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Direct Adaptive Predictive Control for Wastewater Treatment Plant

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Abstract: The purpose of this paper was to design a much simpler control method for a wastewater treatment plant. The work proposes a direct adaptive predictive control (DAMPC) also known as subspace predictive control (SPC) as a solution to the conventional one. The adaptive control structure is based on the linear model of the process and combined with numerical algorithm for subspace state space system identification (N4SID). This N4SID plays the role of the software sensor for on-line estimation of prediction matrices and control matrices of the bioprocess, joint together with model predictive control (MPC) in order to obtain the optimal control sequence. The performances of both estimation and control algorithms are illustrated by simulation results. Stability analysis is done to investigate the response of the system proposed when parameter changes exist. This project proves that subspace-adaptive method has a large number of important and useful advantages, primarily the application ability to Multi Input Multi Output (MIMO) systems, and the low requirements on prior system information. Given the advantages observed, the most likely areas of application for the proposed algorithm are multivariable processes, about which little information is known such as this wastewater treatment plant. Hence, direct adaptive predictive control (DAMPC) can provide simplicity and good performance in of an activated sludge process.

Keywords: Direct adaptive, model predictive control, subspace identification, wastewater treatment plant

1. Introduction

This paper aims to develop a direct adaptive predictive controller (DAMPC) that able to provide simplicity, good performance and stability robustness in controlling an activated sludge process in wastewater treatment plant.

There are several problem statements in control design of an activated sludge process; the dynamical model obtained is most often highly complex and high order non-linear system, lack of cheap and reliable sensors for on-line measurement of the key state variables, laboratory analysis with delays of several days cannot be used for on-line monitoring, low effluent quality and high energy consumption.

Thus, the main objective of this paper is to study the operation of activated sludge process in wastewater treatment plant. In addition to it, the prediction and controller matrices are estimated by using online numerical algorithms for subspace state space system identification (N4SID), and hence design a subspace predictive control (SPC) also known as direct adaptive control with the aims of improving the performance of activated sludge wastewater treatment process. Finally, to analyze the stability issues occur on the system proposed.

2. Bioprocess Modeling

The nonlinear biological wastewater treatment process which has been studied in this paper is taken from [3].

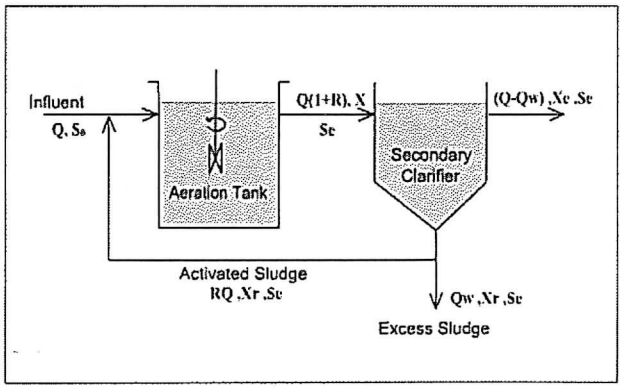

Fig. 1 Activated Sludge Reactor

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The substances from the substrate (S), represents a source of energy and carbon (necessary for the synthesis of new cellular material) that are used by the microorganism (biomass – X) to live and reproduce themselves. This process is aerobic, that means that it happens only if in the tank there is dissolved oxygen (O_2) which is used by the microorganism for their metabolism.

Fig 1 illustrates an activated sludge reactor which comprises a secondary clarifier that is necessary for the settling of the biomass and its removal. Part of the settled biomass is recycled in order to allow the right concentration of microorganism in the aerated tank. This recycled biomass (Xr) has a higher concentration than the biomass in the reactor (Xr > X) related to the fact that is coming from a settling process.

The mass balance around the aerator and the settler give the following set of non-linear differential equations:

$$\dot{X}(t) = \mu(t)X(t) - D(t)(1+r)X(t) + rD(t)Xr(t) \quad (1)$$

$$\dot{S}(t) = -\frac{\mu(t)}{Y}X(t) - D(t)(1+r)S(t) + D(t)S_{in} \quad (2)$$

$$\dot{C}(t) = -\frac{K_0\mu(t)X(t)}{Y} - D(t)(1+r)C(t) + K_{La}(Cs - Ct + DtCin \quad (3)$$

$$\dot{X}r(t) = D(t)(1+r)X(t) - D(t)(\beta+r)Xr(t) \quad (4)$$

where X(t), S(t), Xr (t) and C(t) are the state variables representing the biomass, the substrate, the recycled biomass and dissolved oxygen concentrations, respectively. $D(t)$ is the dilution rate, r and β represent, respectively, the ratio of recycled flow to influent flow and the ratio of waste flow to influent flow, S_{in} and C_{in} correspond to the substrate and dissolved oxygen concentrations in the feed stream, respectively. The kinetics of the cell mass production are defined in terms of the specific growth rate μ and the yield of cell mass Y; the term K_0 is a constant, C_s is the maximum dissolved oxygen concentration and K_{La} represents the oxygen mass transfer coefficient.

The specific growth rate μ is a key parameter for the description of biomass growth and is known to be a complex function of many physic-chemical and biological factors like the biomass concentration, the substrate concentration, the dissolved oxygen concentration, the pH, the temperature, and various others inhibitors. Many different analytical laws have been suggested for modelling this parameter. The most popular is certainly the Monod law.

Here the specific growth rate is assumed to be depending on substrate, dissolved oxygen concentrations and several kinetic parameters. The kinetic model is then given by

$$\mu(t) = \mu_{max}\frac{S(t)}{K_S+S(t)}\frac{C(t)}{K_C+C(t)} \quad (5)$$

where μ_{max} is the maximum specific growth rate, K_s is the so-called affinity constant, expressing the dependency of the degradation rate on the concentration of pollutant S, and K_c is the saturation constant.

The choice of Olsson model is partially motivated by its very large use in aerobic biotechnological applications, and particularly in activated sludge processes.

Kinetic parameters:

$Y = 0.65$ $\quad \mu_{max} = 0.15\ h^{-1}$

$r = Qr/Q = 0.6$ $\quad K_s = 100\ mgl^{-1}$

$\beta = Q_w/Q = 0.2$ $\quad K_0 = 0.5$

$\alpha = 0.018$ $\quad C_s = 10\ mgl^{-1}$

$K_c = 2\ mgl^{-1}$

Initial conditions:

$X(0) = 215\ mgl^{-1}$ $\quad C(0) = 6\ mgl^{-1}$

$S(0) = 55\ mgl^{-1}$ $\quad S_{in} = 200\ mgl^{-1}$

$X_r(0) = 400\ mgl^{-1}$ $\quad C_{in} = 0.5\ mgl^{-1}$

3. Subspace System Identification

Recently a great deal of attention has been given to numerical algorithms for subspace state space system identification (N4SID). The N4SID algorithms are always convergent (non-iterative) and numerically stable since they only make use of QR and singular value decompositions (SVD).

The greater part of the system identification literature is concerned with computing polynomials models, which are however known to typically give rise to numerically ill-conditioned mathematical problems, especially for Multi Input Multi Output (MIMO) systems. Numerical algorithms for subspace state space system identification (N4SID) are then viewed as the better alternatives. This especially true for high order multivariable systems, for which it is not trivial to find useful parameterization among all the parameterizations. This parameterization is needed to start up the classical identification algorithms (see e.g. [1]), which means that a prior knowledge of the order and the observability (or controllability) indices is required.

With N4SID algorithms, most of the prior parameterization can be avoided. Only the order of the system is needed and it can be determined through inspection of the dominant singular values of a matrix that is calculated during identification. Another major advantage of N4SID is that it is non-iterative, with no non-linear optimization part involved. This is why they do not suffer from the typical disadvantages of iterative algorithms such as no guaranteed convergence, local minima of the objective criterion and sensitivity to initial estimates. A final advantage of the N4SID algorithms is that there is no difference between zero and non-zero initial states [4].

The approach adopted here is similar to the identification schemes of [2] for the purely deterministic case and [5] for the stochastic case. First a state sequence is determined from the projection of input-output data. This projection retains all the information (deterministic and stochastic) in the past that is useful to predict the future. Then the state space matrices are determined from this state sequence. Fig 2 shows how these N4SID algorithms differ from the classical identification schemes.

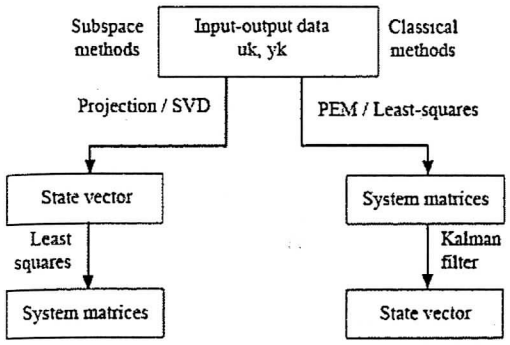

Fig. 2 Subspace and classical methods of system identification

The subspace model identification (SMI) uses projection methods and SVD to obtain the model. The identified models describe the activated sludge process around an operating point and can be in the form of standard linear discrete time invariant state space system:

$$x_{k+1} = Ax_k + Bu_k + w_k \quad (6)$$

$$y_k = Cx_k + Du_k + v_k \quad (7)$$

with

$$E\left[\begin{pmatrix} w_k \\ v_k \end{pmatrix}\begin{pmatrix} w_l^t & v_l^t \end{pmatrix}\right] = \begin{pmatrix} Q^s & S^s \\ (S^s)^t & R^s \end{pmatrix}\delta_{kl} \geq 0^2 \quad (8)$$

and A, $Q^s \in R^{nxn}$, $B \in R^{nxm}$, $C \in R^{lxn}$, $D \in R^{lxm}$, $S^s \in R^{nxl}$ and $R^s \subset R^{lxl}$. The input vectors $u_k \subset R^{mxl}$ and output vectors $y_k \in R^{lxl}$ are measured. $v_k \in R^{lxl}$ and $w_k \in R^{nxl}$ on the other hand are unmeasurable, Gaussian distributed, zero mean, white noise vector sequences. {A, C} is assumed to be observable, while {A, $(B(Q^s)^{1/2})$} is assumed to be controllable.

Input and output block Hankel matrices are defined as:

$$U_{0|i-1} = \begin{pmatrix} u_0 & u_1 & u_2 \cdots & u_{j-1} \\ u_1 & u_2 & u_3 \cdots & u_j \\ \cdots & \cdots & \cdots \cdots & \cdots \\ u_{i-1} & u_i & u_{i+1} \cdots & u_{i+j-2} \end{pmatrix} \quad (9)$$

$$Y_{0|i-1} = \begin{pmatrix} y_0 & y_1 & y_2 \cdots & y_{j-1} \\ y_1 & y_2 & y_3 \cdots & y_j \\ \cdots & \cdots & \cdots \cdots & \cdots \\ y_{i-1} & y_i & y_{i+1} \cdots & y_{i+j-2} \end{pmatrix} \quad (10)$$

where the number of column j is assumed to go to infinity throughout this thesis. The subscripts of U and Y denote the subscript of the first and last element of the first column. The past inputs and future inputs are denote as $U_{0|i-1} = U_p$ and $U_{i|2i-1} = U_f$ respectively. A similar notation applies for the past and future outputs. This notational convention is useful when explaining concepts.

The matrix input-output equations are defined in the following theorem [2]:

$$Y_f = \Gamma_i X_i + H_i U_f \quad (11)$$

where the extended (i > n) observability matrix, Γ_i and the deterministic lower block triangular Toeplitz matrix, H_i are defined as:

$$\Gamma_i = \begin{pmatrix} C \\ CA \\ \cdots \\ CA^{i-1} \end{pmatrix} \quad (12)$$

$$H_i = \begin{pmatrix} D & 0 & 0 & \cdots & 0 \\ CB & D & 0 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & 0 \\ CA^{i-2}B & CA^{i-3}B & CA^{i-4}B \cdots & & D \end{pmatrix} \quad (13)$$

Finally, the future state sequences are denoted as follows:

$$X_i = (x_i \quad x_{i+1} \quad x_{i+2} \cdots \quad x_{i+j-1}) \quad (14)$$

where $X_i = X_f$.

Subspace identification algorithms are often based on geometric concepts. The geometric tools used in SMI are orthogonal and oblique projections of the row space of matrices. These projections are naturally used in QR decomposition as well as for calculating the state vectors. A short description on the projection method is presented in the next following section.

In this subsection, the matrices $A \in \mathbb{R}^{pxj}$, $B \in \mathbb{R}^{qxj}$ and $C \in \mathbb{R}^{rxj}$ are given. The elements of a row of one of the given matrices are considered as the coordinates of a vector in the j-dimensional ambient space. The rows of each matrix A, B, C thus define a basis for a linear vector space in this ambient space.

Π_B denotes the operator that projects the row space of a matrix onto the row space of the matrix $B \in \mathbb{R}^{qxj}$:

$$\Pi_B = B^T.(BB^T)^{\dagger}.B \quad (15)$$

where † denotes the Moore-Penrose pseudo-inverse of the matrix. $A / \boldsymbol{B}$ is shorthand for the projection of the row space of the matrix $A \in \mathbb{R}^{pxj}$ on the row space of matrix B:

$$A / \boldsymbol{B} = A . \Pi_B = AB^T.(BB^T)\dagger.B \quad (16)$$

Note that in the notation $A / \boldsymbol{B}$ the matrix B is printed bold face, which indicates that the result of the operation $A / \boldsymbol{B}$ lies in the row space of B.

Instead of decomposing A as linear combinations of two orthogonal matrices (B and $B^{\perp}$), it can also be decomposed as linear combinations of two non-orthogonal matrices B and C and of the orthogonal complement of B and C. The rows of a matrix A are decomposed as linear combinations of the rows of B and C and of the rows of a third matrix orthogonal to B and C. This can be written as:

$$A = L_B.B + L_C.C + L_{B\perp,C\perp}.\begin{pmatrix} B \\ C \end{pmatrix}^{\perp} \quad (17)$$

The matrix L_C.C is defined as the oblique projection of the row space of A along the row space of B on the row space of C:

$$A/_B C = L_c.C \quad (18)$$

The oblique projection can be expressed as follows:

$$A/_B C = (A/B^{\perp}).(C/B^{\perp})\dagger.C \quad (19)$$

where gives the oblique projection of row space of $A \in \mathbb{R}^{pxj}$ along the row space of $B \in \mathbb{R}^{qxj}$ on the row space of $C \in \mathbb{R}^{rxj}$. Properties of the oblique projection are:

$$B/_B C = 0 \quad (20)$$

$$C/_B C = C \quad (21)$$

4. Direct Adaptive Model Predictive Control

Fuel A data-driven adaptive control is proposed and tested on activated sludge process. In this control design, the subspace identification technique is combined with MPC control design. The design of adaptive MPC can be

performed in two different ways; indirect method and direct method. Fig 3 shows the differences between the two methods.

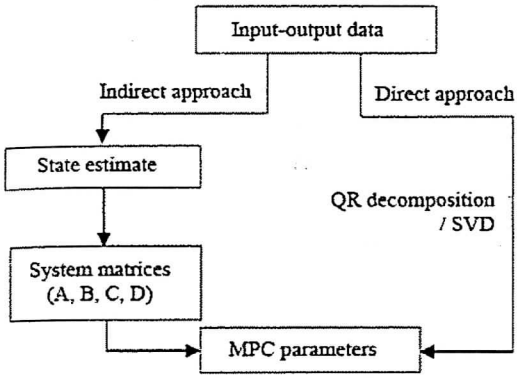

Fig. 3 Comparison between indirect (left) and direct (right) schemes for obtaining controller parameters

This study will only focus on the direct approach. Note that, in the direct method the steps of identification and control design can be carried out simultaneously by applying a single QR decomposition to the input-output data. This stands in contrast to the design of indirect adaptive MPC.

Model Predictive Control or MPC, is an advanced method of process control that has been in use in the process industries since the 1980s. Model predictive controllers rely on dynamic models of the process, most often linear empirical models obtained by system identification. Fig 4 shows the receding horizon control strategy used in MPC.

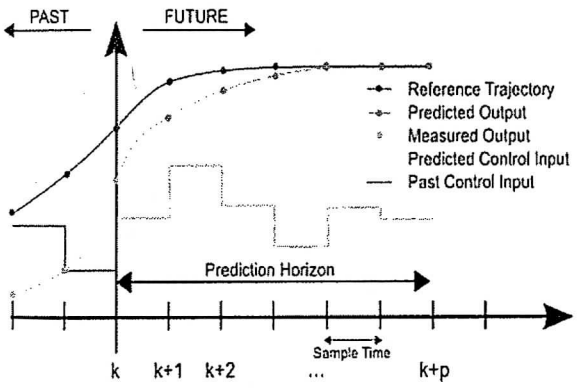

Fig. 4 Principle of receding horizon control strategy

Although this approach is not optimal, in practice it has given very good results. Much academic researches has been done to find fast methods of solution of Euler-Lagrange type equations, to understand the global stability properties of MPC's local optimization, and in general to improve the MPC method. To some extent the theoreticians have been trying to catch up with the control engineers when it comes to MPC.

Model Predictive Control (MPC) is a multivariable control algorithm that uses:

- an internal dynamic model of the process
- a history of past control moves and
- an optimization cost function J over the receding prediction horizon,

to calculate the optimum control moves.

The optimization cost function is given by:

$$J = \sum_{i=1}^{N} w_{xi}(r_i - x_i)^2 + \sum_{i=1}^{N} w_{ui}\Delta u_i^2 \qquad (22)$$

without violating constraints (low/high limits)

With:
$x_i = i$ -th controlled variable (e.g. measured temperature)
$r_i = i$ -th reference variable (e.g. required temperature)
$u_i = i$ -th manipulated variable (e.g. control valve)
w_{xi} = weighting coefficient reflecting the relative importance of x_i
w_{ui} = weighting coefficient penalizing relative big changes in u_i

The data-driven design approach based on direct adaptive MPC in the literature so far has been derived using windowing approach, for instance [7]. One of the main features of MPC is its flexibility to handle constraints.

The computation is more involved for the constrained case, particularly in the multivariable constrained systems. The problem takes the form of a standard quadratic programming which can be solved online. Since the DAMPC uses sliding window method, the solution to the QP problem leads to a highly computational burden as the size of identification window increases. Fig 5 represents the block diagram of a subspace based adaptive MPC.

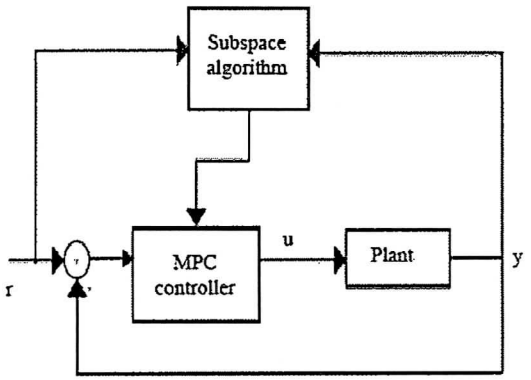

Fig.5 Subspace based adaptive MPC

In DAMPC, the controller parameters can be retrieved directly from the identification steps and the possibility of handling constraint implicitly is explored. To circumvent this problem, we consider the data-driven DAMPC control strategy for increment input constrained multivariable system. The strategy is based on analyzing the SVD of the Hessian of the quadratic performance index considered in DAMPC.

5. Results and Discussion

An interesting link between subspace identification and model predictive control is exploited to implement a predictive controller for an unknown system based on subspace techniques. The algorithm presented does not require computation of the system matrices, and as such this method of control design can be interpreted as 'direct' adaptive control. In addition, a modification was made to the algorithm, and this modified algorithm was successfully implemented in Simulink.

A simulink model of the implemented subspace predictive controller was created to control a stable MIMO system that represents the wastewater treatment plant. The model used is shown in Fig 6, and the SPC controller subsystem can be seen in Fig 7.

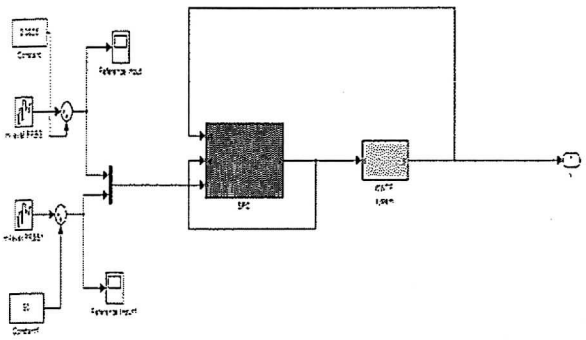

Fig. 6 Simulink model used to implement SPC on a wastewater treatment plant system

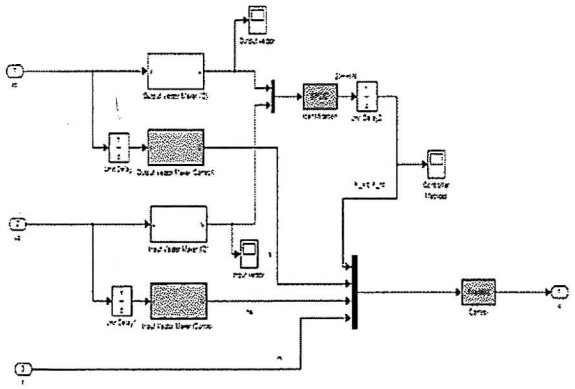

Fig. 7 SPC subsystem Simulink model

The system used was the same linear model obtained previously. In the simulation, the following parameters were used:

Block data size, N	100
Hankel matrix index / MPC horizon, s	10
Sampling interval, h	0.1
Weighting matrix for future error sequence, Q	$400I_{SxS}$
Weighting matrix for future control sequence, R	$10I_{SxS}$
Input dimension, m	2
Output dimension, l	2

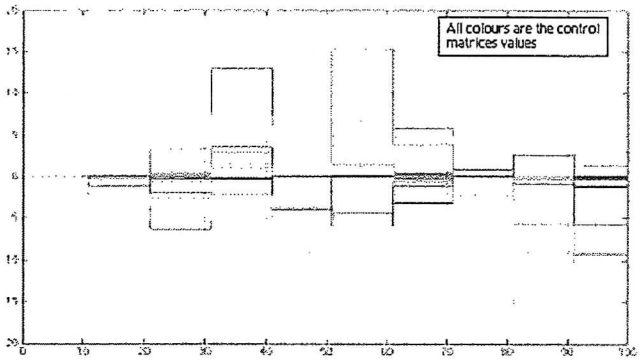

Fig. 8 Controller matrix values change from original dynamics to new dynamics at t=100

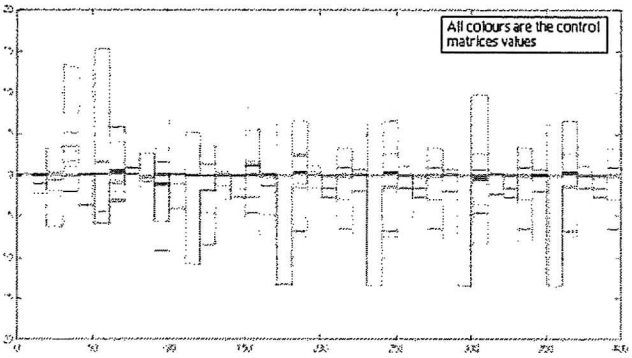

Fig. 9 Controller matrix values change from original dynamics to new dynamics at t=400

From Fig 8, it was found that when the dynamics were changed during the simulation from the original system to a new value of weighting matrix (Q = 4 and R = 1) the system responded well, with the control continuing to stabilize the system before the identification had collected a new set of input-output data and calculated new control matrices. Fig 9 shows the same results but for t=400.

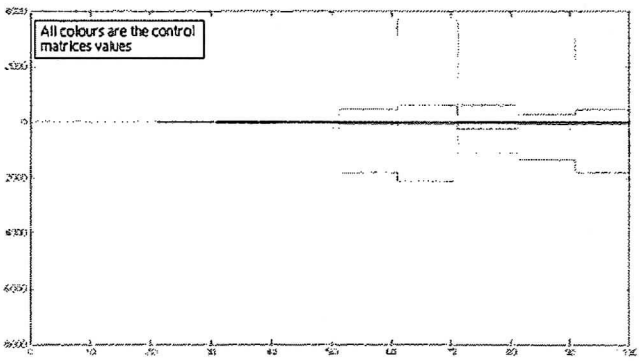

Fig. 10 Controller matrix values change from new dynamics to original dynamics at t=100

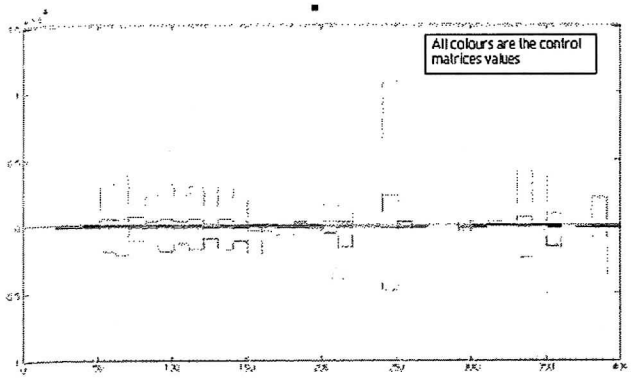

Fig. 11 Controller matrix values change from new dynamics to original dynamics at t=400

However, when the simulation was started with the new values of weighting matrix, and the parameter was changed to the original dynamics, the system became badly unstable for a number of sample periods before being stabilized again by the newly obtained controller matrices. The extent of the instability is shown in Figs 10 and 11, although it should be noted that there was no limitation on the control, and a rather unrealistically low control weighting matrix was used, for the purposes of experiment. Thus the control signal obtained was very large.

This is a good example why the introduction of the MPC methods for dealing with constraints should be introduced in the basic SPC formulation, a higher control weighting in the cost function would negatively affect the control performance. These instability problems arise because of the finite horizon nature of MPC. Concepts of stability are intrinsically asymptotic, and thus control design for finite horizon cannot have guaranteed stability in the same way as is found in linear quadratic Gaussian (LQG) control design. Thus it is unknown whether such instability windows will arise if the simulation is run for an arbitrary length of time. This is clearly a disadvantage of MPC strategies.

The relatively small block data size appears to give fairly poor identification in comparison with larger block sizes. But larger block sizes imply longer delays in responses to parameter changes, and can only be compensated for with smaller sampling periods, which increases the requirement and computational power.

Another possible disadvantage is the tuning of the parameters. In standard MPC, the parameters to be tuned include the weighting matrices Q and R, which are able to allocate different weights to different time steps within the forward horizon. This implies that the tuning is very difficult. Indeed it was found that tuning these matrices for the wastewater treatment plant system to obtain adequate control was not easy.

In SPC, further parameters must be chosen, namely the size of the block data and the size of the block Hankel matrices. While these do not appear to be control parameters, they affect the identification result and thus the control design, and therefore have an effect on stability and performance of the system.

6. Summary

It is clear that subspace-adaptive method have a large number of important and useful advantages, primarily the application ability to MIMO systems, and the low requirements on prior system information. It is also clear that a great many problems need to be solved, including the issues of parameter tuning, response time to parameter changes, and stability. In conclusion, it is proposed that this algorithm shows much promise for further development. At this stage, given the advantages observed and the problems encountered, the most likely areas of application for the proposed algorithm are multivariable processes, about which little information is known such as the wastewater treatment plant. Processes to be controlled with long sampling period are ideal targets, since the issue of computation time is reduced in importance.

7. Acknowledgement

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