron has k membership functions, a total of n×k neurons. In this layer, Gaussian functions are usually chosen to achieve fuzzy operations, which enhances the ability of neural networks to deal with nonlinearities, expressed as:

$$\mu_{ij}(t)=\exp\left(-\left(v_i+r_{ij}\cdot\mu_{ij}(t-1)-c_{ij}\right)^2/\sigma_{ij}{}^2\right) \tag{3}$$

Where c_{ij} and σ_{ij} are the center and width of the membership function respectively; μ_{ij} is its corresponding output; r_{ij} is the internal feedback weight; $\mu_{ij}(t-1)$ is the output of membership level in the last iteration.

The third layer is the regular layer with k neurons. Each neuron represents the rule precursor, and the neuron outputs the excitation intensity of its corresponding rule [20], expressed as:

$$\phi_j(t)=\prod_{i=1}^{n}\mu_{ij}=\exp\left(-\sum_{i=1}^{n}\left(v_i+r_{ij}\cdot ex\mu_{ij}-c_{ij}\right)^2/\sigma_{ij}{}^2\right) \tag{4}$$

$$h_j(t) = \phi_j(t) \Big/ \sum_{j=1}^{k} \phi_j(t) \tag{5}$$

Where ϕ_j and h_j are the output of the jth neuron and the normalized output, respectively.

The fourth layer is the output layer with only one neuron.

$$y(t) = \sum_{j=1}^{k} w_j(t)\, h_j(t) \tag{6}$$

Where y is neuron output; w_j is the connection weight between the rule layer and the output layer, and is also the post output of the jth rule.

2.2.2. MFFNN network parameter optimization based on IABC

It is difficult to determine the center, width and connection weight of hidden layer in FNN, which leads to low prediction accuracy. Therefore, ABC algorithm is used to find the optimal parameters and assign them to MFFNN, which further improves the prediction accuracy of effluent ammonia nitrogen. The basic ABC algorithm has defects such as poor development ability and imbalance between exploration and development[16][17]. An improved ABC algorithm is proposed to optimize the network parameters, and the balance between exploration and development is achieved through population division, multi-strategy selection and double index dynamic subgroup strategy.

The principle of using the IABC algorithm to optimize parameters in the MFFNN structure: the main parameters to be learned are mapped to the targets of particles in the IABC algorithm. Among them, the main parameters include base function center, connection weight, node width, feedback weight. The optimal solution of the parameter is found by using the excellent optimization ability of the artificial bee colony algorithm, and finally returned to the MFFNN structure. In the process of optimization, the one with the smallest root-mean-square error is taken as the fitness function, and the weight is optimized when it is the smallest [3].

2.2.2.1. Population division

The population was divided into good subgroup X1, ordinary subgroup X2, ordinary subgroup X3, and ordinary subgroup X4 by using ranking method and random grouping strategy. First, the individuals of the population were sorted according to the fitness value, and the top 25% individuals were selected to form the good subgroup X1, and then the remaining individuals were randomly divided into three subgroups according to the random grouping strategy.

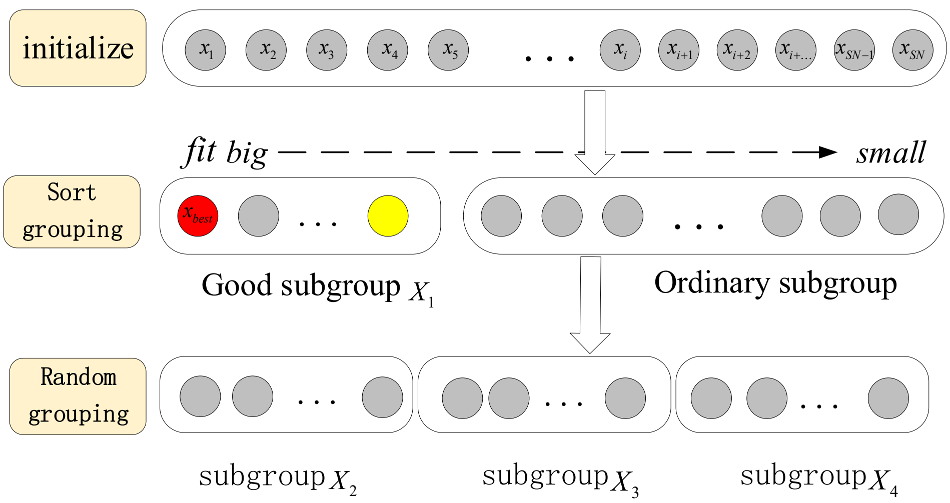

Figure 3 Population division

2.2.2.2. Multi-strategy selection

In view of different characteristics of each subgroup, this paper designs search strategies with different search capabilities for individuals of different subgroups [18].

In view of the characteristic that individuals pay attention to development in good subgroup X1, the search equation (7) is designed to make the search scope concentrate around excellent individuals. In order to prevent falling into local optimum, the average value of the good subgroup is added as the perturbation individual in the search, which provides a certain diversity.

$$v_{ij} = x_{ij} + \phi_{ij}\left(x_{best,j} - x_{ij}\right) + \varphi_{ij}\left(x_{mean,j} - x_{ij}\right) \tag{7}$$

Where $x_{best,j}$ represents the jth dimension of the best food source obtained in the population so far; $x_{mean,j}$ is the average of the jth dimension corresponding to all food source in the good subgroup; ϕ_{ij} is a uniform random number generated between [0,1]; φ_{ij} is a uniform random number generated between [-1,1].

In the ordinary subgroup, search strategy was designed to take into account both exploration and exploitation, which showed different emphasis among the subgroups. Equation (8)-(10) is used for subgroups X2, X3, and X4, respectively. In the whole search process, the solution search strategies coexist in the three subgroups and compete to produce offspring.

$$v_{ij} = x_{ij} + \phi_{ij}\left(x_{gest,j} - x_{ij}\right) + \varphi_{ij}\left(x_{k_1,j} - x_{ij}\right) \tag{8}$$

$$v_{ij} = \phi_{ij} \times x_{ij} + \left(1 - \phi_{ij}\right) \times x_{kj} + \varphi_{ij}\left(x_{kj} - x_{ij}\right) \tag{9}$$

$$v_{ij} = x_{ij} + \phi_{ij}\left(x_{ij} - x_{k_1,j}\right) + \left(1 - \varphi_{ij}\right) \times \left(x_{ij} - x_{k_2,j}\right) \tag{10}$$

2.2.2.3. Double index dynamic subgroup strategy

In order to better play the performance of each subgroup search strategy, the double index dynamic subgroup strategy is used to make the ordinary subgroup compete to generate offspring. The number of individuals in each subgroup is not fixed during the search process, but changes dynamically. Every R generation, the number of individuals in three ordinary subgroups is adaptively allocated. This strategy allows information from each subgroup to communicate with each other, thus improving the ability to jump out of local optimal solutions, with greater flexibility than traditional fixed population numbers. The recombination process of subgroups is shown in Figure 4.

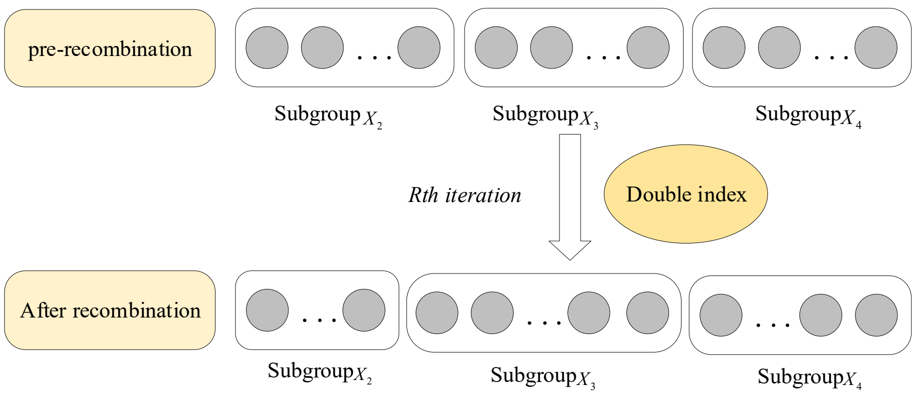

Figure 4 Recombination among ordinary subgroups

Using various key information in the process of population evolution, two indexes are set to reorganize different subgroups. One of them is the change in the fitness value of two adjacent iterations after each particle iteration is successful, and second is the success rate of the current iteration. The greater the change of the fitness value of the two iterations of the particles in the subgroup. It indicates that the search strategy potential in the subgroup is greater. The higher the success rate of the subgroup. It also indicates that the search strategy in the subgroup is better. After R generation, the grouping rate and the number of redistributed populations are calculated. The two indexes α and β of competition mechanism construction are set as follows:

$$\alpha_i = \frac{\left(F(i) - F_n(i)\right)}{\sum_{i=1}^{N}\left(\left(F(i) - F_n(i)\right)\right)} \tag{11}$$

$$\beta_i = \sum\nolimits_{j=1}^{R} S_j \Big/ R \cdot N_i \tag{12}$$

$$p_i = \lambda_1 \beta + \lambda_2 \sum_{k=1}^{N} \alpha_k \tag{13}$$

$$N_i = 75\% \times SN \times p_i \Big/ \sum_{i=1}^{n} p_i \tag{14}$$

Where N_i is the number of populations in the ordinary subgroup X_i; p_i is the next grouping rate of the ordinary subgroup X_i; S is the number of new food sources superior to the original food sources generated in the ordinary subgroup X_i in each iteration; SN is the total population.

During the search period of the algorithm, the number of populations in the good subgroup remained unchanged. In order to enhance the information exchange between good subgroup and ordinary subgroup, and strengthen the guiding role of the ordinary subgroup. After each iteration, the quality of the food source in the four subgroups is compared, If the better individuals in ordinary subgroup are of better quality than the poorer individuals in excellent subgroup, then the two individuals swap subgroups

3. SIMULATION EXPERIMENT

The experimental data came from the sample data collected from a wastewater treatment plant in Beijing. 290 sets of data were obtained after manually removing abnormal data. 200 sets of data were selected as neural network training samples, and 90 sets of data were selected as neural network test samples. In order to verify the performance of ABC-MFFNN in predicting effluent ammonia nitrogen, the performance of BP neural network [5], RBF neural network [6] and FNN [8] were compared under the same simulation experimental conditions. Gradient descent algorithm is used to adjust the parameters of the three compared neural networks. The initial parameters of the neural network are set as follows: the number of hidden nodes m=15, the learning rate η = 0.08, and the maximum number of training steps is 500.

Figure 5 and Figure 6 show the simulation figures of the training and testing of the effluent ammonia nitrogen soft measurement method based on ABC-MFFNN, BP neural network, RBF neural network and FNN, respectively, and show the system error curves under different algorithms.

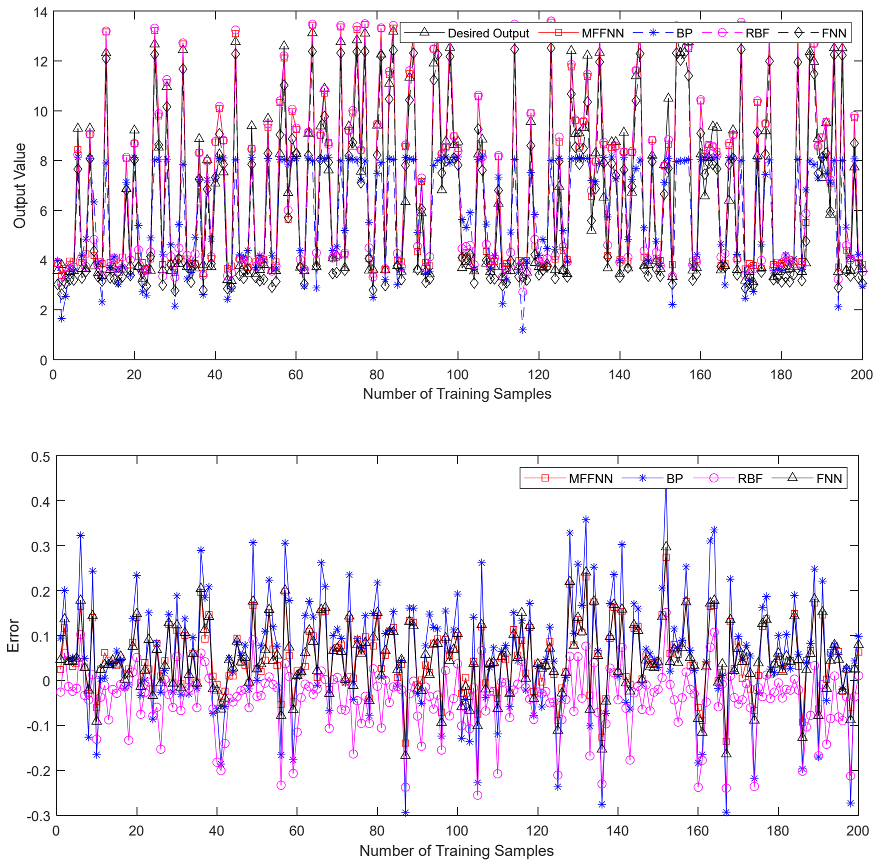

Figure 5 Training results and errors

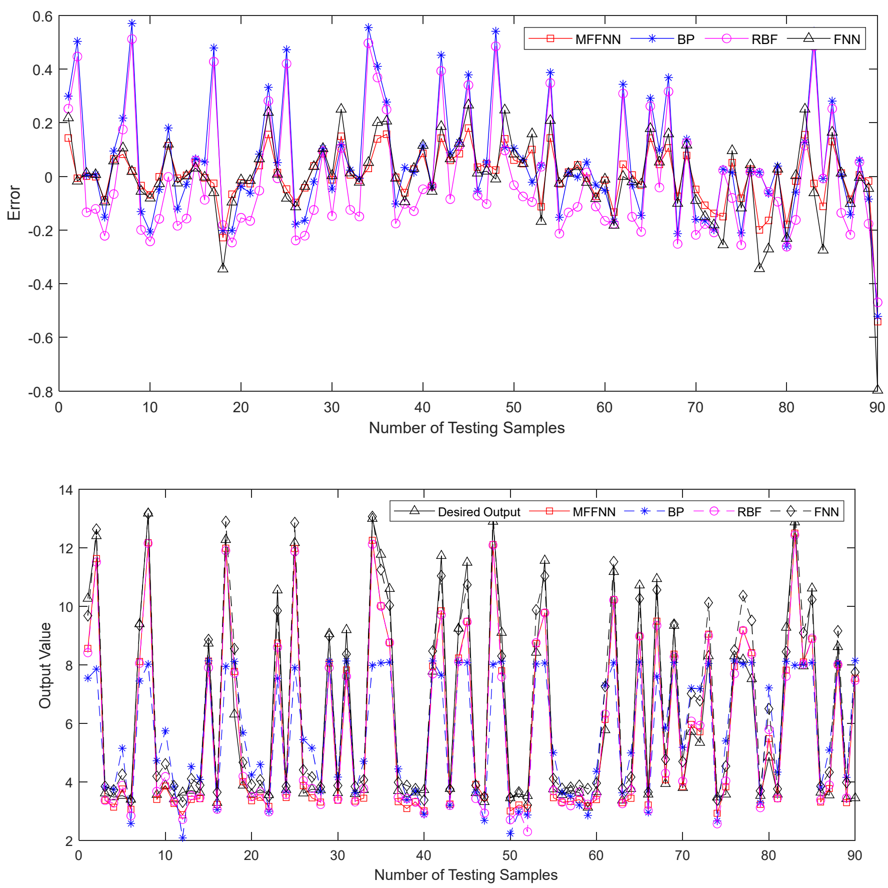

Figure 6 Test results and errors

It can be seen from the simulation curves in Figure 5 and Figure 6 that the prediction curve of the proposed method can track the expected output value well. The prediction effect of ABC-MFFNN for effluent ammonia nitrogen is significantly better than the other three neural networks, and BP neural network has the worst effect. Compared with other neural networks, ABC-MFFNN has better prediction accuracy for effluent ammonia nitrogen, with small error fluctuation range and relatively stable fluctuation.

Table 1 MAD with RMSE under 4 different algorithms

Algorithms	Training RMSE	Testing RMSE	Training MAD	Testing MAD
MFFNN	0.0562	0.0735	0.0423	0.0535
BP	0.2413	0.3865	0.2363	0.2863
RBF	0.1685	0.1754	0.1835	0.2093
FNN	0.1542	0.1845	0.1661	0.1935

Table 1 shows the mean absolute error and root-mean-square error under four different methods. Where, MAD is the average of the absolute deviation between all single predicted values and the arithmetic mean value, which can avoid the problem of errors canceling each other and accurately reflect the actual prediction error size. RMSE is very sensitive to large or small errors in a set of measurements and can reflect the precision of the measurement well.

Analyzing the experimental data of performance indicators under four different algorithms in Table 1, it can be seen that the soft measurement method of ammonia nitrogen in wastewater treatment based on ABC-MFFNN has the smallest MAD and RMSE, with MAD are 0.0423 and 0.0635, RMSE are 0.0562 and 0.0735, respectively. RBF neural network and FNN have higher MAD and RMSE than BP neural network. The MAD of BP neural network training samples was more than quintuple that of ABC-MFFNN, and the RMSE is more than quadruple that of ABC-MFFNN. In the test sample, the MAD and RMSE of ABC-MFFNN are obviously the smallest, and the BP neural network is the largest. This shows that ABC-MFFNN has smaller measurement error and higher precision, while BP neural network has larger measurement error and lower precision.

4. CONCLUSION

In order to solve the problem that effluent ammonia nitrogen is difficult to measure accurately, a soft measurement method of effluent ammonia nitrogen based on IABC-MFFNN is proposed. The multi-feedback link introduced in FNN can make the system adjust adaptively, improve the dynamic characteristics of the system, and increase the stability of the system. The improved ABC algorithm is used to optimize the network parameters and ensure the prediction accuracy of the network. The effectiveness and practicability of the proposed algorithm are verified by the effluent ammonia nitrogen simulation experiment. Simulation results show that ABC-MFFNN has higher prediction accuracy and generalization performance than other neural networks. Since the structure of ABC-MFFNN has a great impact on the generalization performance of the network, the adaptive structure adjustment method will be adopted in the subsequent study to further improve the network performance.

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