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Fuzzy Predictive Control of Highly Nonlinear pH process

Katarina Kavšek-Biasizzo, Igor Škrjanc, Drago Matko

Faculty of Electrical Engineering, Tržaška 25, 1000 Ljubljana
University of Ljubljana, Slovenia
E-mail: katarina.kavsek@fe.uni-lj.si

Abstract - This paper proposes a new approach to predictive control of highly nonlinear processes based on a fuzzy model of the Takagi-Sugeno form. Standard Model Based Predictive Control (MBPC) methods use linear process models and are therefore unable to deal with strong process nonlinearities. But, the advantage of linear MBPC is in implementation due to fast optimization algorithms and guaranteed convergence within each time sample. In our approach, step responses for different operating points are extracted on-line from the nonlinear fuzzy model and a modified linear DMC algorithm is used. In this way, all the advantages of both fuzzy modeling of nonlinear processes and DMC control are accomplished. For performance evaluation of this simple but efficient approach, a nonlinear pH-process is used.

Keywords - nonlinear predictive control, fuzzy models, pH control

INTRODUCTION

The problem of controlling pH-value is found in many practical areas, including waste water treatment, biotechnology processing and chemical processing. There are two common characteristics of pH-control:

- diffuculties in controlling the pH-process, arising mainly from its heavy nonlinearity and uncertainty,
- diversity in control approaches applied, ranging from simple PID control, adaptive control, nonlinear linearization control, gain-scheduling control and various model-based control to modern control systems based on fuzzy systems and neural networks (Gustafsson et al., 1995), (Henson and Seborg, 1994), (Lee et al., 1994), (Ritt et al., 1996), (Ylen and Jutila, 1996).

One reason for the increasing number of papers in recent years is the highly nonlinear character combined with the rather simple structure of mathematical model, which makes pH control suitable for illustrating new nonlinear approaches. Another reason for such attention in the literature is the fact that practical pH-control has not yet been finally solved (Gustafsson and Waller, 1992).

In order to achieve effectiveness and high control performance of difficult nonlinear processes, an advanced control approach is adressed. Since most advanced control techniques are based on a model of the process under consideration, the existence of a good model is of extreme importance.

In the last 10 years, Model Based Predictive Control (MBPC) has become an attractive research field in automatic control because of its advantages over conventional techniques (e.g. PID control) and it has also been also accepted in industry. Hundreds of industrial units all over the world are now running now under predictive control. Model Based Predictive Control is a control strategy based on the explicit use of a process model to predict the controlled variable over a long-range time horizon.

In most applications of generic MBPC techniques (DMC, GPC, PFC,...) the process has been modeled over its operating range by an average linear (linearized) model (transfer function, state space model, impulse or step response model,...). But in the real world, nonlinearities are more the rules than exceptions, and a fixed linear model might not really result in the required performance, especially over wider operating ranges. For control of highly nonlinear pH-processes over a wider range, the use of average linearized model would be absurd. Even though some accurate nonlinear models can be obtained by theoretical modeling, it is usually a difficult and time consuming task. Generic nonlinear black-box models, which are currently quite popular, are fuzzy models and neural network models. Both of them can be easily identified from input-output process measurements and yield good approximation and generalization properties.

In fact, the extension of an MBPC strategy for the use of nonlinear process models is a topic in the academic environment. Originally, MBPC algorithms were developed for linear processes, but the basic idea can be transferred to nonlinear systems. Unfortunately, this leads to a nonlinear non-convex optimization problem with very computationally demanding algorithms, usually too slow for real-time control. This fact has forced the control community to study simplifications of this general approach in order to remove these drawbacks. Following this, the use of different approximate linear models of the process around different operating points appears to be a good approach to simplify the solution of the optimization problem considerably. In our new approach, a black box nonlinear fuzzy model is used, which represents a collection of several local linear models merged together with fuzzy logic. For predictive control, various step responses for different operating points are extracted on-line from the fuzzy model, and a modified Dynamic Matrix Control (DMC) (Cutler and Ramaker, 1980) can be applied. The effectiveness of both the identification algorithm of the fuzzy model and the control approach are demonstrated through a simulated example of a highly nonlinear pH-process in the whole operating range.

FUZZY MODELING

In recent years, fuzzy logic has seemed to be a very promising approach to process automation. The concept of fuzzy logic and fuzzy sets theory can be employed in different ways, not only in the field of control but also in modeling (nonlinear) dynamical systems. A survey of different approaches to fuzzy modeling can be found in (Babuška and Verbruggen 1996).

In this paper, we focus on rule-based fuzzy systems, i.e. systems whose input-output mapping is determined by a collection of fuzzy If-Then rules and by a corresponding fuzzy inference mechanism. Fuzzy modeling is then concerned with building a fuzzy model capable, in some sense, of reflecting the major aspects of the dynamical system, based on available information regarding the input-output of the system. The information may come from domain experts, expressed in terms of linguistic rules. Unfortunately, this usually delivers only a rough idea of the process behaviour, since the human experts cannot sense all the details and might not be able to quantitatively express their observations. Since fuzzy systems are also mathematical models that can realize nonlinear mapping to an arbitrary accuracy, like neural network and universal function approximation, numerous approaches have been proposed for constructing fuzzy models from input-output measurement data. Although the method described in this paper can handle both qualitative and quantitative information, we shall be concerned only with the case based on numerical data. Still, compared to other nonlinear approximation techniques, fuzzy models provide a more transparent representation of the identified model. The fuzzy model identified from numerical data can be expressed in the form of linguistic rules and can be validated by experts. In this way, the usual validation performed on fresh data sets is complemented by another method which enhances the reliability of the model, and helps to reject unreliable models.

Takagi-Sugeno fuzzy models

Depending on the structure of the rules, several types of rule-based fuzzy models can be distinguished: relational models, linquistic fuzzy models and Takagi-Sugeno fuzzy models (Takagi and Sugeno, 1985). The last one is discussed in more detail below.

Suppose the rule base of a fuzzy system is as follows:

$$\mathbf{R}_i : \textbf{if } x_1 \text{ is } A_i \textbf{ and } x_2 \text{ is } B_i \textbf{ then } y_i = f_i(x_1, x_2)$$

$$i = 1, \ldots M \tag{1}$$

where x_1 and x_2 are input variables of the fuzzy system, y is an output variable and A_i, B_i are fuzzy sets characterized by their membership functions. The If-part (antecedents) of the rules describe fuzzy regions in the space of input variables and the Then-parts (consequents) are functions of the inputs, usually in linear form:

$$f_i(x_1, x_2) = a_i x_1 + b_i x_2 + r_i \tag{2}$$

where a_i, b_i and r_i are the consequent parameters. For $a_i = b_i = 0$ the model becomes a Takagi-Sugeno fuzzy model of the zeroth order.

Such a very simplified fuzzy model can be regarded as a collection of several linear models applied locally in the fuzzy regions defined by the rule premises. The idea behind this kind of modeling is close to the well-known concept of gain scheduling.

Rule-premises are formulated as fuzzy AND relations on the cartesian product set $X = X_1 \times X_2$, and several rules are connected by a logical OR. Fuzzification of a crisp value x_1 produces a column vector

$$\mu_1 = \left[\mu_{1A_1}, \mu_{1A_2}, \ldots, \mu_{1A_m}\right]^T \tag{3}$$

and similarly for a crisp value x_2. The degrees of fulfillment of all possible AND combinations of rule premises are calculated and written into matrix **S**. If the algebraic product is used as an AND operator, this matrix can be directly obtained by multiplication:

$$\mathbf{S} = \mu_1 \otimes \mu_2 = \mu_1 \cdot \mu_2^T. \tag{4}$$

A crisp output value y is computed by a simplified algorithm for singletons as a weighted mean value (Center of Singletons):

$$y = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} s_{ij} r_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{m} s_{ij}}. \tag{5}$$

The dimensions of matrix $\mathbf{S}(m \times n)$, which actually represents the structure of the model, depend on the dimensions of input fuzzy sets $\mu_1(m \times 1)$ and $\mu_2(n \times 1)$. Parameters of the fuzzy model r_{ij} are estimated from the measurements, using the standard least-squares algorithm.

Modeling dynamic systems

The described fuzzy model actually represents a static nonlinear mapping between input and output variables. Dynamic systems are usually modeled by feeding back delayed input and output signals. In the same way, the system dynamics is captured in other kinds of nonlinear models, such as neural network models. The common structure for all these nonlinear models is NARX (Nonlinear AutoRegressive with eXogenous input) model, which establishes a relation between past input-output data and the predicted output :

$$\hat{y}(k+1) = F(y(k), y(k-1), \ldots, y(k-n+1), \\ u(k), u(k-1), \ldots, u(k-m+1) \quad (6)$$

where $y(k), y(k-1), , \ldots, y(k-n+1)$ and $u(k), u(k-1), \ldots, u(k-m+1)$ denote the delayed model output and input signals, respectively. The fuzzy model therefore approximates the function F. In terms of Takagi-Sugeno fuzzy rules of the zeroth order, the model is given by:

$$\mathbf{R_i}: \ \textbf{if} \ \ y(k) \text{ is } A_{i,1} \ \textbf{and} \ \ldots y(k-n+1) \text{ is } A_{i,n} \\ \textbf{and} \ u(k) \text{ is } B_{i,1} \ \textbf{and} \ \ldots u(k-m+1) \text{ is } B_{i,m} \\ \textbf{then} \ \hat{y}_i = r_i \quad (7)$$

Until now, we assumed that the dynamic system under study can be adequately characterized by a mapping between past inputs-outputs and the predicted output. Formally, the problem of fuzzy modeling may be formulated as follows (Nie at al. 1996): given a data set M, prior knowledge Q and performance index I, (i) choose a fuzzy model $FM = (S, \theta, U)$ consisting of a structure S, a parameter set θ, and a fuzzy reasoning algorithm U, (ii) design a learning algorithm V, (iii) and use (N, Q, V) to construct (S, θ) subject to I. Each of the fuzzy models discussed in the previous section has its own learning and fuzzy reasoning algorithm and its own set of free parameters θ. In Takagi-Sugeno models, structure identification means specifying operators for logical connectives, inference and defuzzification. Once the structure is determined (e.g. collections of local linear models), membership functions have to be selected (using different sources of information) and finally, consequent parameters can be estimated by least squares.

If there is no prior knowledge, both the consequent parameters and membership functions can be extracted from data using fuzzy clustering techniques, nonlinear optimization, neural networks or inductive learning.

FUZZY MODEL-BASED PREDICTIVE CONTROL

Model Based Predictive Control (MBPC) is a control strategy based on the explicit use of a dynamic model of the process to predict future process output over a certain (finite) horizon and to evaluate control actions to minimize a certain cost function. MBPC stands for a collection of several different techniques all based on the same principles. Originally, the algorithms were developed for linear processes, but the basic idea can be extended to nonlinear systems. This straightforward approach (Braake te et al., 1994) is accompanied by a major drawback: due to the nonlinear nature of the models (fuzzy models, neural network models or any other nonlinear models), a generally nonlinear and non-convex optimization problem has to be solved in each time sample. In real-time applications, we cannot guarantee that the global optimum is found within one sample period.

In order to overcome this disadvantage, some attempts at using approximate local linear models for each operating point and linear MBPC algorithm have been reported (Ritt et al., 1996), (Ayala-Botto et al., 1996). Below, a new approach to incorporating the nonlinear fuzzy model into the DMC algorithm is presented.

DMC Algorithm

One of the first proposed MBPC methods, and still comercially the most succesful one, is Dynamic Matrix Control (DMC), introduced by Cutler (Cutler and Ramaker, 1980). The basic concept of the original algorithm is as follows:

The DMC algorithm is based on a step response model of the process given by

$$y(k) = \sum_{i=1}^{N} g_i \Delta u(k-i) + n(k) \quad (8)$$

where $y(k)$ is the process output, $u(k)$ the manipulated variable, g_i denotes the elements of the process step response and $n(k)$ is a disturbance acting at time instant k.

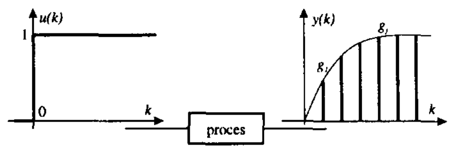

Fig. 1. Step response model

The predictive controller calculates a sequence of the future actuation signal $\Delta u(k), \Delta u(k+1), \ldots, \Delta u(k+N_u)$ over a certain control horizon N_u, such that it brings the predicted output of the process as close as possible to a predefined reference trajectory. This sequence is obtained by minimizing (with respect to $\Delta u(k+j)$) the cost function (9)

$$J = \sum_{j=N_1}^{N_2} [\hat{y}(k+j) - r(k+j)]^2 + \sum_{j=0}^{N_u-1} [\lambda \Delta u(k+j)]^2, \quad (9)$$

assuming that after N_u the future control signal remains constant ($\Delta u(k+j) = 0$ for $j \geq N_u$). In this expression, $r(k)$ is the desired reference trajectory, λ a weighting factor and $\hat{y}(k+j)$ are predictions of the values of the output in the time horizon $j = N_1, \ldots, N_2$. These predictions depend on the manipulated variables $\Delta u(k+j)$ and can be obtained from the process model. N_1 and N_2 are lower and upper prediction horizons for the output signal.

The cost function J (9) can be rewritten in matrix form as:

$$J = \mathbf{\Delta u}^T(k)[\mathbf{G}^T\mathbf{G} + \lambda\mathbf{I}]\mathbf{\Delta u}(k) - 2\mathbf{e}_0^T\mathbf{G}\mathbf{\Delta u}(k) + \mathbf{e}_0^T\mathbf{e}_0 \quad (10)$$

where

$$\mathbf{\Delta u}^T(k) = [\Delta u(k), \Delta u(k+1), \ldots, \Delta u(k+N_u-1)] \quad (11)$$

is the vector of the future control increments to be calculated,

$$\mathbf{e}_0^T = [r(k+N_1) - p_{N_1}, \ldots, r(k+N_2) - p_{N_2}] \quad (12)$$

is a vector of known future errors, p_j represents the free response of the process, and $\mathbf{G}$ is a matrix given by

$$\mathbf{G} = \begin{bmatrix} g_{N_1} & \cdots & g_1 & 0 & \cdots & \cdots & 0 \\ g_{N_1+1} & \cdots & g_2 & g_1 & 0 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ g_{N_2} & \cdots & \cdots & \cdots & \cdots & \cdots & g_{N_2-N_u+1} \end{bmatrix} \qquad (13)$$

$$p_j = y(k) + \sum_{i=j+1}^{N} (g_{j+i} - g_i)\Delta u(k-1) \qquad j = N_1, \ldots, N_2 \qquad (14)$$

The most important **advantage** of the DMC method is that if there are no constraints on the system inputs or outputs, an **analytical solution of the optimisation problem exists**:

$$\Delta u(k) = [\mathbf{G}^T\mathbf{G} + \lambda\mathbf{I}]^{-1}\mathbf{G}^T\mathbf{e}_0 \qquad (15)$$

and gives N_u values of future increments of the control signal. Only the first element of $\Delta u(k)$ is applied to the process, and in the next time sample the solution is calculated again using the receding horizon strategy.

DMC Using the Fuzzy Model

The Takagi-Sugeno fuzzy model described in the second section has to be utilized for the DMC algorithm. The main idea of our approach is to combine the advantages of black-box nonlinear modeling (fuzzy models) and DMC strategy in a way that is fast enough and suitable for real-time implementation. Whereas for linear, time-invariant processes the dynamic matrix $\mathbf{G}$ needs to be calculated only once (off-line), the step response of a nonlinear process strongly varies according to the operating point and range of the signals. Basically, the same DMC algorithm can be employed, but the step response vector $\mathbf{g}$ and the matrix $\mathbf{G}(u, y)$ have to be determined at each time instant (on-line) using a nonlinear model. In the case of nonlinear processes, which can be approximated by local linear models arround different operating points, it is usually good enough to calculate the new matrix $\mathbf{G}$ only when the operating point of the system or the reference signal is changed. Assuming a step-wise set-point trajectory w, time instants for updating matrix $\mathbf{G}$ are well specified by changes in set-point trajectory. The basic control scheme is shown in Fig. 2.

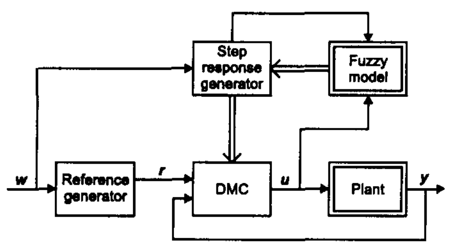

Fig. 2. DMC control using fuzzy model

The DMC controller is placed in the low-level control loop. The current step response for calculating matrix $\mathbf{G}$ is supplied by the step response generator in the upper control level. At steps in the set-point trajectory, this block performs the following actions: step response $\hat{\mathbf{g}}$, which corresponds to the range of current interest (between old and expected steady-state), is calculated using a fuzzy model. For calculation of $\hat{\mathbf{g}}$, the fuzzy model is simulated in "free-run" (as a parallel model), i.e. the calculated outputs from the model are fed back to the input. The length of the step response is chosen with regard to the largest time constant of local models, such that $\hat{\mathbf{g}}$ contains information about both dynamic and static behaviour.

At the first look, one can see some similarities of this control scheme to a multi-model based adaptive control approach (Pickhardt 1996), which is oftenly used for nonlinear processes. The multi-model consists of several linear so called sub-models which describe the characteristics of the system at a certain operating point. There exist several algorithms to detect changes of operating point and to select the best sub-model which meets the actual situation. The main disadvantage of multi-model based approach is that the control performance strongly depends on a number of sub-models. Problem arrises if actual certain operating point does not match any of predefined operating points. In our fuzzy model-based DMC approach, an appropriate model for current operating point is generated on-line from overall nonlinear fuzzy model and actual operating point can take any value between upper and lower limits of operating range.

The next section illustrates the proposed approach for pH-control.

APPLICATION TO pH PROCESS

A simplified schematic diagram of the simulation test bench scale pH neutralization tank is shown in Fig. 3.

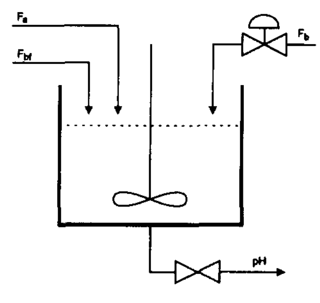

Fig. 3. The pH system

Here, we are looking at a case where a strong acid is neutralized by a strong base in water in the presence of carbonate (buffer), and the output of the process is the effluent pH value as described by (Henson and Seborg, 1994). A dynamical model for the pH process has been derived using conservation equations and equilibrium relations (Gustafsson and Waller, 1992) employing a concept known as reaction invariant. Modeling asumptions include perfect mixing, constant density, fast reactions and completely soluble ions. While keeping acid stream

F_a (HNO_3) and buffer stream F_{bf} ($NaHCO_3$) at a constant rate, the control objective is to follow some desired pH trajectory by manipulating the influent base stream F_b (NaOH and traces of $NaHCO_3$).

The chemical equilibrium for the process is obtained by defining two reaction invariants for each inlet stream and outlet stream ($i \in [1,4]$):

$$W_{ai} = [H^+] - [OH^-] - [HCO_3^-] - 2[CO_3^{2-}] \quad (16)$$

$$W_{bi} = [H_2CO_3] + [HCO_3^-] + [CO_3^{2-}] \quad (17)$$

where W_{ai} is a charge-related invariant and W_{bi} equals the total concentration of carbonate. Using the equilibrium constants:

$$K_{a1} = [HCO_3^-][H^+][H_2CO_3]^{-1} \quad (18)$$

$$K_{a2} = [CO_3^{2-}][H^+][HCO_3^-]^{-1} \quad (19)$$

$$K_w = [H^+][OH^-] \quad (20)$$

an implicit relation for $[H^+]$ can be derived:

$$W_a = [H^+] - \frac{K_w}{[H^+]} - W_b \frac{\frac{K_{a1}}{[H^+]} + \frac{2K_{a1}K_{a2}}{[H^+]^2}}{1 + \frac{K_{a1}}{[H^+]} + \frac{K_{a1}K_{a2}}{[H^+]^2}} \quad (21)$$

$$pH = -\log([H^+]) \quad (22)$$

The above equation defines a static titration curve function relating pH values to reaction variables.

The complete dynamical model is given by a mass balance equation and two differential equations for the effluent reaction invariants (W_{a4}, W_{b4}):

$$\begin{aligned} A\dot{h} &= F_a + F_{bf} + F_b - c_v\sqrt{h} \\ hA\dot{W}_{a4} &= F_a(W_{a1} - W_{a4}) + F_{bf}(W_{a2} - W_{a4}) + \\ &+ F_b(W_{a3} - W_{a4}) \\ hA\dot{W}_{b4} &= F_a(W_{b1} - W_{b4}) + F_{bf}(W_{b2} - W_{b4}) + \\ &+ F_b(W_{b3} - W_{b4}) \end{aligned} \quad (23)$$

Nominal values of these parameters and operating conditions are taken from (Henson and Seborg, 1994). The acid and buffer flow-rates are supposed to be known and kept constant during experiments. This analytical model is used to simulate the "true" system. The sampling period for pH measurement and control is 15s.

Fuzzy modeling of pH-process

The Takagi-Sugeno fuzzy model of the described pH-process was constructed only from input-output data measurements (black-box model). For identifying the model, an amplitude modulated pseudo random binary signal (PRBS) in combination with a step excitation signal was used. The dynamics of the process can be represented as a first order NARX model

$$pH(k+1) = f[F_b(k), pH(k)] \quad (24)$$

where f is an uknown nonlinear function approximated by the fuzzy model. The membership functions for input and output signals, which actually represent the partition of the operating region into sub-regions, were determined by a few human inspections of the behaviour of the process, and are shown in Fig. 4.

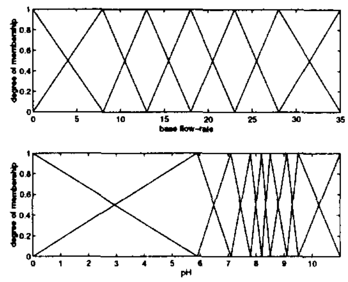

Fig. 4. Membership functions for F_b and pH

In general, the number, position and shape of membership functions can be done by several methods (clustering techniques, neural network, genetic algorithms, etc.). The consequent parameters of the fuzzy model were determined by the ordinary least-squares algorithm.

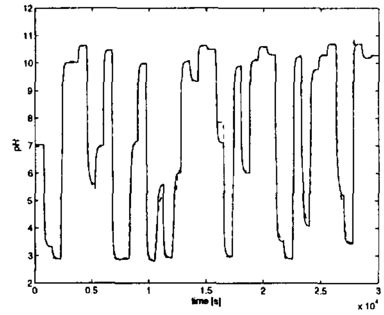

Fig. 5. Validation of the fuzzy model (solid: process, dashed: model

Fig. 5 shows the validation of the obtained fuzzy model using another data set. Additionally, the steady-state response of the fuzzy model, the so-called titration curve, is compared with the steady-state response of the simulated process.

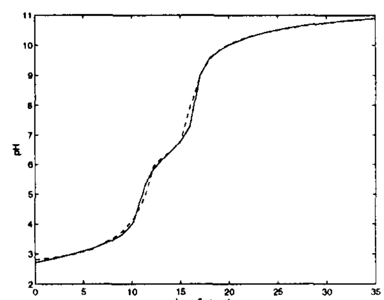

Fig. 6. Steady-state titration curves (solid: process, dashed: model

From the both two figures, one can conclude that for this pH process, the fuzzy model has good dynamic performance and is also able to capture the steady-state relationship of the process.

Fuzzy Predictive Control of pH

The identified fuzzy model is integrated into a DMC predictive control scheme in the manner described earlier in this paper (Fig. 2). The upper prediction horizon for output signal is chosen as $N_2 = 10$ and the control horizon as $N_u = 4$. The cost function also includes penalty on the control effort ($\lambda = 0.3$). Fig. 7 shows the simulation results for the proposed fuzzy predictive approach considering a sequence of step changes in the set-point trajectory. In predictive control, prior knowledge of the set-point trajectory can be exploited by the controller. In this case, controller can generates changes in control signal even before changes in set-point trajectory occur. When the signal is not known in advance, prediction of set-point signal is calculated assuming to keep its current value over the complete prediction horizon.

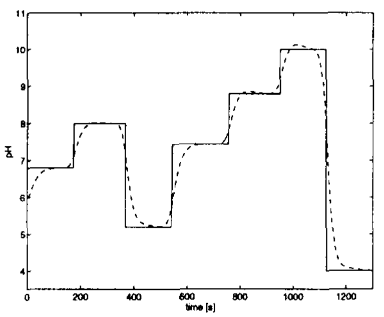

Fig. 7. Predictive control based on fuzzy model

In the complete range of operation, the output stream pH value follows the reference signal fairly well. The good control results indicate that the predictive controller receives adequate information about the changes in process behaviour (gain and dominant time constant) from the step response generator on the basis of the fuzzy model.

Future research will deal with performances of presented control scheme to process disturbances. From the operation standpoint, disturbance rejection properties (in the case of unmeasured disturbances and/or process-model mismatch) can be more critical than reference tracking. Original DMC predictive control successfully rejects step disturbances acting at output of the process. Our latest results show that this stands also for our fuzzy model-based DMC control. Disturbance rejection properties for other types of disturbances and appropriate modification of controller shall be investigated.

CONCLUSION

In the paper, a new idea of fuzzy model-based predictive control for highly nonlinear processes is presented. Different step responses for current operating points are extracted from the fuzzy model of the process on-line, and this concept is integrated into standard linear DMC predictive control in a simple and easily understandable way. In this way, all the advantages of both fuzzy modeling of nonlinear processes and the existence of analytical solution in the case of DMC control are combined. The effectiveness of the control scheme is shown by using simulated bench scale pH-process. Despite its simplicity (fuzzy rules of zeroth order), the presented fuzzy model has good accuracy in steady-state mapping, as well as in prediction of dynamic behaviour. We believe that it could also yield good performance for real-life pH control.

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