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Study on Modeling of Coagulant Dosage System in Water Purification Process

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Abstract: In order to make the coagulant dosage control performance better in water purification process, a mathematic model used for coagulant dosage control in water purification plant is established by the mathematical least square method. We have found the main factors influencing the turbidity water and coagulation thorns dosing quantity of the mathematical relationship and quantitative validate the quantitative, to establish the mathematical relationship in particular waterworks coagulant dosage automation mathematical model. The simulation results and the application results in the Xining No.8 water purification plant of the strategy used in the actual water purification plant verified its higher control accuracy. And also, it improved processing efficiency and the effluent quality, reduced the processing costs.

Key words: Water purification process, mathematical modeling, dosage control

INTRODUCTION

Coagulation process is a very important aspect of the traditional water purification process. The amount of accurate or not will directly affect water quality results. Water quality will not meet the safety standards when the coagulant dosing is insufficient; on the contrary, an excess of the coagulant dosage not only increase the process operation cost but also lead to high aluminum ion in the effluent water and affect human health (Wang *et al*., 2007). This work discusses the coagulant dosing control role combine with the fuzzy control theory in mathematical modeling techniques in achieving the water dosing control of the general situation and the particular circumstances reasonable control. That brings us a new way to achieve a fully automated water dosing control and ultimately to reduce the PAC consumption and the labor intensity, stable the water quality and improve the management efficiency.

Currently, coagulant dosage is determined mainly by experienced visual, beaker experiment, simulation filter and mathematical models (Zou *et al*., 2009). Beaker experiment and mathematical modeling method are the two most common methods at all. Wang *et al*. (2007) established the exponential mathematical models of the dosage by linear regression based identification. Zou *et al*. (2009) found the relationship between the dosage and the turbidity of the raw water by using the beaker experiments method. Zhao *et al*. (2007) successful use the neural network technology to establish a mathematical model of dosage.

At present, dosage control in the Xining No.8 water purification plant is in the semi-automatic control mode. The specific method is the operation workers went to the scene to collect the turbidities of the raw water and the effluent water which for coagulant dosage experiments in the laboratory. According to the relationship among the turbidity of raw water, the turbidity of the pending water and the dosage draw how much volume of the stroke and the dosing should be changed. Therefore, the actual dosage is closely related to the experience of the operation workers. It is randomness and more difficult to ensure the stability of the water quality. In order to control the coagulant dosing more accurately, reduce labor intensity and improve the stability of the water quality, a coagulant dosage mathematical model is established by in-depth analysis the dosing process, combined with the experience of the operating workers and large amounts of the actual production data. It achieved an automatic control of the coagulant dosing process and made the water quality more stable.

LEAST SQUARES METHOD BASED SYSTEM IDENTIFICATION

Least squares method (LSM): General expression for the least squares method is (Ding *et al*., 2007; Liu *et al*., 2006):

$$S = \sum_{i=1}^{n} r_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (1)$$

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where, S is the squared summation of the estimation error; n is the number of data points within the fitted zone; r_i is the residuals of the i-th data point; y_i is the ith observation point; $\hat{y}_i$ is the i-th fitted value.

The coefficients solution in matrix form of this method is:

$$\hat{y} = Xb \quad (2)$$

Where:

$$b = (X^T X)^{-1} X^t y \quad (3)$$

Partial weighted LSM: In partial weighted LSM method, only a part of the fitting points will be considered each time of the fitting process. Values of every fitted point is decided by the distribution points in its neighboring local fitting range and the number of the neighboring points is related with the fitting range setting. Different weighted coefficients (W_i) are given at the each fitting point and the weighted coefficient is equal 1 at the fitting point. The weighted coefficients of points both sides of the fitting point within the local fitting range are decreased to zero by certain rules. The weighted coefficients of the data points beyond the local fitting range are set to zero (Ding *et al*., 2007). Its algebraic expression is:

$$S = \sum_{i=1}^{n} W_i (y_i - \hat{y}_i)^2 \quad (4)$$

The coefficients solution in matrix form of this method is:

$$\hat{y} = Xb \quad (5)$$

Where:

$$b = (X^T W X)^{-1} X^t w y \quad (6)$$

The main difference between the partial weighted LSM and the least square method is the value of the fitting point calculated according to the different weighted coefficient at the different location of the data points and the weights of all data points is 1 in the calculation range of the least square method. Therefore, to some extent, the partial weighted LSM can reduce the impact of the singular point of the fitting results.

Matrix LSM: Let, the relationship of the ideal dosage and the raw water turbidity is:

$$Q = b_2 Z_d^2 + b_1 Z_d + b_0 \quad (7)$$

where, Q is the ideal dosage; Z_d is the raw water turbidity; b_2, b_1, b_0 are the coefficients to be determined.

Considering the certain error of the observation values, the above equation can be modified to:

$$Q = b_2 Z_d^2 + b_1 Z_d + b_0 + V \quad (8)$$

where, V is the certain error vector.

Equation 8 can be written in formula equations like:

$$\begin{cases} Q_1 = b_2 Z_{d_1}^2 + b_1 Z_{d_1} + b_0 + v_1 \\ Q_2 = b_2 Z_{d_2}^2 + b_1 Z_{d_2} + b_0 + v_2 \\ Q_3 = b_2 Z_{d_3}^2 + b_1 Z_{d_3} + b_0 + v_3 \\ \cdots \\ Q_n = b_2 Z_{d_n}^2 + b_1 Z_{d_n} + b_0 + v_n \end{cases} \quad (9)$$

Let:

$$A = \begin{bmatrix} Z_{d_1}^2 & Z_{d_1} & 1 \\ Z_{d_2}^2 & Z_{d_2} & 1 \\ Z_{d_3}^2 & Z_{d_3} & 1 \\ \vdots & \vdots & \vdots \\ Z_{d_n}^2 & Z_{d_n} & 1 \end{bmatrix} \quad (10)$$

$$B = \begin{bmatrix} b_2 & b_1 & b_0 \end{bmatrix}^T \quad (11)$$

$$Q = \begin{bmatrix} Q_1 & Q_2 & Q_3 & \cdots & Q_n \end{bmatrix}^T \quad (12)$$

$$V = \begin{bmatrix} v_1 & v_2 & v_3 & \cdots & v_n \end{bmatrix}^T \quad (13)$$

Then the Eq. 9 can be expressed in matrix style as:

$$Q = AB + V \quad (14)$$

Solving the matrix Eq. 11 by the least-squares method, the solution is:

$$B = (A^T A)^{-1} (A^T Q) \quad (15)$$

To verify the correctness of the established model, the deviation is calculated by Eq. 16:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} v_i^2}{n-1}} \quad (16)$$

where, σ is the standard deviation.

SIMULATION RESEARCH

Colleting the modeling data: The modeling data in this work were collected from the historical operating data of the Xining No.8 water purification plant in 12 months of the year 2012. After screening (Yang *et al*., 2008), more than 400 set qualified production process data were retained. Since, the state of raw water is stability, here, this work ignores the impact of pH and alkalinity in the process.

In order to reduce the workload of subsequent data processing and ensure the validity of the obtained data, it is necessary to make the following requirements in the data collection work for further effective screening of the data:

- Collecting data at two temperature ranges, namely: 5 centigrade <T =15 centigrade, 15 centigrade <T = 25 centigrade
- Collecting data when the alkalinity of the raw water is large than 80 mg L^{-1}, pH value between 7 and 8 and the turbidity of the effluent from the sedimentation tank is meet the requirements of the water quality
- The error interval of the collecting data is -0.5NTU~0.5NTU

Table 1 is a part of the actual operating data after further screening.

Modeling: In order to determine the nonlinear relationship between the dosage amount (Q) and the turbidity of the raw water (Z_d), when the squared summation of the difference (i.e. residual) between the calculated value of the mathematical model and the observed value is the smallest based Table 1, the optimal solution can be obtained by the least square method to fit two quadratic polynomial line.

Table 1: Actual operating data (after further screening)

Turbidity (raw water) (NTU)	Turbidity (effluent) (NTU)	pH	Alkalinity (mg L^{-1})	Dosage (mg m^{-3})
5.1	1.8	7.6	116	11.10
5.2	2.0	7.7	118	11.70
5.3	1.9	7.5	109	12.00
5.4	2.1	7.7	109	12.90
5.5	1.9	7.6	112	12.05
5.6	2.5	7.2	112	12.10
5.8	2.2	7.1	109	12.25
5.9	1.9	7.5	125	11.90
6.0	2.1	7.3	118	12.30
6.2	1.8	7.4	119	11.70
6.4	2.2	7.2	123	11.90
6.5	2.4	7.7	117	12.40
6.6	2.6	7.3	112	12.50
6.7	2.5	7.8	125	11.90
6.8	2.1	7.6	116	12.35
6.9	2.2	7.4	125	12.40
7.2	2.5	7.5	124	13.00
7.4	2.8	7.3	126	12.30
7.6	2.3	7.4	122	12.50

For example, the raw water temperature range is 5 centigrade~15 centigrade, using the least squares method to solve the relationship between the turbidity of raw water and the dosage based on the collected data in Table 1 (Liang *et al*., 2008; Li, 2008). The main data calculation process is as follows:

$$A = \begin{bmatrix} 5.1^2 & 5.1 & 1 \\ 5.2^2 & 5.2 & 1 \\ 5.3^2 & 5.3 & 1 \\ \vdots & \vdots & \vdots \\ 7.6^2 & 7.6 & 1 \end{bmatrix}$$

$$A^T A = \begin{bmatrix} 30865 & 4762 & 745 \\ 4762 & 745 & 118 \\ 745 & 118 & 19 \end{bmatrix}$$

$$(A^T A)^{-1} = \begin{bmatrix} 0.1965 & -2.4712 & 7,6585 \\ -2.4712 & 31.1705 & -96.8970 \\ 7,6585 & -96.8970 & 302.1823 \end{bmatrix}$$

$$Q = [11.1 \quad 11.7 \quad 12.0 \quad \cdots \quad 12.5]^T$$

$$A^T Q = \begin{bmatrix} 9102.1 \\ 1440.5 \\ 231.3 \end{bmatrix}$$

Coefficient matrix:

$$B = (A^T A)^{-1}(A^T Q) = \begin{bmatrix} -0.0477 \\ 0.8925 \\ 8.4941 \end{bmatrix}$$

The elements of the matrix B is the three coefficients of the second-order polynomial:

$$\begin{bmatrix} b_2 \\ b_1 \\ b_0 \end{bmatrix} = \begin{bmatrix} -0.0477 \\ 0.8925 \\ 8.4941 \end{bmatrix}$$

The second-order polynomial (Eq. 8) is determined as:

$$Q = -0.0477 Z_d^2 + 0.8925 Z_d + 8.4941$$

Its standard deviation is:

Table 2: Dosing error

Turbidity (raw water) (NTU)	Dosage ($mg\ m^{-3}$)	Calculations ($mg\ m^{-3}$)	Error
5.1	11.10	11.80	-0.70
5.2	11.70	11.84	-0.14
5.3	12.00	11.88	0.12
5.4	12.90	11.92	0.98
5.5	12.05	11.96	0.09
5.6	12.10	11.99	0.11
5.8	12.25	12.06	0.19
5.9	11.90	12.10	-0.20
6.0	12.30	12.13	0.17
6.2	11.70	12.19	-0.49
6.4	11.90	12.25	-0.35
6.5	12.40	12.28	0.12
6.6	12.50	12.31	0.19
6.7	11.90	12.33	-0.43
6.8	12.35	12.36	-0.01
6.9	12.40	12.38	0.02
7.2	13.00	12.45	0.55
7.4	12.30	12.49	-0.19
7.6	12.50	12.52	-0.02

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} v_i^2}{n-1}} = \sqrt{\frac{\sum_{i=1}^{19} v_i^2}{19-1}} = 0.376$$

Its squared standard deviation is:

$$\sigma^2 = 0.14$$

Simulation results: The results shown in Table 2 are the compared results of the model simulation and the original data. Errors are shown in Table 2, too.

It can be seen clearly from Table 2 that the dosing error between the actual value and the calculated is in the [-0.7, 0.98]. The relative error is in a relatively small area in industry.

Figure 1 shows the compared results of the original data and the model calculations.

It can be clearly seen from Fig. 1 that the model calculations and the actual dosing value is nearly consistent. Therefore, the obtained model has its practical value.

Application results: The model is applied to Xining No. 8 water purification plant for dosing control practices. Fig. 2 shows the curve of the effluent turbidity of the flocculation and sedimentation tank and the time based curve of the dosage.

As it can be seen from Fig. 2, when the raw water turbidity mutated, settling time of the flocculation tank is approximately half an hour or so which correspond with the actual situation. But also the simulation steady-state values of the coagulant dosage and the turbidity is also consistent with the measured values of the water purification process. This can be judged that the start value of the water turbidity in the flocculation and sedimentation tanks does not affect the final steady-state value at all. However, the final steady-state value depends on the final concentration of the coagulant and the turbidity of the raw water.

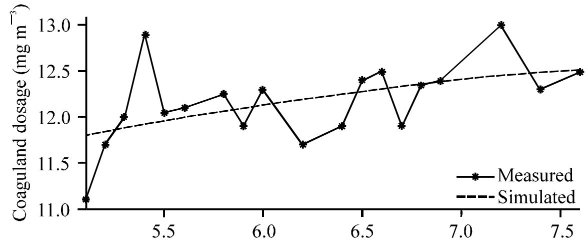

Fig. 1: Compared results of the original data and the model calculations

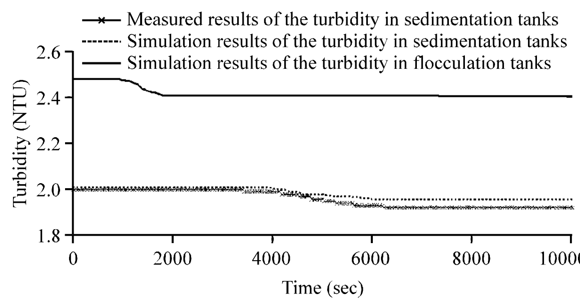

Fig. 2: Curve of the turbidity of the effluent and the dosage

CONCLUSION

A water purification process dosing automation mathematical model is established in this work. The actual operating data is collected from the Xining No. 8 water purification plant. After further collation, the key factors (raw water turbidity and coagulant dosage) that affect the water quality were found in the quantitative mathematical relationships. Before control practice, the mathematical relationship has been theoretical verified. It is proved that the model can effectively control the water quality after nearly a year of application in Xining No. 8 water purification plant. It achieved the automatic control of the dosing process. It has the advantages of flexible parameter modification, small errors and so on. And it is adapted to dosage automatic control in different seasons with good control performance. And also, it improved processing efficiency and the effluent quality, reduced the processing costs and the labor intensity.

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