Intelligent control system for flocculation of water supply

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Abstract. Flocculation which affects the quality of water supply is the main step of water treatment. The most commonly used control method for flocculation is the streaming current detection-based control method using a single-loop feedback. However, the traditional control system cannot adapt to the change of raw water's quality, the set value of streaming current can only be adjusted manually. In order to solve this problem, an intelligent control system for flocculation of water supply is designed based on the neural network and fuzzy control to adjust the set value of streaming current and tune the control parameters automatically in this study. The experimental results show that the proposed intelligent control system can control the flocculant dosage accurately. It is of great significance to improve the quality of water supply and reduce the cost of water treatment.

1. Introduction

The water treatment system is always providing the precious water for human life. The conventional treatment process of surface water includes four basic steps which is flocculation, sedimentation, filtration, and disinfection. Flocculation is the first step of the whole water treatment process, and the flocculation effect affects the subsequent process. The purpose of flocculation is to remove the gel with strong stability [1]. And the dosage of the flocculant affects the effect of water treatment. If the dosage of flocculant is not enough, the turbidity of raw water will not decrease sufficiently which will increase the difficulty of subsequent processes. On the contrary, if the dosage is too much, the gel will be stable again which also cannot reach the purpose of flocculation. Hence, if the dosage of flocculant can be controlled automatically, it is of great significance to reduce the cost of water treatment.

Among the existing automatic control methods for flocculation dosing, the Streaming Current Detection (SCD) based control method is the most widely used one [2]. The Streaming Current (SC) is an important parameter to characterize the surface charge of gel in water, which relatively reflects the stability of gel. The traditional SCD-based control system is a single-loop feedback control that uses a SC detector to measure and fed back the SC signal to Proportional-Integral-Derivative (PID) controller [3]. The measured SC value is compared with the set value and the deviation marked as e is used to control the dosage of flocculant through the PID controller.

However, the single-loop feedback system is only suitable for the applications where the water source is constant, the water quality is stable, and the change of flow is small. If the characteristics of the controlled raw water change, the parameters of the traditional SCD-based controller need to be adjusted manually. If the flow of raw water changes greatly, it will cause the system to oscillate and affect the control of the dosage [4]. Because the dosage is approximated proportional to the flow of raw water when other conditions are stable [5], the Flow-Proportional-Feedforward-Controller (FPFC) using a flow meter to detect and fed back the flow change of raw water is introduced to deal with this
problem. Experimental results show that the FPF C can increase the adaptability of instantaneous changes of raw water flow [6].

In theory, using the above integrated control method can control the dosage of flocculant effectively. However, the main factors affecting the flocculation process are flow, temperature and turbidity of raw water [7], and the effluent turbidity which is generally used as an indicator to judge whether the flocculant dosage has reached the optimal dose in production [8] is the basis of set value of SC. When the effluent turbidity reaches the expected value, the detected value of SC at this time is used as the set value which remains essentially unchanged after being debugged. However, the content of organic matter in raw water and the unstable flocculation time affect the detected value of SC. In order to solve the influence abovementioned, it need long time to track and analyze the statistics of different water quality to find a suitable set value of SC manually. However, the adjustment time of the system is too long which reduces the control effect seriously [9]. Therefore, an intelligent control system for flocculation is designed in this study, the fuzzy control is introduced to self-tune the parameters of PID controller, the neural network control is added to predict the set value of SC.

2. Design of intelligent control system for flocculation

The main strategy of the proposed intelligent control system for flocculation of water supply is using the temperature, turbidity, and flow of raw water to adjust the set value of SC through Back-Propagation-Neural-Network (BPNN), and using the fuzzy controller to tune the parameters of PID controller automatically according to the deviation and deviation change rate of SC as shown in Fig. 1. The BPNN controller is used to calculate the set value of SC according to the raw water, the SCD controller is used to control the dosage of flocculant through a PID controller. The design of BPNN controller and SCD controller are introduced in section 2.1 and 2.2.

2.1. Design of BPNN controller

BPNN is a forward-transfer neural network, but its learning algorithm is reverse propagation. The activation function of the hidden layer uses the sigmoid function, but the function of the input and output layer is linear. The BPNN is trained according to the training samples, the weights and bias are extracted to establish a model for the set value of SC.

As shown in Fig.1, a 3-layer BPNN is used in this study, the flow, temperature, and turbidity of raw water are selected as the input of the neural network, the set value of SC is the output. The training samples are collected by a water treatment plant for many years. In order to speed up the convergence, the data needs to be normalized to [0, 1] using the following formula,
where, \( x \) and \( Y \) are the training samples before and after normalization; \( x_{\text{min}} \) and \( x_{\text{max}} \) are the minimum and maximum values in the training samples.

The training parameters of the BPNN are that the training period is 5000 epochs, and the goal of reducing the error is set to \( 10^{-6} \). After training, the weights and bias can be extracted to establish a model for the set value of SC. Because the transfer function of the input layer of the BPNN is linear, the output \( Y_i \) of the input layer can be calculated as
\[
Y_i = X_i, \quad X_i = \sum_{j=1}^{8} \omega_{ji} Y_j + b_j
\]
where, \( \omega_{ji} \) and \( b_j \) are the weights and bias from input layer to hidden layer, respectively.

Considering the transfer function of the output layer neurons is linear, the input and output of the output neurons can be calculated as
\[
X_k = \sum_{j=1}^{8} Y_j \omega_{kj} + b_k, \quad Y_k = X_k
\]
where: \( X_k \) is the input summation of all output layer neurons, \( \omega_{kj} \) is the weight matrix from hidden layer to output layer, \( b_k \) is the bias from hidden layer to output layer.

According to Eqs. (2 and 3), the output of the trained BPNN can be calculated as,
\[
I_{sc} = \sum_{j=1}^{8} \frac{1}{1 + e^{-\sum_{i=1}^{3} \omega_{ji} Y_i + b_j}} \omega_{kj} + b_k
\]

The weights and bias of the trained BPNN can be extracted from the Matlab as,
\[
\omega_j = \begin{bmatrix} \omega_{01} & \omega_{02} & \omega_{03} \\ \omega_{11} & \omega_{12} & \omega_{13} \\ \vdots & \vdots & \vdots \\ \omega_{31} & \omega_{32} & \omega_{33} \end{bmatrix}, \quad b_j = \begin{bmatrix} b_{00} & b_{01} & \cdots & b_{07} \\ b_{10} & b_{11} & \cdots & b_{17} \\ b_{20} & b_{21} & \cdots & b_{27} \\ b_{30} & b_{31} & \cdots & b_{37} \end{bmatrix}^T
\]

Using Eqs. (4 and 5), the set value of SC can be calculated automatically according to the measured flow, temperature, and turbidity of raw water. It should be noted that the weights and bias in Eq. 5 are not constant, it will change as the training samples increase. Therefore, the weights and bias in the BPNN controller should be automatically updated according to the training results.

2.2. Design of SCD controller.

As shown in Fig. 1, the SCD controller includes a PID controller and a fuzzy controller. The PID controller is used to control the flocculant dosage through metering pumps. For traditional PID controller, the parameters are usually tuned manually which has poor flexibility due to the parameters are not changed once they are set. However, these parameters can only meet the control conditions of the system at that time. Once the parameters of raw water change, it will affect the control accuracy of the system. In order to solve this problem, the fuzzy controller is introduced to self-tune the parameters of PID controller automatically. The design steps of fuzzy SCD controller are as follows,

1) Determination of the input and output variables of the fuzzy controller. The system uses a two-dimensional fuzzy controller, the deviation (e) of SC and deviation change rate (ce) are selected as the
input variables of the SCD controller, and the output variables are proportional coefficient $K_p$, integral coefficient $K_i$, and differential coefficient $K_d$ of the PID controller.

(2) Determination of the fuzzy domain. The fuzzy domain of $e$, $ec$, $K_p$, $K_i$, and $K_d$ are set to [-2, 2]. The input and output variables use the same fuzzy set, and its expression is as follows,

$$T(e) = T(ec) = T(u) = \{NB, NS, ZO, PS, PB\}$$

(6)

where, $T$ is the fuzzy set of variables, $NB$ means maximum negative, $NS$ means minimum negative, $ZO$ means zero, $PS$ means minimum positive, and $PB$ means maximum positive.

(3) Definition of fuzzy subsets in quantitative domain of each variable. The number of fuzzy subsets, the linguistic variables of each fuzzy subset, and the membership function of each linguistic variable should be determined according to the fuzzy control theory. Considering that there may be random measurement noise in the input variable, the triangle function is chosen as the membership function as shown in Fig. 2. The apex of the isosceles triangle corresponds to the mean of the random number, the length of the base is equal to $2\sigma$, and $\sigma$ represents the standard deviation of the random data.

(4) Definition of the fuzzy control table as shown in Table 1. Using the fuzzy control table, the output of $\Delta K_p$, $\Delta K_i$, and $\Delta K_d$ can be calculated according to the deviation $e$ of SC and deviation change rate $ec$.

![Fig. 2 The membership function of fuzzy controller.](image)

Table 1. Fuzzy control table.

| $\Delta K_p$ | $\Delta K_i$ | $\Delta K_d$ |
|--------------|--------------|--------------|
| $\Delta K_p$ | $\Delta K_i$ | $\Delta K_d$ |
| NB, PS, PB   | NB, NS, ZO   | NB, PS, PB   |
| NB, NS, ZO   | NB, PS, PB   | NB, NS, ZO   |
| NB, PS, PB   | NB, NS, ZO   | NB, PS, PB   |
| NB, NS, ZO   | NB, PS, PB   | NB, NS, ZO   |
| NB, PS, PB   | NB, NS, ZO   | NB, PS, PB   |

(5) Parameters tuning rules. If the deviation $|e|$ is large, the effect of integral is more serious which should be limited to $K_i=0$, the proportional coefficient $K_p$ should be larger but the differential coefficient $K_d$ should be smaller, which can make the system have better tracking performance. If the deviation $|e|$ is small, the proportional coefficient $K_p$ and the integral coefficient $K_i$ should be larger, which can make the system have better static performance. If the values of deviation $|e|$ and deviation change rate $|ec|$ are medium, the proportional coefficient $K_p$ and the differential coefficient $K_d$ should be smaller, which can make the system has a reasonable response speed and small overshoot. When the deviation change rate of $|ec|$ is larger, $K_d$ should be smaller, and vice versa. According to the parameters tuning rules, the proportional coefficient $K_p$, the integral coefficient $K_i$, and the differential coefficient $K_d$ of the PID controller can be tuned through the fuzzy controller, and the control signal of the PID controller can be calculated by the following formula,

$$\Delta u(k) = K_p[e(k) - e(k - 1)] + K_i[e(k) + K_i[e(k) - 2e(k - 1) + e(k - 2)]$$

(7)
where, $e$ and $u$ are the deviation and output signal.

Using the abovementioned fuzzy controller, the parameters of PID controller can be self-tuned, and the flocculant dosage can be controlled automatically. In order to realize the intelligent control of the flocculant dosage, an automatic control software should be designed according to the BPNN controller and the fuzzy SCD controller.

2.3. Design of control software

The software of the proposed intelligent control system includes a detection module and a control module. The detection module collects the flow, temperature, turbidity of the raw water, and the SC after flocculation in real time through sensors. The detected data are transferred to the PLC through A/D conversion to control the flocculant dosage. The PLC communicates with the host computer through its communication module and transfer the measured data to the host computer to calculates the set value of SC, the calculated result is transferred to PLC to control the dosage of flocculant through the metering pump. Figure 3 shows the flow chart of intelligent control system for flocculation of water supply.

![Fig. 3 Flow chart of the intelligent control system.](image)

In order to realize the intelligent control of the dosage for flocculation of water supply, the configuration software is used in this study to create an automatic monitoring system through secondary development. The host computer realizes the training of BPNN, and extracts the weights and bias of the trained network to the PLC controller. According to the weights and bias obtained by the BPNN, the set value of the streaming current is obtained. The set value of SC is compared with the feedback value measured by the SC detector, the deviation $e$ is converted into an electric signal and transmitted to the metering pump to adjust the dosage of flocculant.

3. Experimental validation

As shown in Fig. 4, the flocculation experiment was carried out in two parallel water treatment pools using the proposed intelligent control system and manual dosing control method, respectively. The control requirement of the effluent turbidity should reach below 3 NTU.

The experimental setup is as follows, a flow meter, a temperature sensor, and a turbidity meter are installed at the inlet pipe to measure the flow, temperature, and turbidity of the raw water. A streaming current detector is installed between the tubular static mixer and the flocculation tank to measure the SC after flocculation and as the feedback to control the flocculant dosage. A PLC controller is used to control the flocculant dosage as shown in Fig. 4. The experiment process is as follows, the dosage of flocculant is applied to the two water treatment pools through the intelligent control system and manual, respectively. The water quality parameters and dosage of flocculant are collected and recorded. The experiment period is two weeks, and the difference between the manual dosage and the system dosage is compared to ensure that the proposed intelligent control system for flocculation can cope with various water quality. Fig. 5 shows the experimental results.
It can be seen from Fig. 5 that the flocculant dosage applied by the proposed intelligent control system and manual is almost the same. That is to say, the proposed intelligent control system for flocculation of water supply can realize the accurately control for flocculant dosage. It is of great significance to improve the quality of water supply and reduce the cost of water treatment.

4. Conclusions
An intelligent control system for flocculation of water supply is proposed based on the BPNN control and fuzzy control. The main strategy of the proposed intelligent control system for flocculation is using the temperature, turbidity, and flow of raw water to adjust the set value of SC through the BPNN controller, and using the fuzzy SCD controller to self-tuning the parameters of PID controller automatically. According to the experimental results, the following conclusions can be drawn.

(1) The BPNN controller can realize the automatic prediction of the set value of SC. The fuzzy SCD controller can self-tune the parameters of PID controller automatically.

(2) The experimental results show that the proposed intelligent control system can realize the accurately control for flocculant dosage. It is of great significance to improve the quality of water supply and reduce the cost of water treatment.

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