CHEMICAL ENGINEERING TRANSACTIONS

VOL. 65, 2018

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Eliseo Ranzi, Mario Costa

ISBN 978-88-95608-62-4; **ISSN** 2283-9216

DOI: 10.3303/CET1865030

Applied Research on Bio-fermentation Intelligent Online Monitoring System Based on Computer Simulation Technology

Buying Chen

Xingtai Polytechnic College, Xingtai 054035,China
chenmo62@163.com

This paper aims at the shortcomings of manual offline sampling and offline analysis of the traditional bio-fermentation technology, proposes an intelligent online monitoring system for the bio-fermentation, presents the overall system structure, detail hardware and software design, and then using actual examples to verify the effectiveness of the system design in this paper. The system is embedded with improved continuous hidden Markov measurement model, which can effectively monitor the biological fermentation parameters online and utilize the minimum classification error to optimize the CHMM to achieve the purpose of controlling the convergence error of the algorithm. The simulation results show that the mean variance of the proposed algorithm is 0.182, and the calculated mean variance of the neural network algorithm reaches 0.911. The simulation algorithm proposed in this paper is significantly higher in the calculation accuracy than that of the neural network algorithm. At the same time, by using reliability we can better identify the simulation results and avoid blind control.

1. Introduction

Bio-fermentation is a bioengineering technology that utilizes the metabolism of microorganisms for the production of chemical raw materials. The continuous regulation of the technological parameters of bio-fermentation is the most important means of maintaining biological production of chemical raw materials (Bogaerts and Wouwer, 2003; Assis, 2000; Li, 2017; Pederzoli et al., 2017; Gagliardi and Mondini, 2018; Majumdar and Roy, 2018; Zhang et al., 2016; Ma, 2016; Seddak and Liazid, 2016; Quinlan et al., 2017; Amara et al., 2017; Puglia et al., 2017; Calabrò and Panzera, 2017; Quinlan et al., 2017; Malaguti et al., 2017; Borchiellini et al., 2017; Borchiellini et al., 2017; Zaccone et al., 2017; Rajput et al., 2017;).
The essential factors for the growth of microorganisms are temperature, water, nutrients, pH value, etc. Since the bio-fermentation involves many aspects as physics, chemistry and biology, etc, and it is a typical nonlinear and time-varying reaction process (Yong, Huang and Jin, 2004), the existing technologies have many shortcomings in the online monitoring of related metabolic indexes (such as biological concentration, growth rate and metabolic rate) of microorganisms. Currently, the most commonly used method is to manually sample the bio-fermentation and perform offline analysis, however, this method has larger sampling amount and the analysis result is lagging, which severely constrains the development of bio-fermentation technology (Pérez et al, 2013; Desai et al, 2006).
The online monitoring of bio-fermentation is currently a research hotspot in bioengineering. The present online monitoring methods are based on different measure and control units, neural network method, support vector machine (SVM). (Rivera et al., 2009). The neural network method has some defects such as slow rate of convergence and overfitting; SVM also has defects such as inability to adaptively select calculation parameters and large algorithm calculated amount (Shah et al., 2010; Chandola et al., 2007; Tarkiainen et al, 2005; Rhee, Ritzka and Scheper, 2004). Therefore, establishing an intelligent monitoring system for the bio-fermentation is of great practical significance for real-time monitoring of fermentation process and mechanism, and the optimization and regulation of bio-fermentation.

Please cite this article as: Buying Chen , 2018, Applied research on bio-fermentation intelligent online monitoring system based on computer simulation technology, Chemical Engineering Transactions, 65, 175-180 DOI: 10.3303/CET1865030

This paper aims at the shortcomings of manual offline sampling and offline analysis of the traditional bio-fermentation technology, proposes an intelligent online monitoring system for the bio-fermentation, presents the overall system structure, detail hardware and software design, and then using actual examples to verify the effectiveness of the system design in this paper.

2. Design of bio-fermentation intelligent online monitoring system

Figure 1 shows the overall system architecture of the bio-fermentation intelligent monitoring system. The monitoring of traditional bio-fermentation process is mostly conducted and controlled by hardware sensors and microbial metabolic data collectors. The intelligent online monitoring system designed in this paper can analyze the whole process of microbial fermentation, and construct the soft-sensing model by processing the prior knowledge and related parameters. The system has set up several main functional units including intelligent detection unit, data acquisition unit, hardware sensor unit, control unit, network interface unit, the units are described in detail as follows:

(a) Data acquisition unit: it collects relevant data of the bio-fermentation process. This unit consists three parts: sensor, signal conditioner and data collector. The collected bio-fermentation analog quantity is converted into digital quantity that can be processed on computers;

(b) Hardware sensor unit: it includes detection unit, data preprocessing unit and online monitoring real-time data unit, its main role is to conduct related calculation to the converted digital quantity;

(c) Intelligent detection unit: it is the core unit of the whole bio-fermentation intelligent monitoring system, by analyzing the extracted bio-fermentation data, it obtains parameters of the whole bio-fermentation process and finally achieves online detection of microbial fermentation.

(d) Control unit: it includes PID, control of various equipment switch components; modules, predictive control, etc;

(e) Network interface unit: it is used to control the data exchange between the platform and the staff operation layer.

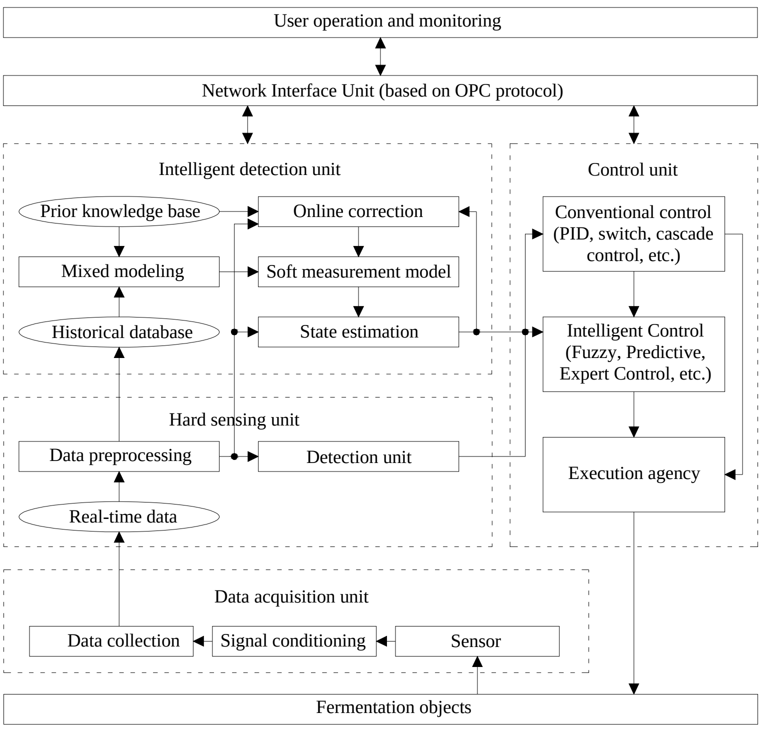


Figure 1: Overall architecture of bio-fermentation intelligent monitoring system

Figure 2 shows the hardware design framework of the bio-fermentation intelligent monitoring system. The hardware in the system can collect core parameters of the bio-fermentation such as pH value, temperature and oxygen concentration etc. The environment temperature of bio-fermentation can be adjusted by the cooling water switch; the fermented nutrient solution is mixed thoroughly by the stirring rod; and the alkaline pump is used to adjust the pH value of the solution.

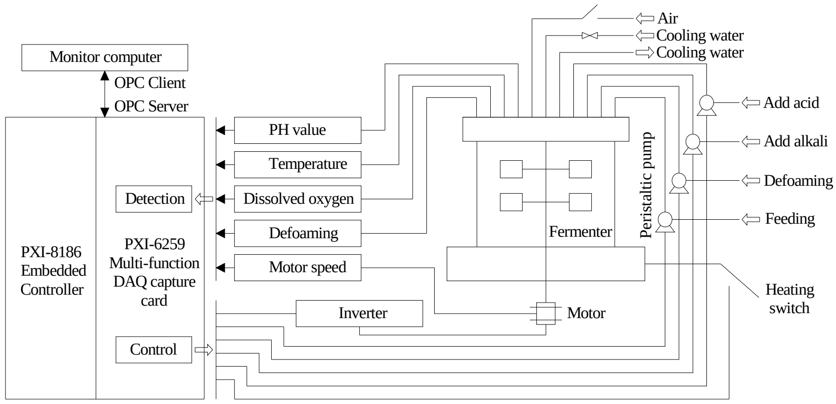


Figure 2: Hardware design framework of bio-fermentation intelligent monitoring system

Figure 3 shows the software design framework of the bio-fermentation intelligent monitoring system. It is mainly consisted of several parts including monitoring task management and operation, data management scheduling and interface software, which are programmed by LabVIEW. Each unit exchanges data through a unified interface of the system. Staff can open the system interface to access different modules uniformly, which effectively increases the reliability of the system and reduces the complexity of the system calculation.

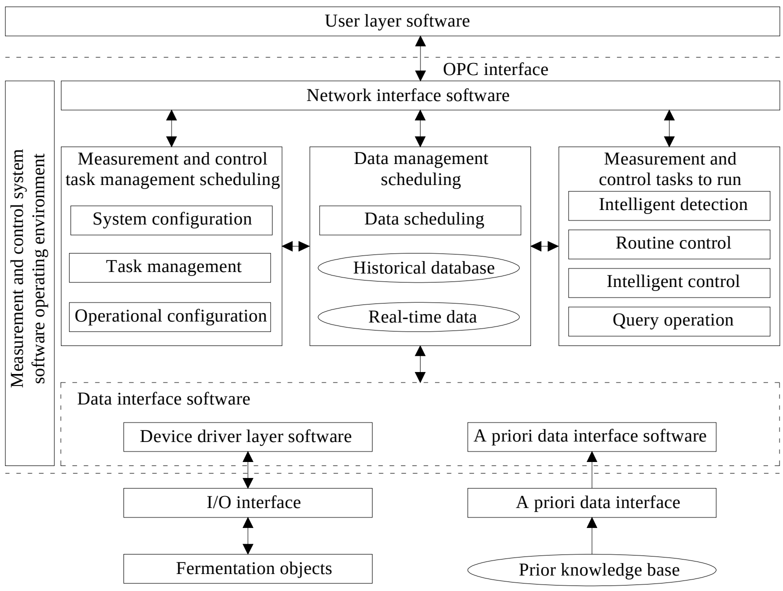


Figure 3: Software design framework of bio-fermentation intelligent monitoring system

The soft-sensing model used in this paper is an improved continuous hidden Markov model (CHMM), the CHMM is optimized by the minimum classification error (MCE), and the MCE expression is:

$$d\left(O_{k,n},\Lambda\right)=-g\left(O_{k,n},\lambda_k\right)+\left[\frac{1}{K-1}\sum_{p\neq k}g\left(O_{k,n},\lambda_p\right)^{\eta}\right]^{1/\eta} \tag{1}$$

By simplifying Formula 1 we can get:

$$d\left(O_{k,n},\Lambda\right)=-g\left(O_{k,n},\lambda_k\right)+g\left(O_{k,n},\lambda_c\right) \tag{2}$$

λ_c is the optimal competition model; g ($O_{k,n}$, λ_c) is discrimination function. By embedding a Sigmoid function into Formula 2 we get:

$$l\left(O_{k,n},\Lambda\right)=\frac{1}{1+\exp\left(-d\left(O_{k,n},\Lambda\right)\right)} \tag{3}$$

Formula 3 is the loss function of the CHMM model. When there are K subcomponents in the system, the total loss function is the sum of K subcomponents:

$$L\left(O,\Lambda\right)=\sum_{k=1}^{K}\sum_{n=1}^{N}l\left(O_{k,n},\Lambda\right) \tag{4}$$

3. Test and analysis

Conduct verification to the bio-fermentation intelligent online monitoring system established in this paper, and take the fermentation of erythromycin as an example. The fermentation cycle of erythromycin is about 170h, and its main fermentation stage is 50h-150h. Manually take offline samples of the microbial fermentation every 6h, and collect several core parameters of the bio-fermentation of each single sampling. Figure 4 shows the offline sampling and fitting results of erythromycin concentration. The overall offline sampling data is divided into training set and test set, the maximum number of iterations is 200 times.

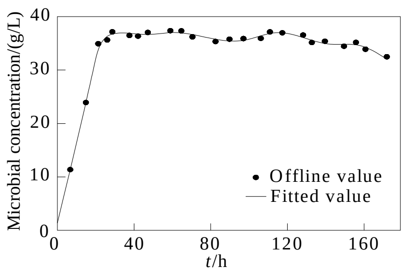


Figure 4: Erythromycin concentration offline sampling results and fitting results

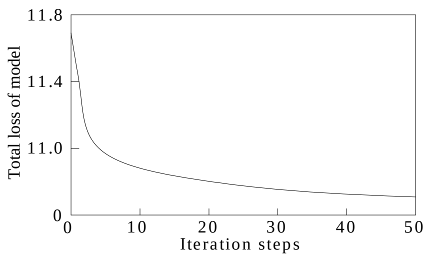
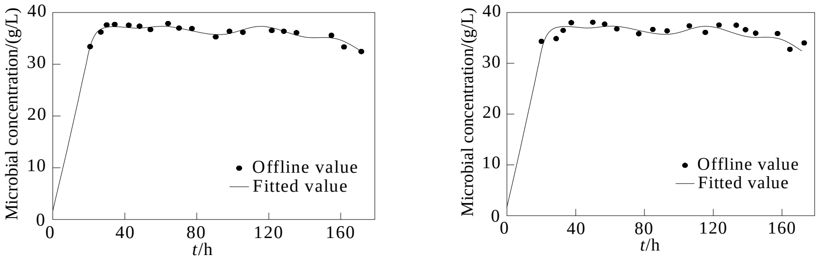


Figure 5: Total loss curve of the improved CHMM method

Set the convergence error of the algorithm as 10^{-4}. Figure 5 shows total loss curve of the model of the proposed algorithm, when the loss severity reaches 50 steps, the model is convergent.

Figure 6 shows the computer simulation results of the proposed algorithm and the traditional neural network algorithm of bio-fermentation. It can be seen from the figure that the prediction results of the proposed method are better than those of the neural network algorithm. Using mean variance to calculate both algorithms, the mean variance of the proposed algorithm is 0.182, while the calculated result of the mean variance of the neural network algorithm reaches 0.911.



(a) Proposed model *(b) Neural network model*

Figure 6: Simulation prediction of microbial fermentation concentration based on neural network model and the proposed model

The reliability V is expressed as:

$$V = \frac{\max_k \left(P\left(O|\lambda_k\right) \right)}{\sum_{k=1}^{K} P\left(O|\lambda_k\right)} \times 100\% \tag{5}$$

Using the proposed algorithm and NN algorithm to calculate 10 samples, the predicted value, prediction error and reliability are obtained. The statistical results are shown in Table 1. From Table 1, we can see that the simulation algorithm proposed in this paper has significantly higher computational accuracy than the neural network algorithm. The fifth and seventh samples in the 10 samples have relatively lower reliabilities of 57% and 35%, respectively, while the predictive results of the two samples are higher than the actual offline sampling results, the prediction error is larger, which indicates that the use of reliability can better identify the simulation results, and avoid blind control.

Table 1: Prediction results and reliability of the proposed algorithm and neural network (NN) algorithm

Serial number	Offline analysis of the value/(g/L)	Predictive value/(g/L)		Error/(g/L)		Credibility/%	
		Proposed	NN	Proposed	NN	Proposed	NN
1	38	37.01	37.98	0.02	0.78	98	-
2	36	37.56	37.72	0.01	0.78	99	-
3	35	37.23	37.38	0.03	1.21	100	-
4	33	33.96	36.55	0.04	1.08	94	-
5	34	35.16	35.69	0.46	1.44	57	-
6	38	35.88	35.71	0.09	0.62	90	-
7	36	38.25	36.93	0.82	1.73	35	-
8	32	35.78	36.97	0.01	0.89	97	-
9	35	37.39	37.04	0.03	0.66	95	-
10	38	32.74	35.84	0.02	1.15	93	-

4. Conclusion

This paper aims at the shortcomings of manual offline sampling and offline analysis of the traditional bio-fermentation technology, proposes an intelligent online monitoring system for the bio-fermentation, presents the overall system structure, detail hardware and software design, and then using actual examples to verify the effectiveness of the system design in this paper. The research conclusions are as follows:

(1) The system is embedded with improved continuous hidden Markov measurement model, which can effectively monitor the biological fermentation parameters online and utilize the minimum classification error to optimize the CHMM to achieve the purpose of controlling the convergence error of the algorithm.

(2) The simulation results show that the mean variance of the proposed algorithm is 0.182, and the calculated mean variance of the neural network algorithm reaches 0.911. The simulation algorithm proposed in this paper is significantly higher in the calculation accuracy than that of the neural network algorithm. At the same time, by using reliability we can better identify the simulation results and avoid blind control.

References

Amara I., Mazioud A., Boulaoued I., Mhimid A., 2017, Experimental study on thermal properties of bio-composite (gypsum plaster reinforced with palm tree fibers) for building insulation, International Journal of Heat and Technology, 35(1), 576-584. DOI: 10.18280/ijht.350314

Assis A.D. 2000, Soft sensors development for on-line bioreactor state estimation, Computers & Chemical Engineering, 24(2), 1099-1103, DOI: 10.1016/s0098-1354(00)00489-0

Bi S., Feng D. 2012, Modeling for liquid-level control system in beer fermentation process, Control Conference, 1739-1744, DOI: 10.1016/s0959-1524(00)00065-2

Bogaerts, P., Wouwer, A.V. 2003, Software sensors for bioprocesses, Isa Transactions, 42(4), 547, DOI: 10.1016/s0019-0578(07)60005-6

Borchiellini R., Corgnati S.P., Becchio C., Delmastro C., Bottero M.C., Dell'Anna F., Acquaviva A., Bottaccioli L., Patti E., Bompard E., Pons E., Estebsari A., Verda V., Santarelli M., Leone P., Lanzini A., 2017, The Energy Center Initiative at Politecnico di Torino: Practical experiences on energy efficiency measures in the municipality of Torino, International Journal of Heat and Technology, 35(S1), S196-S204. DOI: 10.18280/ijht.35Sp0128

Calabrò P.S., Panzera M.F., 2017, Biomethane production tests on ensiled orange peel waste, International Journal of Heat and Technology, 35(S1), S130-S136. DOI: 10.18280/ijht.35Sp0118

Chandola V., Vatsavai R.R. 2011, A scalable gaussian process analysis algorithm for biomass monitoring, Statistical Analysis & Data Mining, 4(4), 430-445, DOI: 10.1002/sam.10129

Desai K., Badhe Y., Tambe S.S., Kulkarni B.D. 2006, Soft-sensor development for fed-batch bioreactors using support vector regression, Biochemical Engineering Journal, 27(3), 225-239, DOI: 10.1016/j.bej.2005.08.002

Gagliardi E., Mondini G., 2018, DNA modifications through remote intention, NeuroQuantology, 16(1), 1-6. DOI: 10.14704/nq.2018.16.1.1129

Li J.F., 2017, Biological origin of consciousness and a physical model of human brain, NeuroQuantology, 15(3), 89-93. DOI: 10.14704/nq.2017.15.3.1102

Ma L., 2016, Bare hands threshing stress analysis and bionics bare hand threshing device test, Mathematical Modelling of Engineering Problems, 3(4), 171-174. DOI: 10.18280/mmep.030403

Majumdar S., Roy S., 2018, Relevance of quantum mechanics in bacterial communication, NeuroQuantology, 16(3), 1-16. DOI: 10.14704/nq.2018.16.3.1057

Malaguti V., Lodi C., Sassatelli M., Pedrazzi S., Allesina G., Tartarini P., 2017, Dynamic behavior investigation of a micro biomass CHP system for residential use, International Journal of Heat and Technology, 35(S1), S172-S178. DOI: 10.18280/ijht.35Sp0124

Pederzoli L., Giroldini W., Prati E., Tressoldi P., 2017, The physics of mind-matter interaction at a distance, NeuroQuantology, 15(3), 114-119. DOI: 10.14704/nq.2017.15.3.1063

Pérez P.A.L., Yescas R.M., Acata R.V.G., Caballero V.P., López R.A. 2013, Software sensors design for the simultaneous saccharification and fermentation of starch to ethanol, Fuel, 110(4), 219-226, DOI: 10.1016/j.fuel.2012.11.020

Puglia M., Pedrazzi S., Allesina G., Morselli N., Tartarini P., 2017, Vine prunings biomass as fuel in wood stoves for thermal power production, International Journal of Heat and Technology, 35(S1), S96-S101. DOI: 10.18280/ijht.35Sp0113

Quinlan B., Kaufmann B., Allensina G., Pedrazzi S., Whipple S., 2017, Application of OLTT in gasification power systems, International Journal of Heat and Technology, 35(4), 773-778. DOI: 10.18280/ijht.350411

Quinlan B., Kaufmann B., Allesina G., Pedrazzi S., Hasty J., Puglia M., Morselli N., Tartarini P., 2017, The use of on-line colorimetry for tar content evaluation in gasification systems, International Journal of Heat and Technology, 35(S1), S145-S151. DOI: 10.18280/ijht.35Sp0120

Rajput G.R., Patil V.S., Krishna P.J.S.V.R., 2017, Hydromagnetic bioconvection flow in the region of stagnation-point flow and heat transfer in non-Newtonian nanofluid past a moving surface with suction: similarity analysis, International Journal of Heat and Technology, 35(1), 25-31. DOI: 10.18280/ijht.350104

Rhee J.I., Ritzka A., Scheper T. 2004, On-line monitoring and control of substrate concentrations in biological processes by flow injection analysis systems, Biotechnology & Bioprocess Engineering, 9(3), 156-165, DOI: 10.1007/bf02942286

Rivera E.C., Atala D.I.P., Costa A.C.D., Filho F.M., Filho R.M. 2009, Soft-sensor for real-time estimation of ethanol concentration in continuous flash fermentation, Computer Aided Chemical Engineering, 27(09), 1653-1658, DOI: 10.1016/s1570-7946(09)70666-2

Riverol C., Cooney J. 2007, Estimation of the ester formation during beer fermentation using neural networks, Journal of Food Engineering, 82(4), 585-588, DOI: 10.1016/j.jfoodeng.2007.03.016

Seddak M., Liazid A., 2016, The effects of using a biofuel on the performance of a marine diesel engine, Mathematical Modelling of Engineering Problems, 3(4), 195-197. DOI: 10.18280/mmep.030408

Shah S.L., Gray M.R., Gudi R.D., Yegneswaran P.K. 2010, Adaptive multirate estimation and control of nutrient levels in a fed-batch fermentation using off-line and on-line measurements, Canadian Journal of Chemical Engineering, 75(3), 562-573, DOI: 10.1002/cjce.5450750310

Tarkiainen V., Kotiaho T., Mattila I., Virkajärvi I., Aristidou A., Ketola R.A. 2005, On-line monitoring of continuous beer fermentation process using automatic membrane inlet mass spectrometric system, Talanta, 65(5), 1254-63, DOI: 10.1016/j.talanta.2004.08.051

Zaccone R., Sacile R., Fossa M., 2017, Energy modelling and decision support algorithm for the exploitation of biomass resources in industrial districts, International Journal of Heat and Technology, 35(S1), S322-S329. DOI: 10.18280/ijht.35Sp0144

Zhang L., Zhang T.D., Gao R., Tang D.Y., Yang J.Y., Fu T.L., Zhan Z.L., 2016, Phenol adsorption property of high specific surface areas biomass based porous carbon materials, Mathematical Modelling of Engineering Problems, 3(4), 157-161. DOI: 10.18280/mmep.030401