Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 13 (21): 4869-4874, 2013
ISSN 1812-5654 / DOI: 10.3923/jas.2013.4869.4874

Clustering Multi-model Generalized Predictive Control and its Application in Wastewater Biological Treatment Plant

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Abstract: The model mismatch problems can be avoided by using multi-modeling method based on cluster analysis, against using a single model for describing nonlinear process. The sub-models set output error is high precision and it can accurate fitting of non-linear characteristics of the system. Firstly, the generalized predictive controllers are designed based on the clustering multi-model of the wastewater treatment process, then, the overall control increment is synthesized based on the weight of each controller output. The clustering multi-model generalized predictive control strategy of the ammonia concentration is proposed in this study. The simulation results and the application results of the strategy used in the actual wastewater treatment plant verified its higher control accuracy. The effluent ammonia concentration can be controlled effectively. And also, it improved processing efficiency and the effluent quality, reduced the processing costs.

Key words: Wastewater treatment process, clustering multi-model, generalized predictive control, ammonia concentration

INTRODUCTION

The process of biological wastewater treatment system due to its characters of nonlinear, uncertainties and other factors make the process mechanism is very complicated, so it is very hard to establish the nonlinear mechanism model of the system. So researchers often use the input-output data to model it by use of the system identification. However, a single global model is often difficult to meet the modeling accuracy and the decomposition principle based multi-model modeling method can effectively improve the modeling accuracy of the system. In recent years, researchers have a lot of simulation and practical application in nonlinear systems and complex industrial process, the attention on it has been maintained at a high level (Li *et al*., 2010; Cong *et al*., 2010; Zhang *et al*., 2012; Frey and Dueck, 2007).

Predictive control is an advanced control method. It can efficient handling of control problem with large inertia and large delay, also, it can direct processing the various constraints of input and output. It is widely applied in the optimal control problems. But because the predictive control is a control strategy based on model and it is very robust with the model uncertainty but when the object have a wide range operating conditions, the ideal control effect also difficult to obtain with the designed model predictive controller based on the fixed model (Liu *et al*., 2008). Generalized Predictive Control (GPC) is appeared after the Dynamic Matrix Control (DMC), Model Algorithm Control (MAC), Internal Model Control (IMC) and the Output Predictive Control (OPC), it is a more effective prediction control algorithm with a broader applicable range. Since, Clarke (1987), it has been widely applied in the control problems of nonlinear systems and it is more suitable for industrial process (Clarke *et al*., 1987a, b; Zeng *et al*., 2009; Wang and Li, 2007).

In this study, a clustering multi-model generalized predictive control strategy based on the principle of decomposition and synthesis is proposed. The GPC controller output is weighted synthesis by the sub-GPC controller outputs and this method is applied to the Benchmark simulation (Alex *et al*., 2008) and the real A^2/O wastewater treatment plant control practice, the results validate the effectiveness of the algorithm and a good control effect.

MATERIALS AND METHODS

Off-line clustering multi-model identification: k-means clustering is one of the most simple unsupervised data clustering algorithm with fast convergence, it is suitable for large-scale data set classification (Likas *et al*., 2003). But it has many deficiencies. For example, the clustering result depends on the selection of the k value, so the

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proper value of k is difficult to select when in the absence of a clear understanding of data characteristics; The initial value of the cluster centers is randomly selected, it making the clustering process may be local optimal ended, at the same time, there may appear the sample data set is empty and can not be effectively update; The clustering quality is sensitive to those isolated data points; Unsupervised mechanisms data classification is just consider the difference between the input data, without considering factors such as output, however, in multi-model modeling process, the final modeling errors can not be reflected in the classification process, so it will prone to large modeling errors.

In this study, we first use the improved k-means clustering algorithm to classify the data and then get the multi-model through off-line identification. The basic idea is for the clustering of data points in each category, if the error is too large for the corresponding parameters of the model, we put this point to the other cluster which to make the model error smaller; then, re-identification of the model parameter after this operation. The flow chart of the improved clustering algorithm is shown in Fig. 1.

At last, we can use the standard deviation formula Eq. 1 and the maximum absolute error formula Eq. 2 to calculate the standard deviation and the maximum absolute error in modeling and verify process:

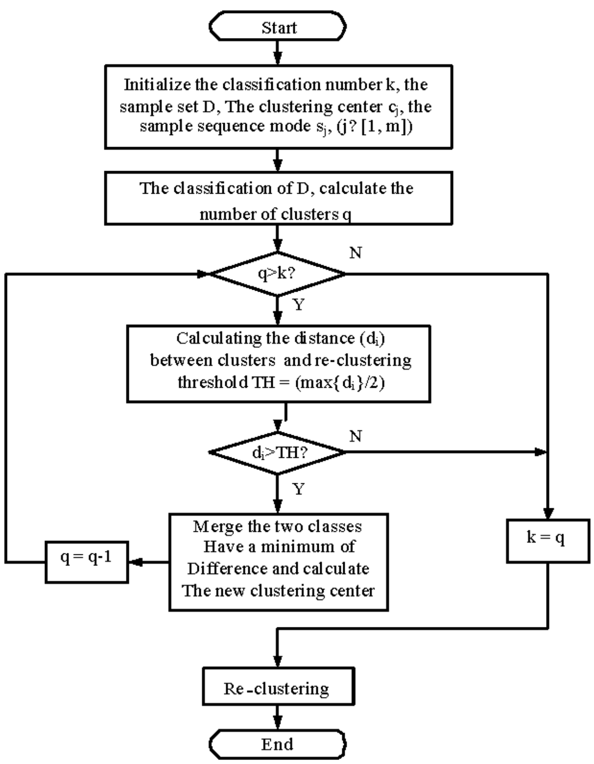

Fig. 1: Improved k-means clustering algorithm

$$\sigma = \sqrt{\frac{\sum_{k=1}^{N}(y(k)-\hat{y}(k))^2}{N}} \tag{1}$$

$$MAXE = \max_{k\in[1,N]} |y(k)-\hat{y}(k)| \tag{2}$$

where, N represents the number of data points.

When the error reaches the set target, clustering multi-model identification process is finished and then we can design the predictive controller.

Multi-model generalized predictive control

- **Sub-GPC control algorithm:** Consider a MIMO process with n_y dimension output vector y, n_u dimension input vector u and n_v dimensional measuring interference vector v, the k moment CARIMA-model can be described as Eq. 3 (Camacho and Bordons, 1999):

$$A(z^{-1})y(k) = B(z^{-1})u(k-1) + D(z^{-1})v(k-1) + \frac{C(z^{-1})e(k)}{\Delta} \tag{3}$$

where, e(k) is a white noise; differential operator $\Delta = 1\text{-}z^{-1}$:

$$A(z^{-1}) = I_{n_y \times n_y} + A_1 z^{-1} + A_2 z^{-2} + \cdots + A_{n_a} z^{-n_a}$$

$$B(z^{-1}) = B_0 + B_1 z^{-1} + B_2 z^{-2} + \cdots + B_{n_b} z^{-n_b}$$

$$C(z^{-1}) = I_{n_y \times n_y} + C_1 z^{-1} + C_2 z^{-2} + \cdots + C_{n_c} z^{-n_c}$$

$$D(z^{-1}) = D_0 + D_1 z^{-1} + D_2 z^{-2} + \cdots + D_{n_d} z^{-n_d}$$

Calculated by Diophantine equation:

$$\begin{aligned}\hat{y}(k+j|k) &= G_j(z^{-1})\Delta u(k+j-1) + H_j(z^{-1})\Delta v(k+j) \\ &+ G_{jp}(z^{-1})\Delta u(k-1) + H_{jp}(z^{-1})\Delta v(k) + F_j(z^{-1})y(k)\end{aligned} \tag{4}$$

Define $f_i = G_{jp}(z^{-1})\Delta u(k\text{-}1) + H_{jp}(z^{-1})\Delta v(k) + F_j(z^{-1})y(k)$, Eq. 4 can be written in:

$$\hat{y}(k+j|k) = G_j(z^{-1})\Delta u(k+j-1) + H_j(z^{-1})\Delta v(k+j) + f_j \tag{5}$$

Considering the p step after k moment prediction, Eq. 5 can be written in matrix form:

$$\begin{bmatrix} \hat{y}(k+1|k) \\ \hat{y}(k+2|k) \\ \vdots \\ \hat{y}(k+j|k) \\ \vdots \\ \hat{y}(k+P|k) \end{bmatrix} = \begin{bmatrix} G_0 & 0 & \cdots & 0 & \cdots & 0 \\ G_1 & G_0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ G_{j-1} & G_{j-2} & \cdots & G_0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ G_{P-1} & G_{P-2} & \cdots & \cdots & \cdots & G_0 \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+j-1) \\ \vdots \\ \Delta u(k+P-1) \end{bmatrix} + \begin{bmatrix} H_0 & 0 & \cdots & 0 & \cdots & 0 \\ H_1 & H_0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ H_{j-1} & H_{j-2} & \cdots & H_0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ H_{P-1} & H_{P-2} & \cdots & \cdots & \cdots & H_0 \end{bmatrix} \begin{bmatrix} \Delta v(k) \\ \Delta v(k+1) \\ \vdots \\ \Delta v(k+j-1) \\ \vdots \\ \Delta v(k+P-1) \end{bmatrix} + \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_j \\ \vdots \\ f_P \end{bmatrix} \tag{6}$$

i.e.:

$$y = Gu+Hv+f \tag{7}$$

Set the control objectives for the finite field as the follows two objective function:

$$J(M,P) = \sum_{j=1}^{P} \left\| \hat{y}(k+j|k) - w(k+j) \right\|_Q^2 + \sum_{j=1}^{M} \left\| \Delta u(k+j-1|k) \right\|_\lambda^2 \tag{8}$$

where, Q is the output deviation penalty weight coefficient; ë is the penalty weight coefficient of input control increment; M is the control domain; w(k+j) is the desired output trajectory. It is assumed that the interference of incremental v future is 0, so the best input increment is:

$$\Delta u(k) = [G^TQG+\lambda I]^{-1}G^TQ(W-f) \tag{9}$$

- **Control incremental weighted synthesis strategy:** Using the matching error probability $P_{j,k}$ between the j sub-model at k moment and the object to determine the control increment of the multi-model control system weighted synthesis by the sub-GPC controller output. Where:

$$P_{j,k} = \frac{\exp\left(-\frac{1}{2}\varepsilon_{j,k}^T K \varepsilon_{j,k}\right) P_{j,k-1}}{\sum_i \left(\exp(-\frac{1}{2}\varepsilon_{j,k}^T K \varepsilon_{j,k}) P_{j,k-1} \right)} \tag{10}$$

In Eq. 10, $\varepsilon_{j,k}$ is the matching error; K is the convergence coefficient. Control increment at k moment of the system is:

$$\Delta U(k) = \sum_j \Delta u_i(k) P_{j,k} \tag{11}$$

Figure 2 shows the clustering multi-model generalized predictive control principle diagram. In the figure, d is the outside interference

RESULTS AND DISCUSSION

Control simulation under wastewater treatment benchmark: Wastewater treatment Benchmark BSM1 (Benchmark Simulation Model No.1) (Fig. 3) is developed by the COST (the European Co-operation in the field of Scientific and Technical Research) group 682, 624 and IWA (International Water Association) (Alex *et al*., 2008; Du *et al*., 2011), it is based on ASM1 (Activated Sludge Model No.1), focused on the carbon and the nitrogen removal, covered with the process of sewage treatment

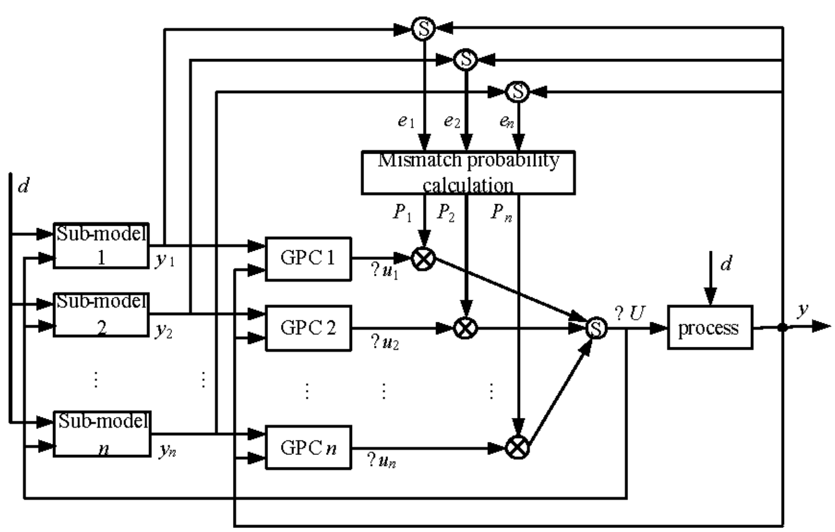

Fig. 2: Compared results of minimum error of classical

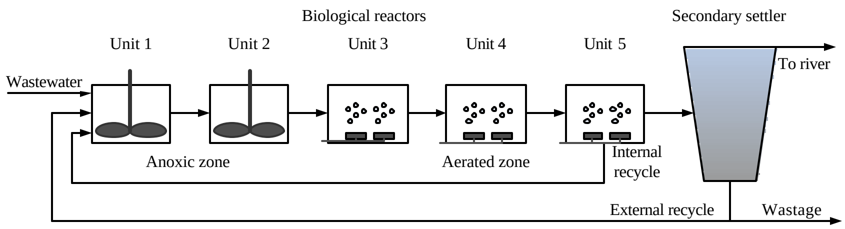

Fig. 3: Benchmark simulation model No.1 for WWTPs

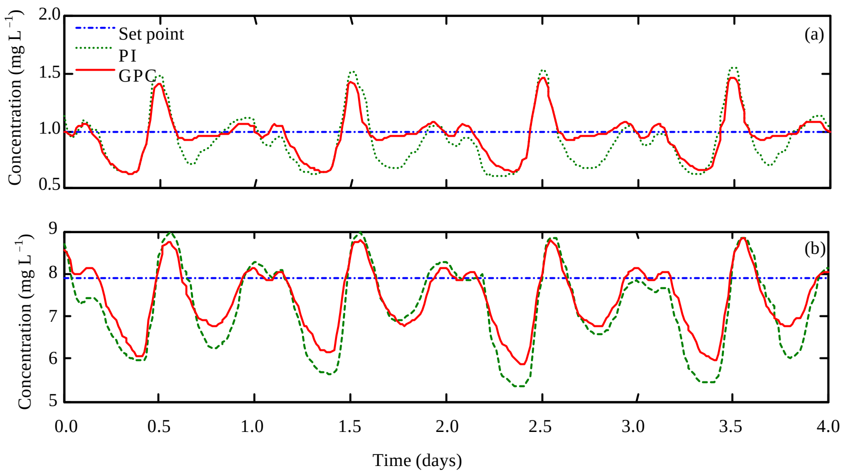

Fig. 4(a-b): Clustering multi-model generalized predictive control under dry weather (a) Ammonia outputs and (b) Nitrate nitrogen outputs

system, the simulation model, the simulation steps, the water data under a variety of weather source and the evaluation standards.

We select the dry weather data as input during the simulation and the simulation length is 4 days. Controller tuning parameters are as follows: the predictive domain P = 8, control time-domain M = 3; the output ammonia deviation penalized weighted coefficient is Q_{NH} = 20; nitrate nitrogen variation penalized weighted coefficient is Q_{NO} = 1; all the control increment penalty coefficients are set to 1. At the same time, the control effect is compared with the classic PI algorithm, the control results is shown in Fig. 4. As can be seen from the graph, this method can better track the set value.

The operation variables changes under dynamic simulation with dry weather data are shown in Fig. 5. The dissolved oxygen concentration range is set in 1-3 mg L^{-1}, it reflects the aeration quantity, at the same time, the additional carbon source flow is set in 0-3 m^3 d^{-1}. As can be seen from the graph, the aeration air and the carbon source volume is lower than the PI method, so the method in this study can effectively reduce the operation costs.

Table 1: Part of the operating data of the wastewater treatment plant

Year	2011	2012
The average yield (million tons)	44.236	48.608
The average ammonia emission reduction (tons)	20.932	20.572
The average power consumption (degrees/tons)	0.458	0.376

Control practice of A^2/O process: A^2/O (A-A-O) process is referred to Anaerobic-Anoxic-Oxic process. A^2/O technology has the simplest process and the most extensive in application of nitrogen and phosphorus removal process. The process is shown in Fig. 6.

Gansu PingLiang sewage treatment plant renovation project is started at the beginning of 2011. The original Carrousel oxidation ditch process is been transformed into A^2/O process and it has put into operation by the end of 2012. In practice, the method in this study is applied to control the nitrification process, the goal is in order to meet the effluent discharge standards and reduce the power consumption of the blower at the same time.

Table 1 shows the part (5 months) summary data of the wastewater treatment factory from May to September in 2011 (before transformation) and 2012 (test run in transformation). It can be calculated from Table 1, if the

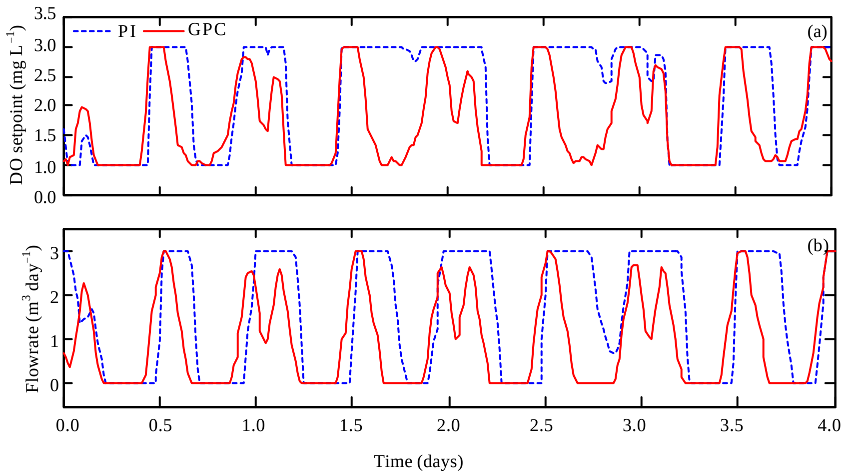

Fig. 5(a-b): Dynamics of the manipulated variables with clustering multi-model generalized predictive control under dry weather (a) Dissolved oxygen concentration and (b) Additional carbon source flow

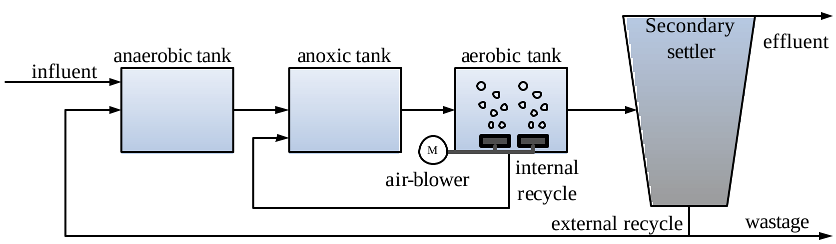

Fig. 6: Sketch of A2/O process

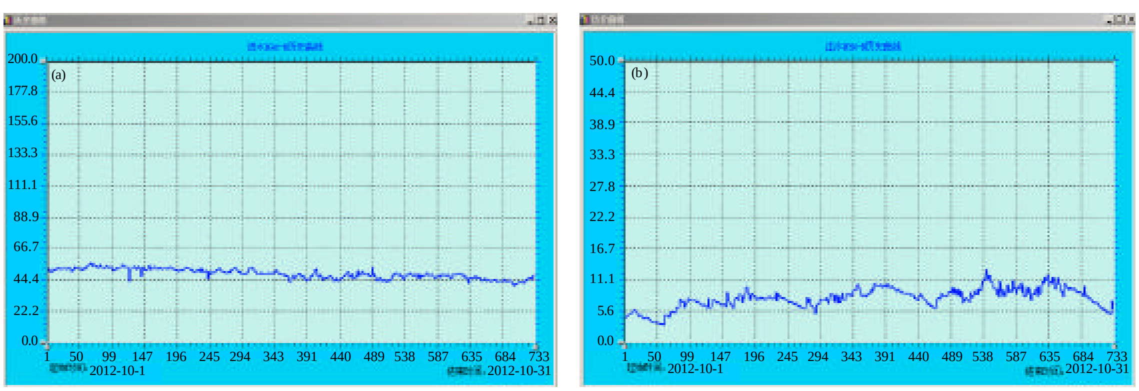

Fig. 7(a-b): Influent and effluent ammonia concentration (a) Influent and (b) Effluen

average monthly sewage treatment amount is 450,000 tons, it will save power consumption 36900 degrees and electricity costs ¥28863.18 each month with the high load industry electricity price ¥0.7822/degree in China. For the non-profit and supported by the government enterprises like sewage treatment plants, it will save a lot of running costs, make them more competitive and the enterprise will prolong the life cycle.

Figure 7 shows the influent and effluent ammonia concentration and Figure 8 shows the dissolved oxygen

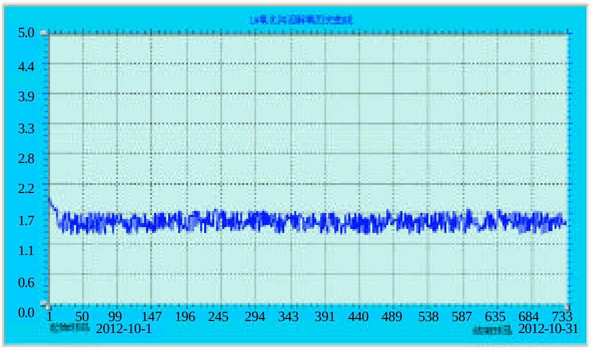

Fig. 8: Dynamics of the dissolved oxygen

concentration history curve in October, 2012. As can be seen, the concentration of ammonia nitrogen is been effectively controlled and the dissolved oxygen concentration is relatively smooth.

CONCLUSION

Application research and simulation research of the clustering multi-model generalized predictive control algorithm in the biological wastewater treatment process are shown in this study. Combined with the improved k-means clustering method using the least squares identified the ARX multi-model of the system, after that, the generalized predictive control is proposed to control the concentration of ammonia nitrogen and nitrate nitrogen concentration. Results of simulation study under the Benchmark and application study under the actual sewage treatment plant show that the proposed method is effectively. It achieves the effective control of water quality and it is an economic method with great practical value.

ACKNOWLEDGMENT

This study is supported by the National Natural Science Foundation of China (No. 61064003, No. 61263008) and the National Natural Science Foundation of Gansu Province (No. 1212RJYA031).

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