A SYSTEM FOR DISSOLVED OXYGEN CONTROL IN INDUSTRIAL AERATION TANK

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Abstract. The control system is developed for accurate set-point control of dissolved oxygen concentration in industrial aeration tank based on adaptation of PI controller to time-varying dynamics of the controlled process. The controller adaptation algorithm refers to the process state model-based transfer function that follows changes in process dynamics by updating the function parameters with online measurements of process variables, and the controller tuning rules developed for typical structure transfer function models.

The control system was investigated in a computer simulation of the dissolved oxygen concentration set-point control in an industrial aeration tank under process disturbances and set-point step changes. The control system demonstrates fast adaptation of PI controller parameters and no noticeably higher accuracy control compared to that of ordinary fixed gain PI controller.

Keywords: mathematical model; adaptive control; dissolved oxygen concentration; wastewater treatment process.

1. Introduction

One of the key technological factors of the activated sludge treatment process in aerated tanks is oxygen supply, and the oxygen supply rate is the main parameter affecting biological treatment process. Basic requirement for oxygen supply is that the dissolved oxygen concentration (DOC) in the nitrification zone is not less than predetermined levels (2 kg m⁻³) [1]. If the nitrification and de-nitrification processes take place in the same aeration tank, the energy saving and maintenance balance between aerobic/anoxic sections of the sludge flocks can be achieved by accurate control of DOC for keeping the optimal technological regime, usually 0.15-0.5 kg m⁻³ [1]. As the controlled process is highly nonlinear and non-stationary, an ordinary PID control is not adequate to cope with the DOC control task. The DOC control problem in industrial aerobic tank is illustrated by a graph in Figure 1, which shows the performance of ordinary PID controller and self-tuning control.

Various adaptive and nonlinear control approaches have been proposed for controlling DOC in aerotanks under time-varying operating conditions. Turnel et al. [2] investigated several control methods (PID, fuzzy logic, and self-tuning control) by computer simulation of the activated sludge plant using the Activated Sludge Model 1 (ASM1). The self-tuning controller based on generalized predictive control method demonstrated robust behaviour and proper responses to various operating conditions. There was indicated a problem of reliable measurements, which can be used to implement the control system. Galluzzo et al. [3] proposed an expert control structure for controlling the DOC, which takes into account several processes.

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that are influenced by oxygen concentration in aerator. In the control system, a supervisory fuzzy controller determines the DO set-point for the control loop, in which an adaptive robust generic model control is used. T zoneva [4] presented an approach of periodic retuning of DO controller that does not require disturbing of the control process. Identification of process dynamic parameters is performed on personal computer with the Matlab/Simulink environment, connected to PLC. De Leon et al. [5] proposed two dimensionless parameters, which relate the physiological, operational, and bioreactor design parameters with the tuning parameters of the PID control algorithm. These dimensionless parameters can be incorporated into a adaptive control strategy without disturbing the ongoing process. Chiang Yao et al. [6] used the Kalman filter to estimate two important parameters that characterize dynamics of the biological treatment process—oxygen transfer rate and respiration rate. These parameters were further applied for online monitoring of DO. Caraman et al. [7] proposed a predictive controller of DOC with a neural network as internal model of the controlled process. The similar approach is used by Holenda et al. [8], only the ASMI model is used for the process modeling.

In the presented paper, an adaptive control system of DOC in industrial aeration tank is proposed, in which a priori knowledge of the controlled process and available on-line measurements of process variables are exploited. The process know ledge is included in a simple model, which is updated with online measurements of process variables and applied for parameter retuning of controller parameters. Advantage of the proposed control system is fast adaptation of controller to operating conditions and avoidance of process disturbances for the dynamic parameters estimation.

2. Aero-tank process

Technological scheme of the wastewater treatment process is shown in Figure 2.

Incoming wastewater flow $F_{\text{inlet}}$ through the distribution chamber, which has an aerator with air flow $F_{\text{aer}}$ falling into the distribution chamber, in which the wastewater is mixed with the returned sludge flowing in at rate $F_{\text{ret}}$. The mixed wastewater flow $F_{\text{mix}}$ falls into the aerobic tank (biological treatment tank). In the aeration tank, the wastewater to be purified is brought into contact with the activated sludge from the aerator. Oxygen required for the biological process is supplied to the aeration tank through the air blowing equipment. The airflow $u$ for aeration comes from the blower station. In the mixing system, the best possible contact between the bacteria cells and the nutrient, the widespread diffusion of oxygen to the areas requiring oxygen, and prevents formation of deposits. The purified water falls in to the final settling tank, in which the water is separated from the microorganisms in the tank. The biological sludge collected from the settling tank is returned to the aeration tank. The excessive sludge with the flow rate $F_{\text{exs}}$ is removed for digestion.

The most important technological parameter actively affecting the biological treatment process is the DOC, which is controlled by manipulating the air flow rate. To ensure the most effective biotechnological regime, the DOC in the aeration tank is to be accurately controlled at predetermined optimal level. Importance of the DOC accurate control is also related to significant energy expenses for aeration.

The main problem that complicates accurate set-point control of DOC is the variation of the controlled process dynamics caused mainly by unpredictable changes of oxygen uptake rate as well as the flow rate of incoming wastewater and the DOC concentration in incoming wastewater.

Figure 2. Technological scheme of the wastewater treatment process
3. Development of control system

The approach to the process controller adaptation is based on using the DOC control system an adaptive transfer function model for tracking time-varying dynamical parameters of the process and permanent tuning of the feed-back control parameters [9].

Development of the transfer function model refers to a first principles model describing the mass balance for DOC in aeration tank:

\[
\frac{dc}{dt} = K_z \alpha \cdot (c^* - c) + (c_{in} - c) \frac{F_{bio}}{V} - OUR, \tag{1}
\]

\[
K_z \alpha = \alpha \cdot u^\gamma, \tag{2}
\]

where \( c \) is the DOC (control variable), kg m^\(-3\); \( c^* \) is the saturation value of DOC, kg m^\(-3\); \( K_z \alpha \) is volumetric oxygen transfer coefficient from gas to liquid phase, h^\(-1\); \( c_{in} \) is DOC in the inlet wastewater, kg m^\(-3\); \( F_{bio} \) is the inlet flow rate of wastewater, m^3 h^\(-1\); \( V \) is volume of aeration tank, m^3; \( OUR \) is oxygen uptake rate, kg m^\(-3\) h^\(-1\); \( \alpha, \gamma \) are the model parameters.

Time-varying dynamics of the controlled process in the vicinity of operating point can be described by linearization of equation (1) with respect to variables \( c \) and \( u \) around the process state point at time \( t_k \):

\[
\frac{d \Delta c}{dt} = -\frac{1}{T(t_k)} \cdot \Delta c + \frac{K(t_k)}{T(t_k)} \cdot \Delta u, \tag{3}
\]

or by a 1st order transfer function model:

\[
G_{\Delta c/\Delta u}(s) = \Delta c(s) / \Delta u(s) = \frac{K(t_k)}{T(t_k)} s + 1, \tag{4}
\]

\[
K(t_k) = \left[ \frac{\gamma \alpha u^\gamma (c^* - c) V}{u (\alpha u^\gamma V + F_{bio})} \right]_{t=t_k}, \tag{5}
\]

\[
T(t_k) = \left[ \frac{V}{\alpha u^\gamma V + F_{bio}} \right]_{t=t_k}, \tag{6}
\]

where \( s \) is the Laplace operator; \( \Delta c, \Delta u \) are small deviations of \( c \) and \( u \) from the current state point; \( \Delta c(s), \Delta u(s) \) are the Laplace transforms of \( \Delta c \) and \( \Delta u \), \( K(t_k), T(t_k) \) are process gain coefficient and time constant at time point \( t_k \), respectively.

The parameters \( \alpha, \gamma, c^* \) that define oxygen transfer conditions in aeration tank can vary with the time-varying state of aeration tank process, therefore, estimation of the dynamic parameters \( K \) and \( T \) by formulas (5), (6) with predetermined parameter values does not ensure the desirable accuracy. The dynamic parameter estimation can be improved at quasi-steady state conditions with respect to DOC (\( dc/dt \approx 0 \)) by using estimated values of \( OUR \). At the steady state conditions, the oxygen transfer rate term \( K_z \alpha (c^* - c) \) can be estimated from the equation (1) and the \( F_{bio}, c_{in} \) and \( OUR \) measurements:

\[
K_z \alpha (c^* - c) V = OUR_{i} - F_{bio} (c_{in} - c), \tag{7}
\]

where \( OUR_{i} \) is the total oxygen uptake rate (\( OUR_{i} = V \cdot OUR \)).

Taking into account the relationship (7), the dynamic parameters \( K \) and \( T \) can be estimated from the following relationships:

\[
K(t_k) = \left[ \frac{\gamma (c^* - c) (OUR_{i} - F_{bio} (c_{in} - c))}{u (OUR_{i} + F_{bio} (c^* - c_{in}))} \right]_{t=t_k}, \tag{8}
\]

\[
T(t_k) = \left[ \frac{V (c^* - c)}{OUR_{i} + F_{bio} (c^* - c_{in})} \right]_{t=t_k}, \tag{9}
\]

By updating the transfer function model (4), (8), (9) with the control variable value \( u(t_k) \), the set-point value corresponding to the DOC (\( c(t_k) = c_{set}(t_k) \)), the measured value uses \( F_{bio}(t_k) \), \( c_{in}(t_k) \) and the estimated value \( OUR_{i}(t_k) \), the model (4) follows variations of the process dynamics under real-time operating conditions.

For tuning the feed-back controller, along with the time-varying dynamics described by the model (4), (8), (6), the time-invariant dynamics of the DOC electrode and the air blowing machines, as well as the flow rate dependent transport delay are taken into account. Assuming that dynamics of the DOC electrode and the blowing machines can be described by first order plus time delay models, the resultant transfer function of the controlled process is as follows:

\[
G_{\Delta c/\Delta u}(s) = \frac{K(t_k)}{T(t_k) s + 1} \cdot \frac{1}{T_{s} s + 1} \cdot \frac{1}{T_{m} s + 1} e^{-\tau_{p}(t_k)}, \tag{10}
\]

\[
\tau_{p}(t_k) = \frac{V}{u(t_k)}, \tag{11}
\]
where $T_e$, $T_{bm}$ are time constants of the DOC electrode and the blowing machines, respectively; $\tau_p$, $\tau_{bm}$ are time delays of the air flow and the blowing machines, respectively; $V_i$ is volume of the air supply pipeline, m$^3$.

In order to apply the controller adaptation to the tuning rules developed for first order plus time delay (FOPTD) models [10], the transfer function (10) is further reduced on-line to the FOPTD model:

$$G_{pr}(s) = \frac{K_{pr}(t_k)}{T_{pr}(t_k)} \exp\left(-\tau_{pr}(t_k)\right),$$  \hspace{1cm} (12)

where $K_{pr}(t_k)$, $T_{pr}(t_k)$ and $\tau_{pr}(t_k)$ are resultant gain, time constant and resultant time delay of the controlled process at time $t_k$, respectively. The model parameters $T_{pr}(t_k)$ and $\tau_{pr}(t_k)$ are updated by fitting the FOPTD model (12) to the simulated step response of the transfer function (10) at each sampling time. The Smith’s approximation [10] is applied for fitting the FOPTD model.

Taking into account a noticeable process noise influencing the feedback signal from the DOC electrode, we use in the control system the PI controller (instead of PID) that is less sensitive to input signal noise. The velocity of the modified discrete PI control algorithm is

$$u(t_k) = u(t_{k-1}) + Du(t_k),$$  \hspace{1cm} (13)

$$e(t_k) = c_{set}(t_k) - c(t_k),$$  \hspace{1cm} (15)

$$Du(t_k) = \frac{K}{T_{pr}(t_k)} \left[ \frac{b(t_k)c_{set}(t_k) - c(t_k)}{\tau_{pr}(t_k)} \right] - \frac{\Delta t}{T_{pr}(t_k)} e(t_k),$$  \hspace{1cm} (14)

$$e(t_k) = c_{set}(t_k) - c(t_k),$$  \hspace{1cm} (15)

where $Du$ is increment/decrement of air flow rate, m$^3$ h$^{-1}$; $K_c$ is controller gain coefficient, m$^3$ h$^{1/2}$/kg m$^{-3}$; $T_i$ is controller integration constant, h; $b$ is set-point weighting; $\Delta t$ is time discretization step of control action, h; $c_{set}$ is measured value of DOC, kg m$^{-3}$.

The controller parameters $K_c(t_k)$, $T_i(t_k)$, $b(t_k)$ are recalculated at each sampling instant using updated values of the FOPTD model (12) parameters $K_{pr}(t_k)$, $T_{pr}(t_k)$, $\tau_{pr}(t_k)$ and the Kappa-Tau tuning rules for maximum sensitivity $M_s = 2.0$ developed for the FOPTD model [11]:

$$K_c = 0.78 \frac{T_{pr}(t_k)}{K_{pr}(t_k) \tau_{pr}(t_k)} \cdot \exp\left(-4.1 \cdot \tau_{pr}(t_k) + 5.7 \left(\tau_{pr}(t_k)^2\right)\right),$$  \hspace{1cm} (16)

$$T_i(t_k) = 0.79 \cdot T_{pr}(t_k) \cdot \exp\left(-1.4 \cdot \tau_{pr}(t_k) + 2.4 \left(\tau_{pr}(t_k)^2\right)\right),$$  \hspace{1cm} (17)

$$b(t_k) = 0.44 \cdot \exp(0.78 \cdot \tau_{pr}(t_k) - 0.45 \left(\tau_{pr}(t_k)^2\right) - \tau_{pr}(t_k) + T_{pr}(t_k)).$$  \hspace{1cm} (18)

The structure of the DOC adaptive control system is presented in Figure 3.

![Figure 3. Block-scheme of the adaptive control system](image-url)

In the adaptation algorithm, the controller action, calculated at time point $t_k$ for sampling interval $t_k \leq t < t_{k+1}$, refers to the process state at time $t_k$. Preliminary tests of the adaptive control system have shown that the system performs well if there is no significant change of process state during the sampling interval. Although the control angles of process state variables are relatively slow, the above condition is often violated by the controller action itself, as the process gain is dependent on the control variable value (equation (8)). Under such conditions, the control action in consecutive sampling intervals can differ. The calculated value of control variable is actually different from the optimal one, i.e. stimulation of process dynamic parameters in the controller adaptation algorithm refers to a previous value of the control action at $t_{k-1}$ and the intended action at $t_k$. This computation problem is so solved at...
each sampling time by using the iterative procedure presented in Figure 4.

\[
\text{Given: } u(t_{k-1})
\]

\[
\begin{aligned}
\text{Given: } & c(t_k), \text{OUR}(t_k), c(t_{k-1}), F_{bio}(t_k) \\
\text{For: } & t_k \leq t < t_{k+1} \\
\text{Compute parameters of } & G_p, (12) \\
\text{Compute } & u(t_k) \text{ (10)-(16)} \\
\frac{u(t_k) - u(t_{k-1})}{u(t_{k-1})} < & \varepsilon
\end{aligned}
\]

\[
\begin{aligned}
\text{y} \\
u(t_k)
\end{aligned}
\]

**Figure 4.** Flowchart of computation algorithm

### 4. Simulation of the control system performance

Performance of the control system (Figure 3) has been investigated via computer simulation, using Matlab/Simulink tools. In the simulation experiments, the controlled process was modeled by equations (1)-(2) and the first order dynamic models of the control system elements: the DOC electrode and the air blowing machine. The delay of the controller action (aeration rate) due to air flow transportation time that depends on the air flow rate is also taken into account. The model parameters and initial values of process variables applied in the simulation experiment are given in Table 1 [12].

<table>
<thead>
<tr>
<th>Values of model parameters</th>
<th>Initial values of process variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c_p = 6 \text{ kg m}^{-3} ), ( c = 10 \text{ kg m}^{-2} )</td>
<td>( V_p = 3.31 \text{ m}^3 ), ( c = 0.15 \text{ kg m}^{-2} )</td>
</tr>
<tr>
<td>( T_{br} = 3.33 \cdot 10^{-3} \text{ h} ), ( \tau = 5.09 )</td>
<td>( \alpha = 0.138 ), ( \text{OUR} = 175 \text{ kg m}^{-2} \cdot \text{h}^{-1} )</td>
</tr>
<tr>
<td>( T_c = 2.22 \cdot 10^{-3} \text{ h} ), ( T_{br} = 1.11 \cdot 10^{-3} \text{ h} )</td>
<td>( u_{aer} = 1197 \text{ m}^3 \cdot \text{h}^{-1} ), ( F_{bio} = 403 \text{ m}^3 \cdot \text{h}^{-1} )</td>
</tr>
</tbody>
</table>

The changes in process dynamics were simulated by varying the oxygen uptake rate (OUR) and the inlet flow rate of wastewater (\( F_{bio} \)). In the control algorithm (10)-(12), the sampling time \( \Delta t = 0.01 \text{ h} \) was used.

Responses of the adaptive control system to the DOC set-point step changes under the OUR and the wastewater flow-rate disturbances are presented in Figure 5. The set-point and the disturbance time-
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Figure 5. Performance of the control system at the OUR and the inlet flow rate disturbances and the controlled DOC set point changes.

The simulation results demonstrate fast adaptation of controller parameters and noticeable improvement of the DOC control accuracy by tracking set-point with the adaptive controller compared to that of conventional PI controller.

5. Conclusions

An adaptive control system is developed for set-point control of dissolved oxygen concentration at wastewater treatment processes. A derivation of process controller to time-varying operating conditions is based on the process model-based transfer function, which follows the process dynamics changes by updating it with the on-line measurements of process variables. The a adaptive transfer function is applied in the control system for permanent retuning of PI controller parameters.

Performance of the control system is investigated by computer simulation of the DOC set-point control under process disturbances: oxygen uptake rate and inlet wastewater variations, and the set-point step changes. Simulation results demonstrate fast adaptation of controller and significant improvement in set-point tracking accuracy compared to that with ordinary PI controller.

References


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