Study of Multiple Model Predictive Control on a pH Neutralization Plant

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***Abstract*— Nonlinear behavior and disturbance sensitivity of the pH processes causes them to be known as an appropriate test bench for advanced controllers. Because of special behavior and varying parameters of pH processes, Multiple Model Predictive Controllers (MMPC) outperform other controllers from both regulation and disturbance rejection points of views. Two new supervisory methods based on prediction error and fuzzy weighting for MMPC are presented. Better regulation in special condition and most excellent disturbance rejection in comparison to other MMPC methods are achieved.**

***Index Terms* — pH Process, Multiple Model Predictive Control, Prediction Error, Fuzzy Weighting.**

I. INTRODUCTION

pH control plays an important role in chemical processes such as neutralization of wastewater, biotechnological processes and electrochemistry. Wastewater neutralization processes present a very challenging control problem because of two major difficulties. First neutralization process is highly nonlinear, and second only a small portion of titrating reagent can result in a change up to one pH. A single linear model cannot describe these behaviors in the whole operating range. The overall system can be modeled as a set of linear systems. Each single model is valid in a narrow region around one of the operating points. Sensitivity to disturbance is one of the most important specifications of pH processes. Disturbances highly affect model parameters in pH process thus robust control methods are considered.

Model predictive controller (MPC) is well known for its robustness and has a rich theoretical background. Dynamic matrix control is the most popular MPC algorithm used in the chemical process industries [9]. Also it is easy to implement because of available linear optimization methods and low cost computations. On the other hand, multiple model methods are recently applied to a broad class of control schemes, such as multiple model adaptive control [10, 11], multiple model fuzzy control [8] and multiple model predictive control [7, 6, 5, 4, 3]. Multiple model method has been used for disturbance rejection as in [12].

Each multiple-model control scheme has 3 parts. The first Two other parts are model\controller bank and decision making or supervisory unit. There are two types of supervision known as switching and weighting. The last part is control design method. Here, it is based on the model predictive control. This paper tries to show the effect of supervisory in MMPC algorithm applied to a pH neutralization process. The control objectives are to force the system to track different pH setpoints, and keep the pH in neutrality in the presence of disturbances in buffer and acid inputs.

This work continues with fundamental control design method. After that, switching and weighting multiple-model predictive control approaches explained. Immediately after that, pH neutralization plant and MMPC control strategies explained and simulation results for regulating and disturbance rejection presented. Finally, the paper is concluded in the last section.

II. FUNDAMENTAL CONTROL DESIGN METHOD

Model Predictive Control (MPC) is established as an important form of process control. Dynamic Matrix Control (DMC) [1] is a popular MPC algorithm which is used in many of chemical process industries. In DMC, quadratic performance objective function is minimized over a prediction horizon to compute the optimal controller output moves as a least square problem. In [2] easy-to-use and reliable tuning strategies for unconstrained SISO dynamic matrix control (DMC) are presented. The tuning strategy for set point tracking with minimal overshoot and modest manipulated input move sizes is considered. This method describes move suppression coefficient λ, from a first order plus dead time (FOPDT) model approximation of the process dynamics. λ has a dual purpose effect on conditioning the system matrix before inversion and preventing from aggressive control action. It is often used as the main adjustable parameter to finely tune DMC to desirable performance. Past researches have focused mostly on the latter effect in the selection of λ The DMC control law is given by:

$$\Delta\bar{U} = \left(A^T A + \lambda I\right)^{-1} A^T \bar{e} \tag{1}$$

where A is the dynamic matrix, $\bar{e}$ is the vector of predicted errors over the next P sampling instants, prediction horizon, λ is the move suppression coefficient, and $\Delta\bar{U}$ is the manipulated input profile computed for the next M sampling instants, M is called the control horizon. $A^T A$ is referred as the system matrix. In [3] a step-by-step procedure for computing the DMC tuning parameters and calculation of λ is derived assuming a user defined control horizon and given sampling time.

III. MULTIPLE MODEL PREDICTIVE CONTROL

When DMC applied to nonlinear plants its performance deteriorates. One approach to overcome this problem is, model the overall system by a set of linear models, each model is valid in a narrow region around an operating point. As illustrated in "Fig.1", each model in the bank defines a new control problem. Insufficient number of models causes imprecise modeling while excessive number of models causes complexity in the supervision procedure and undesired overshoots. So the number of models is a very critical decision regarding appropriate closed loop performance. More details on the model bank are offered in [14]. After construction of model\controller bank the decision or supervisory unit should be designed. There are two types of supervision; switching supervisory and weighting supervisory, which are described in the sequel of this section.

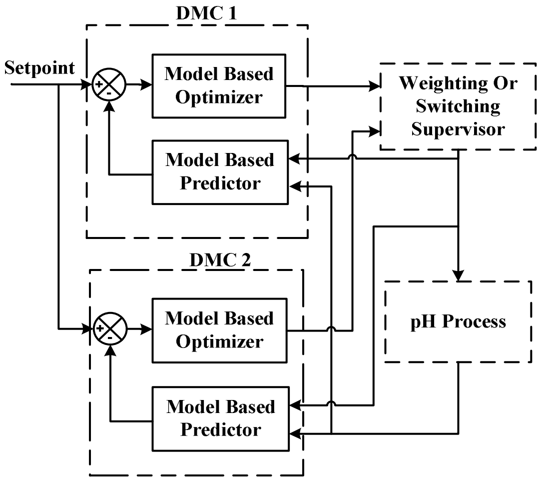


Fig. 1. MMPC Strategy

A. Switching Multiple Model Predictive Control (SMMPC)

In switching supervisory of Multiple Model Predictive Control (SMMPC), in each cycle, based on rules of supervisor, the best controller is selected. There are two methods for SMMPC.

The first is gain schedule method, [15], where the output of systems divided to various sections and for each region of output, model\controller of that region will be chosen. For example for $4.5 < pH < 5.5$ the selected model\controller, is region of pH=5 model\ controller.

The second method is a new method described here. Supervisor gets the difference between predicted outputs of the models $\hat{y}$ and real output of the process, called the prediction error and calculates performance indexes, using (2):

$$J_s(t) = \alpha e_s^2 + \beta \sum_{k=1}^{M} \gamma^k e_s^2(t-k) \qquad (2)$$
$$\alpha, \beta, M > 0, 0 < \gamma \le 1$$

In (2), $e_s = y_f - \hat{y}_s$ and according to "Fig .2", $\hat{y}_s$ is the predicted output of s^{th} model, y_f is the filtered output of the process, α, β, M are the free-design parameters, which are effective in the control system performance, and γ is forgetting factor. The supervisor calculates minimum performance index from "(3)":

$$\bar{J} = \min_i \{J_i\} \qquad i \in [1, P] \qquad (3)$$

P is the number of models. To limit hard switching speed, a hysteresis cycle gain h is used. The previous model will be changed if $J_B < hJ_A$, Subscripts 'A' and 'B' point to the current active model and the current best model respectively.

The blocks H_f in "Fig.2" are high-pass filters which are necessary to discard biases of data for more details, see [14]. Using these filters is necessary in order to compare linear models outputs with the nonlinear process.

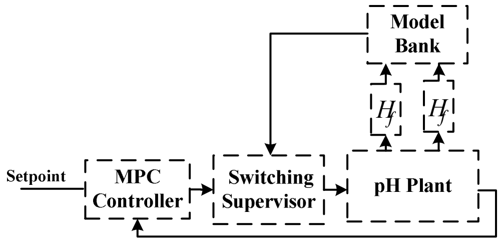


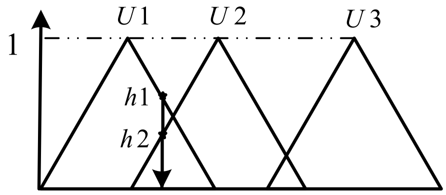
Fig. 2. Prediction error based SMMPC.

B. Weighting Multiple Model Predictive Control (WMMPC)

In each cycle, SMMPC method chooses best model\controller for calculating control signal and controlling the process. Another method for calculating control signal is Weighting Multiple Model Predictive Control (WMMPC). In this method, as shown in "Fig.3", all control signals produced by several controllers are weighted and normalized and then given to plant. For example for 3 model\controller the control signal calculated from (4):

$$U = U_1 w_1 + U_2 w_2 + U_3 w_3 \qquad (4)$$

where $w_1 + w_2 + w_3 = 1$ and $w_1, w_2, w_3 \ge 0$ weighting gains. There are two methods for supervisory or decision making in WMMPC. In "[3]", the final control output forwarded to the plant by interpolating between the individual controller outputs and defining some mathematical formulations. Fuzzy weighting is a new method that is suggested here for combination of signals by means of fuzzy membership functions. In this method a fuzzy membership function is designed based on system and model \controller behaviors and control objectives, as shown in "Fig. 3". In high gain region, low weighting is specialized for high gain controller and high weighting for low gain controller, to contrast from overshoots and instabilities. Preserving desired performance, in low gain dynamic behavior region, high weighting is specialized for high speed controller and low weighting for low speed controller .



$$U = U_1 \frac{h1}{h_1 + h_2} + U2 \frac{h2}{h_1 + h_2}$$

Fig. 3. Fuzzy membership function.

IV. MULTIPLE MODEL PREDICTIVE CONTROL OF PH NEUTRALIZATION PROCESS

There is an increasing attention to pH processes as a bench mark of new advanced control problems, because of strong nonlinear behavior of these processes. This paper tries to show effect of supervisory in MMPC to control a pH neutralization process. As shown in following, MMPC methods have ability to control pH in different reference points with different settling times of process. The control objective is to force the system to change its pH value, and keep it in neutrality in the presence of disturbance.

A. System Description

pH process has three reaction streams: HNO_3, $NaOH$, $NaHCO_3$ and two output variables: liquid level h and pH . Acid, base and buffer flow rates are known as F_a, F_b, F_{bf} respectively. According to [15, 16], the overall model including the dynamical part in terms of state and output equations is described as "(5)"

$$\begin{aligned} \frac{dx}{dt} &= f(x) + g(x) + p(x)d \\ c(x, y) &= 0 \end{aligned} \tag{5}$$

Where $x = [h, w_a, w_b]$, $u = [F_a, F_b]$, $d = F_{bf}$, $c = [c_1, c_2]$ $y = [h, pH]^T$. From control view point, the process regarded as single-input F_b and single-output pH system, the buffer stream $NaHCO3$ and acid stream HNO_3 are considered as disturbances.

"Fig .4" shows Titration curve of the typical solutions. "Fig .5" demonstrates the variations of static gain of the process versus the pH values. Highest static gain of the process occurred at pH=8.1 and lowest static gain in the range of pH of [3.5, 10] is 0.2 at pH=3.6. Thus, it results that the static gain of the process changes 14 times in the whole operating point.

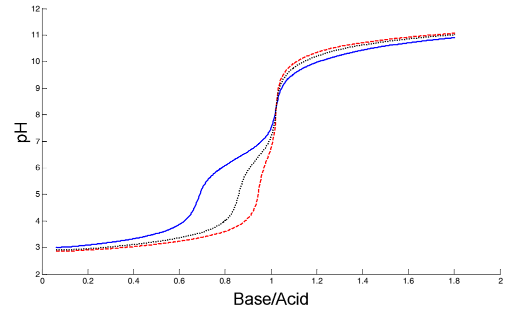


Fig. 4. Titration curve .buffer=0.55 (solid), buffer =0.25 (dot) buffer =0.1(dash)

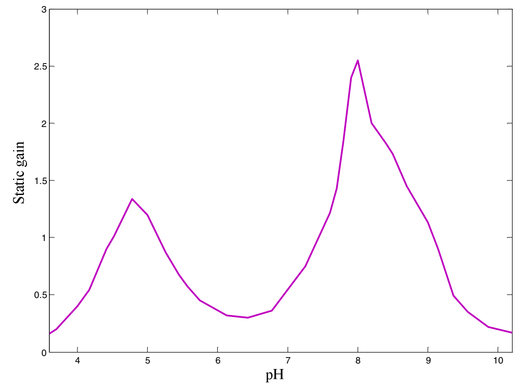


Fig. 5. Static gain of pH process

In order to testing applicability of control methods on real system, 20 second delay and uniform random noise with amplitude of 0.1, added to output of pH process.

B. MMPC for pH Neutralization Process

In this section, the proposed SISO MMPC algorithm is evaluated on pH neutralization process, regulating the desired set-point while rejecting the disturbances. The parameter tuning methods for MMPC controllers are mentioned in section 2. Acid and buffer inputs act as immeasurable disturbances. For a pH control problem, it is essential that the volume of solution in the CSTR stays in a predefined value. Thus, a classical PI controller is designed to hold volume in predefined level, as shown in "Fig .6".

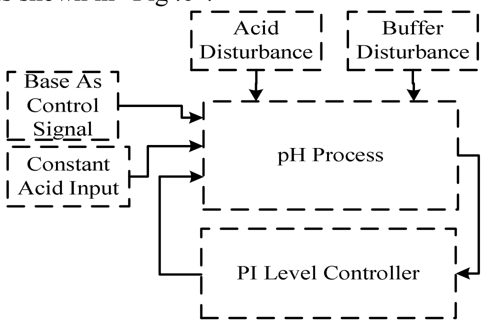


Fig. 6. SISO MMPC Scheme.

There are various methods distinguishing different regions, such as Self-Organizing Map (SOM) neural network [18] and gap metric method [19]. Here from experience as in [3], three regions models are picked out for describing entire behavior of pH process, as shown in "Table .1".

TABLE I. FOPDT MODELS AND STATIC GAINS IN 3 REGIONS

PH=	5	6	8
Model	$\frac{1.289e^{-20s}}{64.350s+1}$	$\frac{0.356e^{-20s}}{65.445s+1}$	$\frac{2.541e^{-20s}}{80.515s+1}$
Static Gain	1.2896	.3562	2.5411

Constants of performance index of switching supervisor based on prediction error, was $\alpha = \beta = 1$, $M = 10$, hysteresis constant $h = 0.9$ and forgetting factor $\gamma = 0.9$. In fuzzy weighting approach in WMMPC the membership functions selected as "Fig.7". Membership functions are chosen in some way which combines the low speed controllers output in high speed dynamical region and high speed controllers output in low speed dynamical regions.

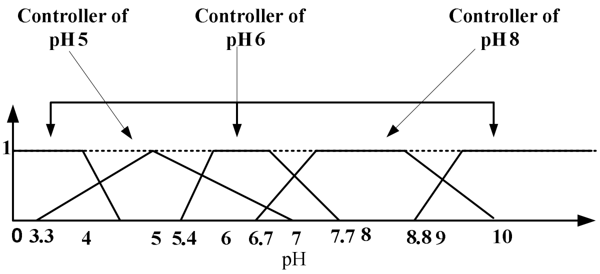


Fig. 7. Fuzzy membership function for pH simulated process

Various scenarios are performed to compare MMPC methods, in regulation at varying pH values and in disturbance rejection at neutrality i.e. pH=7.

Scenario 1: controllers are compared from regulation point of view. This test involves 3 parts: small changes in the setpoint "Fig .8", medium changes in setpoint "Fig.9", and large changes in the setpoint "Fig .10". In order to preventing from overshoot and increasing regulating speed, various settling times for setpoints have been choosed. Settling times for references input of $\mathrm{pH} = 5$ ad $\mathrm{pH} = 8$ because of sensitivity of plant in these regions considered, 600 second and for the other pH's the considered settling time is 200 second. Hardest changes and overshoots in control effort are taken place in large changes of the setpoint as "Fig .11". Maximum over shoot of 0.73% occurs when changing from $\mathrm{pH} = 5$ to $\mathrm{pH} = 8$. In other scenarios the control signal changes are smaller.

Scenario 2: In the second scenario, the acid stream flow rate is changed as a disturbance. This feed rate is changed from 16.6 to 14.6 and 18.6. MMPC using gain scheduling method became unstable when acid stream decreasing with disturbance, as simulation results are shown in "Fig .12". Acid stream increasing disturbance and disturbance rejection results shown in "Fig .13".

Scenario 3: In the third scenario, the buffer stream flow rate is changed as a disturbance. This feed rate is changed from 0.55 to 0.25 and 1.35. Buffer stream decreasing disturbance unstablized all of controllers except prediction error based MMPC. The simulation results are shown in "Fig.14". Buffer stream increasing disturbance and controllers behaviors shown in "Fig .15".

Sum of squares error for numerical comparison of different controllers executions in each scenario is picked up. The numerical results are shown in "Table .2".

C. Discussion

In regulation of small changes in pH reference and disturbance rejection, MMPC with prediction error supervisor has best control behavior and minimum sum of square error. The similar results for large and medium changes obtained for MMPC with fuzzy weighting supervisor. Repetitive experiments shows unpredictability of performance of the previous MMPC methods and it may be worse or better than what is proposed in this paper. However, the presented methods do not have such negative aspect.

V. CONCLUSION

In this paper two innovative supervisory methods for multiple model dynamic matrix control are presented with detail. The controllers are selected, based on practical preliminary and numerical analysis shows that the MMPC with fuzzy weighting supervisor results in a better tracking performance for regulation for large changes in pH setpoint. MMPC with prediction error supervisor shows better disturbance rejection and regulation performances for small changes in pH reference in comparison with other multiple model predictive controls.

It is obvious that the presented MMPC approaches outperform the conventional MPC, when pH crosses from or stays at given set point having the greatest gain and more specially form disturbance rejection view point.

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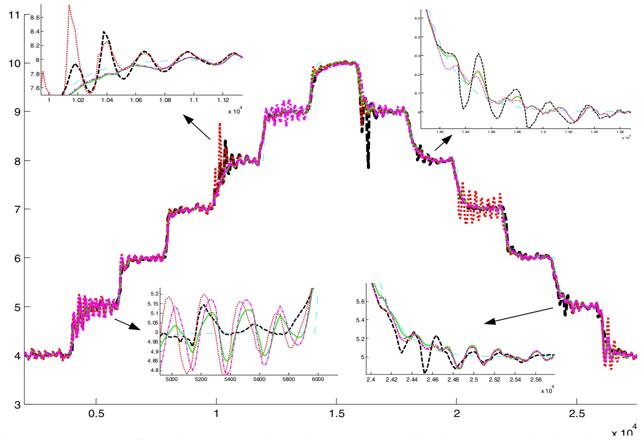

Fig. 8. MMPCs for short set point changes. Prediction error (dashed), Fuzzy weighting (solid), gain schedule (dot), conventional weighting (dash-dot) and set-point (big dash)

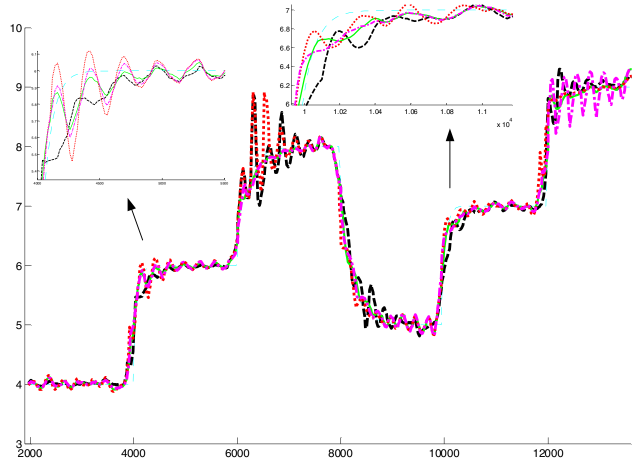

Fig. 9. MMPCs for medium set point changes. Prediction error (dashed), Fuzzy weighting (solid), gain schedule (dot), conventional weighting (dash-dot) and set-point (big dash)

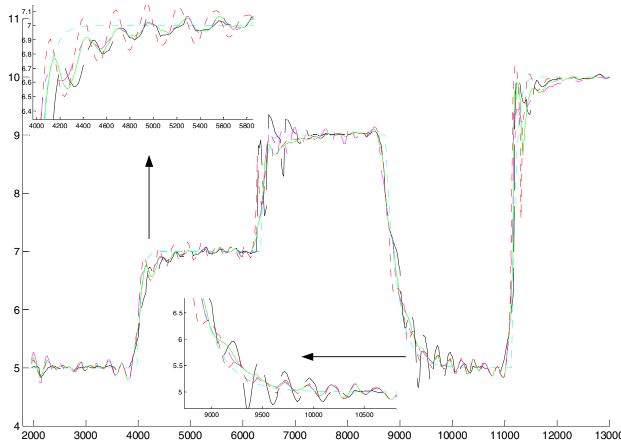

Fig. 10. MMPCs for large set point changes. Prediction error (dashed), Fuzzy weighting (solid), gain schedule (dot), conventional weighting (dash-dot) and set-point (big dash)

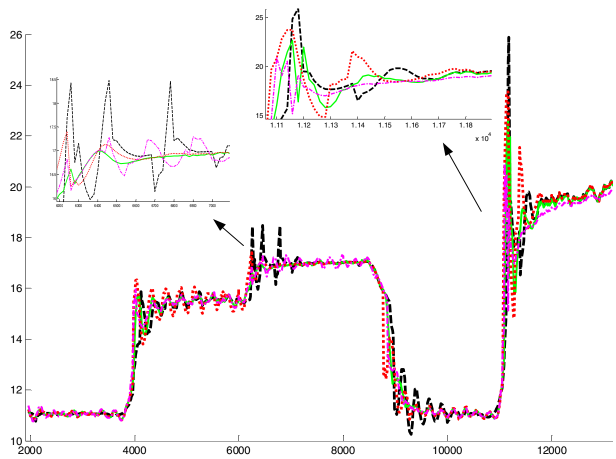

Fig. 11. MMPCs control signal for large changes . Prediction error (dashed), Fuzzy weighting (solid), gain schedule (dot), conventional weighting (dash-dot) and set-point (big dash)

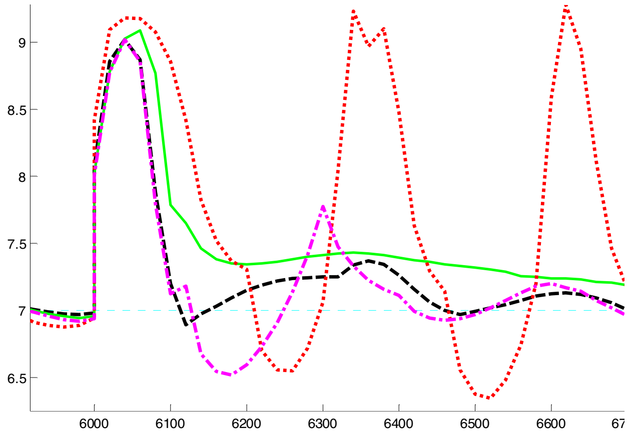

Fig. 12. MMPCs for acid decreasing disturbance rejection. Prediction error (dashed), Fuzzy weighting (solid), gain schedule (dot), conventional weighting (dash-dot) and set-point (big dash)

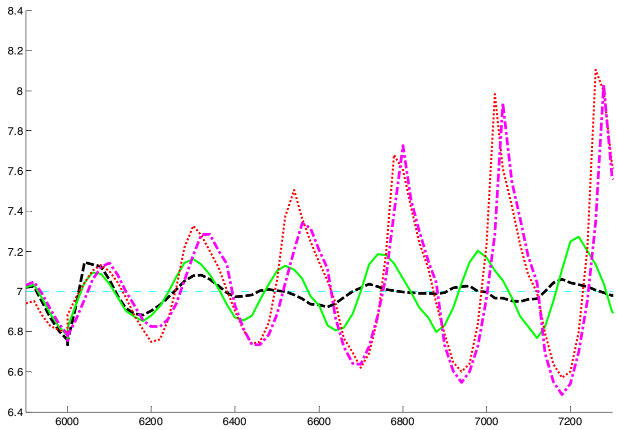

Fig. 14. MMPCs for buffer decreasing disturbance . Prediction error (dashed), Fuzzy weighting (solid), gain schedule (dot), conventional weighting (dash-dot) and set-point (big dash)

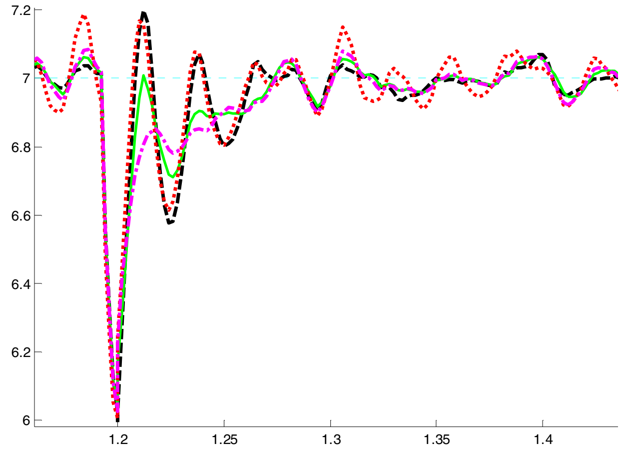

Fig. 13. MMPCs for acid increasing disturbance rejection. Prediction error (dashed), Fuzzy weighting (solid), gain schedule (dot), conventional weighting (dash-dot) and set-point (big dash)

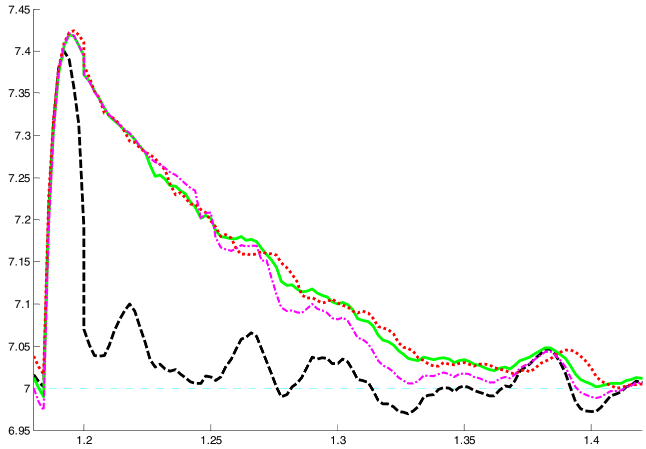

Fig. 15. MMPCs for buffer increasing disturbance . Prediction error (dashed), Fuzzy weighting (solid), gain schedule (dot), conventional weighting (dash-dot) and set-point (big dash)

TABLE II. SUM OF SQUARE ERROR

Method / Scenario	Prediction error	Gain scheduling	Fuzzy weighting	Conventional weighting
Small step	5.1680	10.9894	7.0758	5.7029
Medium step	28.0871	39.8473	21.5036	28.2080
Large step	42.8606	66.5466	30.7334	33.4920
Acid disturbance (Decreasing)	14.0692	Inf	14.6559	20.4919
Acid disturbance (Increasing)	6.3639	5.7376	5.5252	5.4580
Buffer disturbance (Increasing)	0.9972	4.0662	3.9653	3.8684
Buffer disturbance (Decreasing)	0.4277	Inf	Inf	Inf