MODELLING AND ADAPTIVE CONTROL OF A CONTINUOUS ANAEROBIC FERMENTATION PROCESS

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Abstract. The treatment of organic wastes from food industry, agriculture, sewage water for depollution purposes with co-production of methane gas through anaerobic fermentation has been given a growing interest these last years. This paper describes an attempt to fully automatize this fermentation process. The various steps are the following ones : modeling and identification, choice of an optimal steady state w.r.t. a cost criterium, automatic control of the process with an adaptive regulator. At this stage, the feasability of the regulator has only been tested on a mathematical model of the process.

Keywords. Modeling of biochemical process ; identification ; adaptive control of a biochemical process.

INTRODUCTION

The degradation of organic wastes (from the food industry, agriculture, sewage water) through anaerobic fermentation is given a growing interest these last years. This is due to the fact that this waste treatment (depollution) process produces methane gas which can be used as an energy supply elsewhere in the factory, the farm, etc.

However this process - which does not seem to be fully understood - is not easy to control if one wants a constant, high efficiency in both tasks of depollution and energy recuperation, as it is the case in the factories and animal farms.

At this stage we felt providing this process with automatic control devices could greatly improve its reliability and its economy.

A fruitful collaboration started with the laboratory of Biotechnology of the same University aimed at the implementation of feasible industrial automatic control schemes for such fermentation processes.

At first, a mathematical model was developped and analysed through simulation on a PDP 11 digital computer (Sinéchal and others, 1979; Antunes and Installé, 1980, 1981). This model was validated through comparison of computed data with real-life data from industrial fermentors (Chalon and others, 1982).

This paper presents new results on the automatic control of the fermentation process : the choice of a suitable steady-state as a function of various parameters of the process and the implementation of an adaptive regulation scheme in order to stabilize the process around the chosen working state, despite of various perturbations affecting the process.

This regulation scheme has been tested through simulation and will soon be implemented on an already existing pilot-plant equipped with a microprocessor.

THE MATHEMATICAL MODEL

The proposed model (Fig. 1) is a modified version of the model of Hill and Barth, 1977 :

$$\frac{dS_o}{dt} = -GS_o - \beta X_1 S_o + GPS_{oi} \qquad (1)$$

$$\frac{dX_1}{dt} = (\mu_1 - k_{d_1} - G)\, X_1 \qquad (2)$$

$$\frac{dS_1}{dt} = -GS_1 + \beta X_1 S_o - \frac{\mu_1 X_1}{Y_1} \qquad (3)$$

$$\frac{dX_2}{dt} = (\mu_2 - k_{d_2} - G)\, X_2 \qquad (4)$$

$$\frac{dS_2}{dt} = -GS_2 + Y_b \mu_1 X_1 - \frac{\mu_2 X_2}{Y_2} \qquad (5)$$

$$Q = Y_G \mu_2 X_2 \qquad (6)$$

$$\mu_1 = \frac{\hat{\mu}_1}{1 + \frac{K_{m1}}{S_1}} \qquad (7)$$

$$\mu_2 = \frac{\hat{\mu}_2}{1 + \frac{K_{m2}}{S_2}} \qquad (8)$$

For simplicity of notations, we make $Z(t) = Z$.

It is suited to continuously fed, completely mixed, constant temperature fermentors working outside the acid-inhibition area (Fig. 2).

S_{oi}; S_o, S_1, S_2 are resp. concentrations (mg/l) in volatil solids in the influent ; volatil solids, solubilized volatil organics and volatil fatty acids in the fermentor.

X_j, j=1,2, are resp. concentrations (mg/l) in acidogenic and methanigenic bacteria in the fermentor.

$\mu_j(d^{-1})$, j=1,2, are growth rates for bacteria.

G is the dilution rate (d^{-1}) and the Y's are conversion factors.
P is the fraction of volatil solids in the influent that can be solubilized.
β is the solubilization rate per unit of acidogenic biomass.
Q is the methane production rate ($1/1_{ferm}$,d).
Finally, $K_{m,j}$ (j=1,2) are the saturation constants.

As it is shown in Chalon and others (1982), such a model cannot be uniquely identified from sequences of measurements of G, S_{oi} and Q. Indeed, for such a sequence, there exists an infinity of values for the 12 parameters (P, β, $\hat{\mu}_1$, K_{m1}, k_{d1}, Y_1, $\hat{\mu}_2$, K_{m2}, k_{d2}, Y_b, Y_2, Y_G) that will give a same $[(S_{oi},G) \longrightarrow Q]$ relationship.

In order to solve this indetermination problem, it was necessary to reduce the number of parameters through the following transformations :

$$\tilde{X}_1 = \beta X_1 \qquad \tilde{X}_2 = Y_G X_2 \qquad \alpha = \frac{P}{K_{m1}}$$

$$\tilde{S}_o = \frac{S_o}{K_{m1}} \qquad \tilde{S}_1 = \frac{S_1}{K_{m1}} \qquad \tilde{S}_2 = \frac{S_2}{K_{m2}}$$

$$\tilde{Y}_1 = \beta K_{m1} Y_1 \qquad \tilde{Y}_2 = Y_G K_{m2} Y_2 \qquad \tilde{Y}_b = \frac{Y_b}{\beta K_{m2}}$$

Hence, the transformed model becomes :

$$d\tilde{S}_o/dt = -G\tilde{S}_o - \tilde{X}_1\tilde{S}_o + \alpha G S_{oi} \tag{9}$$

$$d\tilde{X}_1/dt = (\mu_1 - k_{d1} - G)\,\tilde{X}_1 \tag{10}$$

$$d\tilde{S}_1/dt = -G\tilde{S}_1 + X_1\tilde{S}_o - \tilde{Y}_1^{-1}\,\mu_1 X_1 \tag{11}$$

$$d\tilde{X}_2/dt = (\mu_2 - k_{d2} - G)\,\tilde{X}_2 \tag{12}$$

$$d\tilde{S}_2/dt = -G\tilde{S}_2 + \tilde{Y}_b\mu_1\tilde{X}_1 - \tilde{Y}_2^{-1}\,\mu_2\tilde{X}_2 \tag{13}$$

$$Q = \mu_2\tilde{X}_2 \tag{14}$$

$$\mu_1 = \frac{\hat{\mu}_1\tilde{S}_1}{1 + \tilde{S}_1} \tag{15}$$

$$\mu_2 = \frac{\hat{\mu}_2\tilde{S}_2}{1 + \tilde{S}_2} \tag{16}$$

It contains only 8 parameters and it is the model that we shall use in the following, omitting for simplicity of notations the symbol "~".

Through an identification procedure described in Dochain and Opdenacker (1982), this model was fitted to real-life data consisting in a sequence of daily measurements of Q, G and S_{oi} taken during 140 days, except from the 61st to the 84th day (Fig. 3).

These measurements were made on a 80 liters fermentor fed with chicken manure diluted in water. The set of parameters minimizing the squared error :

$$E^2 = \frac{1}{N}\sum_{i=1}^{N}(Q_i - \hat{Q}_i)^2$$

where :

N = number of triple of measurements (G, S_{oi}, Q)

Q_i = gas production at day i

$\hat{Q}_i$ = estimate of gas production at day i computed from the model

is the following one :

$\hat{\mu}_1 = \hat{\mu}_2 = \pm\ 0.4\ (d^{-1})$ $\qquad$ $\tilde{Y}_2 = 1.1\ (1_G/1_f)$

$k_{d1} = k_{d2} = \pm\ 0.02\ (d^{-1})$ $\qquad$ $\tilde{Y}_b = 40\ (d)$

$\tilde{Y}_1 = \pm\ 0.006\ (d^{-1})$ $\qquad$ $\alpha = 2\ (1/g)$

However, the sensitivity of the error to a variation of the parameters ($\hat{\mu}_i$, k_{di}; i=1,2) was found to be quite low so that their optimal value is not critical. These values were chosen according to past experiments on laboratory-scale fermentors and were found to be satisfactory ones. Fig. 3 shows the values of G, S_{oi}, Q and $\hat{Q}$ for a period of 170 days. Note that the identification was implemented using only the measurements made during the first 140 days.

STEADY-STATE ANALYSIS

If one makes all the derivatives equal to zero in the reduced model, one obtains algebraic equations whose solutions give the steady states of the fermentation process :

$$\mu = \mu_1 = \mu_2 = k_{d_1} + G = k_{d_2} + G \quad \text{(since here } k_{d_1} = k_{d_2}\text{)}$$

$$S = S_1 = S_2 = \frac{\mu}{\hat{\mu} - \mu} \quad \text{where } \hat{\mu} = \hat{\mu}_i,\ i = 1 \text{ or } 2$$

$$S_o = \frac{\alpha G S_{oi}}{X_1 + G}$$

X_1 solution of :

$$\frac{\mu}{Y_1} X_1^2 + G\left(\frac{\mu}{Y_1} + S_1 - \alpha S_{oi}\right) X_1 + G^2 S_1 = 0 \qquad (17)$$

$$X_2 = (Y_b \mu X_1 - G S_2) \frac{Y_2}{\mu}$$

$$Q = (k_{d2} + G) X_2$$

Although it is possible to find, for suitable values of G and S_{oi}, two different steady states, it can be shown (Dochain and Opdenacker, 1982) that only the one corresponding to the greatest values of X_1 gives a steady state close to the one observed on the real-life process. Fig. 4 to 7 give the computed steady-state values of S_o, S_1, X_1, X_2 and Q as a function of G, taking S_{oi} as a parameter.

Observations

i) The steady-state dilution rate G must be smaller than $G^* = \hat{\mu} - k_d$ in order to get a non trivial solution. If G is greater than $\hat{\mu} - k_d$, one obtains the solution :

$$X_1 = X_2 = 0, \; S_o = \alpha S_{oi}, \; S_1 = S_2 = Q = 0$$

ii) The steady-state values of $S_1 = S_2$ are independent of S_{oi}, the influent concentration. These values are small compared to the values of S_o, the steady-state solubilized volatil organics concentration in the fermentor. Note that as G comes close to G^*, the concentration S_2 in volatil acids rises sharply and it would be necessary to take into account inhibition phenomena in the fermentor.

iii) For large values of S_{oi} and values of G not too close to G^*, the steady-state values of S_o are almost linearly related to G.

iv) For every steady-state value of S_{oi}, there exists a steady-state value of G which maximizes the daily gas production Q.

Choice of a Suitable Steady-state

In order to choose a suitable steady-state, we need to describe quantitatively the objectives of the process. These objectives were chosen as follows :

i) The S_j, j = 0,1,2 levels in the effluent must be smaller than given values $S_{j,max}$ (depollution)

ii) Energy in the produced gas must be greater than the energy consumed for the heating of the influent at 35 °C (autonomy and economy)

iii) The daily amount G of processed wastes may be maximized

iv) The "net energy" (see ii) produced by the fermentor may be maximized.

Taking G as the control variable, it is possible to choose, for every given S_{oi}, a value for G which satisfies the objectives i) and ii) and iii) or iv). A diagram which may be used for this choice is given at Fig. 8. It is simply a combination of Fig. 4 and 7. The curve "e" represents the amount of energy required to heat the influent at 35°C. Note that there exists a lower limit for S_{oi} : for S_{oi} values under this limit, the amount of gas produced cannot cover the energy requirements for the heating of the influent.

ADAPTIVE CONTROL

In order to drive automatically the output of the process (daily gas production) from a starting one to an optimal one and to maintain it close to a (fluctuating) optimal value despite of perturbations (ΔS_{oi}, $\Delta \hat{\mu}_i$, ΔY) it was necessary to implement a regulation scheme.

Since the model is time-varying, both because of the internal perturbations ($\Delta \mu_i$, ΔY) and because of its linearization around a fluctuation state, it was decided to use an indirect adaptive regulation scheme. In this scheme the parameters of the regulator are continuously updated according to the values of the model's parameters which in turn are periodically adjusted through an on-line mean-square identification procedure.

Linearization of the model

In order to be able to implement such an adaptive control algorithm, it is first tried to find a simpler, linear, parameter-adjustable model of the process by linearizing the fifth order non-linear model (eqs. 9-16) around a nominal steady-state. It is this simpler, linear model which will be used to compute the control law.

If one linearizes the given model (eqs. 9-16) around the nominal steady-state :

$$G = 0.05 \; d^{-1} \qquad S_{oi} = 50 \; g/l,$$

the following transfer function is obtained :

$$\frac{Q(S)}{G(s)} = \frac{K(S+0.07)^2}{(S+0.07)(S+0.072)(S+0.35)(S+4.01)(S+17.2)} \qquad (18)$$

The following observations may be made :

i) The model is stable around the nominal steady-state. Furthermore, the stability has been proven - by computation - for steady states such that $0.03 \leq G \leq 0.1$ and $25 \leq S_{oi} \leq 70$.

ii) There is a double pole-zero cancellation

such that the model behaves like a third-order system with poles at -0.35, -4.01 and -17.2.

iii) The pole at -0.35 dominates the two other poles so that the model may be approximated by a first order model with a time constant of approximately 3 days. This approximation is illustrated by a step response experiment represented at Fig. 9.

Hence, a first order parameter-adaptive model was tried to drive the adjustable parameters of the regulator, even though the above observations were made for a given steady-state.

Control Algorithm

The chosen regulator was proposed by Clarke and Gawthrop (1975, 1979). In our case, it is designed to minimize the following cost function:

$$J = E\{(\hat{Q}_{k,k+1} - \bar{Q}_{k+1})^2 + \lambda (G_k - \bar{G}_k)^2\}$$

where :

$\hat{Q}_{k,k+1}$ is the predicted value at time k of the daily gas production at time k+1

$\bar{Q}_{k+1}$ is the desired steady-state gas production at time k+1

G_k is the value of control variable (dilution rate) at time k

$\bar{G}_k$ is the value of the control variable corresponding to a steady-state daily gas production $\bar{Q}_{k+1}$

λ is a constant whose value controls the stability and the dynamics of the adaptive feedback loop.

The predicted value of the daily gas production is computed by a discrete version of the first-order linear model of the biomethanization process :

$$\hat{Q}_{k,k+1} = -\hat{a}_k Q_k + \hat{b}_k G_k + \hat{c}_k \qquad (19)$$

where

$$\hat{c}_k = \hat{a}_k \bar{Q}_k - \hat{b}_k \bar{G}_k + \bar{Q}_{k+1} \qquad (20)$$

Q_k is the measured gas production at time k.

Now, defining

$$\hat{q}_{k,k+1} = \hat{Q}_{k,k+1} - \bar{Q}_{k+1}$$

$$q_k = Q_k - \bar{Q}_k$$

$$g_k = G_k - \bar{G}_k$$

and replacing $\hat{c}_k$ in (19) by its value given in (20), one obtains (Kurz and others, 1980) :

$$\hat{q}_{k,k+1} = -\hat{a}_k q_k + \hat{b}_k g_k$$

Hence $\hat{a}_k$ and $\hat{b}_k$ are the parameters of the perturbation model around the desired steady-state $(\bar{Q}_k, \bar{G}_k)$.

The parameters $\hat{a}_k$, $\hat{b}_k$ and $\hat{c}_k$ are updated on-line through a least-square recursive algorithm with a forgetting factor γ equal to 0.9 (Kurz and others, 1980).

Finally it may be shown that the control input G_k minimizing J is given by the following expression :

$$G_k = \frac{\bar{Q}_{k+1} + \hat{a}_k \bar{Q}_k - \hat{c}_k}{\hat{b}_k} + \frac{\hat{a}_k (Q_k - \bar{Q}_k)}{\hat{b}_k + (\lambda / \hat{b}_k)}$$

Experiments

Before to use this adaptive regulator on the real-life biomethanization process, it is necessary to test its performances through various simulations.

Such simulations were performed on a PDP 11/34 using a discrete version of the fifth-order model (eqs. 9 to 16) as simulator of the real-life biomethanization process, with a sampling period of 4 hours.

Through various simulations, it was found that the dynamics of the closed-loop system was at an optimum when :

i) The parameters of the first-order model were adapted every 12 hours, with a forgetting factor $\gamma = 0.9$. Smaller adaptation periods decreased the relative stability of the system.

ii) The control input G was re-computed every 4 to 12 hours.

iii) The constant λ was choosen to be equal to 5. Smaller values for λ rised instability within the system.

Fig. 10 a) and b) show the response of the system and the behaviour of the control input G when the desired gas production is switched from 1.1 $1/l_D$,d to 1.3 $1/l_D$,d.

Fig. 11 a) and b) show the same results as above when the maximum specific growth rate $\hat{\mu}_1$ is switched from its nominal value $0.4(d^{-1})$ to $0.15(d^{-1})$. Such a variation could simulate the introduction of toxic matter into the fermentor.

Fig. 12 a) and b) show the same results as above when the volatil solids concentration in the influent, S_{oi} is switched from 45 g/l to 65 g/l.

Curves "a" were obtained with the adaptive regulator described above. Curves "b" were obtained with the assumption that the value of S_{oi} is measured on-line. In this latter case, the model (19) is modified by replacing G_k by $G_k S_{oi}$ as equation (9) suggests it. Note that this modification improves the performances of the regulator. The noisy behaviour of the results is due to another modification : a zero-mean white noise was superimposed to the out-

put of the model simulating the real-life process. It was indeed observed that such a noise adjonction improved the dynamics of the adaptive regulator by increasing the identifiability of the process.Note that such a noise is always present in real-life processes.

CONCLUSION

This paper represents an attempt to apply modern regulation techniques to the control of a biotechnical process. The next step will consist in experimenting this adaptive controller on a real-life fermentor and this will in turn require further refinements of the control algorithm.

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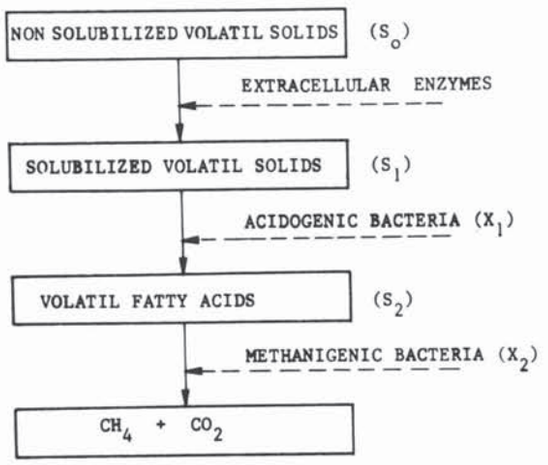


Fig. 1

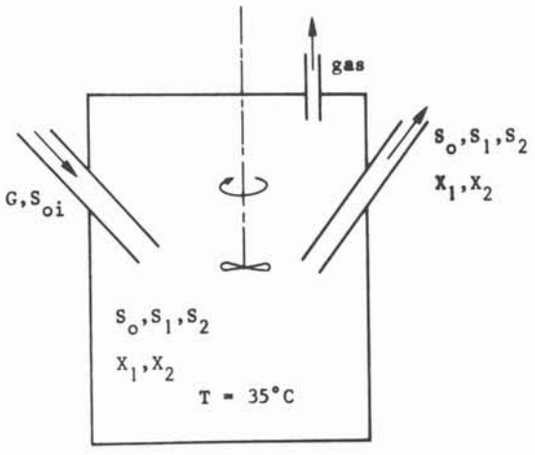
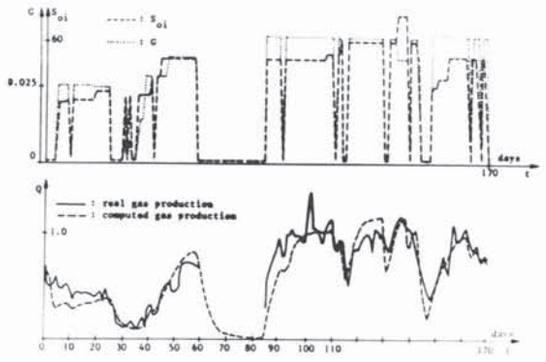


Fig. 2



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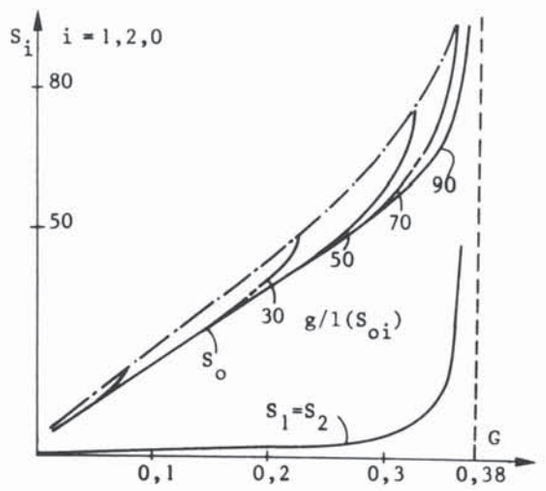
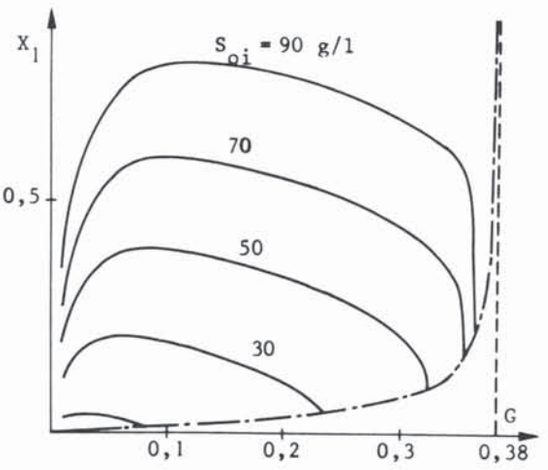


Fig. 4



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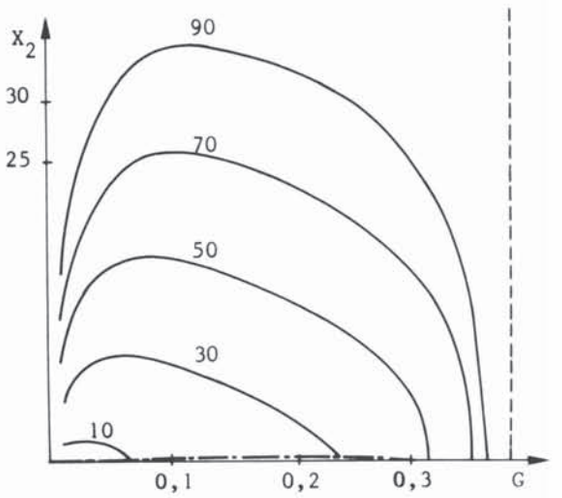

Fig. 6

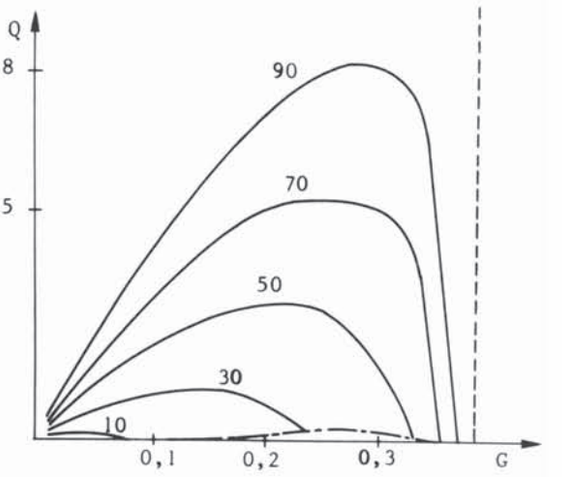

Fig. 7

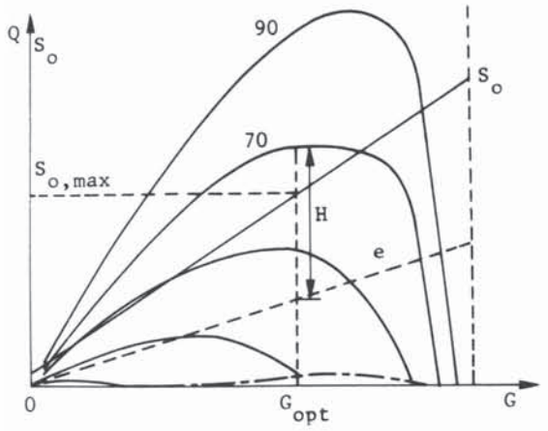

Fig. 8

$S_1(G) << S_o(G)$

$S_2(G) << S_o(G)$

e : daily energy consumed for the heating of the influent

H : "net daily energy" produced by the fermentor

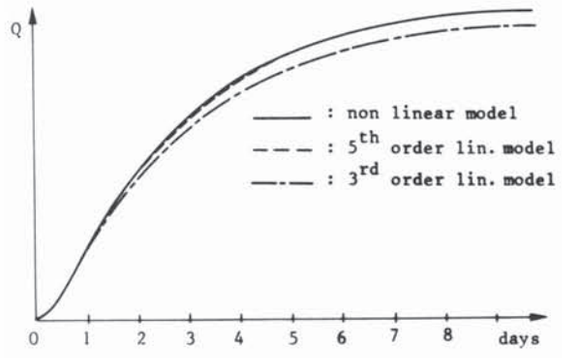

Fig. 9

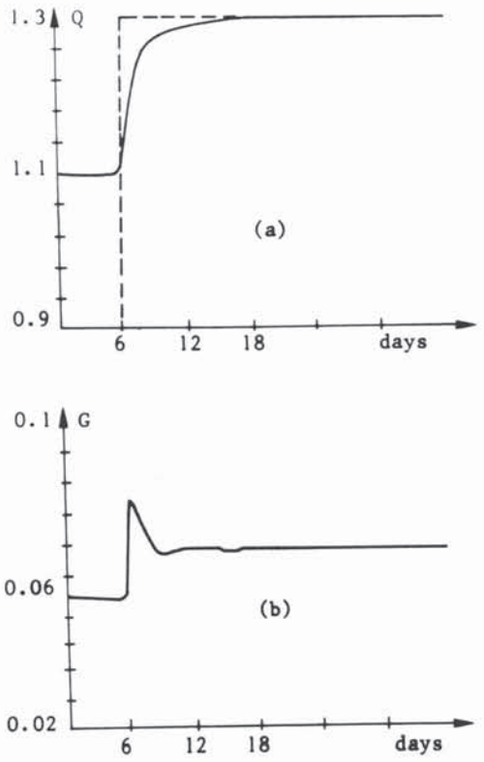

Fig. 10

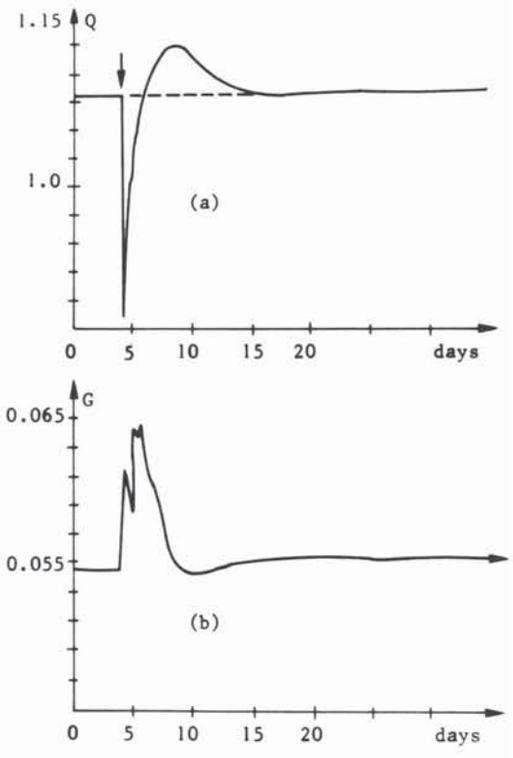

Fig. 11

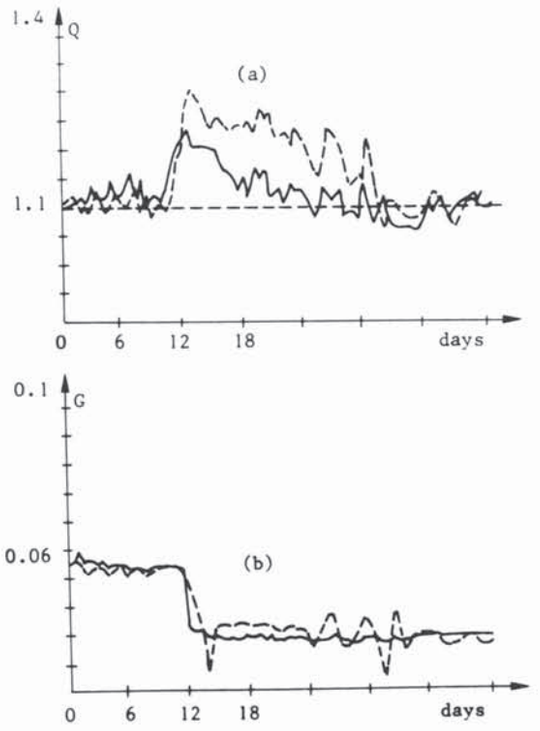

Fig. 12