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Model Predictive Control for the Activated Sludge Process

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Abstract

To address the issues of large fluctuations in influent load, high aeration energy consumption caused by conservative traditional on-off control strategies, unstable dissolved oxygen (DO) concentration, and poor sensor reliability in the activated sludge wastewater treatment process, a Model Predictive Control (MPC) method integrating data quality monitoring and a feedforward disturbance mechanism is proposed. A multi-input multi-output prediction framework based on an incremental Auto-Regressive eXogenous (ARX) model is constructed. The influent disturbance observer (BOD) load is introduced into the model as a feedforward variable. An MPC method based on a feedforward disturbance mechanism is designed to solve the hysteresis problem of feedback control. For the discrete characteristics of the actuators, PWM modulation is used to realize continuous control. Long-term actual engineering verification was carried out in a wastewater treatment plant in Jiaozuo, Henan. The results show that compared with the traditional PLC on-off control, this system reduces the average aeration energy consumption by more than 25%. The treatment efficiency is increased by 25%. The energy consumption per unit BOD removal stably reaches 0.8 kWh/kg BOD, which is an excellent industry level. The annual CO_2 emission is reduced by about 260 tons. The effluent quality compliance rate is not affected. This system can effectively suppress the invalid overshoot of DO concentration. It solves the control problems caused by multi-variable strong coupling and sensor failures. On the premise of ensuring absolute safety of effluent quality, significant energy saving, economic and environmental benefits are realized.

Keywords

Water Pollution; Wastewater Treatment; Model Predictive Control; Disturbance Observer.

1. Introduction

The activated sludge process (ASP) in wastewater treatment plants is typically operated conservatively. The primary objective is to maintain stable system performance despite fluctuations in influent flow and quality. While ensuring effluent compliance is paramount, practical operation must also consider both physical constraints and financial limitations. Currently, to guarantee safety, systems are often designed with excessive safety margins, leading to consistently high operational costs, particularly in aeration energy consumption [1]. For the water industry to meet the increasingly stringent efficiency requirements set by regulators, improvements in existing operational management are essential. Applying advanced control technologies can effectively leverage the dynamic nature of the process. This approach ensures operational reliability while significantly reducing energy use. Furthermore, these technologies can mitigate the impact of external disturbances, thereby enhancing overall operational efficiency.

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Traditional activated sludge processes were seldom designed with dynamic operational characteristics in mind, resulting in very limited controllable variables. In recent years, driven by stricter effluent standards, rising operational costs, and growing public environmental awareness, the wastewater treatment industry has actively promoted the development of control technologies and instrumentation automation. This paper presents a practical case study involving the development of an advanced control system based on ASP for a specific wastewater treatment plant. The study aims to evaluate the economic and environmental benefits offered by this system. Employing a Model Predictive Control (MPC) strategy that integrates feedback and feedforward mechanisms, the system utilizes real-time data for dynamic process adjustment. Its goal is to automatically tune process parameters in response to changes in plant loading, ultimately achieving reduced energy consumption.

Given the process characteristics of this study, special attention must be paid to the reliability of measurement data. Although advanced instruments like spectroscopic sensors are increasingly used in ASP, measurement data are often unstable due to complex underwater conditions, fouling, and other factors. To address this, a dedicated Data Quality Monitoring (DQM) system was designed to operate concurrently with the control system, screening out anomalous data to ensure the accuracy of control decisions.

Currently, the wastewater treatment industry rarely adopts advanced process control. Most plants still rely on PLC and SCADA systems, using conventional on/off control logic to maintain parameters within fixed setpoints without accounting for upstream influent variations [2]. This lack of information limits the application of advanced control strategies. However, recent advancements in instrumentation have made obtaining accurate process data feasible, laying the groundwork for implementing advanced control [3]. The activated sludge process requires continuous aeration, and adjusting the aeration rate is one of the most effective means of process control. Previous aeration optimization efforts have primarily focused on controlling the dissolved oxygen (DO) concentration [4].

In practice, however, the aeration process is co-influenced by multiple variables such as nitrate, ammonia nitrogen, BOD, and COD [5]. These variables change at vastly different rates: DO concentration can shift within minutes, while BOD variations may occur over hours. Although large-scale nonlinear mechanistic models like the Activated Sludge Model (ASM) series are widely used in research [6], their computational complexity prohibits direct application in real-time control. While simplified practical models can be developed [7], determining their parameters (e.g., microbial growth rates) still requires extensive site-specific data [8]. As noted by Brdys et al. [9], directly identifying models from actual operational data is a more efficient approach. This paper adopts this method, establishing a linear multi-input multi-output (MIMO) model for the aeration process of a specific wastewater treatment plant. Although Model Predictive Control (MPC) is not yet widespread in practical plant operations [10], it has been extensively applied in academic research and simulations [11].

2. Sewage Treatment Control Model

The performance of any closed-loop process is inherently dependent on the quality and reliability of its measurement data. In wastewater treatment, sensors are particularly prone to errors. Therefore, the monitoring system employs a Data Quality Monitor (DQM). The DQM is responsible for checking both the logical and statistical characteristics of process signals and assigning corresponding quality tags based on these checks. The logical characteristics check primarily considers the data's rate of change, adherence to the sensor's operational range limits, and whether signal fluctuations remain within a specified threshold. The statistical characteristics check, on the other hand, focuses on data variance, the presence of outliers, and the detection of significant changes in the mean value.

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A wastewater treatment plant located in Jiaozuo, Henan Province, was selected for this case study. The plant serves a population of approximately 100,000. It employs a typical tertiary treatment process: primary treatment for solid removal, secondary treatment using the activated sludge process for organic degradation, and tertiary treatment involving UV disinfection and a nitrifying trickling filter for further purification. As ammonia removal is guaranteed by the tertiary trickling filter, the activated sludge system in this case is primarily tasked with carbonaceous pollutant removal.

As shown in Figure 1, the activated sludge process consists of two parallel trains, each comprising an anoxic tank followed by five surface-aerated tanks. The key process parameters are listed in Table 1. For modeling purposes, given that the two trains exhibit essentially identical dynamic behavior, they are treated as identical systems to simplify the model. Dissolved Oxygen (DO) sensors are installed in the second, fourth, and fifth tanks (in the flow direction). The original PLC control strategy relied solely on adjusting the aeration in individual tanks based on the DO concentration measured at these points, maintaining the values within their setpoint ranges. This control approach represents a typical local (or decentralized) control strategy, lacking coordination between the different aeration units

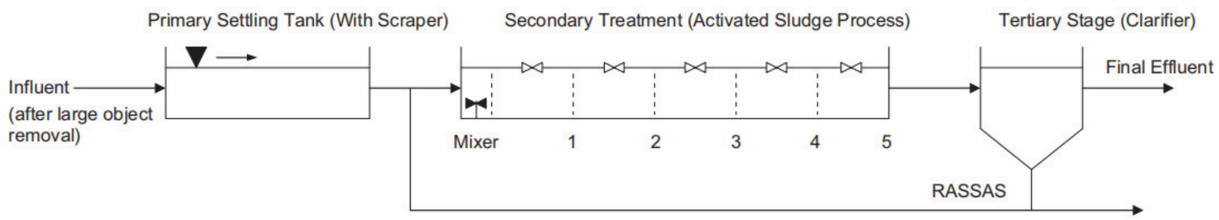

Figure 1. Schematic of the Activated Sludge Process

Given the relative scarcity of other means to regulate and control the process, current control efforts are predominantly focused on aeration control. This paper, therefore, achieves precise control of the aeration process by dynamically adjusting the Dissolved Oxygen (DO) levels throughout the treatment train. The primary source of disturbance for wastewater treatment processes is the diurnal, periodic fluctuation in influent load characteristics.

The model-based control tool used in this study was initially developed by Sandoz [12] and has been extended over the subsequent decades. The model predictive algorithm employs a "moving horizon" approach, whereby a sequence of control actions is calculated over a given prediction horizon. Only the first control action in this sequence is implemented, while the remaining calculated actions are discarded. This entire process is then repeated at the next sampling instant. For industrial applications, Model Predictive Control (MPC) is typically implemented using a linear process model. The process model developed in this paper adopts an incremental ARX form, which has proven suitable for online process control due to its flexibility and compact structure. This incremental ARX form, when combined with a variable-coefficient "delay spreads" mechanism, provides an efficient method for capturing both the fast and slow dynamics of the process.

The MPC algorithm employed in this study is based on the minimization of the following cost function, J:

$$J = \sum_{i=1}^{N} \left[\mathbf{e}_{i+1} \mathbf{P} \mathbf{e}_{i+1}^{\mathrm{T}} + \Delta \mathbf{u}_i \mathbf{Q} \Delta \mathbf{u}_i^{\mathrm{T}} \right] \tag{1}$$

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where the vector of current and future control moves, Du, are determined subject to physical constraints on the process and e is the vector of set-point tracking errors (i.e. the difference between the estimated value of the output at sample point, i, in the future and the set-point). The cost function is solved with consideration of the weighting matrices P and Q over the horizon, N. In this application the set-point was fixed throughout the horizon and Eq. (1) was solved at each sampling instant using standard Quadratic Programming[13].

The estimate of the control variable, y, at sample time k, is determined from the following incremental ARX model:

$$A(z)\Delta y(k) = B(z)\Delta x(k) + \xi(k) \tag{2}$$

where A(z) and B(z) are polynomials in z-1, x(k) is a vector of manipulated and disturbance variables, measured at sample time k, –x(k) is a white noise sequence and D is the difference operator. Further information on modelling is available in Soderstrom and Stoica[14]. The relative merits of the incremental ARX model are discussed in Sandoz et al.[15], however, an important advantage with this form of model is that the inclusion of the integral term allows steady state, plant-model mismatch errors to be handled seamlessly by the controller.

3. Activated Sludge Process Data Collection and Process Control

In order to implement an appropriate control strategy, it is essential to acquire sufficient process information and execute process control based on information collected on-site.

3.1. Data quality inspection

The following sensors were installed on-site to provide reliable online measurements of water quality entering and exiting the Activated Sludge Process (ASP). Both devices, which are commercially available products from S::CAN Instruments, are as follows: the Spectrolyser (a spectral analyzer) and the Ammolyser (an ammonia analyzer).

The Spectrolyser is a spectral analyzer capable of measuring BOD, COD, TSS, nitrate, pH, and temperature. Two units of this device were installed, located at the inlet and outlet of the ASP, respectively. The Ammolyser is an analyzer specifically designed for measuring ammonia concentration. Two units of this instrument were also installed on-site, positioned similarly at the influent and effluent points of the ASP.

In conjunction with standard process measurements (as shown in Table 1) and knowledge of the process aeration status, these instruments provide a range of information concerning the operational health of the process. Furthermore, during the experimental period of this case study, they also served as a means to monitor the efficiency of the ASP in removing carbonaceous pollutants.

Table 1. Analysis of Sensor Fault Types

Sensor Type	Determinable Error Types	Corresponding Traditional Sensor Fault
Dissolved Oxygen Sensor	93%	Sensor drift (manifested as a mean shift in process measurements)
Turbidity Sensor	97%	Sensor clogging (manifested as sensor noise or signal freezing)
Ammonia Sensor	97%	Sensor performance degradation (manifested as a mean shift in process measurements)

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The variables presented in Table 1 carry specific meanings in the context of monitoring the activated sludge process. Flow refers to the total volume of wastewater entering the activated sludge plant after primary treatment. This flow, combined with the BOD value, determines the biological load imposed on the activated sludge system. Dissolved Oxygen (DO) and aeration, which are integral throughout the ASP, are crucial for the biological degradation of organic load. Maintaining an adequate DO level (typically an average of 0.8 mg/L is sufficient to meet the demand for aerobic degradation of carbonaceous substances) is vital. Monitoring DO levels and the extent of aeration serves as a good indicator of the process's operational status. Laboratory data, which include tests for BOD, COD, ammonia, and suspended solids conducted on the influent and effluent, traditionally provided single-point measurements of these parameters at intervals of approximately four days. However, with the aid of advanced instruments like spectral analyzers, online, real-time measurement of these variables is now achievable.

3.2. ARX Prediction Model

As noted by Sandoz et al. [15], ARX models demonstrate superior robustness and applicability in practical industrial settings compared to alternative approaches. Building on this, this paper utilizes historical data collected from on-site testing. A linear incremental ARX model suitable for this wastewater treatment scenario is constructed through parameter identification via the Recursive Least Squares (RLS) method based on UD decomposition [16]. Consequently, the model in Equation (2) is updated as follows:

$$A(z)\Delta y(k) = B_u(z)\Delta u(k) + B_d(z)\Delta d(k) + \xi(k) \tag{3}$$

In the model, Δ is the difference operator, used to eliminate steady-state error; $y(k)$ is the vector of controlled output variables, specifically the dissolved oxygen (DO) concentrations measured at the six aeration tanks; $u(k)$ is the vector of manipulated input variables, representing the power demands for the three groups of aerators, which are modulated via PWM to drive the actuators; $d(k)$ is the measurable disturbance, namely the BOD load, which serves as a feedforward compensation for influent fluctuations; $\xi(k)$ is a zero-mean white noise sequence representing the model residuals; and $A(z), B_u(z), B_d(z)$ are polynomials in the unit delay operator z^{-1}, where $z^{-1}x(k)=x(k-1)$.

To select the most concise model structure that avoids overfitting while ensuring model accuracy, it is necessary to determine the lag orders (i.e., the number of past data points) for the polynomials of the manipulated variables and the disturbance variable. Since the ARX model in this study is a first-order model, meaning the order of $A(z)$ is fixed as 1, only the lag terms for $B_u(z)$ and $B_d(z)$ need to be determined using cross-validation.

Historical operational data from the wastewater treatment plant were collected and chronologically divided into a training set (70%) and a validation set (30%). The training set was used to fit ARX models with different lag structures, while the independent validation set, which was not involved in the modeling process, was employed to evaluate the generalization performance of the models.

To account for the range of possible dynamic response times—for instance, the effect of aeration power changes on dissolved oxygen (DO) typically occurs on a minute scale, corresponding to 6–10 sampling intervals, while influent load fluctuations have longer periods, with BOD responses potentially lasting several hours, corresponding to 20–30 sampling intervals—the candidate range for the lag order of the manipulated variable $u(k)$ is set to $n_{bu} \in \{1, 2 \ldots, 10\}$, and for the disturbance variable $d(k)$ to $n_{bd} \in \{1, 2 \ldots, 30\}$

For each candidate combination, the model parameters are estimated using the training set. The generalization performance is then evaluated by calculating the Prediction Mean Squared Error (MSE) on the validation set:

$$\mathrm{MSE}(n_{bu}, n_{bd}) = \frac{1}{N_v}\sum_{k=1}^{N_v}(y(k) - \hat{y}(k \mid n_{bu}, n_{bd}))^2 \tag{4}$$

where N_v is the number of samples in the validation set, and $\hat{y}(k \mid n_{bu}, n_{bd})$ is the model's prediction of y(k)based on historical data.

The combination that yields the minimum MSE is selected as the optimal lag structure. Based on the measurement data, the minimum MSE was achieved with 6 lag terms for the manipulated variable and 20 lag terms for the disturbance variable. Consequently, the specific form of the ARX model is updated from Equation (2) to:

$$\begin{aligned}(1 - a_1 z^{-1})\Delta y(k) = &\sum_{i=1}^{6} b_{u,i} z^{-i} \Delta u(k-i) \\ &+ \sum_{j=1}^{20} b_{d,j} z^{-j} \Delta d(k-j) \\ &+ \xi(k)\end{aligned} \tag{5}$$

Here, a_1 is the first-order autoregressive coefficient, describing the historical dependence of the controlled output; $b_{u,i}(i = 1,\ldots,6)$ are the lag coefficients for the manipulated input, reflecting the dynamic weighting of aeration power's influence on DO; $b_{u,j}(j = 1,\ldots,20)$ are the lag coefficients for the disturbance input, reflecting the lagged weighting of influent BOD's influence on DO. Rearranging terms gives:

$$\begin{aligned}\Delta y(k) = a_1 \Delta y(k-1) + &\sum_{i=1}^{6} b_{u,i} \Delta u(k-i) \\ + \sum_{j=1}^{20} b_{d,j} \Delta d(k-j) &+ \xi(k)\end{aligned} \tag{6}$$

The specific values of the model parameters $a_1, b_{u,i}(i = 1,\ldots,6), b_{u,j}(j = 1,\ldots,6)$ are estimated via the UD decomposition-based Recursive Least Squares (RLS) method:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + K(k)\Big(\Delta y(k) - \phi^T(k)\hat{\theta}(k-1)\Big) \tag{7}$$

Where, $\hat{\theta}(k) = [a_1, b_{u,1},\ldots,b_{u,6}, b_{d,1},\ldots,b_{d,20}]^{\mathrm{T}}$ is the parameter vector; $\phi^T(k)$ is the regression vector; and $K(k)$ is the gain matrix, computed via UD decomposition to ensure numerical stability.

Through the steps described above—fitting on the training set and screening on the validation set—a concise model structure with 6 lag terms for the manipulated variable and 20 lag terms for the disturbance variable was ultimately determined, achieving a balance between accuracy and complexity.

4. Feedforward MPC-based Wastewater Treatment Process Control

The controller structure selected in this paper aims to accurately capture the dynamic characteristics of the aeration process in the activated sludge stage. This controller adopts a multi-input multi-output system architecture and incorporates measurable feedforward disturbance signals. Integrating feedforward variables (in this paper, the influent BOD load entering the process) into the process model can provide highly valuable early warning signals for predicting potential future disturbances to the process operating state.

4.1. MPC-based wastewater treatment process control

In the basic MPC control model, the manipulated variables are the aeration power, and the controlled variables are the individual dissolved oxygen (DO) measurements. The motors used for surface aeration in each stage are single-speed or two-speed motors, which aligns with the current "on/off" control strategy based on upper and lower DO concentration limits. However, the Model Predictive Control (MPC) strategy considers the (continuous) power delivered to each compartment. Therefore, for MPC implementation, the aerators are divided into three groups: Group 1 includes aerators in compartments 1 and 2; Group 2 includes aerators in compartments 3 and 4; Group 3 includes only the aerator in compartment 5.

In the Model Predictive Control (MPC) strategy, it is necessary to predict future outputs $\Delta y(k+1|k), \Delta y(k+2|k), \ldots, \Delta y(k+N|k)$ over the prediction horizon . This is achieved by recursively expanding Equation (6):

$$\begin{aligned}\Delta y(k) = a_1 \Delta y(k-1) + \sum_{i=1}^{6} b_{u,i} \Delta u(k-i) \\ + \sum_{j=1}^{20} b_{d,j} \Delta d(k-j) + \xi(k)\end{aligned} \tag{8}$$

Since $\Delta y(k+1) = y(k+1) - y(k)$,rearranging yields:

$$\begin{aligned}y(k+1|k) = y(k) + a_1 \Delta y(k) + \sum_{i=1}^{6} b_{u,i} \Delta u(k+1-i) \\ + \sum_{i=1}^{20} b_{d,i} \Delta d(k+1-j)\end{aligned} \tag{9}$$

For the output at time $\Delta y(k+p|k)$, it can be expressed in the same manner:

$$\begin{aligned}&y(k+p|k) = y(k) \\ &+ \sum_{m=1}^{p} \left[a_1 \Delta y(k+m-1) + \sum_{i=1}^{6} b_{u,i} \Delta u(k+m-i) + \sum_{j=1}^{20} b_{d,j} \Delta d(k+m-j) \right]\end{aligned} \tag{10}$$

However, although the traditional MPC algorithm benefits from the linearization simplification of the incremental ARX model and its capability to handle multivariable constraints, achieving basic process stability in the aeration control of wastewater treatment, it still has the following shortcomings when dealing with severe influent load fluctuations and model mismatch issues, which can be improved. Therefore, a feedforward MPC process control method that introduces the influent BOD load, as shown in Figure 2, is designed:

(1) Traditional MPC constructs its prediction model based solely on historical data, neglecting the feedforward compensation for measurable/immeasurable disturbances such as influent flow and BOD load. This results in a passive response to shock loads: the controller can only

initiate corrective actions after water quality deviates from the setpoint, leading to significant dynamic overshoot and recovery lag. Therefore, a Feedforward MPC (FF-MPC) mechanism is introduced. By incorporating the influent BOD as a leading variable into the prediction horizon, the controller gains the ability to "foresee" disturbances and adjust aeration intensity proactively. This reduces the system's sensitivity to sudden disturbances and shortens the response time.

(2) Traditional MPC relies on fixed ARX model parameters (as described in the text, "parameters remain fixed"), which, while ensuring operational stability, cannot handle model mismatch caused by seasonal variations in microbial activity or sensor aging. A single, fixed model leads to the accumulation of prediction bias over long-term operation, subsequently causing control performance degradation. Therefore, a Disturbance Observer (DOB) is designed. It utilizes the residual between the actual effluent quality and the model-predicted value to estimate, in real-time, the "lumped disturbance" composed of model mismatch and unknown interferences. This estimated value is then fed back to the MPC's input for dynamic compensation. Through this dual closed-loop structure of "model prediction + disturbance feedback", the system's robustness to uncertainties is enhanced, balancing control accuracy with long-term operational stability.

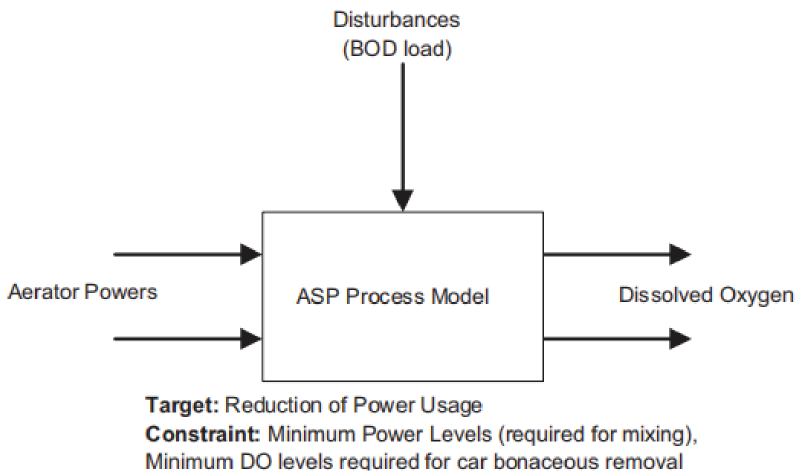

Figure 2. Schematic of the Feedforward MPC Structure Incorporating BOD

4.2. Feedforward MPC design

When dealing with abrupt data with multiple order-of-magnitude variations, optimization becomes challenging, and the parameter solutions often struggle to converge within constraint boundaries. Therefore, based on the fact that accelerometer errors originate from identifiable types of interference downhole, a population initialization strategy based on historical data is proposed. This strategy establishes a historical database, endowing the HBA algorithm with dynamic awareness derived from historical data. This addresses the mismatch between initial positions and optimal distribution regions caused by data magnitude differences, significantly enhancing the stability of global optimization under complex constraint conditions.

To facilitate the MPC optimization solution, Equation (10) is organized into the matrix form $Y = G_u \Delta U + G_d \Delta D + G_x \Delta x_0$, thereby standardizing the prediction equation. Here, $\Delta U = [\Delta u(k), \Delta u(k+1), \dots, \Delta u(k+N-1)]^T$ is the vector of control increments, $\Delta D = [\Delta d(k), \Delta d(k+1), \dots, \Delta d(k+N-1)]^T$ is the vector of disturbance increments, and $\Delta x_0 = [\Delta y(k), \Delta y(k-1), \dots, \Delta y(k-n_a+1), \Delta u(k-1), \dots, \Delta u(k-n_b+1), \Delta d(k-1), \dots, \Delta d(k-n_c+1)]^T$ is the historical data vector.

The control dynamic matrix G_u , which describes the influence of control increments on the predicted outputs, is constructed from the coefficients $b_u(z)$:

$$G_u = \begin{bmatrix} b_{u,1} & 0 & \cdots & 0 \\ b_{u,1}a_1 + b_{u,2} & b_{u,1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^{6} b_{u,i}a_1^{N-i} & \sum_{i=1}^{5} b_{u,i}a_1^{N-i-1} & \cdots & b_{u,1} \end{bmatrix}_{N\times N} \tag{11}$$

Disturbance dynamic matrix G_d describes the influence of disturbance increments on the predicted outputs and is constituted by the coefficients of $b_d(z)$.

$$G_d = \begin{bmatrix} b_{d,1} & 0 & \cdots & 0 \\ b_{d,1}a_1 + b_{d,2} & b_{d,1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{j=1}^{20} b_{d,j}a_1^{N-j} & \sum_{j=1}^{19} b_{d,j}a_1^{N-j-1} & \cdots & b_{d,1} \end{bmatrix}_{N\times N} \tag{12}$$

The initial state matrix G_x describes the influence of historical data on the predicted outputs and is constructed from the coefficients of $A(z),\ B_u(z),\ B_d(z)$.

Thus, the final prediction equation is updated from Equation (10) to:

$$Y = G_u \Delta U + G_d \Delta D + G_x \Delta x_0 \tag{13}$$

4.3. Disturbance Observer (DOB) design

Disturbance Observer (DOB) primarily utilizes the prediction error to estimate the lumped disturbance and feeds it back to the prediction model, thereby achieving passive compensation for errors to avoid control decision-making problems caused by sensor inaccuracies.

Assuming the disturbance is modeled as a random walk process, and letting the state vector be $x_w(k) = \Delta w(k)$, the state-space form of the DOB at this point is:

$$\begin{cases} x_w(k+1) = x_w(k) + v(k) \\ e(k) = y(k) - \hat{y}(k) = Cx_w(k) + \xi(k) \end{cases} \tag{14}$$

where $v(k)$ is the disturbance noise, and $e(k)$ is the prediction residual.

Based on the Kalman filter update logic, the optimal estimate is achieved:

$$\hat{x}_w(k \mid k) = \hat{x}_w(k \mid k-1) + L \cdot e(k) \tag{15}$$

Here, $P$is the error covariance matrix; $R$is the measurement noise covariance; and $L$is the Kalman gain, calculated as:

$$L = P(k \mid k-1)C^T (CP(k \mid k-1)C^T + R)^{-1} \tag{16}$$

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The estimated value of $\hat{w}(k)$ can be obtained as:

$$\hat{w}(k) = \lambda \hat{w}(k-1) + (1-\lambda)(y(k) - \hat{y}(k)) \quad (17)$$

where $\lambda \in [0.95, 0.99]$ is the forgetting factor, used to balance the tracking speed and noise suppression.

By incorporating the DOB into the feedforward MPC prediction equation, the prediction model of Equation (10) is modified to:

$$\hat{y}(k+p \mid k) = G_u \Delta U(k) + G_d \Delta D(k) + G_x \Delta x_0 + \hat{W}(k) \quad (18)$$

Expressed in matrix form, Equation (13) is updated to:

$$Y = G_u \Delta U + G_d \Delta D + G_x \Delta x_0 + \mathbf{1} \otimes \hat{w}(k) \quad (19)$$

By incorporating the DOB to modify the cost function, Equation (1) is updated to:

$$J = \sum_{i=1}^{N} \left[(y_{sp} - \hat{y}_{i+1})^2 P + \Delta u_i^2 Q \right] + \rho \| \hat{w}(k) - \hat{w}(k-1) \|^2 \quad (20)$$

where ρ is the penalty term for disturbance variation, preventing observer divergence.

5. Experiment and Analysis

5.1. Simulation experiments

The design philosophy of the Model Predictive Control (MPC) system in this paper lies in treating the power consumption of each group of aerators as the manipulated variables (i.e., actuators). The system then employs Pulse Width Modulation (PWM) technology to convert the calculated power demand into discrete aerator speed pulse signals. In this conversion process, the actual average output power is proportional to the modulation duty cycle. Here, the minimum pulse width and the pulse width of the periodic PWM signal determine the power delivered to the aeration tanks by the on/off aerators; this power value is achieved through the combined effect of both parameters. Therefore, for control purposes, the process is considered to consist of 6 manipulated input variables (the aerators of Groups 1, 2, and 3 for Train 1 and Train 2, respectively) and 6 controlled output variables (the dissolved oxygen concentrations in aeration tanks 2, 4, and 5 for Train 1 and Train 2, respectively). The Biochemical Oxygen Demand (BOD) flowing into the Activated Sludge Process (ASP) system is used as the sole feedforward variable or disturbance variable to respond to changes in upstream conditions. The results are shown in Figure 3.

Figure 3 visually demonstrates the diurnal variation dynamics of influent flow and the corresponding fluctuation trend of BOD concentration. It can be seen that the BOD load (i.e., the product of flow and concentration) exhibits significant non-stationarity and impulse characteristics during the observation period. In the activated sludge process, such abrupt changes in load directly lead to alterations in the microbial oxygen uptake rate, thereby disrupting the supply-demand balance of the aeration system. Therefore, real-time monitoring of influent BOD concentration and quantifying it as the core disturbance variable affecting the aeration process is of decisive significance for enhancing the anti-interference capability of the closed-loop system.

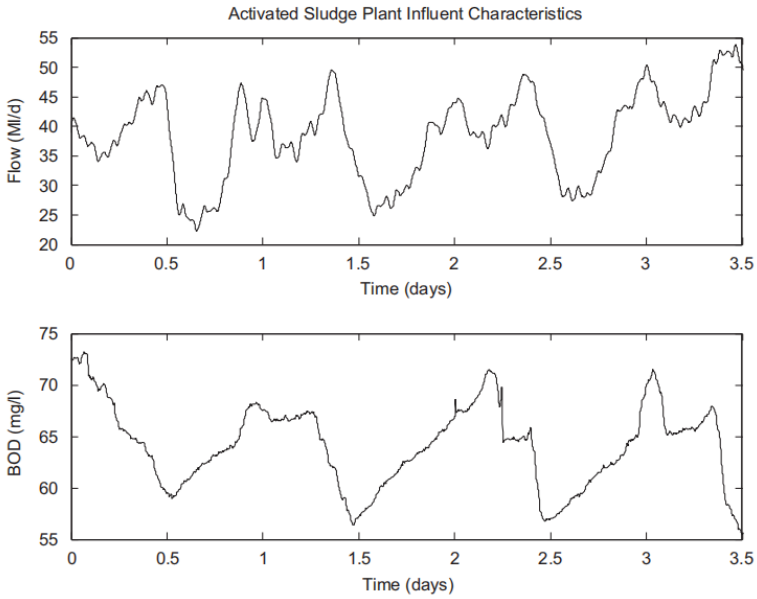

Figure 3. Influent Flow and Biochemical Oxygen Demand (BOD) under MPC Control

Furthermore, this paper compares the actual dissolved oxygen readings from three of the six DO sensors (one from each reaction tank) with the predictions made by the incremental ARX model on a validation dataset that was not involved in model training. As shown in Figure 4, although the model is not perfect, it captures the main transient changes in the data, which is generally sufficient to support accurate Model Predictive Control (MPC).

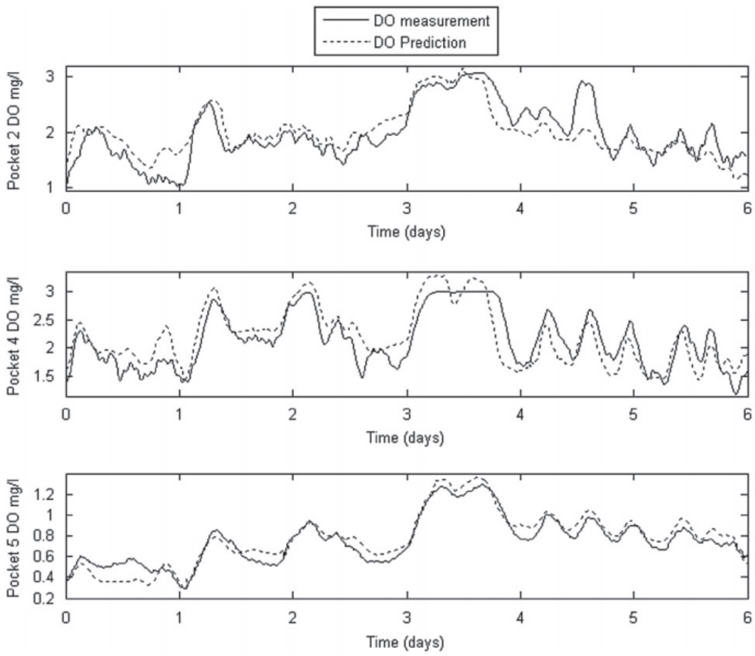

Figure 4. Measured vs. Predicted Dissolved Oxygen (DO) Values in Three Reactors

5.2. Actual sewage treatment experiments

To verify the practical effectiveness of the proposed control strategy in the Activated Sludge Process (ASP), a comparative operation experiment was conducted over 14 days at a wastewater treatment plant in Jiaozuo, comparing the traditional PLC control strategy with the MPC strategy presented in this paper. The experimental results are shown in Figure 5.

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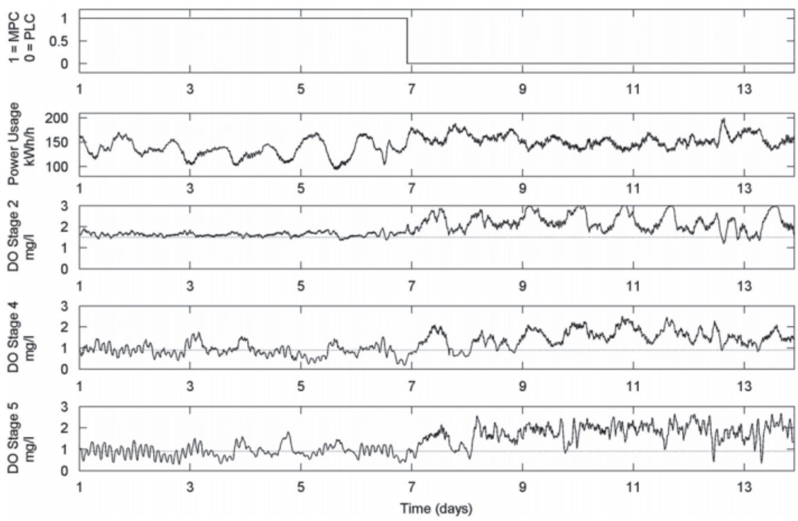

Figure 5. Experimental Comparison of PLC vs. MPC Control Strategies

The experiment employed an alternating control scheme: the MPC system was activated for the first 7 days, followed by a switch back to the traditional local on/off control system for the subsequent 7 days. As shown in Figure 4, the MPC system was capable of stably tracking the dissolved oxygen (DO) concentration at each stage near the setpoint (indicated by the dashed line). In contrast, the traditional on/off control failed to effectively suppress large DO fluctuations, often causing the DO concentration to significantly exceed the upper limit, leading to unnecessary increases in energy consumption.

Specifically, constrained by its control structure, the plant's original PLC strategy could only execute an "either-or" on/off logic within the range of 0.5 mg/L to 1.5 mg/L. Historical operational data, as well as Figure 6, indicate that to ensure the effluent carbon removal rate (typically requiring DO > 1 mg/L), the system was often forced to maintain high aeration levels for extended periods. This resulted in frequent exceedances of the DO upper limit, causing energy waste. In contrast, the MPC strategy treats wastewater treatment as a multivariable coupled process influenced by diurnal load variations, enabling dynamic adjustment of aeration intensity and DO distribution based on real-time influent load. It is important to note that, limited by the existing hardware conditions of single-speed/two-speed aerators, the continuous control output from MPC needed to be discretized via a PWM (Pulse Width Modulation) scheme, which to some extent restricted the further improvement of control precision.

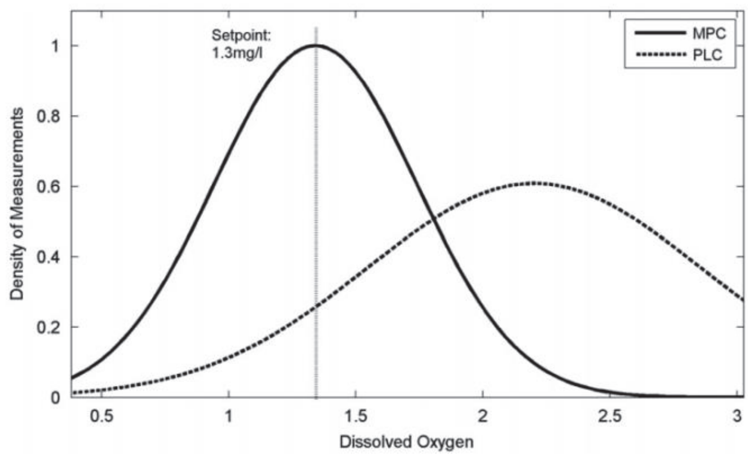

Figure 6. Effluent Carbon Removal Efficiency

Based on statistical results from long-term operation from March 2024 to 2025, compared to traditional on/off control, the MPC strategy reduced average aeration energy consumption by more than 25%, increased treatment efficiency by 25%, equivalent to an annual reduction of approximately 260 tons of CO_2 emissions. Furthermore, traditional local control, due to the lack of a feedforward mechanism, cannot respond to upstream influent load fluctuations. In contrast, the MPC strategy, by introducing influent BOD as a feedforward variable, achieves predictive compensation for plant disturbances, effectively resolves the DO limit violation problem, and ensures the rationality of dissolved oxygen distribution throughout the entire process.

The performance of the Model Predictive Control (MPC) system can be evaluated by analyzing its operational efficiency. This efficiency metric is defined as the ratio of energy consumed for aeration (kWh) to the mass of BOD removed (kg BOD). A process efficiency of approximately 0.8 kWh/kg BOD is typically considered indicative of good operational status. Therefore, the controller uses this steady-state target value as its operational benchmark. Figure 7 shows the plant's operational performance over the 2.5 months prior to implementing the MPC system and the performance improvement achieved during the 4 months after its application. In Figure 7, a higher efficiency value indicates lower electrical energy consumption required to remove 1 kilogram of BOD. By comparing the energy efficiency (in kWh/kg BOD) with the load treated by the Activated Sludge Process (ASP), the overall energy-saving benefit achieved by adopting the MPC solution can be intuitively observed.

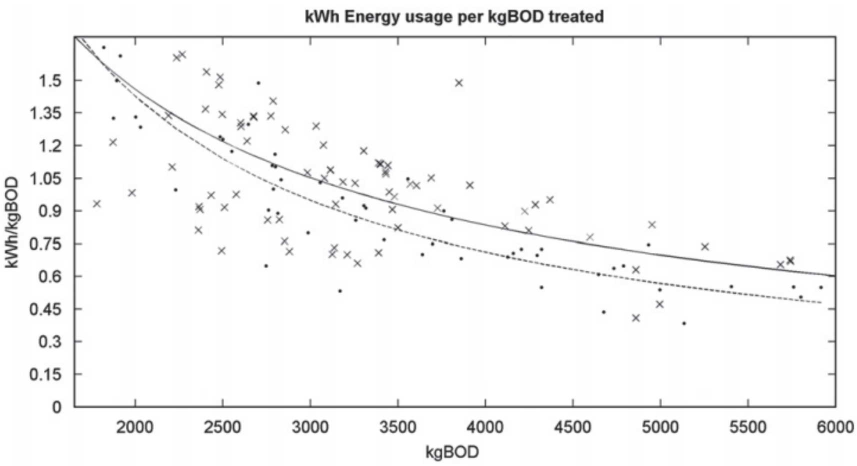

Figure 7. Variation in Energy Consumption under MPC

Evidently, adopting the MPC strategy can yield significant economic benefits. Another crucial factor of concern for the wastewater treatment industry is "compliance risk." During operation under MPC control, the removal efficiency of carbonaceous pollutants showed no decline. Furthermore, throughout the entire period the MPC system was active, the final effluent quality did not deteriorate. Over the entire case study period, the removal efficiencies for BOD, suspended solids, and ammonia nitrogen remained consistently stable.

6. Summary and Outlook

This paper proposes an integrated model predictive control and monitoring system for wastewater treatment plants, aiming to reduce operational costs and enhance process stability. Through a wastewater treatment plant located in Jiaozuo City, Henan Province, the practical application effectiveness of the proposed predictive control strategy is demonstrated. This control strategy is implemented in real-time during the wastewater treatment process and is used in conjunction with the plant's supervisory system for process monitoring.

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This wastewater treatment process control method reduces aeration costs at low BOD load levels and possesses the capability to predict dynamic process conditions. Beyond the tangible economic benefits derived from process control, the monitoring system also provides useful information regarding sensor quality, which has been utilized for maintenance work. The application of this process control system results in smoother operation of the wastewater treatment plant, reducing the volatility of process variables. The online measurement of influent behavior and the prediction of final effluent values not only provide more detailed process information but also serve as a supplement to laboratory sampling measurements.

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