MPC for Ozone Dosage in Water Treatment Process based on Disturbance Observer

Dan Niu[1,2], Xisong Chen[1,2], Jun Yang[1,2], Fuchun Jiang[3] and Xingpeng Zhou[1,2]
[1]*Key Laboratory of Measurement and Control of CSE, Ministry of Education, China*
[2]*School of Automation, Southeast University, No.2, Sipailou, Nanjing 210096, China*
[3]*Xiangcheng Water Treatment Plant, Suzhou Running-water Company, Suzhou 215002, China*

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Abstract: In the drinking water treatment, determining optimal ozone doses is vital for the treated water quality. An effective control scheme is to control the dissolved ozone residual constant. However, it is not easy to be achieved since some external disturbances always exist, such as large changes in water flow rate and raw water quality. Moreover, the ozonation is a nonlinear process with long time delay and large time constant. The conventional control strategies such as PID and traditional MPC reject disturbances merely through feedback regulation, which will cause performance degradation in the presence of strong disturbances. In this paper, a composite control scheme integrating MPC method as feedback controller and disturbance observer (DOB) as feed-forward compensation is proposed to improve disturbance rejection of ozone dosage control system. The test results demonstrate that the proposed method possesses a better disturbance rejection performance than the MPC method in the ozonation process.

1 INTRODUCTION

In the water treatment, ozonation is considered as an attractive alternative to chlorine for the disinfection, oxidation of micropollutants and organic matter, color and odor removal(Xie, 2016)(GAD et al., 2015)(Hubner et al., 2015). In this process, determining the optimal ozone dosage is critical for its effective application, since insufficient dosage is difficult for reliable disinfection and removel of water matrix compounds(Lee et al., 2014). On the other side, too high doses are uneconomical and also lead to health problems related to high levels of disinfection byproducts (such as bromate)(Silva et al., 2014)(Kaiser et al., 2013). A commonly used and effective control strategy for ozone dosage is to maintain a constant dissolved ozone residual(Kang et al., 2008)(der Helm AWC et al., 2009). However, it is known that apart from the ozone dosage, the raw water quality (such as COD, turbidity and temperture) and the water flow rate will also greatly affect the dissolved ozone residual(Shin et al., 2015). In practice, the raw water quality and the water flow rate always vary and these variations are hard to express with an accurate mathematical model(der Helm AWC et al., 2007). Moreover, the ozonation process consists of many complicated chemical and physical reactions(Shin et al., 2015). In this case, undesirable characteristics such as long time delay and nonlinear exist when controlling the dissolved ozone residual(Oh et al., 2003). It is a challenge to control the ozonation process with constant dissolved ozone residual under the unpredictable raw water quality change and water flow rate change.

To control the dissolved ozone residual, a widely used method is to form a feedback control loop. The classical PID control algorithm(der Helm AWC et al., 2009) and some more advanced control algorithms are proposed, including fuzzy logic algorithm(Heo and Kim, 2004)(Chowdhury et al., 2007), neural network(Wang et al., 2014)(Zahedi et al., 2014), internal model control(Wang et al., 2013), model-predictive control(Wang et al., 2014)(Taylor and Akida, 2007)(Wang Dongshen, 2010) and so on. Among these algorithms, traditional MPC algorithm is very popular and widely adopted in the industrial process control(Prakash et al., 2010)(Maciejowski, 2001), since MPC method has advantages for those systems with long time delays due to its prediction mechanism(Wang et al., 2013). However, the above-mentioned advanced control principles can only reject disturbances by the feedback regulation in a rel-

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atively slow way and not directly by controller design. In the constant dissolved ozone residual control system, various disturbances exist, including external ones (raw water quality and flow rate changes) and internal ones (model mismatches). Considering the disturbances are difficult to measure or forecast, disturbance observer (DOB) is introduced, which is an effective technique to estimate disturbances and widely applied in various practical systems(Kobayashi et al., 2007)(Chen et al., 2015)(Li et al., 2014).

This work is based on a pilot-scale ozonation facility of Xiangcheng water treatment plant in Suzhou, China. A DOB-MPC scheme is proposed to improve the disturbance rejection performance of the ozonation process. The proposed scheme consists of a feedforward compensation based on DOB and a feedback regulation using MPC. It can take advantages of both MPC and DOB.

2 CONTROL SCHEME BASED ON MPC AND DISTURBANCE OBSERVER

In the ozonation control system, the dissolved ozone residual y(mg/L) is the most important controlled variable, which needs to be kept at a desired setpoint. Larger or smaller dissolved ozone residual than the setpoint will influence the treated water quality or degrade the production efficiency. The ozone dosage x(mg/L), controlled by the PLC controller, is the manipulated variable. Note that, the changes of raw water quality (mainly the COD value d_c) and water flow rate d_f will cause the continuous fluctuations of the dissolved ozone residual. They are deemed as external disturbances in the control system.

The ozonation is a typical and commonly used industry process. In this process, the dissolved ozone residual can be regulated by controlling the ozone dosage. As shown in(Wang Dongshen, 2010)(Wang et al., 2013), this dynamic can be modeled as a first-order plus dead-time (FOPDT) form, which is most commonly used model to describe the dynamic of industrial process. Here the nonlinear parts can be deemed as the unmodeled dynamics (internal disturbances)(Chen et al., 2015)(Li et al., 2014). The transfer function can be represented as

$$G_1(s) = \frac{K_1}{T_1 s + 1} e^{-\theta s}, \tag{1}$$

where K_1 is the static amplification coefficient, T_1 is the time constant, θ is the time delay.

Moreover, the bandwidth of the dissolved ozone concentration analyzer can satisfy the system requirements, so the transfer function of the dissolved ozone concentration analyzer can be approximated by a proportional cycle K_2.

In summary, the total transfer function of the dissolved ozone residual control can be represented as

$$G_P(s) = K_2 G_1(s) = \frac{K_1 K_2}{T_1 s + 1} e^{-\theta s}. \tag{2}$$

The control system can be considered using the following model

$$Y(s) = G_P(s)X(s) + D_{ex}(s), \tag{3}$$

where

$$G_P(s) = g(s)e^{-\theta s}, \tag{4}$$

$$D_{ex}(s) = \sum_{i=1}^{M} G_{di}(s)D_i(s). \tag{5}$$

In Eqs. (3)-(5), $X(s)$ the manipulated variable; $Y(s)$ the controlled variable; $D_{ex}(s)$ the effects of external disturbances on $Y(s)$; $D_i(s)$ (i=1,2,$\cdots$,M) the ith external disturbances. $G_P(s)$ is the model of the process channel. $g(s)$ is the minimum-phase part of $G_P(s)$. $G_{di}(s)$ (i=1,2,$\cdots$,M) is the model of ith disturbance channel. The nominal model $G_n(s)$ can also be represented as a product of a minimum-phase part $g_n(s)$ and a dead-time part $e^{-\theta_n s}$.

$$G_n(s) = g_n(s)e^{-\theta_n s}. \tag{6}$$

2.1 Model Predictive Control

The process dynamic of system (Eq. (6)) can be shown as

$$y(t) = \sum_{k=1}^{\infty} T(k)\Delta x(t-k), \tag{7}$$

$$\Delta x(t) = x(t) - x(t-1), \tag{8}$$

where $x(t)$ the manipulated variable; $T(k)$ the dynamic matrix got from the coefficients of unit step response; $y(t)$ the output under the $\Delta x(t-k)(k = 1,\cdots,\infty)$. From the Eq. (7), the qth step ahead prediction of the output with the prediction correction term $\widetilde{y}(t+q)$ can be shown as

$$\widetilde{y}(t+q) = \sum_{k=1}^{q} T(k)\Delta x(t+q-k) + \sum_{k=1}^{\infty} T(k+q)\Delta x(t-k) + \xi(t), \tag{9}$$

$$\xi(t) = \widetilde{y}(t) - y(t), \tag{10}$$

where $\xi(t)$ the prediction correction term. In Eq. (9), $\Delta x(t+q-k)(k=1,\cdots,q)$ represents the future manipulated variable moves, which can be obtained by computing the below optimization problem

$$\min_{\Delta x(t)\cdots\Delta x(t+C-1)} J = \sum_{m=1}^{P}[e^T(t+m)M_e e(t+m)] + \sum_{m=0}^{C-1}[x^T(t+m)M_i x(t+m)], \quad (11)$$

$$e(t+m) = \widetilde{y}(t+m) - r(t+m), \quad (12)$$

where $r(t+m)$ the desired reference trajectory; $e(t+m)$ the prediction error. P denotes the prediction horizon. C denotes the control horizon. M_e is the error weighting matrix and M_i is the input weighting matrix. Only the first move is employed. For the next sampling instance, this step is repeated.

The parameters, such as control horizon (C), prediction horizon (P) and sampling time T_s, are very important for the robustness and stability performance. The readers can refer to (Maciejowski, 2001) for detailed tuning guidelines of MPC parameters.

2.2 Disturbance Observer-enhanced MPC Algorithm

In this paper, a composite control scheme is proposed to enhance the performance of the MPC feedback controller by adding a disturbance observer. The block diagram is presented in Fig. 1.

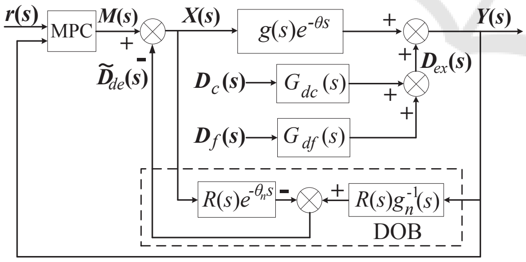


Figure 1: Block diagram of the disturbance observer-enhanced MPC control.

In this figure, $r(s)$ denotes the reference trajectory of controlled variable. $M(s)$ represents the output of the MPC controller. $\widetilde{D}_{de}(s)$ is the disturbance estimation. The output can be represent as

$$Y(s) = G_m(s)M(s) + G_d(s)D_{ex}(s), \quad (13)$$

with

$$G_m(s) = \frac{g(s)e^{-\theta s}}{1+R(s)g_n^{-1}(s)[g(s)e^{-\theta s} - g_n(s)e^{-\theta_n s}]}, \quad (14)$$

$$G_d(s) = \frac{1-R(s)e^{-\theta_n s}}{1+R(s)g_n^{-1}(s)[g(s)e^{-\theta s} - g_n(s)e^{-\theta_n s}]}. \quad (15)$$

From the Eqs. (13)-(15), it can be obtained that the performance of disturbance rejection mainly depends on the design of filter $R(s)$. It can be found that $\lim_{w\to 0} G_d(jw) = 0$ when $R(s)$ is selected as a low-pass filter with a steady-state gain of 1, i.e., $\lim_{w\to 0} R(jw) = 1$. It means that low-frequency disturbances can be attenuated asymptotically. In this work, $R(s)$ is selected as a first-order low-pass filter with a steady-state gain of 1, which can be represented as

$$R(s) = \frac{1}{\eta s+1}, \eta > 0. \quad (16)$$

2.3 Control Implementation

In this work, the proposed control scheme focuses on disturbance rejection against external disturbances as well as model mismatches. The detailed control structure is shown in Fig. 2. The variations of water COD value d_c and water flow rate d_f are the main external disturbance variables.

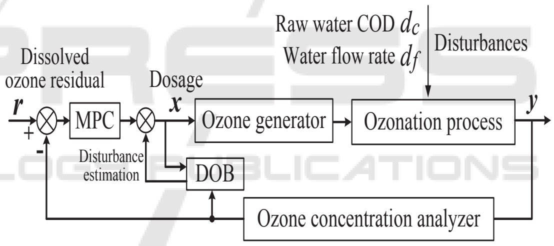


Figure 2: Control structure of constant dissolved ozone residual.

From Fig. 2, the ozone dosage directly affects the primary output (the dissolved ozone residual). For control study, step response of ozone dosage in pilot-scale facilities has been tested to develop the transfer function as follows:

$$G_n(s) = \frac{0.42}{148s+1}e^{-86s}. \quad (17)$$

The nominal value of the dissolved ozone residual is 0.3 mg/L. The external disturbances are imposed on the process through disturbance channels. It is known that the water COD and water flow rate have great influences on the dissolved ozone residual. These dynamics can be also modeled as a first-order plus dead-time (FOPDT) form (Wang Dongshen, 2010). Note that DOB does not reply on precise disturbance models(Li et al., 2014). The transfer functions of disturbance channels $G_{dc}(s)$ and $G_{df}(s)$ are also obtained by step response tests in pilot-scale facilities and expressed as follows

$$G_{df}(s) = \frac{0.19}{108s+1}e^{-60s}, \qquad (18)$$

$$G_{dc}(s) = \frac{-0.23}{165s+1}e^{-108s}. \qquad (19)$$

The time constants are expressed in seconds here. $G_{dc}(s)$ and $G_{df}(s)$ donote the transfer functions of disturbance channels water COD value variation and water flow rate variation, respectively. Here the disturbances are expressed in a relative change form rather than a real physical unit form. For example, d_f=10% means that the water flow rate has an increase of 10% compared with its nominal value.

Moreover, based on the above discussions, the filter of DOB is employed as

$$R(s) = \frac{1}{0.2s+1}. \qquad (20)$$

The MPC controller parameters are designed as

$$P = 20, C = 1, T_s = 1min, M_e = 1, M_i = 1. \qquad (21)$$

3 PERFORMANCE ANALYSIS AND COMPARISONS

In this part, some results are shown to demonstrate the benefits of the proposed method. For comparison, the MPC controller is employed. Meanwhile, the disturbance rejection performance is studied not only in the nominal case but also in the model mismatch case.

3.1 Disturbance Rejection in Nominal Case

Firstly, the nominal case is considered, which means that $G_n(s) = G_P(s)$ holds.

Step external disturbances in the nominal case: the water flow rate has an increase of 20% at $t = 20min$, while the water COD value has an increase of 20% at $t = 50min$.

Figure 3(a) shows the response curves of the dissolved ozone residual under the control of both DOB-MPC and MPC in this case. Fig. 3(b) gives the effects of external disturbances and the estimations on the controlled variables. From Fig. 3(a), the dynamic performance of the dissolved ozone residual under the proposed method is much better than those under the MPC method. Compared with the MPC method, the proposed method can obtain a faster convergence speed, smaller overshoot amplitudes. From Fig. 3(b), it can be observed that the errors between the estimated and real external disturbances are very small, which means that the disturbance observer can effectively estimate the effects caused by disturbances.

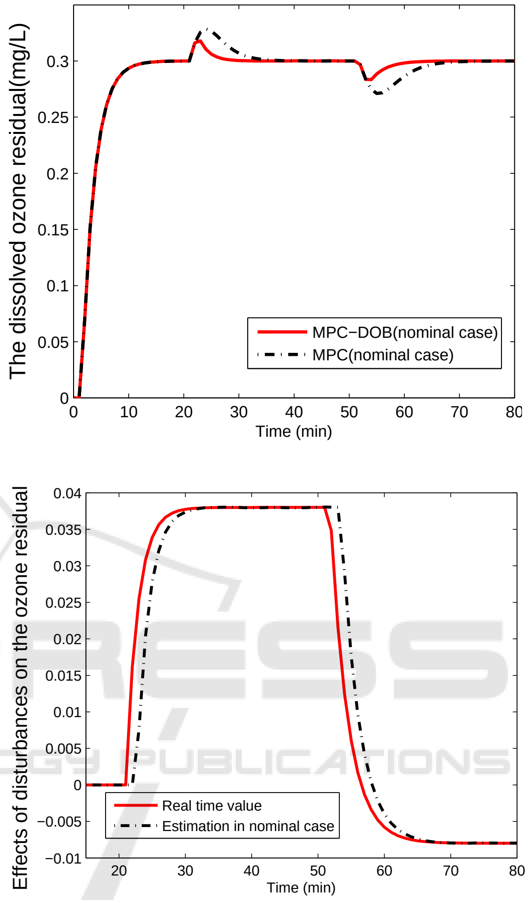


Figure 3: Response curves of variables in the presence of step external disturbances under DOB-MPC and MPC schemes in the nominal case: (a) controlled variable, (b) disturbances and their estimations.

In order to quantitatively analyze the disturbance rejection performance, two performance indexes including peak overshoot and integral of absolute error (IAE) are employed, which are shown in Table 1. From Table 1, it is clear that both the overshoot and the IAE value under the proposed method are much smaller than those under the MPC method.

3.2 Disturbance Rejection in Model Mismatch Case

In real practice, besides external disturbances, internal disturbances caused by model mismatches are another important factors for the control performance of

Table 1: Performance indexes under step external disturbances in the nominal case.

Performance index	the dissolved ozone residual (MPC)	the dissolved ozone residual (MPC-DOB)
Overshoot(%)	9.63%	5.65%
IAE	0.402	0.132

the closed-loop system. As illustrated in section 2, the proposed method can reject not only external disturbances, but also the internal disturbances caused by model mismatches. In this part, some simulation studies are done to demonstrate the lumped disturbance rejection performance of the proposed method.

Suppose that the transfer function model of process channel is expressed as

$$G_P(s) = \frac{0.47}{168s+1}e^{-72s}. \tag{22}$$

Comparing (22) with (17), it is clear that severe model mismatch exists.

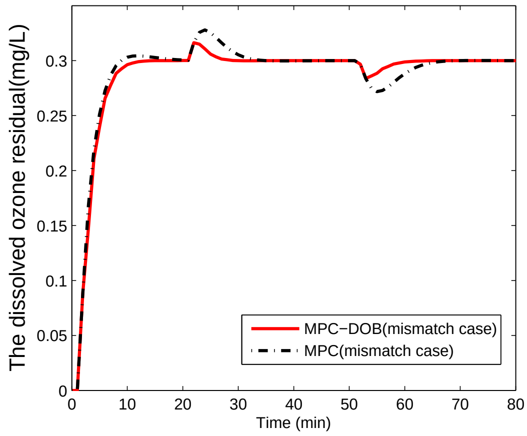
Step external disturbances in the model mismatch case: the the water flow rate has an increase of 20% at $t = 20min$, while the water COD value has an increase of 20% at $t = 50min$.

The response curves of the dissolved ozone residual under the two methods in this mismatch case are shown in Fig. 4(a). The effects of lumped disturbances and the estimations in this mismatch case are presented in Fig. 4(b). It can be observed from Fig. 4(a) that the proposed method possesses a smaller peak overshoot and a faster convergence speed. This means that the proposed method has achieved a much better step disturbance rejection performance than that of the MPC method even in the case of severe model mismatches. Moreover, the errors between the estimated and the real lumped disturbances are also very small.

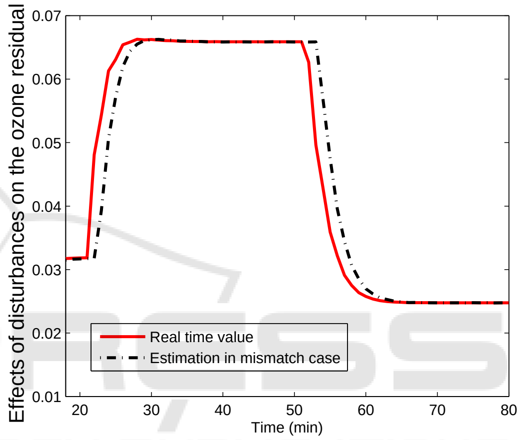
Those results demonstrate that the proposed method has remarkable superiorities in rejecting such lumped disturbances consisting of external disturbances and internal disturbances caused by model mismatches.

4 CONCLUSIONS

In the ozonation process, various disturbances have undesirable influences on the control of the dissolved ozone residual. Many existing methods including MPC have limitations in handling strong disturbances. For improving the disturbance rejection performance, a compound control structure combining of a feedforwad compensation part using DOB with a feedback regulation part based on MPC is proposed. Both external disturbances and internal disturbances caused by model mismatches are taken into consideration. The results have demonstrated that, compared with the MPC method, the proposed method has exhibited excellent disturbance rejection performance, such as a smaller overshoot and a shorter settling time.



(a)



(b)

Figure 4: Response curves of variables in the presence of step external disturbances under DOB-MPC and MPC schemes in the mismatch case: (a) controlled variable, (b) disturbances and their estimations.

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