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Optimal control during anaerobic digestion of highly concentrated organic wastewater

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ABSTRACT

Anaerobic biological treatment of wastewater is an important technology in environmental engineering and energy engineering, and it is one of the methods for powerful treatment of highly concentrated organic wastewater. The study was conducted to design an optimal control strategy based on the anaerobic digestion model ADM1. Taking the maximisation of total gas production as the control objective, the Composite Intelligent Optimised Extreme Value Control Algorithm (CIOEC) was designed by combining the extreme value search control method with the model-free optimisation algorithm. The effectiveness of the proposed algorithm is verified by a combination of simulation tests and empirical analyses, and the CIOEC algorithm can maintain fast convergence and relative stability under both stable and changing input materials, and obtain the highest real-time gas production. Among them, the average daily gas production of the ADM1 system with the addition of the CIOEC algorithm can reach 873.9 mL, which is an increase of 124.3% compared with the original system. It shows that the algorithm proposed in this paper can enhance the total gas production and optimise the treatment effect in performing anaerobic digestion of high concentration organic wastewater.

Keywords: CIOEC algorithm, ADM1, anaerobic digestion, high concentration organic wastewater

1. Introduction

The treatment of highly concentrated organic wastewater is a difficult task. In order to effectively solve the problem of environmental pollution caused by organic wastewater, both domestic and foreign countries are committed to the research and development of new technologies. Currently, biotechnology is considered to be the most promising method for the treatment of organic pollutants, which is more effective and less expensive than chemical and physical treatment technologies [1-4]. The treatment method of organic wastewater, especially high concentration organic wastewater, mainly depends on the nature of the wastewater. Generally speaking, the nature of wastewater can be roughly divided into three categories: easily biodegradable wastewater, difficult biodegradable

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organic wastewater, harmful organic wastewater. As for high concentration organic wastewater, anaerobic digestion treatment technology should be prioritised as the main means of removing organic matter [5-8].

Anaerobic digestion is a widely used biological treatment technology for high-concentration organic wastewater, which is advantageous for the energy recovery of wastewater treatment process and green energy production. Anaerobic digestion can effectively remove organic pollutants from wastewater by microorganisms and convert them into biogas, a renewable energy source [9-11]. Anaerobic digestion for biogas production has been developed as an important method for organic wastewater treatment. However, anaerobic digestion technology still has some problems that need to be solved [12-13], including low efficiency of organic matter conversion, poor system stability, etc. To solve these problems, different methods can be used to enhance anaerobic digestion, mainly including microbial colony improvement, reactor operation regulation, parameter optimisation and addition of exogenous substances [14-16].

Feng, D. et al. explored the effect of adding carbon cloth and increasing the organic loading rate under different mixing conditions on the synergistic degradation of wastewater produced. The results showed that the addition of carbon cloth to the unmixed reactor increased the methane yield by 10.1-23.0% and chemical oxygen demand (COD) removal by 14.6% at olr of 2.1-4.2 gCOD/L-d, which indicated the formation of electroactive biofilm on the surface of activated carbon cloth [17]. Li, P. et al. mentioned that high salinity (concentration) organic wastewater discharged directly into the environment without treatment will kill aquatic organisms and cause damage to the soil. Li, P. To evaluate the feasibility of BESs for the treatment of high-salinity organic wastewater, the effect of the applied potential on the anaerobic digestion of high-salinity organic wastewater was discussed in an upflow anaerobic sludge blanket (UASB) reactor at -0.6 V (vs.Ag/AgCl). This suggests that the application of an external potential has a negative effect on the anaerobic treatment of HSOW [18]. Yang, S. et al. aimed to evaluate the production of trace organic pollutants in waste cement and the elimination of these pollutants in anaerobic digestion. More than ten pollutants were observed in the waste cement and some of them were in very high concentrations. And the molecular structure of anaerobic digestion affects its elimination of pollutants [19]. Laskri, N. et al. measured the CDO and the amount of tidal gas formed during digestion, temperature and other aspects in order to optimise the degradation of organic matter and found that the amount of tidal gas produced by the sludge digestion process was much higher than the amount of organic matter digested at the landfill [20]. Xiong,W. et al. used a gradual increase in the proportion of anaerobically digested wastewater with the aim of reducing the instability of high-strength anaerobically digested wastewater to AGSs, and the method achieved AGSs with high performance and stability, which can effectively treat high-strength anaerobically digested wastewater [21]. Kong, Z. et al. compared the advantages and disadvantages of anaerobic digestion with conventional physical/chemical/biological methods. It is shown that improved design is required to increase the efficiency of ‘degradation from non-degradable to fermentable organics’. Challenges faced by anaerobic digestion technology in chemical organic wastewater treatment, including high energy consumption and low efficiency, were also discussed [22].

This paper investigates the optimal control in anaerobic digestion process on the basis of ADM1 model. Combining the extreme value estimation with the intelligent anti-disturbance model-free controller, the composite intelligent model-free extreme value control algorithm is designed by using the extreme value search control algorithm and combining with the expansion state observer to generate the extreme value estimation trajectory. The algorithm estimates the maximum value of the total gas production during anaerobic digestion in real time, and based on the idea of the extreme local model, the maximum value of the target gas production is tracked by designing a model-free intelligent control algorithm, so that the ADM1 system always keeps in the maximum state of gas production. The proposed algorithm, the perturbed ESC algorithm and the sliding mode extreme value search control algorithm are respectively used as the extreme value estimation module, and are applied to the ADM1 control process for simulation and comparison to verify the effectiveness of the proposed algorithm.

2. Mechanism of anaerobic digestion of wastewater

Anaerobic digestion of wastewater refers to the process of decomposing and converting various complex organic matter in wastewater into substances such as methane and carbon dioxide through the action of anaerobic microorganisms (including parthenogenetic microorganisms) under the condition of no molecular oxygen, also known as anaerobic digestion [23]. The fundamental difference with aerobic process is that it does not use molecular oxygen as a hydrogen acceptor, but chemosynthetic oxygen, carbon, sulphur, nitrogen, etc. as a hydrogen acceptor.

Organic matter $(C_nH_aO_bN_c)$ The general formula for the chemical reaction of anaerobic digestion process can be expressed as:

$$\begin{gathered} C_nH_aO_bN_c+(2n+c-b-\frac{9sd}{20}-\frac{ed}{4})H_2O\rightarrow \\ \frac{ed}{8}CH_4+(n-c-\frac{sd}{5}-\frac{ed}{8})CQ+\frac{sd}{20}C_5H_7O_2N \\ +(c-\frac{sd}{20})NH_4^+ +(c-\frac{sd}{20})HCQ \end{gathered} \tag{1}$$

In the above equation, the symbols and values in parentheses are the equilibrium coefficients of the reaction, where:

$$d=4n+a-2b-3c \tag{2}$$

A value of s represents the fraction of organic matter converted to cells and a value of e represents the fraction of organic matter converted to biogas. Setting:

$$s+e=1 \tag{3}$$

s values varied with organic matter composition, sludge sludge age $\theta_c(d)$ in the anaerobic reactor and the auto-oxidation coefficient $k_d(1/d)$ of the microbial cells:

$$s=a_e\frac{1+0.2k_d\theta_c}{1+k_d\theta_c} \tag{4}$$

where 0.2 represents the coefficient of cellular non-degradability and a_e is the maximum value of organic matter converted into microbial cells.

Anaerobic biological treatment is a complex microbial chemical reaction process that relies on the combined action of three major groups of bacteria, i.e., hydrolytic acidifying bacteria, hydrogen-acetic acid-producing bacteria and methanogenic bacteria. The anaerobic process can be divided into three phases as follows, i.e., hydrolysis-acidification phase, hydrogen-acetic acid-producing phase and methanogenic phase. The anaerobic biochemical reaction process is shown in Figure 1.

The first stage is the hydrolysis acidification stage. Complex macromolecules and insoluble organic matter are first hydrolysed and acidified into small molecules and soluble organic matter under the action of extracellular enzymes, and then infiltrated into the cell body to decompose and produce volatile organic acids, alcohols, aldehydes and so on. This stage mainly produces higher fatty acids.

In addition to providing a source of nitrogen for the synthesis of cellular material, the NH_3 produced by the decomposition of nitrogen-containing organic matter is partially ionised in water to form NH_4HCO_3, which has the effect of buffering the pH value of the digestive juices, and so the ammonia-producing process of proteolysis, which follows the decomposition of carbohydrates, is also sometimes referred to as the period of acid reduction, and the reaction is:

$$NH_3 \underset{\leftarrow}{\xrightarrow{+H_2O}} NH_4^+ + OH^- \xrightarrow{+CO_2} NH_4HCO_3 \tag{5}$$

$$NH_4HCO_3 + CH_3COOH \rightarrow CH_3COONH_4 + H_2O + CO_2 \tag{6}$$

The second stage is the hydrogen and acetic acid production stage. Under the action of the hydroacetic acid producing bacteria, the various organic acids produced in the first stage are broken down and converted into acetic acid and H_2. CO_2 is also formed in the degradation of odd carbon organic acids. e.g.:

$$\begin{aligned} &CH_3CH_2CH_2CH_2CH_2COOH + 2H_2O \rightarrow \\ &CH_3CH_2COOH + CH_3COOH + 2H_2 \end{aligned} \tag{7}$$

$$CH_3CH_2COOH + 2H_2O \rightarrow CH_3COOH + 3H_2 + CO_2 \tag{8}$$

The third stage is the methanogenic stage. Methanogenic bacteria convert acetic acid, acetate, CO_2 and H_2 into methane. This process is carried out by two physiologically distinct groups of methanogenic bacteria, one group converting hydrogen and carbon dioxide to methane and the other group decarboxylating from acetic acid or acetate to produce methane, with the former accounting for about 1/3 of the total and the latter accounting for about 2/3 of the reaction:

$$4H_2 + CO_2 \xrightarrow{\text{Methanogenic bacteria}} CH_4 + 2H_2O \quad (1/3) \tag{9}$$

$$\left.\begin{aligned} CH_3COOH &\xrightarrow{\text{Methanogenic bacteria}} 2CH_4 + 2CO_2 \\ CH_3COONH_4 + H_2O &\xrightarrow{\text{Methanogenic bacteria}} CH_4 + NH_4HCO_3 \end{aligned}\right\} (2/3) \tag{10}$$

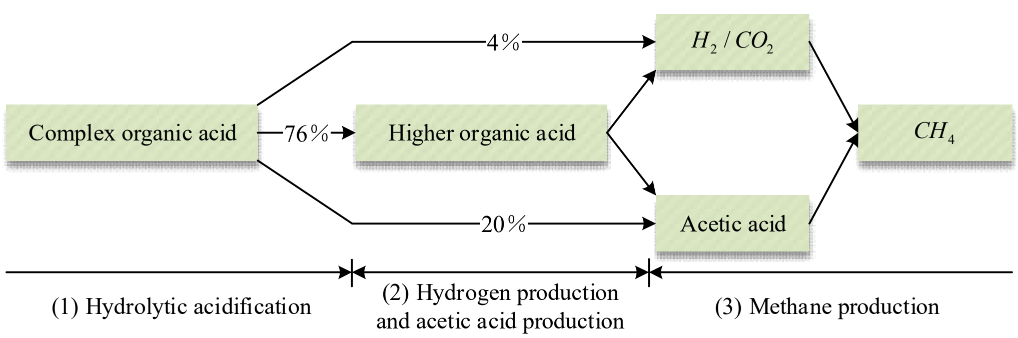


Fig. 1. Anaerobic biochemical reaction process diagram

The reaction rate of the above three stages varies according to the nature of the wastewater, with the ease of hydrolysis becoming the rate-limiting step in wastewaters containing predominantly pollutants such as cellulose, hemicellulose, pectin and lipids. Simple sugars, starch, amino acids and proteins in general can be rapidly decomposed by microorganisms, and the ease of methanogenesis becomes the limiting stage in wastewater containing such organic matter-based wastewater.

Although theoretically, the anaerobic digestion process is divided into the three phases mentioned above, in a conventional anaerobic reactor, the three phases are carried out simultaneously and maintain a certain degree of dynamic equilibrium, which, once disturbed by pH, temperature, organic load and other external factors, will firstly inhibit the methanogenic phase, and as a result, lead to the accumulation of low-grade fatty acids and an abnormal change in anaerobic processes, and lead to the stagnation of the whole anaerobic digestion process.

3. Optimal control of anaerobic digestion process based on ADM1 model

In this paper, ADM1 model is selected to deal with anaerobic digestion of high concentration organic wastewater, and the optimal control method is based on the anaerobic digestion process of this model.

3.1. Mechanistic model of anaerobic digestion process ADM1

In anaerobic digestion modelling studies, the anaerobic digestion 1 model ADM1, proposed by the IWA, is considered the richest and most complex model. The most important feature of ADM1 is an extensible structured model, which can be used to establish an open and universal modelling platform, on the basis of which different example objects can be modelled and simulated in real projects by simplifying, expanding or amending the mathematical model of the constructed real process [24]. In this paper, a control optimisation strategy is designed based on the good scalability of ADM1.

The anaerobic processes considered in ADM1 involve biochemical kinetic processes, gas-liquid mass transfer kinetic processes, and acid-base reaction processes. The biochemical kinetic processes include: decomposition of complex particulate matter, hydrolysis of organic matter (sugars, proteins and lipids), and degradation of intermediate products acid and methane production accompanied by anaerobic bacterial growth and decay processes. The structural overview is shown in Figure 2.

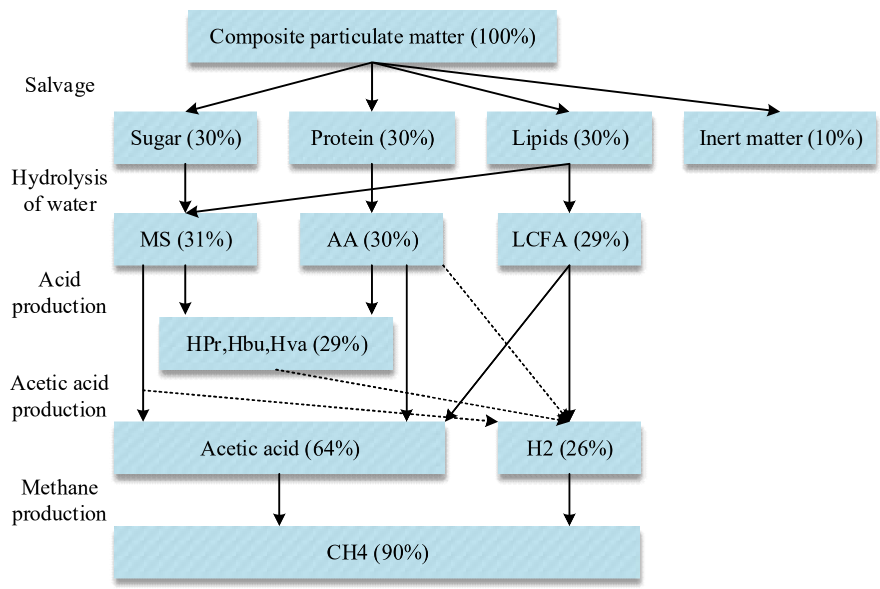


Fig. 2. Anaerobic digestion conversion process used in the model

For each component of the system, the mass balance within the system is expressed as cumulative production per unit time = input per unit time - output per unit time + reaction production per unit time. The input and output terms describe the flow through the system boundary, which is determined by the physical properties of the modelled system. The reaction yield per unit time is based primarily on the kinetics of the Monod form at the substrate level. The matrix approach describes the reaction terms for each individual component refined by process, with reaction rate ρ_j in the rightmost column of the matrix, in addition to stoichiometric coefficients $v_{i,j}$ in each row to describe the effect of the process on the individual components in each row. The total reaction rate for each component i is expressed as the biochemical rate coefficients corresponding to process j for component i and the dynamic rate for each process j multiplied and summed.

For each soluble component:

$$\frac{dS_{liq,i}}{dt} = \frac{q_{in}}{V_{liq}}(S_{i,in} - S_{\mathrm{liq},i}) + \sum_{j=1-19} \rho_j v_{i,j} \tag{11}$$

Each granular component:

$$\frac{dX_{liq,i}}{dt} = \frac{q_{in}}{V_{liq}}(X_{i,in} - X_{\text{liq},i}) + \sum_{j=1-19} \rho_j v_{i,j} \tag{12}$$

Where, V_{liq} is the volume of the liquid reactor. q_{in}, q_{out} is the inflow-outflow feed flow rate, respectively. $S_{i,in}$ is the ith soluble component concentration. $X_{i,in}$ is the concentration of the particulate component. $S_{liq,i}$ is the ith soluble component concentration ($X_{liq,i}$ is the particulate component concentration).

The gas-phase rate equation is similar to the rate equation for the liquid phase but instead of a substrate input flow rate, there is only an output component. The gas pressure is calculated according to the ideal gas law $p = SRT$ relying on the concentration variable S. The pressure of the total biogas is the sum of the pressures of methane, carbon dioxide, hydrogen and water vapour. The flow rate of the biogas can be calculated algebraically from the pressure values along the gas. For the three gas components methane, carbon dioxide and hydrogen:

$$\frac{dS_{gas,i}}{dt} = -\frac{q_{gas} S_{gas,i}}{V_{gas}} + \rho_{T,i} \frac{V_{liq}}{V_{gas}} \tag{13}$$

where $\rho_{\tau,i}$ is the gas kinetic rate of the ind gas component. V_{gar} is the gas volume in the digester, and the item V_{liq} / V_{gas} is added because the gas transfer kinetic rate is calculated conditional on the unit liquid volume. q_{gax} is the outflow rate per unit of gas flow. $S_{gas,i}$ is the generation concentration of the ith gas.

The acid-base rate equation is an integral part of ADM1 and is a necessary step in calculating pH. The components total valeric acid S_{va}, total butyric acid S_{bu}, total propionic acid S_{pro}, inorganic carbon content S_{IC}, inorganic nitrogen content S_N consist of acid-base pairs (e.g. $S_{va} = S_{va^-} + S_{hna}$).

In ADM1 modelling for the biochemical reaction process some inhibition effects are added, these inhibition coefficients mainly work by affecting the magnitude of the reaction rate ρ_j. pH inhibition is mainly considered in ADM1:

$$I_{pH,x} = \begin{cases} \exp(-3\left(\dfrac{pH - pH_{UL,x}}{pH_{UL,x} - pH_{LL,x}}\right)^2) : pH < pH_{UL,x} \\ 1 : pH > pH_{UL,x} \end{cases} \tag{14}$$

Where, x denotes the processes are amino acid anaerobes, acetate anaerobes, and hydrogen anaerobes, respectively.

Inorganic nitrogen inhibition:

$$I_{IN,\lim} = \frac{1}{1 + K_{S,IN} / S_{IN}} \tag{15}$$

Hydrogen inhibition:

$$I_{h2,x} = \frac{1}{1 + S_{h2} / K_{I,h2,x}} \tag{16}$$

Where, x denotes the process for long chain fatty acid anaerobes, pentanoate and butyrate anaerobes, and propionate anaerobes, respectively.

Free ammonia inhibition:

$$I_{nh3} = \frac{1}{1 + S_{nh3} / K_{I,\text{nh3}}} \tag{17}$$

3.2. *Composite Intelligent Optimal Extreme Value Control Algorithm*

In this section, the extreme value estimation is combined with the intelligent anti-perturbation model-free controller to design the composite intelligent model-free extreme value control algorithm by using the extreme value search control algorithm and combining with the dilated state observer to generate the extreme value estimation trajectory. The maximum value of the total gas production is estimated in real time, and the maximum value of the target gas production is tracked by designing a model-free intelligent control algorithm based on the idea of the extremely localised model, so that the ADM1 model is always kept at the maximum value of the gas production. The specific structure of the designed composite intelligent model-free extreme value controller based on the extremely localised model and the expansion state observer is shown in Figure 3 below.

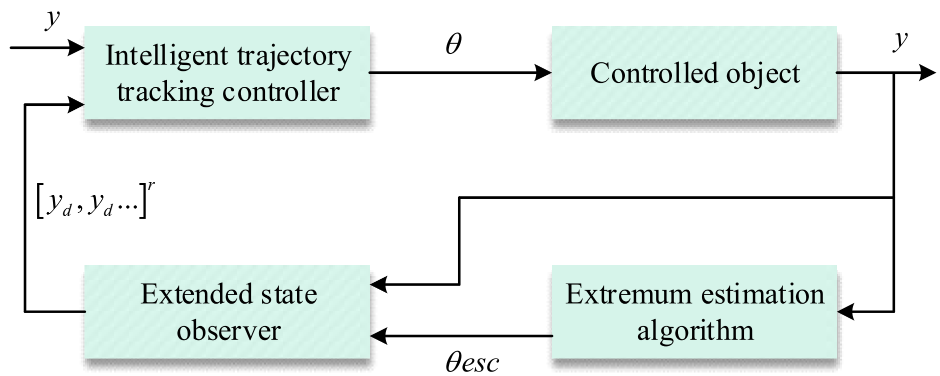


Fig. 3. The composite intelligence has no model extreme value controller structure

3.2.1. Expansion state observer. This paper introduces the idea of expanding state observer, which expands the total perturbations in the ADM1 system due to changes in operating variables or changes in the external environment into new state quantities, establishes a feedback mechanism, and observes the polar trajectories of the output of the system in real time by combining with the polar searching control structure, which does not need to know the exact mathematical model of the system, but only needs to observe the states and total perturbations according to the input/output data, and has good control effect for process systems that are highly nonlinear or subject to strong perturbations. It is still very effective in controlling process systems with a large degree of nonlinearity or subject to strong perturbations [25].

Since the dynamic behaviour of the ADM1 system can be approximated as a second-order system based on the assumption that there exists only one unique extremum, a generalized single-input, single-output second-order system of the following form is considered:

$$\ddot{y}(t) = f(y(t), \dot{y}(t), w(t), t) + b_d \mu(t) \tag{18}$$

where u is the input quantity of the system, y is the measurable system output, w denotes the external perturbation, $f(\cdot)$ denotes the known or unknown system dynamics containing the nonlinear disturbances within the system, and b_0 is the control gain. Based on the design method of the expanded state observer, the total disturbance of the system (18) is defined as the state quantity x_3, which satisfies $x_3 = f(\cdot) + w$ as an expanded state quantity, so the above system can be reconstructed as:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 + b_0 u \\ \dot{x}_3 = \dot{f}(x_1, x_2, w) + \dot{w} \\ y = x_1 \end{cases} \tag{19}$$

The following third-order linearly expanding state observer can then be built:

$$\begin{cases} \dot{z}_1 = z_2 - \beta_1 e_1 \\ \dot{z}_2 = z_3 + b_0 u - \beta_2 e_1 \\ \dot{z}_3 = -\beta_3 e_1 \end{cases} \tag{20}$$

where z_1, z_2, z_3 denotes the estimate of the system state quantity x_1, x_2, x_3, $\beta_1, \beta_2, \beta_3$ denotes the observer gain, and $e_1 = z_1 - y$ is the observation error. It has been shown in the literature that for the dilated state observer, the error of the dilated state observer is guaranteed to converge even when the system function is discontinuous or not derivable, as long as the perturbation quantity $f(\cdot) + w$ is bounded in the process.

In order to reduce the complexity of parameter tuning in the expanded state observer and make it more widely applicable to more scenarios, the observer gain can be designed according to the '3w' method, with:

$$\beta_1 = 3w_0, \beta_2 = 3w_0^2, \beta_3 = w_0^3 \tag{21}$$

where w_0 is the controller bandwidth. This design ensures that the eigenroots of the observed system are all negative and there is only one tuning parameter, which greatly simplifies the design of the expanded state observer. In the case of unknown perturbation, by choosing the appropriate controller gain and bandwidth, the expanded state observer can estimate the corresponding desired extreme value output trajectory y_d of the system based on the desired extreme value input $\theta_d = \theta esc$ obtained by the extreme value control method, and the expanded state observer is independent of the specific form of the ADM1 system, and it has stronger adaptability and robustness compared with other observers.

After the total perturbation of the system is observed in real time by the expanded state observer, the following system control law is designed to compensate the perturbation in real time in the form of:

$$\theta = \frac{\theta_0 - z_3}{b_0} \tag{22}$$

In turn, the desired closed-loop control system performance is obtained and the purpose of disturbance compensation is achieved.

3.2.2. Intelligent trajectory tracking control algorithm design. In the traditional self-resilient control strategy, the state error feedback control law is generally designed by designing a controller in the form of PD or a sliding mode controller θ_0. In this paper, we mainly adopt the model-free intelligent PID algorithm based on the pole-local modelling and time-delay estimation with higher convergence accuracy and faster convergence speed, to further improve the control performance of the system.

1) Model-free intelligent pole tracking controller design. Considering a general generalised higher-order nonlinear single-input single-output system, a very-local model can be used instead of the complex constant differential expression modelling. For the ADM1 system, the pole-local model can be modelled as:

$$y^{(v)}(t) = F(t) + \alpha\theta_0(t) \tag{23}$$

where v is the order of the system output γ, which is usually set to 1 or 2. In this paper, $v = 1$ is set. F is a centralised perturbation value that is continually updated iteratively, and can be viewed as the sum of known system dynamics, unmodelled system dynamics and uncertainties, and some external disturbances. α is a non-physical parameter that can be adjusted to ensure that $\alpha\theta$ and $y^{(v)}$ change in the same order of magnitude, with α being a constant by default in this paper. Through the very local modelling approach, the complex higher-order ADM1 process can be regarded as a 'virtual object', only the transient characteristics of the system are considered, and the system can be downgraded by iterating the history of the model parameters through the input and output data.

The general form of the model-free intelligent tracking controller is:

$$\theta_0(t) = \frac{-F + y_d^{(\nu)} + R(e)}{\alpha} \tag{24}$$

where $R(e)$ is a convergence term associated with the error $e(t) = y_d(t) - y(t)$, generally given by the classical PID form of the control law, and y_d is the desired output trajectory. In order to avoid higher order terms in the output, the integral term coefficients are generally set to zero, so that the corresponding optimal control strategy can be obtained as:

$$\theta_0(t) = \frac{-F + y^{(\nu)}{}_d + (k_p e(t) + k_d \dot{e}(t))}{\alpha} \tag{25}$$

Combined with the extremely localised model (23), the corresponding systematic process error is satisfied:

$$e^{(\nu)}(t) + k_p e(t) + k_d \dot{e}(t) = 0 \tag{26}$$

When no unknown term exists in the system, i.e., the influence of F on the controller is eliminated, the control algorithm (24) degenerates to the classical PD control algorithm form. However, in practice, the perturbation F is an unknown kinetic ensemble term, which needs to be estimated online.

2) Design of time delay estimation algorithm. In model-free intelligent tracking control algorithms, the estimation of the perturbation term F is one of the key factors. In this paper, we adopt the method in and introduce a time-delay estimation algorithm to compute an estimate of the total system perturbation $\hat{F}$. According to the extremely local model (23), the unknown perturbation term F can be expressed as:

$$F(t) = y^{(\nu)}(t) - \alpha\theta_0(t) \tag{27}$$

Due to the lack of control-relevant information at the current moment t, it cannot be used directly to estimate unknown disturbances, i.e., $\theta_0(t)$ cannot be used directly to estimate $F(t)$. The basic idea of the time-delay estimation algorithm is to proactively introduce a small delay τ into the design of the control structure, and then use historical information about the control inputs and observations of the system's response to simultaneously compensate for unknown dynamics, external disturbances, and other uncertainties. Assuming that the disturbance $F(t)$ is continuous and the time delay τ is sufficiently small, the disturbance term can be approximated as:

$$F(t) \cong \hat{F}(t) = F(t-\tau) = y^{(\nu)}(t-\tau) - \alpha\theta(t-\tau) \tag{28}$$

Therefore, the model-free intelligent tracking controller based on delay estimation can be defined as:

$$\begin{cases} \theta_0(t) = \dfrac{-\hat{F} + y_d^{(\nu)} + (k_p e(t) + k_d \dot{e}(t))}{\alpha} \\ \hat{F}(t) = y^{(\nu)}(t-\tau) - \alpha\theta(t-\tau) \end{cases} \tag{29}$$

Combined with the desired gas production output trajectory obtained from the expansion state observer estimation, the final structure of the optimisation algorithm for composite intelligent model-free control is shown in Fig. 4.

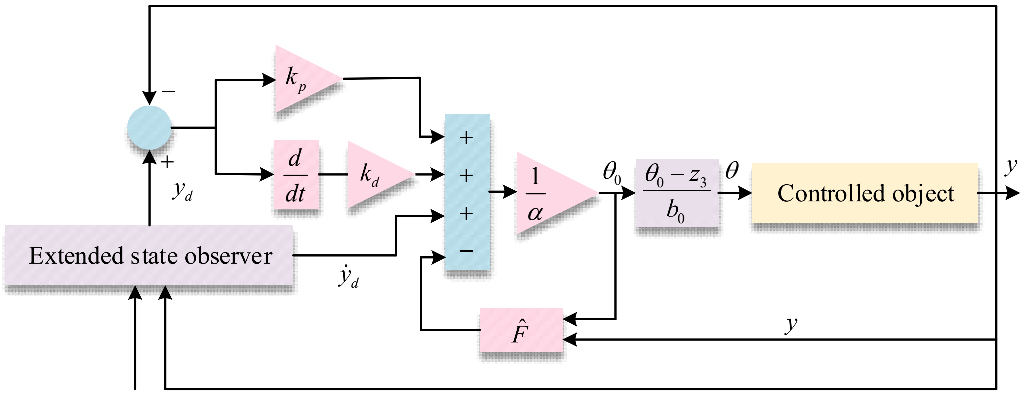


Fig. 4. The composite intelligent model control optimization algorithm structure

The specific expression is:

$$\begin{cases} \theta_0(t) = \dfrac{-\hat{F} + y^{(v)}{}_d + k_p e(t) + k_d \dot{e}(t)}{\alpha} \\ \hat{F}(t) = y^{(v)}(t-\tau) - \alpha\theta(t-\tau) \\ \theta = \dfrac{\theta_0 - z_3}{b_0} \end{cases} \tag{30}$$

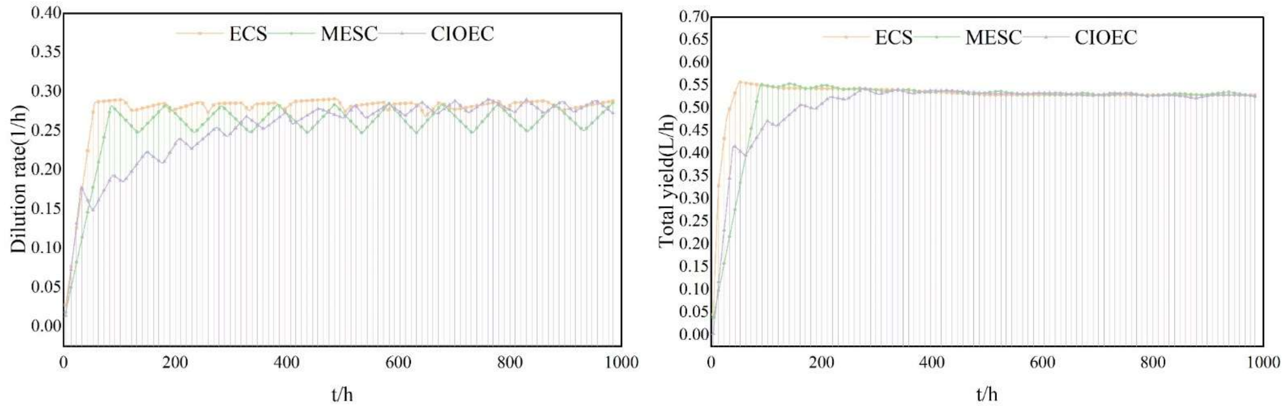
where z_3 is the perturbation estimation result of the expanded state observer, and combining Eqs. (20), (22) and (30), the composite intelligent optimisation model-free extreme value control algorithm expression can be finally obtained.

4. Simulation tests and empirical analyses

4.1. Simulation test results

4.1.1. Numerical simulation of ADM1 with input material stabilization. In order to verify the effectiveness of the proposed composite intelligent optimisation-based extreme value control algorithm, the proposed algorithm (CIOEC), the perturbed ESC algorithm (ESC) and the sliding mode extreme value search control algorithm (MESC) were applied to the ADM1 anaerobic digestion process model of 3.1 to form a comparative simulation analysis, respectively.

Under the input material of 28g/L, the dynamic trajectories of the feed dilution rate and the optimisation target total gas production rate during the simulation process are shown in Fig. 5, with (a) and (b) showing the changes of the dilution rate and the total gas production rate, respectively. the CIOEC algorithm improves the convergence speed of the ADM1 input and output quantities and at the same time, it reduces the time taken for ADM1 to arrive at the extreme point of final gas production rate from the initial stage of the reaction, and the total gas production rate gradually converges to the stable point at t=500h. The total gas production rate gradually tends to stabilise. Meanwhile, as far as the effect of steady state oscillations in the subsequent output of ADM1 is concerned, there are tiny oscillations in the CIOEC algorithm and the perturbed ESC, and regular small-amplitude steady state oscillations in the sliding mode extremum search control. In summary, compared with the control algorithms ESC and MESC, the proposed algorithm has better real-time, fast convergence and relative stability, and more real-time gas production can be obtained, and the effectiveness of the composite intelligent optimised polar control algorithm based on the composite intelligence is proved.

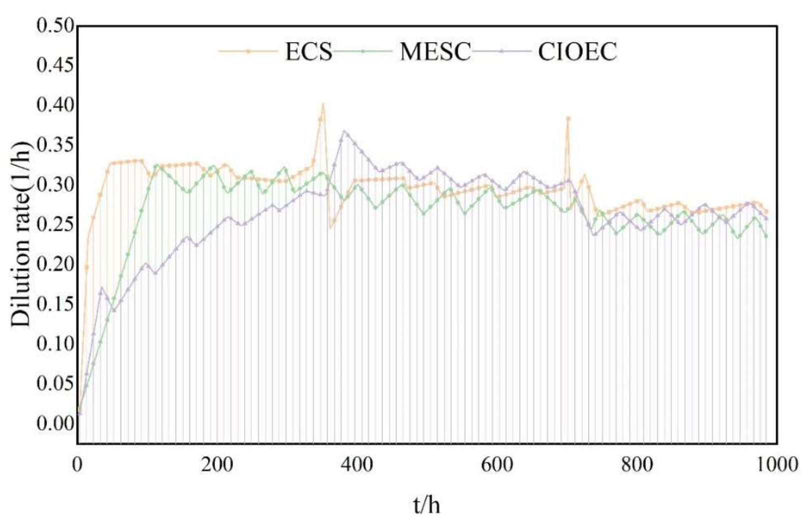


(a) Dilution rate (b) Total yield

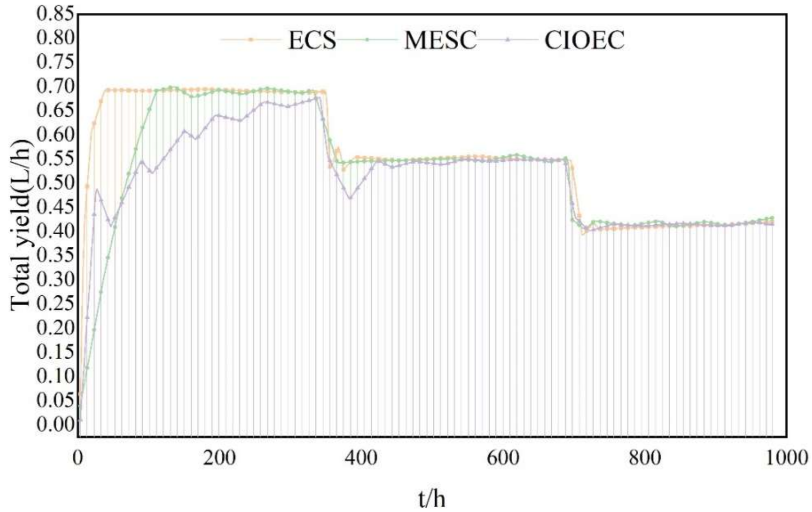
Fig. 5. The feed dilution rate and the optimized target total yield dynamic trajectory

4.1.2. Numerical Simulation of ADM1 under Input Material Variation. Considering the fluctuation of the input material in the actual anaerobic digestion process of ADM1, the material concentration is defined as 36 g/L, and the inlet material concentration becomes 28 g/L at the reaction time of 350 h, and 24 g/L at 700 h. In order to analyse the validity of the proposed algorithm for the ADM1 process model in a clearer way, a comparative simulation was carried out by combining the perturbed ESC algorithm and MESC algorithm to carry out comparative simulation.

The dynamic trajectories of the system feed dilution rate and the optimisation target total gas production rate throughout the simulation are shown in Fig. 6, with (a) and (b) showing the changes of the dilution rate and total gas production rate, respectively. The CIOEC algorithm can quickly stabilise the gas production rate after changing the material concentration at 350h and 700h. Further verification of the adaptivity of the proposed algorithm's extreme value search control shows that the proposed algorithm still maintains a better adaptive tracking performance compared with the perturbed ESC algorithm and the MESC algorithm in the face of the continuous decrease of the change of material concentration.



(a) Dilution rate



(b) Total yield

Fig. 6. The flow rate and the dynamic trajectory of the total yield rate of the target

4.2. Results of empirical analyses

4.2.1. Experimental design. Domestic waste, faeces, food waste and sludge are sorted, crushed and pulped to formulate digested raw materials. The domestic waste, faeces and kitchen waste came from a waste treatment plant, and the sludge came from a water purification plant. In order to ensure that the starting properties of the materials are the same, the formulated materials were divided into packages according to the experimental design dosage, put into the refrigerator at -20°C for freezing and storage, and then taken out and thawed before the start of the experiment.

CIOEC, perturbed ESC and MESC control algorithms were added to the ADM1 system to investigate the treatment effect of the ADM1 system on high concentration organic wastewater under different control algorithms.

4.2.2. Experimental results:

1) The effect of control algorithm on the removal of organic matter by anaerobic digestion. In three groups of anaerobic digestion tests, the change rule of the removal rate of (chemical oxygen demand) COD is shown in Fig. 7. When the ADM1 system was subjected to anaerobic digestion by adding the perturbed ESC algorithm, the average removal rate of COD by the acid-producing phase, the methane-producing phase, and the system was 6.83%, 28.29%, and 36.9%, respectively. Whereas, under the condition of adding CIOEC algorithm, the removal of COD by acid-producing phase, methanogenic phase and system reached 13.68%, 41.96% and 51.98%, respectively. Compared with the ESC algorithm with the addition of perturbation, the acid-producing phase of the CIOEC algorithm nearly doubles the removal rate of COD, indicating that the digested feedstock has already reached a higher level of digestion in the acid-producing phase, and the residence time of the digested feedstock in the acid-producing phase can be appropriately shortened to keep the equilibrium of the acid-producing phase and the methane-producing phase. Thus, in practical application, the volume of the acid-producing phase structure can be reduced to save cost.

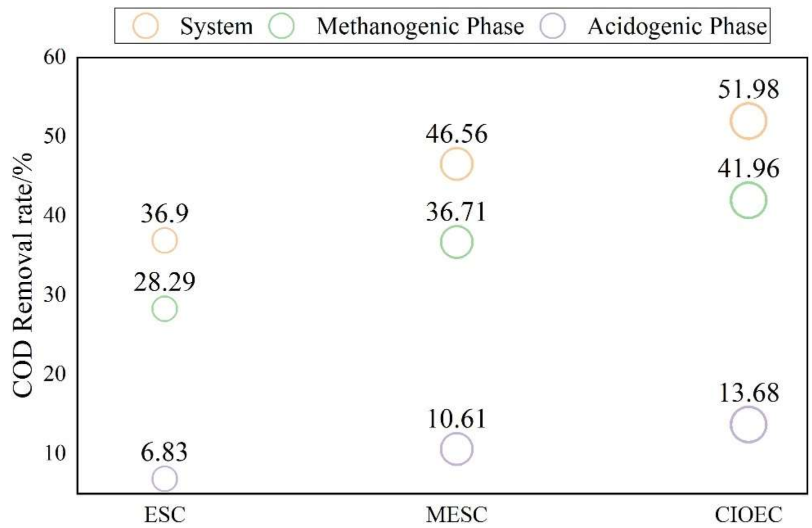


Fig. 7. Effect of ultrasonic disintegration on COD removal efficiency

The changing pattern of the removal rate of (volatile solids) VS is shown in Fig. 8. The ADM1 system with the addition of the perturbed ESC algorithm treated the digested feedstock with the acid-producing phase, methane-producing phase and the system removal rate of VS of 8.77%, 26.1% and 31.3%, respectively.The MESC algorithm had a better removal rate of VS than the ESC algorithm. While with CIOEC algorithm, the removal rates were 13.25%, 30.1% and 40.8% respectively. The digested feedstock has reached high digestibility in the acid-producing phase.

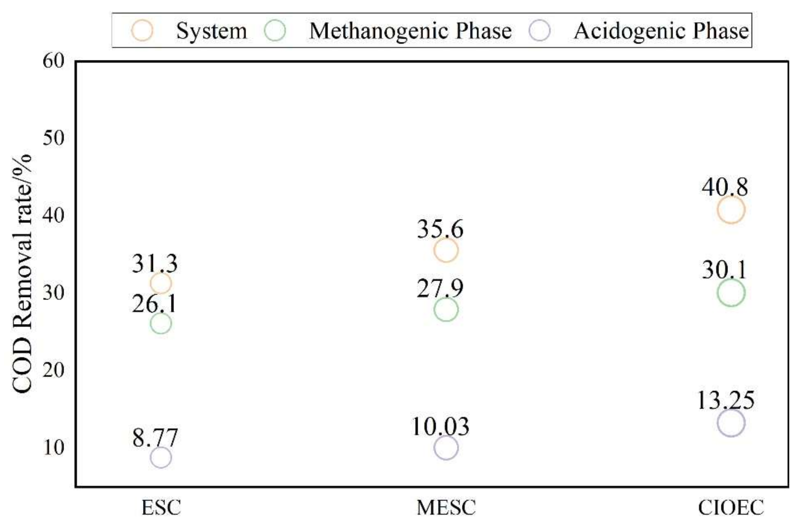


Fig. 8. Effect of ultrasonic disintegration on VS removal efficiency

The above experiments show that the removal rate of organic matter by the ADM1 system under different control algorithms varies, and the CIOEC algorithm proposed in this paper has the highest removal rate.

2) Effect of control algorithms on gas production performance. The test recorded the total gas production of the original system and the anaerobic digestion system under three groups of different control algorithms per 24 h. The gas production rate (volume of gas produced by removing unit mass of VS) under different control algorithms is shown in Table 1. The total gas production of the original ADM1 system for anaerobic digestion was small, with an average daily gas production of 389.6 mL. The addition of the control algorithm resulted in a significant increase in gas production, with the ADM1 system with the CIOEC algorithm producing 873.9 mL of gas per day, which is an increase of

124.3% over the original system. During the 12 days of normal operation of the anaerobic digestion reaction, the average gas production rate of the system with the addition of the control algorithm increased significantly compared with the original system, and the ADM1 system with the addition of the CIOEC algorithm had the highest gas production rate. The gas production rate of the original system showed an overall increasing trend with the extension of residence time, while the gas production rate of the ADM1 system with the control algorithm increased and then decreased, and the average gas production rate of the first 6 days was greater than that of the last 6 days. This indicates that the control algorithm can enhance the anaerobic digestion rate and shorten the anaerobic digestion reaction time.

Table 1. The yield rate of the different control algorithm

System	Average daily gas production/mL	Output growth rate/%	Gas yield/(L·g-1VS)		
			0~6d	7~12d	Average
ADM1	389.6	0	0.219	0.231	0.335
ADM1+ESC	482.4	23.8	0.257	0.241	0.378
ADM1+MESC	687.6	83.5	0.364	0.327	0.528
ADM1+CIOEC	873.9	126.8	0.417	0.384	0.609

5. Conclusion

A composite intelligent optimised extreme value control (CIOEC) algorithm has been designed to maximise the total gas production during anaerobic digestion in the ADM1 system.

Compared to the ESC algorithm and the sliding mode extreme value search control algorithm, the CIOEC algorithm can accelerate the convergence speed and increase the total gas production of the ADM1 system under stable or changing input materials. Compared with the original system, the average daily gas production of the ADM1 system with the addition of the CIOEC algorithm can reach 873.9 mL, which is an increase of 484.3 mL compared with the original system, indicating that the algorithm proposed in this paper can achieve the optimal treatment effect when applied to the ADM1 system for anaerobic digestion.

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