# Influence and Simulation Model of Operational Parameters on Hydrogen Bio-production Through Anaerobic Microorganism Fermentation Using Two Kinds of Wastes

Yue Shi, Guo-sheng Gai., Xiu-tao Zhao, *Yin-yin Hu*

[1]*Abstract*—**The bio-hydrogen producing process has complex interactions; thus, constructing a detailed mechanistic model and proper control architecture is difficult. Artificial neural networks (ANNs) are capable of inferring the complex relationships between input and output process variables without a detailed characterization of the mechanisms governing the process. This work presents a novel ANN that accurately predicts the steady-state performance of bioreactors for the bio-hydrogen producing processes. In this experiment, producing hydrogen from kitchen wastes and sugar refinery wastewater was studied in two kinds of bioreactors. And a simulation model of operational parameters was also established based on theory of back propagation neural network (BPNN). The effects of operational parameters on bio-hydrogen production bioreactors were considered. The results showed that simulation model well fitted the laboratory data, and could well simulate the production of hydrogen in these two reactors. Also it showed that volume loading rate(VLR), pH, oxidation reduction potential(ORP) and alkalinity could influence the fermentation characteristics and hydrogen yield of the anaerobic activated sludge. And the weight of the influence factors was as follows: VLR>pH values> ORP> alkalinity in continuous stirred tank reactor (CSTR),and VLR> alkalinity > pH values> ORP in the integrative biological reactor (IBR)..**

***Key words: back propagation neural network (BPNN), bio-hydrogen production, partitioning connection weights***

## I. INTRODUCTION

Hydrogen energy has been paid attention gradually, for its advantages as high energy density and no recontamination. Bio-hydrogen production which is environmentally friendly and less energy intensive compared to chemical process has become a hot research. Most of researchers, in the studies on bio-hydrogen production including sterile fermentation and mixed fermentation, used glucose and settle as substrates〔1-3〕. But, the price of the substrate was expensive causing the hydrogen production costly. The key to depress the cost of hydrogen production was using the low-cost substrates. Research had studied the impact of the fermentation methods, temperature, pretreatment and additives to bio-hydrogen production. The highest volume fraction of hydrogen was 69%, the largest hydrogen production rate was 100-200 (mL/g COD) 〔4-8〕. Otherwise, few studies had investigated deeply the effect of different operational parameters on hydrogen production efficiency. These problems were very important to depress operating cost. Artificial neural networks (ANNs) are universal approximators for Boolean and continuous functions that are capable of modeling the complex relationships between input and output parameters without requiring a detailed mechanistic description of the phenomena governing the process〔9,10〕. Therefore, ANNs have gained an increasing consideration in wastewater treatment and biogas production modeling and controlling 〔11-16〕. Hamed et al. 〔17〕 modeled the effluent biochemical oxygen demand (BOD) and suspended solids (SS) concentration at a major wastewater treatment plant using two ANNs. Ruey-Fang et al.〔18〕 improved the nitrogen removal rate in a sequential batch reactor using an ANN-based real-time control strategy. Aguado et al. 〔19〕utilized ANNs as a software sensor for inferring wastewater quality parameters such as effluent chemical oxygen demand (COD) or total nitrogen concentrations.

In this study two kinds of cheap substrates were used in two type of bioreactors. A continuous stirred tank reactor (CSTR) was used to ferment kitchen wastes in order to produce hydrogen. And an integrative biological reactor (IBR) was used to produce hydrogen by fermenting sugar refinery wastewater. A lab scale experiment was conducted study the effects of volume loading rate (VLR), oxidation reduction potential (ORP), alkalinity and pH values on hydrogen production. At the same time, a simulation model of operational parameters was established based on theory of back propagation neural network (BPNN) and linear regression of traditional mathematical model. The simulation model realizes prediction of which were the key impact factor and the optimum operational parameters of this hydrogen producing system.

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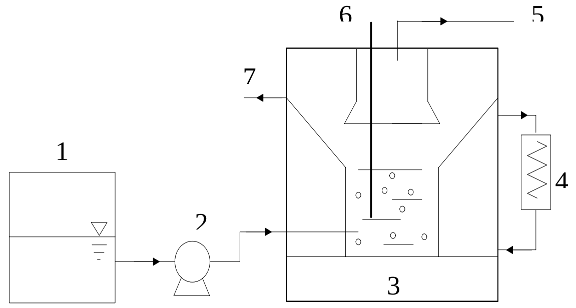
## II. MATERIALS AND METHODS

### *2.1 substrate of bio-hydrogen production*

The kitchen waste was the substrate of CSTR. And the sugar refinery wastewater was the substrate of IBR. The COD of influent for the bioreactors was 1000–13000mg/L.

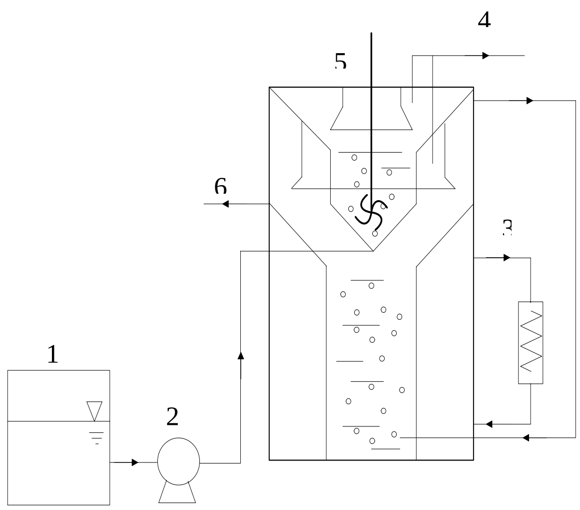
### *2.2. Experimental apparatus and operational conditions*

There are two kinds of bioreactors in this experiment: CSTR and IBR. A schematic diagram of the CSTR was shown in Fig.1, and IBR was shown in Fig.2 .The CSTR has a working volume of about 2.0L, the IBR has a volume of about 2.75L.




1. Feed tank 2.Pump 3.Magnetically driven agitator 4. Water heating 5.Gas 6. Thermometer 7.Effluent

Fig.1.Schematic diagram of the CSTR




1.Feed tank 2.Pump 3.Water heating 4.Gas 5. Impeller 6. Effluent

Fig.2.Schematic diagram of the IBR

The mixed liquor suspended solids (MLSS) was about 1400 mg/L. Through the peristaltic pump the influent was pumped into the bioreactor. In CSTR, the influent and suspended solids were mixed by propeller. IBR was a novel patent bioreactor which was the integration of the respective merits of CSTR and up flow anaerobic sludge bed(UASB). In the IBR, the mixed water from the upper part of the CSTR reaction zone removed inlet through gravity into the lower part of the UASB reaction zone, as to be used further. The hydrogen that comes from the bioreactor was measured by the gas flow meter and then it was collected.

There were two controlling conditions: the temperature inside the reactor was at about 37℃, the influent pH value was between 5.0-6.0.

### *2.3.CSTR and IBR operational conditions*

In order to achieve a definite COD, the concentration of the influent was adjusted. Taking into account the VLR, the HRT was from 2h to 12h and was adjusted by the peristaltic pump. Regulation of the alkalinity and ORP was achieved by the Pharmacy.

### *2.4. Analytical Methods*

Standard methods 〔20〕 were used to measure the value of COD, alkalinity. The pH and ORP could be measured by the instruments.

Test Equipment: Acidity meter was with pHs-25 type, produced by Shanghai Sheng Magnetic Instruments Ltd. FML type wet gas Flow-meter produced by Changchun Automotive Filter Co., Ltd. which was used as the gas Chromatographic.

### *2.5. The foundation of BP Neural Network Model*

In order to predict the various factors on the impact of gas production, BP neural network was used to simulate. Based on matlab platform the BP Neural Network Model was established. By using big function of matlab Neural Network toolbox, mathematical model of bioreactor was established and used to simulate.

Reorganization of the main factor and multi-factors simulation for the Prototypes experiments means to take advantage of BP network to set up the mapping relationship between all relative factors and results, which was able to reflect the direct and indirect influences of all the factors on the reactor performances. The weights of neural units in the network not only can store information but also can guide the direction of the information. According to information flow theory, the value of weights determines the direction which information flow towards. As a result, the value of weights is able to show the contributions, which the factors in input layers bring to the final output.

Using partitioning connection weights (PCW) method to separated weights of hidden layer and output layer can connect them with input layer directly 〔21〕. Then, the relative importance (RI) of all the input factors were calculated, and the importance of input factors were quantitatively analyzed. The algorithm was expressed by the formula 1-1 and 1-2.

$$Q_{ih} = \frac{|W_{ih}|}{\sum_{i=1}^{ni} |W_{ih}|} \tag{1-1}$$

$$RI(\%)_i = \frac{\sum_{h=1}^{nh} Q_{ih}}{\sum_{h=1}^{nh} \sum_{i=1}^{ni} Q_{ih}} \times 100 \tag{1-2}$$

$W_{ih}$ --weights between input layer and hidden layer;

$n_i$, $n_i$ -- numbers of neural units in input layer and hidden layer.

## III. RESULTS AND DISCUSSION

### *3.1.Effect of VLR on hydrogen production*

The changes in hydrogen production and VLR with time are illustrated in Fig.3, Fig.4.

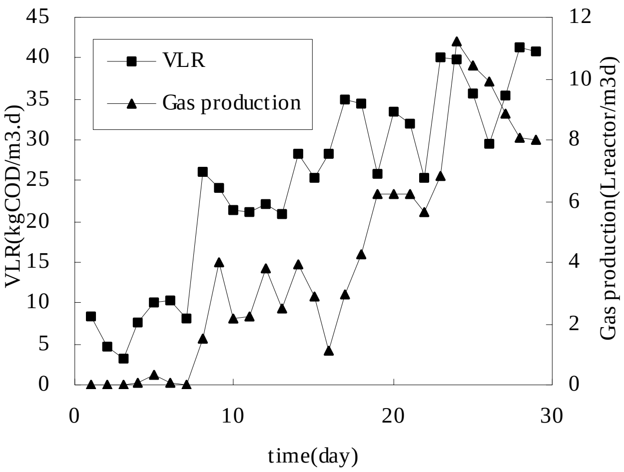



Fig.3. VLR and hydrogen production of CSTR

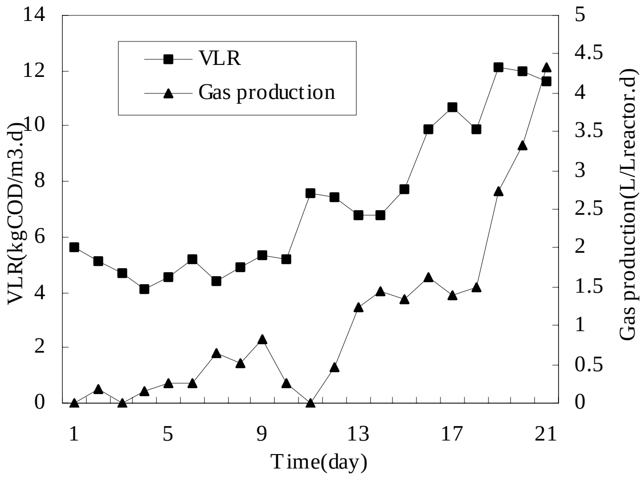



Fig.4. VLR and hydrogen production of IBR

As showed in the fig.3 CSTR, with increasing VLR that corresponds to hydrogen production increased. When the VLR was fluctuated between 1.5kgCOD/($m^3$·d) to 2.5 kgCOD/($m^3$·d), the hydrogen production was at low values. As the VLR increasing to 6 kgCOD/($m^3$·d),the hydrogen production increased sharply, about was at 2L/(Lreactor·d) to 3 L/(Lreactor·d). While VLR was 25 kgCOD/($m^3$·d) to 40 kgCOD/($m^3$·d),the gas production was at high values: 11.5L/(Lreactor·d). From the Fig.4, the similar relationship IBR can be observed. Therefore the VLR was crucial to the impact of gas production.

### *3.2. Effect of alkalinity on hydrogen production*

Alkalinity was very important parameter to the CSTR and IBR. Alkalinity was not only relating to the hydrogen production, but also influenced the activity of sludge. Effect of alkalinity on the hydrogen production was illustrated in Fig.5,Fig.6. As shown in Fig.5, alkalinity and the hydrogen production rate was positively correlated. In CSTR, when the gas production rate was at 0 to 0.4L/d, the alkalinity was at 1.8mg/L to 2.4mg/L but special days; when the gas production rate increased and was at 3L/d to 5L/d, the alkalinity stayed at 500mg/L to 1000mg/L. Whit increasing hydrogen production rate, that corresponds to the alkalinity increased, while the gas production rate was at the max as high as 11.5L/d, the alkalinity increased sharply and was higher than 2000mg/L. Note that with the decline in hydrogen production, alkalinity declined significantly. In the Pig.6.IBR, as showed the alkalinity was increasing with the rate of hydrogen production increased slowly. When the hydrogen production rate was at a low values, the alkalinity was at about 400mg/L, then the alkalinity increased with the increase of the hydrogen production rate. Thus the alkalinity trends reflect in hydrogen production rate changing.

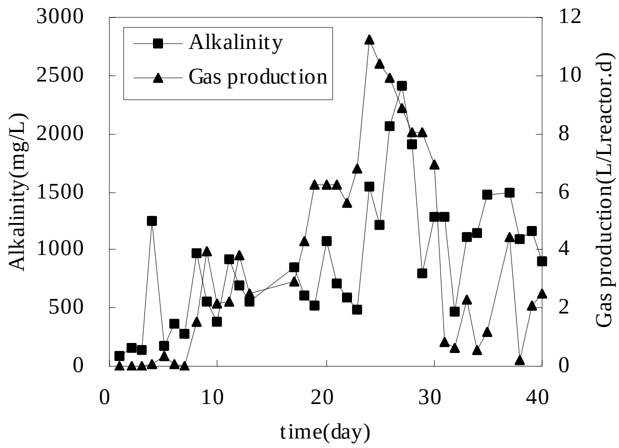



Fig.5.Alkalinity and Hydrogen production of CSTR

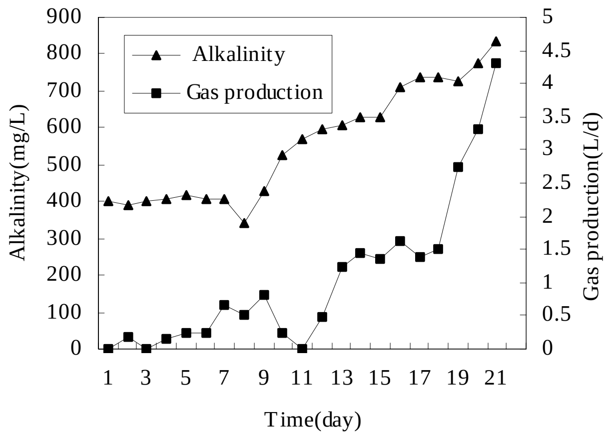



Fig.6.Alkalinity and Hydrogen production of IBR

### *3.3. Simulation model of hydrogen production rate*

In order to optimize operational parameters and predict the effluent quality of the CSTR for kitchen waste treatment, a simulation model was established based on back-propagation neural network (BPNN). At last, we also used this model to study the IBR. BP Neural Network had stronger approximation and generalization ability to nonlinear systems. At the same time, the perfection and precision of data determined the applicability of the model. This provided a feasible way for on-line control in process. The topological architecture of BPNN was illustrated in Fig.7.

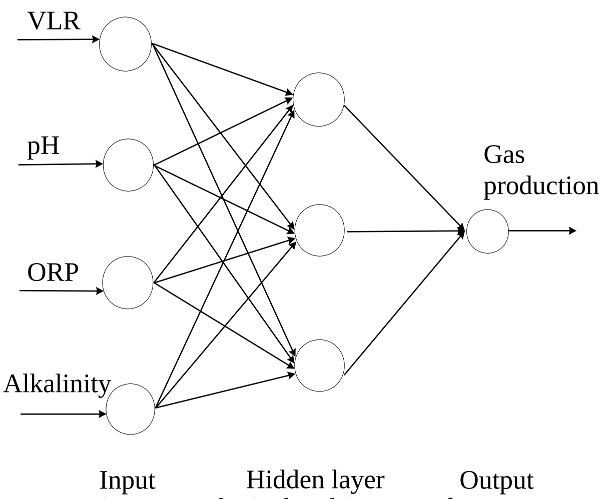



Fig. 7. Topological architecture of BPNN

As shown in Fig.7, there were four nodes on input layer, three nodes on hidden layer and one node on output layer. Each node was a BP neuron. The input layer of network was four parameters: VLR, ORP, alkalinity and pH values on the effluent quality. These four parameters had the operational characteristics of bioreactor, played a key role, and easy to be quantified. These parameters had the peculiarities of generality and were used in neural network. The hidden layer adopted monolayer structure and includes three neurons to ensure the uncertain weights occupied half of the training sample. In this way, it ensured not only the network had moderate scale and compact structure, but also was trained effectively and to be avoid the phenomena of over-fit. The output of the whole network was the hydrogen producing efficiency.

BP neural network model was used to simulate the system and t includes three layers: input layer, hidden layer and output layer. Hidden layer and Output layer adopted tansig and purelin as the activation functions respectively. Traingdx, one of adaptive training function with momentum was utilized by the network training. This algorithm, based on the classical BP algorithm, was able to modulate learning rate automatically and incidental momentum, which avoided local minimum and accelerated the convergence rate greatly.

For debugging and perfecting program, the comparisons between experimental value and BPNN value were showeded in Fig.8, Fig.9.

As shown in Fig.8, Fig.9, the program was comparatively perfect. The results of debugging program showed that amounts of hidden layer and node could better realize approximation and generalization effect, and mean square error (MSE) was 0.00963. Fig.8, Fig.9 showed that simulated results by the simulation model were basically consistent with experimental value. This indicated that the simulation model on basis of BPNN was practical. Thus, we could use the program to establish the simulation model of hydrogen production rate and some designs, choice of operational parameters and prediction of hydrogen production rate in the CSTR and IBR could be finished on computer by the simulation model, and this model could be extended to other bioreactors.

The final objective of this study was not only establishing the simulation model but also ascertaining the optimum

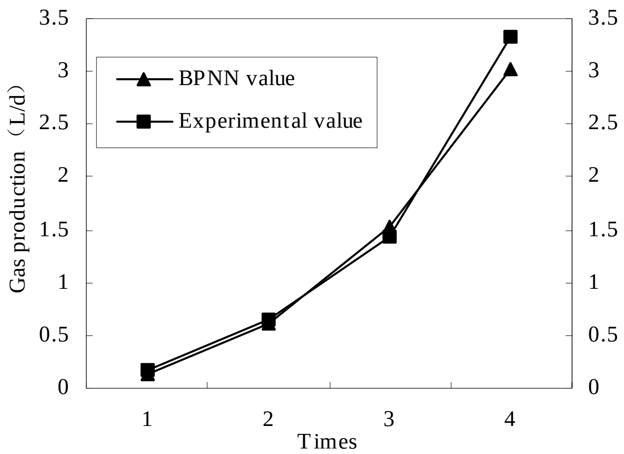



Fig.9. IBR Comparison between experimental value and BPNN value

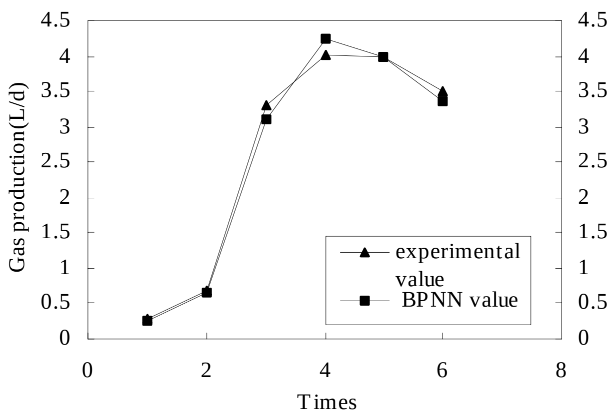



Fig.8. CSTR Comparison between experimental value and BPNN value

operational parameters and criteria for the design and the operation of the CSTR and IBR by the simulation model. The method of PCW was used to compare each parameter influencing the performance of the reactor. Through calculating the RI of all the input factors, the weight of the influence factors of CSTR was: VLR>pH values>ORP>alkalinity.(fig.10); The weight of the influence factors of IBR was: VLR >alkalinity>pH values >ORP.(fig. 11) .So we can draw the conclusion that in CSTR and IBR,

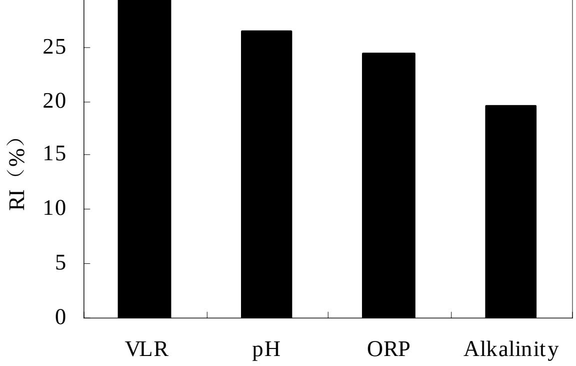



Fig.10. The weight of the influence factors in CSTR

the VLR was significant to improve the hydrogen production.

Thus, we could use the simulation model to control the operational parameters for obtaining

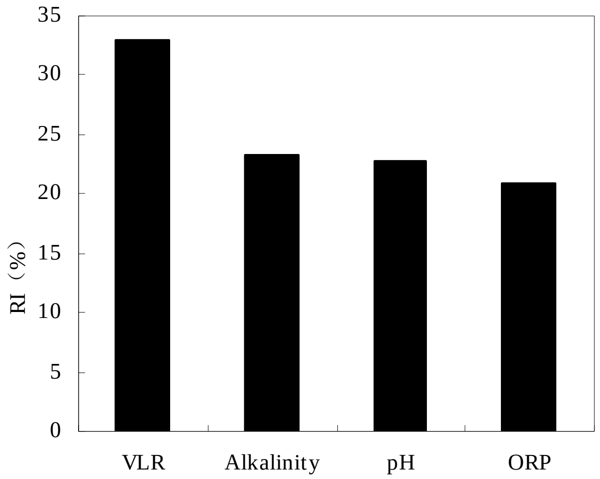



Fig.11. The weight of the influence factors in IBR

the best effluent quality and the highest hydrogen production rate in the CSTR and IBR for kitchen waste and sugar refinery wastewater treatment.

## IV. CONCLUSIONS

1) In CSTR and IBR, the VLR was significant to improve the hydrogen production. With VLR increasing, hydrogen production has been increased. In CSTR, while VLR was 25 kgCOD/($m^3$·d) to 40 kgCOD/($m^3$·d),the hydrogen production was at high values: 11.5 L/(Lreactor·d).
2) Alkalinity and the hydrogen production rate were positively correlated, and in CSTR the stage of high-yield hydrogen, alkalinity maintained at 300mg / L or more.
3) The method of PCW was used to compare each parameter influencing the performance of the reactor. The weight of the influence factors of CSTR was: VLR>pH values>ORP>alkalinity; The weight of the influence factors of IBR was: VLR>alkalinity>pH values >ORP.
4) The simulation model could finish designs, choice of operational parameters and prediction of the hydrogen production in CSTR and IBR on computer, and the model could be extended to other bioreactors. At the same time, we could use the simulation model to control the operational parameters.

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