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Optimization of wastewater anaerobic digestion treatment based on GA-BP neural network

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ABSTRACT

In the process of anaerobic digestion of wastewater, effluent chemical oxygen demand (COD) and gas production are important parameters to measure the effect of anaerobic biological treatment, and are also important indicators for evaluating the performance of water treatment. At present, most of these values in anaerobic biological treatment systems for wastewater are often obtained through manual tests. The disadvantage of manual assays is the long detection time and poor stability. Therefore, the prediction of water COD and gas production based on back propagation neural network (BPNN) is proposed in this paper. Then, aiming at the problems of speed sluggishness and lopsided one-sided minimization in traditional BP neural networks, an improved BP neural network prediction model based on genetic algorithm (GA-BPNN) is proposed. Experimental results show that the performance of GA-BPNN is better than traditional BPNN. In effluent COD prediction, the mean absolute percent error (MAPE) of BP neural network prediction is 60.7234%, while the MAPE of GA-BPNN algorithm is only 20.9854%. In the prediction of gas production, the MAPE of BP neural network prediction is 10.5521%, while the MAPE of GA-BPNN algorithm is only 7.5677%. Moreover, both the effluent COD prediction and the gas production forecasting, GA-BPNN algorithm's mean square error (MSE), root mean square error (RMSE) and Pearson's correlation coefficient are all better than BP neural network.

Keywords: Wastewater anaerobic digestion; BP neural network; Genetic algorithm; Prediction model

1. Introduction

With the development of modern industry and the acceleration of urbanization, the scale and speed of economic development go far beyond the endurance of resources. For this reason, all countries in the world have proposed the construction of a resource-conserving and environment-friendly society in recent years, and encouraged the development and use of renewable energy [1,2]. Development of anaerobic treatment of wastewater and utilization of biogas resources is an important aspect of building an environmentally friendly society [3].

The anaerobic digestion process of wastewater is a complex process that is affected by physical, chemical, and biological processes [4,5]. In order to improve the efficiency of anaerobic treatment and maximize the output of biogas while ensuring the quality of effluent, it is necessary to optimize the parameters of

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anaerobic process for multi-objective optimization. However, in the multi-objective optimization problem, most of the subgoals are linked and mutually restricted, not independent individuals [6]. The relationship between these subgoals and the overall multi-objective optimization problem is complex. To solve this problem, the traditional method is to manually establish a relatively accurate mathematical model. However, anaerobic digestion processes are complex, constrained, nonlinear, and uncertain. Therefore, the traditional manual modeling method cannot solve the multi-objective optimization problem in anaerobic process well. At present, intelligent algorithms from the perspective of biological evolution can be used to solve complex real-world problems. Intelligent algorithms have been regarded as the latest tool to solve complex problems that cannot be solved by traditional methods [7–9]. Intelligent algorithms have been widely used in process optimization and controller designing because they do not require the establishment of accurate mathematical models in advance. However, this method is rarely used to solve the optimization problem of anaerobic digestion process. In recent years, many researchers have done a lot of research on applying neural networks to wastewater treatment. Guclu et al. [10] used the artificial neural network model to predict and model the anaerobic digestion system under changing conditions. An artificial neural network model was established based on the lower MSE and higher degree of fitness, but the solid and methane concentrations forecast is not very satisfactory. Pai et al. [11] used a fuzzy inference system to optimize the artificial neural network. The results showed that the optimized artificial neural network model had a better prediction effect, and the minimum average mean error for the effluent chemical oxygen demand (COD) prediction reached 11.99%.

Aiming to increase the efficiency of anaerobic digestion treatment of papermaking wastewater and the intelligent level of anaerobic digestion of papermaking wastewater, intelligent algorithms used in wastewater anaerobic digestion multi-objective optimization process is studied. We constructed an effluent COD prediction model and gas production prediction model based on GA-BP neural network. The constructed model can provide help for the application of intelligent algorithms in wastewater anaerobic treatment and reference for anaerobic wastewater treatment process design.

2. Anaerobic digestion of wastewater

Anaerobic biological processing, also called anaerobic digestion or methane fermentation, refers to a biochemical process in which organic matter is converted into methane under the action of anaerobic bacteria in anaerobic conditions [12]. During anaerobic digestion, complex organic matter is degraded and converted into simple and stable substances. In the process, it also releases energy. The final conversion of anaerobic digestion is methane and carbon dioxide, as well as small amounts of NH_3, H2, H_2S, and N_2 [13]. Energy is mainly stored in methane. Anaerobic digestion of organic matter is a very complicated microbial process and biochemical process. The reaction can be simplified as follows [14].

$$\text{Organic matter} + H_2O = CH_4 + CO_2 + \text{product} + NH_3 + H_2S + \text{energy} \tag{1}$$

Anaerobic digestion of wastewater is an extremely complex process. Over the years, anaerobic digestion has been summarized as a two-stage process [15]. The first stage is acidification and fermentation. Under the action of acid-producing bacteria, organic matter decomposes into fatty acids and other products and synthesizes new cells. The second stage is the stage of methane fermentation. The fatty acids are transformed into CH_4 and CO_2 by the action of obligate anaerobe. However, in fact, the final product of the first stage is not only the acid, but also the gas produced by the fermentation is not all from the second stage. Therefore, a more appropriate definition of the first phase is the non-methane generation phase and the second phase, the methanogenesis phase. With the deepening of research on anaerobic digestion of microorganisms, the relationship between non-methane-producing bacteria and methanogenic bacteria in anaerobic digestion is clearer. Bryant [16] and Wang and Liu [17] proposed the three-stage theory of anaerobic digestion based on the physiological population of microorganisms, which is a currently recognized theoretical model. Three-stage digestion highlights the role of hydrogen-producing acetogenesis and separates it into a phase. Since then, a four-stage theory of anaerobic digestion, emphasizing the role of homoacetogenic bacteria is proposed [18]. In 2002, the anaerobic digestion of organic matter was expanded into five stages of decomposition, hydrolysis, acid production, acetogenesis and methanogenesis [19], which is shown in Fig. 1.

The processes of decomposition, hydrolysis, acid production, acetogenesis, and methanogenesis (Fig. 1) are briefly described as follows.

2.1. Stage 1: Decomposition

Decomposition refers to disruption of the particle complex, phase separation, non-enzymatic degradation, and lysis of the entire cell.

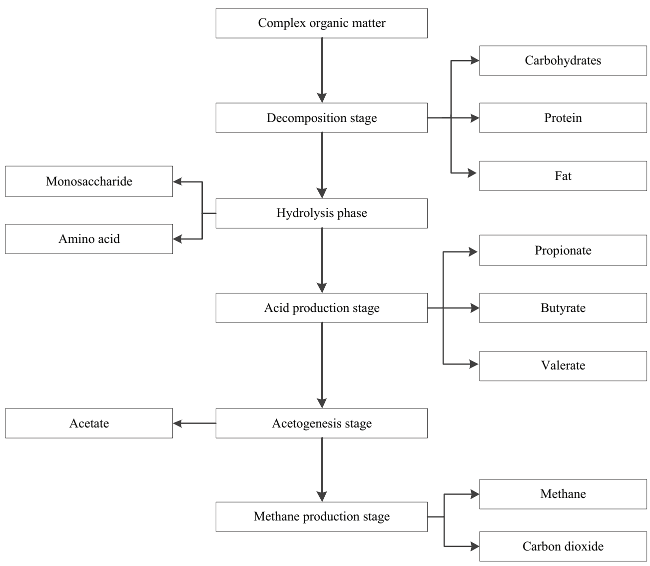

Fig. 1. Anaerobic digestion of organic matter conversion process.

2.2. Stage 2: Hydrolysis

Hydrolysis refers to the degradation of particles into soluble monomers. In this process, the complex degrades into carbohydrates, proteins, and fatty acids after hydrolysis.

2.3. Stage 3: Acid production

The acid-producing bacteria convert the small molecule compounds produced by the hydrolysis into volatile organic enzymes and carbon dioxide, which in turn produce methanol and other alcohols.

2.4. Stage 4: Acetogenesis

Acetogenesis is the first step in the stabilization of sludge and refers to the degradation of long-chain fatty acids and organic acids to acetic acid and hydrogen. This relatively slow process takes about 84 h.

2.5. Stage 5: Methane production

The methanogenic stage is the final conversion process for anaerobic digestion and the slowest pH-sensitive stage in the five processes. It should be noted that methanogens can only grow using CO_2, acetic acid, and hydrogen.

3. GA-BP neural network

Artificial neural network, abbreviated as neural network, is a Frontier Science that has developed rapidly since the 1990s. It has gradually become a hot topic in the field of mathematical modeling and is widely used in engineering. It simulates the human brain's structure and information processing mechanism. It is a large-scale, nonlinear parallel distributed information processing system composed of a large number of neurons (or nodes) connected to each other. It not only handles half of the processing power of numerical data processing, but also has the ability to think, learn, and remember knowledge. It can solve many problems that conventional information processing methods cannot solve or even solve.

3.1. BP neural network

BP neural network is one of the most widely used neural networks [20]. As early as in 1986, Rumelhart and McCulland [21] presented concise and complete a neural network error back propagation training algorithm, namely BP neural network. It systematically solves the learning and training problem of nonintuitive unit connection weights in multilayer networks, realizes the description of input to output in arbitrary nonlinear systems, and has good self-organization ability, automatic adaptability, and fault tolerance.

The BP neural network usually includes three parts: the input layer, the hidden layer, and the output layer. There is no connection between the neuron nodes in the same layer. The input data are processed by the neuron node and passed to the next layer of neuron nodes through the transfer function. The transfer function is generally a Sigmoid type function above the output. The network adjusts the weights and enthalpies according to the gradient descent method by comparing the simulated output values with the expected output values. Through adjustment, the MSE between the analog output value and the expected output value is gradually minimized or reaches the set effect, so that the mapping from the input to the output is realized [22].

Fig. 2 shows a three-layer BP neural network. The input layer consists of i input nodes, the hidden layer consists of n nodes, and the output layer consists of j output nodes. The input data from the input layer are passed to the output layer via the hidden layer. The value of each neuron can only affect the value of the next layer of neurons. According to the set output expectation, if the analog output value does not meet the desired output, then the network will compare the analog output value with the expected output value and send the difference of the them back to the network along the connection path. According to the difference, the system corrects the connection weights between the neurons at each layer and retrains the network until the difference is meeting the requirements.

The neurons serve as basic computational units and components of the neural network. When subjected to certain input stimuli, the neuron nodes will generate corresponding responses. As we can see from Fig. 3, when a set of data $x_1, x_2, \ldots, x_n$ activates a neuron node A_i, the neurons first weighted this set of data. And then, the obtained value is added to the value of b_i to get u_i, and finally u_i is processed by the transfer function $f(x)$ to obtain the output value y_i. Specific calculations are as follows

$$u_i = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b_i \tag{2}$$

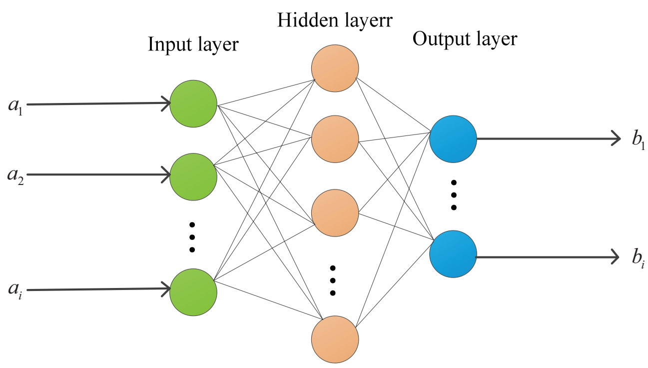

Fig. 2. BP neural network structure.

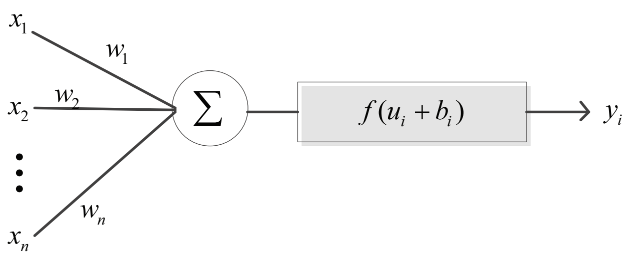

Fig. 3. Neuron structure.

$$y_i = f(u_i + b_i) = f(w_1x_1 + w_2x_2 + \cdots + w_nx_n + b_i) \quad (3)$$

where $w_1, w_2, \ldots, w_n$ is the weight corresponding to $x_1, x_2, \ldots, x_n$.

3.2. Improved BP neural network

In order to explain, the adaptive process of biology use logic theory and apply the theory of the relationship between populations and individuals to the real world, genetic algorithm proposed is inspired by the theory of biological evolution in nature [23].

The genetic algorithm inherited the idea of "survival of the fittest" in evolution theory. The basic principle of genetic algorithm is to simulate the biological behavior and introduce chromosome coding mechanism and fitness function evaluation strategy. Firstly, it encodes all individuals in the population. And then, high-quality individuals with high fitness are retained using fitness functions to evaluate their superiority and inferiority. A second-generation population is generated by selecting, crossing, and mutating these individuals. Then use the fitness function again to evaluate the pros and cons of the individual, retain the high degree of fitness, and use them to generate the third generation of three algorithms: selection, crossover, and mutation. Repeat the above steps until the desired requirements are met. The specific operation flow of the algorithm is shown in Fig. 4.

The core part of genetic algorithms is the selection-copy operations, crossover operations, and mutation operations. They best reflect the basic ideas of Darwinian evolution. Genetic algorithm has the following features.

3.2.1. Wide applicability and global search capabilities

The genetic algorithm introduces the encoding mechanism, which only needs to encode the research object without considering other factors, so the application scope is wide. The algorithm uses the selection, crossover, and mutation operations to manipulate the encoded genes. Compared with traditional single-site optimization, the search coverage is broader and global.

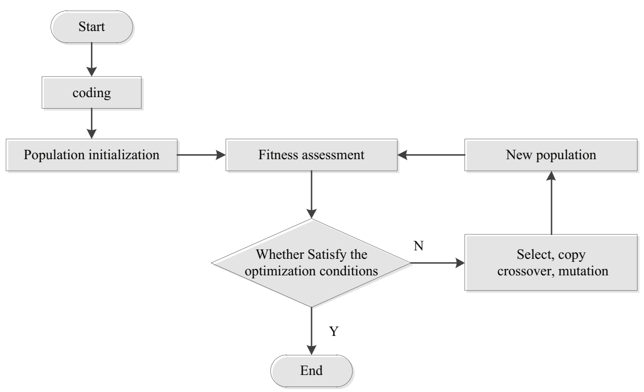

Fig. 4. Genetic algorithm.

3.2.2. Simple operation with strong parallelism

The algorithm uses an encoding operation to perform multi-bit encoding of an individual. Only desired information and a fitness function need to be set during the operation without other guidance information. Therefore, multiple possible solutions can be evaluated at the same time, so the operation is simple, and the parallelism is good.

3.2.3. Self-exploratory

The genetic algorithm introduces the mechanism of uncertain parameters, uses the vicissitudes of the parameters to guide the direction of optimization, and improves self-exploration and exploration capabilities for optimization.

3.2.4. Adaptive, self-learning, and self-organizing

The genetic algorithm uses a fitness function to evaluate individual individuals, selectively retains individuals with higher fitness, and generates more adaptive offspring through crossover and mutation operations.

4. Neural network prediction model construction

According to the above description of the GA-BP neural network, two anaerobic digestion models for wastewater treatment, prediction models for COD removal rates, and gas production forecast models were established. The input layers of the model are all set to the inflow flow Q, influent COD, influent pH, and temperature four nodes. The model output layer selects the COD removal rate and gas production amount as nodes, respectively. The number of first-level nodes in both models is four, and the number of third-level nodes is one. Therefore, the number of layers and nodes of the input layer and output layer of the model have been mastered, but the number of layers and nodes of the hidden layer still need to be set meticulously.

In general, the more hidden layer layers, the higher the accuracy of the prediction. However, more hidden layers can result in slower neural network operations and longer training times. And too many hidden layers are prone to overfitting, which reduces the generalization ability of the network. Researchers have pointed out that a BP neural network containing only one hidden layer can be used to fully approximate any nonlinear relationship. Therefore, the COD removal rate prediction model and the gas production prediction model established in this study are all set as a layer 1 hidden layer. In addition, the number of nodes in the hidden layer also affects the performance of the neural network. If the number of hidden layer nodes is too small, then the neural network's data mining ability is relatively poor; but if the number of nodes is too many, the network structure will become complicated, resulting in a slow operation time and an overfitting phenomenon. A large number of experimental results show that the number of nodes in the network can be set according to the following formula.

$$d = \sqrt{b + c} + e \quad (4)$$

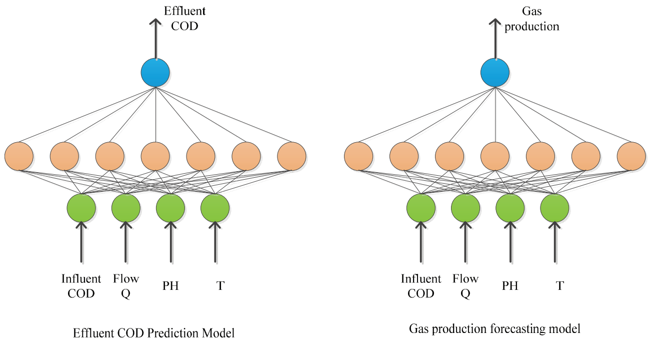

Fig. 5. Predictive model structure.

where d is the number of nodes in the hidden layer, b is the number of nodes in the input layer, c is the number of nodes in the output layer, and e is a constant between 1 and 10. In this paper, b is set to 4, and c is set to 1. The trial and error method is used to set the hidden layer to 7, so the structure of the two neural network prediction models is 4-7-1. The learning rate of the network is 0.01, the learning momentum constant is 0.001, the target error is 0.05, and the maximum iteration is 100. The data between the three-layer structures are realized by linear function and s-function. The structure of created GA-BP neural networks COD model and gas production model is shown in Fig. 5.

5. Simulation experiment analysis

Table 1 compares the prediction effect of the effluent COD prediction model of the GA-BP neural network and the effluent COD prediction model of the BP neural network. The comparison includes four indicators: MAPE C, mean square error (MSE), root mean square error (RMSE), and Pearson correlation coefficient (R). The absolute percentage error of the effluent COD prediction model of GA-BP neural network is about 20.98 %, while the absolute percentage error of BP neural network effluent COD prediction model prediction is as high as 60.72 %. The mean squared deviation of the effluent COD prediction model of GA-BP neural network is smaller than that of the effluent COD prediction model of BP neural network. The RMSE and Pearson correlation coefficient predicted by the effluent COD prediction model of GA-BP neural network is also better than BP neural network. Comprehensively comparing the above four indicators, it is not difficult to find that the BP neural network model optimized by the genetic algorithm is superior to the unoptimized neural network prediction model.

Table 2 shows the comparison of GA-BP neural network gas production prediction model and BP neural network gas production prediction model. The examined indicators are the same as those for the effluent COD model experiment. As we can see from the experimental results, BP neural network prediction model optimized by genetic algorithm is superior to the unoptimized neural network prediction model. Therefore, the prediction effect of the GA-BP prediction model is better.

Comparing GA-BPNN and BPNN simulation results of effluent COD and gas production, we can find that the neural network model parameters optimized by genetic algorithm are superior to simple BP neural network. GA-BP predictive model has smaller MSE, lower absolute error, lower RMSE, and higher correlation coefficient. This is because the genetic algorithm introduces coding and fitness mechanisms, and uses selection, crossover, and mutation to find the weights and values that are more suitable for the network. It improves the prediction accuracy of BPNN and overcomes the shortcomings of its easy to fall into one-sided minimization, making the entire network globally optimized. Therefore, GA-BP neural network is better for modeling effluent COD and gas production and is more suitable for follow-up research.

Table 1
Comparison of predictive effect of GA-BP and BP prediction models on effluent COD

	BP neural network		GA-BP neural network	
	Training	Prediction	Training	Prediction
MAPE (%)	13.7892	60.7234	2.5675	20.9854
R	0.9032	0.5487	0.9964	0.8743
MSE	1.8434e4	2.2355e5	346.9761	3.7658e4
RMSE	137.9763	446.9862	19.8432	197.0974

Table 2
Comparison of predictive effects of GA-BP and BP prediction models on gas production

	BP neural network		GA-BP neural network	
	Training	Prediction	Training	Prediction
MAPE (%)	1.0345	10.5521	1.0123	7.5673
R	0.9674	0.7865	0.9673	0.9074
MSE	0.0531	5.8345	0.0514	4.0234
RMSE	0.2245	2.3457	0.2320	2.0043

6. Conclusion

According to the construction of multi-objective optimization model and the characteristics of anaerobic process of papermaking wastewater, the effluent COD model and gas production model of wastewater anaerobic treatment process were established based on BP neural network. Then, the genetic algorithm with global exploration capability was used to optimize the BP neural network prediction model. The predictive performance of original BP neural network and GA-BP neural network was compared by simulation experiment. In the effluent COD prediction, the absolute percentage errors predicted by BP neural network, Pearson's correlation coefficient, MSE, and RMSE were 60.7234%, 0.5487, 2.2355e5, and 446.9862, respectively. The corresponding indicators of GA-BP NNMP algorithm are 20.9854%, 0.8743, 3.7658e4, and 197.0974, respectively. In the prediction of gas production, the absolute percentage errors predicted by BP neural network, Pearson's correlation coefficient, MSE, and RMSE were 7.5674%, 0.9074, 4.0234, and 2.043, respectively. The results show that the prediction model established by GA-BP neural network is better, and it is more suitable for the modeling of effluent COD and gas production.

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