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RECENT DEVELOPMENTS IN MODELING OF MONITORING IN THE ANAEROBIC BIOREACTOR SYSTEM

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Abstract

Monitoring in the anaerobic bioreactor system is requiring understanding the occurred situation in the bioreactor process. Bioreactor is complex designed to accelerate waste degradation by combining attributes of the aerobic and anaerobic bioreactors involves many variables. Multivariate Statistical Process Control (MSPC) models are a statistical solution to the problem of directly calculating physical and biological properties of molecules from their physical structure. QSAR model is utilized to extract information from a set of numerical descriptors characterizing molecular structure and use this information to develop inductively a relationship between structure and property. The goal of a (MSPC) model is to replace the conventional methods univariate Statistical Process Control (SPC) to analyze the state of the multivariate process of anaerobic bioreactor. The objective of the sequential aerobic-anaerobic treatment is to cause the rapid biodegradation of degradable waste in the aerobic stage in order to reduce the production of organic acids in the anaerobic stage resulting in the earlier onset of methanogenesis. The monitoring of process uses principal component analysis (PCA) to reduce multivariate data. Further, hotelling T^2 values were used to monitor the quality of the bioreactor operating condition. Hence, fuzzy logic was used to determine the present condition of the bioreactor based on the value of T^2 related. The simulation results indicate that the offered method is able to determine four bioreactor process states, i.e. normal, organic overload, hydraulic overload, and fluctuations in temperature, with the success rate 100%.

Keywords: Bioreactor, Multivariate statistical process control, Principal component analysis, Fuzzy logic.

Nomenclatures

A_1	Factor of input S_c variable
A_2	Factor of input S_2 variable
A_3	Factor of input D variable
B	Bicarbonate, mol/L
CO_{2D}	Dissolve carbon dioxide, mol/L
D	Dilution rate, hr
H^+	Hydrogen ion, mol/L
HS	Acid (non ionized) form of S_2 , mol/L
IC	Inorganic carbon, mol/L
K_a	Equilibrium constant of H^+S^-, mol/L
K_b	Equilibrium constant of H^+B, mol/L
K_h	Henry's constant, mmol/L/Atm
K_{I2}	Inhibition constant of substrate S_2, mmol/L
K_{IC}	Inhibition constant of substrate S_c, g/L
K_{S2}	Dissociation constant of substrate S_2, mmol/L
K_{Sc}	Dissociation constant of substrate S_c, g/L
N	Number of data
P_{CO2}	Partial pressure for the dissolved carbon dioxide, Atm
P_R	Matrix of principal component
P_t	Total pressure, Atm
Q_{CH4}	Flow rate of CH_4 output, L/hr
Q_{CO2}	Flow rate of CO_2 output, L/hr
R_1	Substrate degradation
R_2	S_2 production, mmol/g
R_3	S_2 consumption, mmol/g
R_4	CO_2 production by X_c, mmol/g
R_5	CO_2 production by X_2, mmol/g
R_6	CH_4 production, mmol/g
S	Standard deviation
S^-	Base (ionized) form of S_2 , mol/L
S_2	Fastly degradable substrate, g/L
S_c	Slowly degradable substrat, g/L
S_R	Matrix containing R first eigen value in its diagonal
T	Temperature, ^oC
T^2	Hotelling T^2 value
t_R	Score space
$\boldsymbol{U}$	Unitary matrix
$\boldsymbol{V}$	Matrix containing the eigenvector
X	Input data
X_2	Methanogenic bacteria, g/L
X_c	Acidogenic bacteria, g/L
$\overline{x}$	Mean
$\tilde{x}$	Residual
$\hat{x}$	Projection matrix X
Z	Total kation, mol/L

Subscript

C	Acidogenic bacteria
I	Index of batch process
In	Input
J	Index of measured variable
K	Index of times
Max	Maximum
R	Number of principal component
0	Initial condition
2	Methanogenic bacteria

Greek Symbols

θ	Activation energy, kJ/mol
λ	Coefficient of gaseous carbon dioxide
μ_2	Specific growth rate of methanogenic bacteria, 1/hr
μ_χ	Specific growth rate of acidogenic bacteria, 1/hr
Σ	Diagonal matrix containing the nonnegative square roots of the Eigen values of $\mathbf{x}^T\mathbf{x}$, ordered from the largest to the smallest

1. Introduction

A bioreactor is a container in which is carried out a chemical process which involves organisms or biochemically active derivative substances from such organisms. Bioreactors are frequently cylindrical, ranging in size from several liter to cube meters, and are often made of stainless steel.

Bioreactor design is fairly a complex engineering mission. Under optimum conditions, the microorganisms or cells will reproduce at surprising rate. The container's environmental conditions like gas (i.e., air, oxygen, nitrogen, carbon dioxide) flow rates, temperature, pH and dissolved oxygen levels, and agitation speed require monitoring and controlling. A single bioreactor manufacturer, Broadly-James Corporation, uses vessels, sensors, controllers, and a control system, digitally networked together for their bioreactor scheme.

Continuous flow stirred tank reactors in the continuous flow, stirred tank reactor (CSTR) fresh medium was feed into the bioreactor at a constant rate, and medium mixed with cells leaves the bioreactor at the same rate. A fixed bioreactor volume is maintained and ideally, the effluent stream should have the same composition as the bioreactor contents. The culture is fed with fresh medium containing one and sometimes two growth limiting nutrients such as glucose. The concentration of the cells in the bioreactor is controlled by the concentration of the growth-limiting nutrient. A steady state cell concentration is reached where the cell density and substrate concentration are constant. The cell growth rate, μ, is controlled by the dilution rate, D, of growth limiting nutrient.

Cell culture bioreactors classified into two types, those that utilized for cultivation of anchorage dependent cells (e.g., primary cultures derived from normal tissues and diploid cell lines. Those that used for the cultivation of suspended mammalian cells (e.g., cell lines derived from cancerous tissues and tumors, transformed diploid cell lines, hybridomas). In some cases, the bioreactor

may be modified to grow both anchorage dependent and suspended cells. Ideally, any cell culture bioreactor must maintain a sterile culture of cells in medium conditions, which maximize cell growth and productivity.

Anaerobic wastewater treatment systems generally use the anaerobic bioreactor. In this bioreactor occurred biological process that converts the substrate or organic waste into methane (CH_4) and carbon dioxide CO_2 by utilizing the activity of microorganisms in the environment without air (anaerobic). Microorganisms can grow by consuming the available nutrients or substrate on support environmental conditions.

Determination of optimal substrate feed rate is a problem in singular control, so called because the control variable appears linearly both in the dynamic equations describing the process and/or in the performance index which is to be optimized. In many industrially important fermentation processes, microorganisms require more than one substrate for their growth and product formation [1]. It has long been realized that the production of antibiotics and enzymes requires precise control of the nitrogen source in addition to the carbon source. The production of a desired chemical from recombinant cell cultures often involves addition of either an inducer or repressor along with the primary growth-limiting nutrient. The optimization problem for such processes involves the determination of the optimal feed rates of two nutrients: either two growth-limiting substrates such as carbon and nitrogen or one growth-limiting substrate and an inducer or a repressor. The feed rate optimization of fed-batch bioreactors involving multiple singular control variables is a numerically difficult problem.

Bioreactor is extremely vulnerable to fluctuations in the substrate, temperature and pH [2]. Those variables affect the viability of microorganisms. When these variables are not maintained, they will result in death of microorganisms and further microorganisms in the reactor will totally dead. This event is called washout and recovery time for this event requires a long time. Hence, a monitoring system is required to give information about the state of the process and about the process behaviour. Then, based on that information, further handling or action can be taken to ensure optimal running of the plant.

Anaerobic bioreactor is a complex process therefore; it involves multiple process variables, including physical and chemical variables. Due to the number of variables, it will be difficult to design a control or monitoring system for the process. To solve this problem, it can be used the Multivariate Statistical Process Control (MSPC) method. MSPC changes multidimensional information into a number of latent variables that explain the variability of the measured variable, including the relations between measured variables. MSPC makes use of statistical methods to analyze, control and influence improvement on process performance based on the existing multivariable.

Reducing multivariable to a few main variables can be done by using the Principle Component Analysis (PCA) [3]. The use of PCA to diagnose the condition and behaviour of an anaerobic bioreactor has been reported by Olson [4] for a batch system. However, the latent variable acquired from PCA cannot explain the condition of the ongoing process. This can cause difficulties for operators to interpret them into physical forms. Therefore, to interpret these new variables and to classify the current condition of the process, an algorithm for decision-making is required.

Marco S. R. et al. [5] presented an approach for conducting multivariate statistical process control (MSPC) in noisy environments, i.e., when the signal to noise ratio is low, and, furthermore, noise standard deviation (uncertainty) affecting every collected value can vary over time, and is assumingly known. This approach is based upon a latent variable model structure, HLV (standing for heteroscedastic latent variable model), that explicitly integrates information regarding data uncertainty. Reasonable amounts of missing data can also be handled in a coherent and fully integrated way through HLV. Various examples exhibit the added value achieved under noisy conditions by adopting such an approach and a case study illustrates its application to a real industrial context of pulp and paper product quality data analysis.

The use of fuzzy as decision makers has been conducted by the researchers. Murnleitner et al. [6] used a fuzzy logic system in order to predict the biological state of the reactors. Carrasco et al. [7] have developed a diagnosis system based fuzzy logic for the determination of acidification states on an anaerobic wastewater treatment plants. In this paper, monitoring system algorithm based on fuzzy assisted multivariate statistical process control for oxidation ditch has developed. However, PCA was applied statically in the data matrix X, since it was assumed there was no correlation over time. When this is the case the exact relations between the variables will not be revealed. In this paper, the algorithm was refined to handle this dynamic PCA for continuous process and was applied to a plant bioreactor by a simulation.

2. Anaerobic Bioreactor Model

Substrate of organic waste is very complex, so it is impossible to include the overall organic material conditions into a model. But there are approaches that can be used to anticipate the complex nature of the substrate, i.e., by representing them into two groups, namely the equivalent glucose substrate (Glucose, S_c) and the equivalent acetic acid substrate (acetate, S_2) [2].

The choice of the number of considered bacterial populations involved in the anaerobic bioreactor process directly linked to the model complexity. Since the objective is to obtain a model that would be able to represent the destabilization phenomenon while being identifiable, it is assumed that bacterial population can be divided into two main groups of homogeneous characteristics and that the anaerobic digestion can be described by a two stage process. In the first step (acidogenesis), the acidogenic bacteria (X_c) consume the organic substrate S_c and produce inorganic carbon (*IC*) and acetic acid (S_2) with the specific growth rate μ_c. The population of methanogenic bacteria (X_2) uses in a second step acetic acid (S_2) as substrate for growth and produce dissolved inorganic carbon (*IC*) and methane (CH_4). Substrate S_2 is a weak acid dispatched between HS (acid form) and S^- (base form). It is important to notice that HS excess inhibits the growth rates μ_2.

The inorganic carbon *IC* is made up of dissolved inorganic carbon, which is, dispatched between the bicarbonate base form (B) and the dissolved carbon dioxide acid form (CO_2), following an equilibrium function on the pH. Gaseous carbon dioxide (CO_2) was, transferred in the gas phase from dissolved CO_2. The simplified functional diagram of anaerobic bioreactor process is shown in Fig. 1.

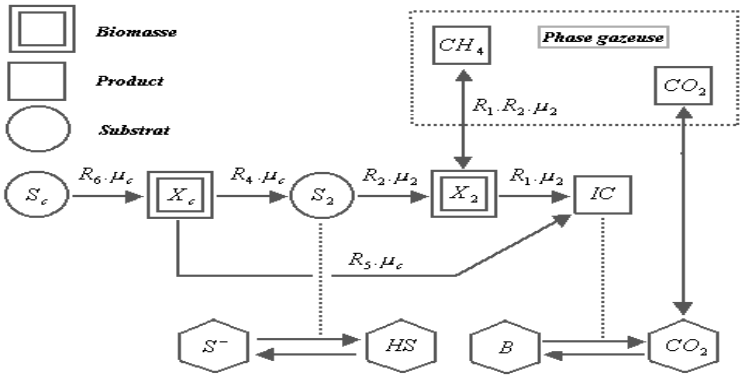

Fig. 1. Functional Diagram of Anaerobic Digestion [2].

Stage of the process that occurred in the bioreactor can be can be explained by a number of algebraic equations describing the physical-chemical equilibrium and differential equations that describe the dynamics of the system, as well as supported by several equations that describe biological processes in the bioreactor. The complete model is as follows [2]:

The systems of equations describing chemical equilibrium have a individual algebraic structure which can be exploited to significantly reduce their algebraic complexity as follow:

$$HS + S^- - S_2 = 0 \tag{1}$$

$$H^+ S^- - K_a HS = 0 \tag{2}$$

$$B + CO_{2D} - IC = 0 \tag{3}$$

$$H^+ B - K_b CO_{2D} = 0 \tag{4}$$

$$B + S^- - Z = 0 \tag{5}$$

The differential equations describing the dynamics of the systems as follow:

$$\frac{dX_C}{dt} = (\mu_C - D).X_C \tag{6}$$

$$\frac{dS_C}{dt} = -R_1.\mu_C.X_C + D.(S_{Cin} - S_C) \tag{7}$$

$$\frac{dX_2}{dt} = (\mu_2 - D).X_2 \tag{8}$$

$$\frac{dS_2}{dt} = -R_3.\mu_2.X_2 + R_2.\mu_C.X_C + D.(S_{2in} - S_2) \tag{9}$$

$$\frac{dIC}{dt} = R_5.\mu_2.X_2 + R_4.\mu_C.X_C - \lambda..R_5.\mu_2.X_2 + D(IC_{in}\text{-}IC) \tag{10}$$

$$\frac{dZ}{dt} = D(Z_{in} - Z) \tag{11}$$

Output equations that are consider as the process output.

$$Q_{CH_4} = R_6.\mu_2.X_2 \tag{12}$$

$$Q_{CO_2} = \lambda.R_6.\mu_2.X_2 \tag{13}$$

with

$$P_{CO_2} = \frac{CO_{2D}}{K_h} \tag{14}$$

$$\lambda = \frac{P_{CO_2}}{P_t - P_{CO_2}} \tag{15}$$

$$\mu_2 = \frac{\mu_{2\max}.HS}{K_{S_2} + HS + \frac{HS^2}{K_{I2}}} \tag{16}$$

$$\mu_C = \frac{\mu_{C\max}.S_C}{K_{S_C} + S_C + \frac{S_C.HS}{K_{IC}}} \tag{17}$$

where: R_1, R_2, R_3, R_4, R_5, and R_6 are the yield coefficients. μ_1 and μ_2 are the Haldane growth rates. λ is a coefficient for gaseous carbon dioxide. D is dilution rate. K_{IC} stands for the inhibition constant for substrate S_c, K_{I2} stands for the inhibition constant for substrate S_2, K_{Sc} stands for the dissociation constant for substrate S_c and inorganic carbon, K_{S2} stands for the dissociation constant for substrate S_2 and others acids, K_h stands for an equivalent of the Henry constant, P_{CO2} stands for the partial pressure for the dissolved carbon dioxide and P_t stands for the atmospheric pressure.

While the relationship between growth rate and temperature can be explained by the formulas from Arhenius, as follows [8]:

$$\mu_{C\max} = \mu_{C,0}\left(e^{-\frac{\theta_c}{T}}\right) \tag{18}$$

$$\mu_{2\max} = \mu_{2,0}\left(e^{-\frac{\theta_2}{T}}\right) \tag{19}$$

Hypothetically, and through literature [9], there are seven modes of unstable bioreactor conditions. However, at this paper, the considered state mode for the plant comprises of normal mode, *organic overload*, *hydraulic overload*, and temperature change. To acquire simulation data, it was assumed that for every Fstate, changes in input variables are occured as described in Table 1.

Table 1. State Mode in Bioreactor.

Condition	State in Bioreactor
Normal behavior	No changes that affects the process state
Organic overload	Provision of excess substrate to make a drastic growth of biomass, making an imbalance in the reactor and the reactor slowly poisoned and biomass - dead land
Hydraulic overload	Dilution are given in the bioreactor was too excessive, so that biomass cannot be adapted and then die
Temperature fluctuation	Conditions where temperatures are beyond the range of biomass, so biomass death

3. Monitoring System Design

The design of monitoring system based MSPC are mentioned in the following section:

- **Multiway PCA Implementation**

Principal Component Analysis (PCA) is one of MSPC methods, which are usually applies to analyze a set of variables. The purpose of PCA is to reduce data dimension by finding a new variables (called as principal components) which is a linear combination of the original set of variables so that the variation of the new components became maximum and the new components became independent to each other. There are some PCA methods that have been developed, and for the monitoring system design in this paper, the applied method is multi-way principal component analysis (MPCA).

In simple terms, the data grouping in MPCA is described in Fig. 2. Measurement data acquired from bioreactor is grouped based on the matrix x $\in R^{IJK}$, for i bioreactor with $j = 1,2...J$ measurement variable based on time $k = 1, 2...K$. The matrix data ($I \times J$) represents the numbers of bioreactor variables $j = 1, 2....J$, and the matrix ($J \times K$) at horizontal side represent changes in every variable for bioreactor at time of k.

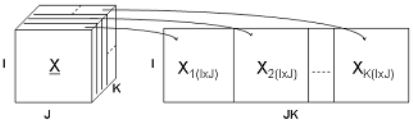

Fig. 2. Data Grouping in MPCA.

The principle components are not correlated to each other and group from the smallest to biggest variant. The first principle component is the linear combination of the maximum variant value. Generally the MPCA method is described in Fig. 3.

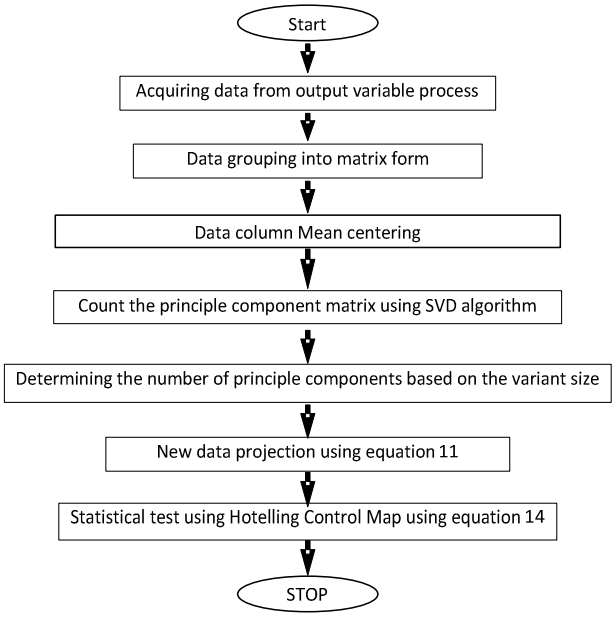

Fig. 3. The Flowcart of MPCA Method.

In MPCA, the data must be changed into 2 dimensional form. From the simulation result of the bioreactor model, a three dimensional data is acquired *(i,j,k)* for i bioreactor, j measurement variable, and *k* time. Then they are grouped into a *(ij×k)* matrix form. For the case in this paper, i = 1 and k = 1500 with sampling time of 1 hour. j is the number of variables (pH, flow rate of CH_4, and temperature). Mean of each variable can be determine as:

$$\bar{x}_j = \frac{1}{n}\sum_{k=1}^{n} x_k \tag{20}$$

and the standard deviation is:

$$s_j = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}\left(x_{kj} - \bar{x}_j\right)^2} \tag{21}$$

The principal compo

Principle components can be calculated directly or, more commonly, after different centering and scaling operations on the data matrix **x** according to: $\frac{x_j - \bar{x}_j}{s}$

One of the techniques to find principle components are Singular Value Decomposition (SVD) algorithm, where the matrix for principle components and it's variations could be find directly. In singular value decomposition, SVD, the matrix **x** is decomposed according to:

$$\mathbf{x} = \mathbf{U}\Sigma\mathbf{V}^{\mathbf{T}} \tag{22}$$

which **U** is a matrix (k×j), **V** is a matrix (j×j), T is transpose matrix operator and **Σ** is a diagonal matrix (k×j) containing the eigenvalue of covariance matrix **x**, i.e., σ on the diagonal. The largest singular value (σ) in column of matrix **V**, (p_1), determines the direction of the first principal component, and the second largest singular value (σ) in column of matrix **V**, (p_2), determines the direction of the second principal component, and so on.

Each observation in time $x(k) \in R^J$ of the variables is projected on to the score space $t_R(k)$, by multiplying x(k) with matrix of principal components P_R^T , with R is the number of principal components in the model, and it is defined as:

$$t_R(k) = P_R^T x(k) \tag{23}$$

A new matrix projection is acquired and giving the residual

$$x(k) = P_R t_R(k) \tag{24}$$

$$\tilde{x}(k) = x(k) - \hat{x}(k) \tag{25}$$

To determine if the value of principle component stays within the limit, a statistical test Hotelling T^2 control map is used to check whether the process is in controlled state. The statistical test used is:

$$T^2(k) = t_R S_R^{-1} t_{R(k)} \tag{26}$$

which $S_R \in R^{R\times R}$ is the matrix containing R first eigenvector.

- **Determining State Mode Using Fuzzy**

From the hotelling T² control chart, it can be acquired the data of the deviation value in every state, by finding the mean and deviation from the T^2 value. Then, those values are used to build a membership function for the input of fuzzy (takagi sugeno).

The fuzzy rule for determining bioreactor condition is:

If (input 1 is state 1) **then** (output is state 1)

4. Results and Discussion

- **Model Response for Some State Mode**

From the SVD result, the variation of the principle components matrix (3x3) is:

a) First principal component = 96.58% of variation
b) Second principal component = 3.41% of variation
c) Third principal component = 0.0001% of variation

Principle Components analysis shows that the first principle components has the biggest variation so it can be picked to be used in finding the original data projection.

For the normal condition of bioreactor, the variable input is listed in Table 2. There was no change in S_c (10 gr/L) and D (0.00277778 h^{-1}) for over time of simulation. While the value of S_2 changed to be two times of initial value at the specific step time (from 0.07 mol/L to be 0.21 mol/L). The respond of simulator is shown in Fig. 4.

Table 2. Input Variables for Normal State Plant.

Input Variable	Value
A_1 (S_c)	0
A_2 (S_2)	2
A_3 (D)	0
T (temperature)	30±1°C

By looking at the Fig. 4 can be concluded that the increasing of S_2 concentration still result normal condition of the bioreactor. The substrate processed properly by the biomass, which marked by growing biomass and the reduction in COD. In Fig. 5 is shows the Hotelling control chart of this simulation. The value of T^2 is never increase above upper control limit (UCL) of the control chart.

To obtain the organic overload condition, the thing to do is add the concentrations of the substrate which was represented by the larger change of S_2 (become sixteen times of initial value, see Table 3), as one cause of excessive substrate concentration [9]. The respond of simulator and the hotelling T^2 control chart for this case as shown in Figs. 6 and 7 respectively. From this, it can be concluded that the bioreactor did not produce methane anymore and pH values

down to 3.8 because biomass is not capable of processing the excessive substrate concentration, so that the substrates were toxic to microorganisms.

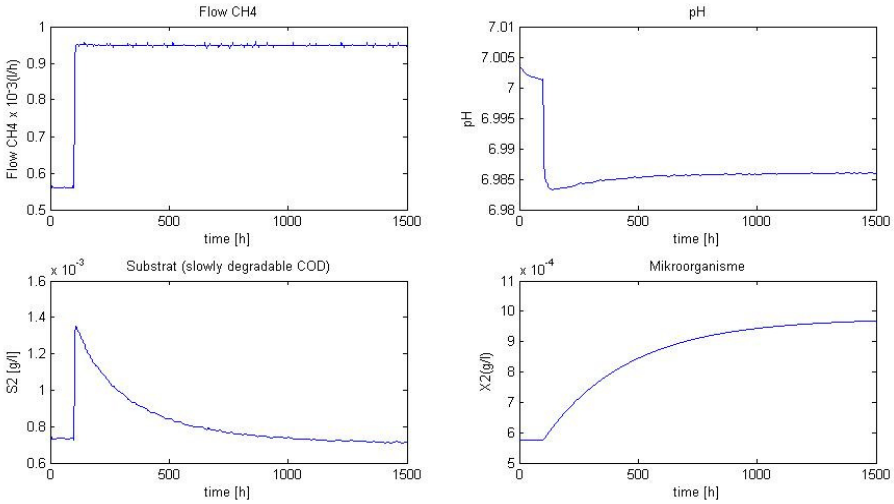

Fig. 4. Model Respond with Increase of S_2 concentration (A_2=2).

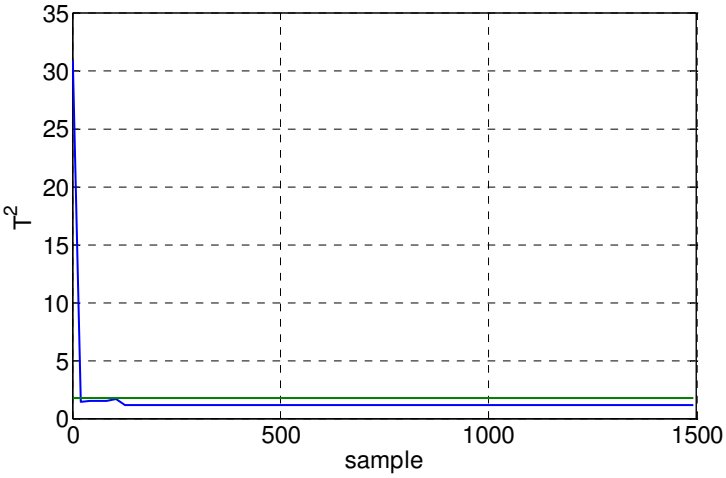

Fig. 5. Hotelling T^2 Control Chart for A_2=2.

Table 3. Input Variables for Organic Overload State Plant.

Input Variable	Value
A_1 (S_c)	0
A_2 (S_2)	16
A_3 (D)	0
T (temperature)	30±1°C

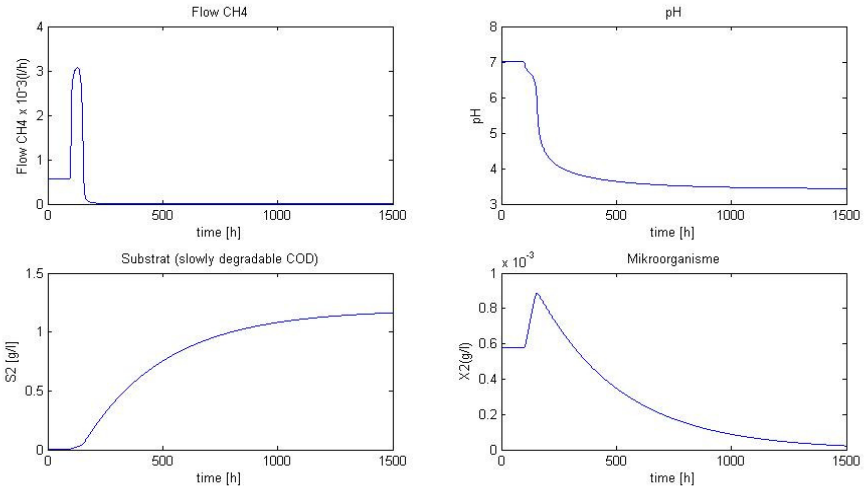

Fig. 6. Model Respond with Increase of S_2 Concentration (A_2=16).

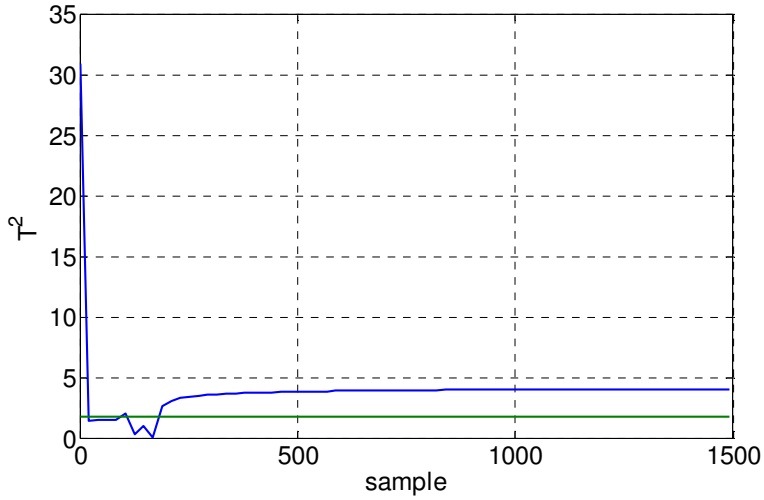

Fig. 7. Hotelling T^2 Control Chart for A_2=16.

The hydraulic overload condition was simulated by changing the dilution rate (D) to the excess value (four times to initial value) as shown in Table 4.

Table 4. Input Variables for Hydraulic Overload State Plant.

Input Variable	Value
A_1 (S_c)	0
A_2 (S_2)	0
A_3 (D)	4
T (temperature)	30±1°C

The respond of the simulator for this case is the same with one for the organic overload case, as shown in Fig. 8. The T^2 values are above the upper control limit of the hotelling T^2 control chart, as shown in Fig. 9. The same result is obtained for the temperature change case described in Table 5 (from 30±1°C to be 41±1°C), as shown in Figs. 10 and 11 for the respond and the hotelling T^2 control chart respectively.

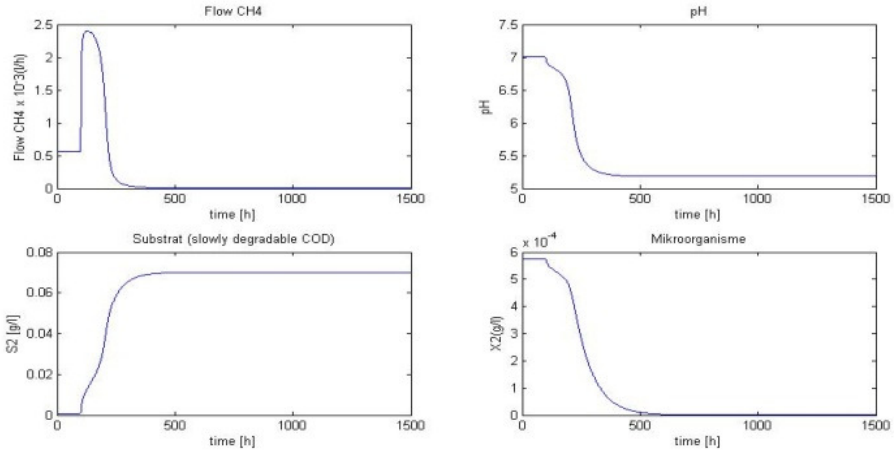

Fig. 8. Model Respond with Increase of Dilution Rate (A_3=4).

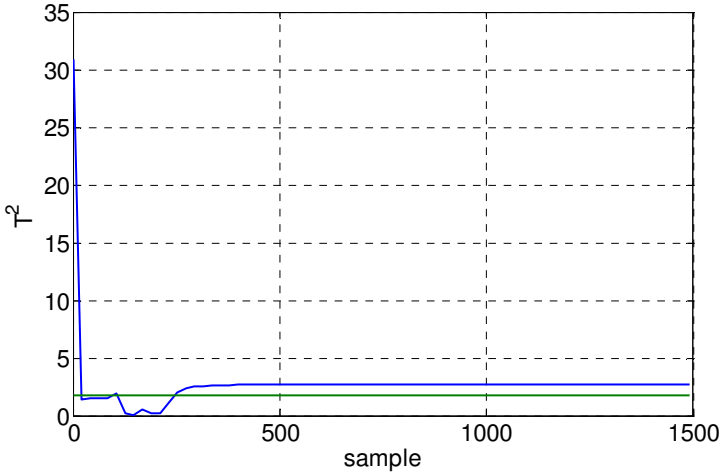

Fig. 9. Hotelling T^2 Control Chart for A_3=4.

Table 5. Input Variables for Temperature Fluctuation State Plant.

Input Variable	Value
A_1 (S_c)	0
A_2 (S_2)	10
A_3 (D)	4
T (temperature)	41±1°C

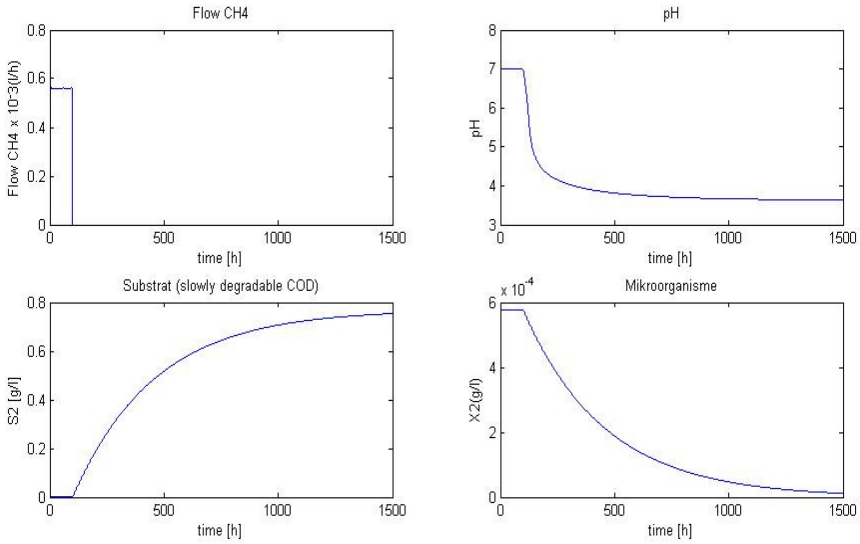

Fig. 10. Model Respond with Increase of Temperature (*T*=41±1°C).

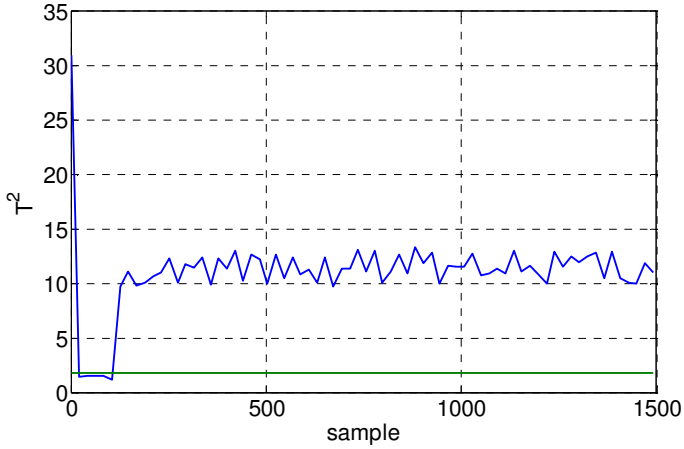

Fig. 11. Hotelling T^2 Control Chart for *T*=41±1°C.

- **Determining the membership function for fuzzy Input**

Based on the T² value of the first principal component for every state mode, then the mean value and its deviation was got as follows:

Table 6. Mean and Standard Deviation of T^2 at each State Plant.

State	Mean	Standard Deviation
Normal	0.9145	0.6205
Hydraulic Overload	2.5	0.4515
Organic Overload	4.015	0.407
Temperature disturb	10.54	2.74

A fuzzy membership function was made due to each state by using Gaussian function. The result is shown in Fig. 12.

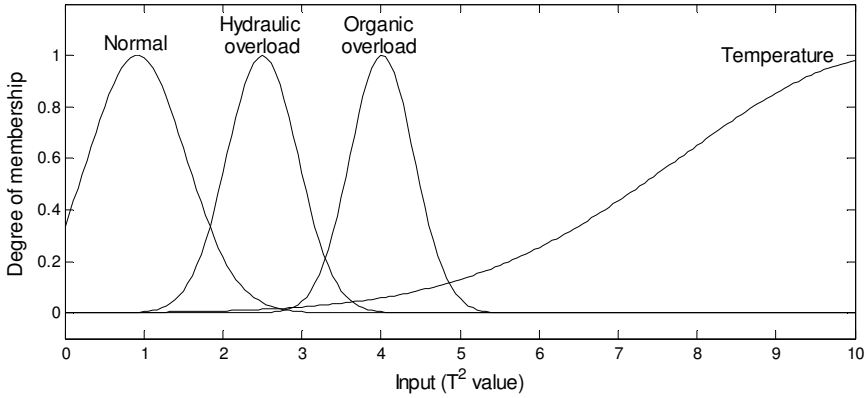

Fig. 12. Input Membership Function.

- **Mode state classification**

The proposed monitoring system had been applied to the anaerobic bioreactor model. To investigate the performance of the monitoring system, it was conducted three experiments due to four mode state. The simulation result is shown in Tables 7 to 9. Based on the results, it is shown that the proposed monitoring system yields decision of the state condition correctly.

Table 7. Simulation Results for Dilution Rate Change.

Condition	Input Value				Classification Result
	A_1	A_2	A_3	T	
1	0	0	2	30±1	Normal
2	0	0	4	30±1	Hydraulic Overload
3	0	0	6	30±1	Hydraulic Overload
4	0	0	7	30±1	Hydraulic Overload
5	0	0	8	30±1	Hydraulic Overload

Table 8. Simulation Results for Substrate S_2 Change.

Trail	Input Value				Classification Result
	A_1	A_2	A_3	T	
1	0	15	0	30±1	Normal
2	0	16	0	30±1	Organic Overload
3	0	17	0	30±1	Organic Overload
4	0	18	0	30±1	Organic Overload
5	0	19	0	30±1	Organic Overload

Table 9. Simulation Results for Temperature Change.

Trail	Input Value				Classification Result
	A_1	A_2	A_3	T	
1	0	0	0	30±1	Normal
2	0	0	0	20±1	Temperature fluctuations
3	0	0	0	22±1	Temperature fluctuations
4	0	0	0	46±1	Temperature fluctuations
5	0	0	0	47±1	Temperature fluctuations

5. Conclusions

This research presented and discussed an approach of a (MSPC) model capability on replacing the conventional methods univariate Statistical Process Control (SPC) to analyze the state of the multivariate process of anaerobic bioreactor for performing SPC in a multivariate process, explicitly incorporating measurement uncertainty information. Moreover several conclusions, namely: graph control Hotelling T^2 from the principle component gives a different pattern for each state and membership function using the one main component can detect conditions that happen.

It is the generalization of the present latent variable approach to MSPC based on PCA to a more general situation where measurement uncertainties can be vary from observation to observation. A statistical model was defined and statistics analogous to T^2 and Q were derived, that allow one to monitor both the within model variability as well as the variability around the identified model. Furthermore, this approach adequately handles the presence of missing data in a simple and consistent way. Preliminary results point out in the direction of advising the use of this framework when measurement uncertainties are available and significant noise affects process measurement behaviour. Consequently, the approach has been implemented and tested in examples that do cover dozens of variables. Practical, in larger scale problems, a similar methodology may be applied over a subset of variables where heteroscedasticity is believed to be more crucial.

Overall simulation results shown that the proposed algorithms is capable for monitoring four conditions that occurred in the bioreactor with 100% success rate.

While some suggestions may be submitted for further research are increasing measurement variables and state modes that may be occurred in bioreactor. Furthermore, the algorithm should be developed for real time application in a real plant.

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