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Self Tuning Adaptive Multiple Model Predictive Control

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ABSTRACT: In this paper a novel automatic learning and self tuning multivariable adaptive multiple model predictive control based on self organizing map neural network and optimized real time soft analyzer studied, characteristics are stated and implemented on a laboratory scale pH pilot plant. Generalized Predictive Control based on Independent Model and Dynamic Matrix Control are used as fundamental controllers. Because of hard noisy environment real time soft analyzer based on optimized multi layer perceptron designed for parameter estimation. The Kohonen's self organizing map neural network is used for automatic model bank generation. A new disturbance rejection supervisor planned to improve the performance of automatic controller in presence of disturbances. Exhaustive implementation analyses are provided to assess the abilities of the presented algorithms.

KEYWORDS*:* Self tuning adaptive multiple model predictive control, generalized predictive control based on independent model, dynamic matrix control, self-organizing map, multi layer perceptron.

1. INTRODUCTION

Usually in control system design, especially in practical implementation of control methods, it must be considered that former information of plant is insufficient. Asymmetric data detract the control quality or even can unstabilize the plant. One of the recent methods which provide pragmatic approach for uncertain and unknown systems is self tuning method (Bobal, et. al, 2005). In this method internal running parameters optimized by maximization or minimization of an objective function. Typically every self tuning system composed from four sections: expectation, measurement, control and action. Only the expectation section is in the access of operator or automation personnel and by that the operator describes how the system should behave (Budaciu, et. al, 2012). The control section can be divided into two sections of explicit self tuning control and implicit self tuning control. In the explicit ones the model of the system is estimated and in the implicit control, parameters of controller are estimated (Kaminskas, et. al, 2006).

Diverse control solutions for optimal and robust control of multivariable nonlinear processes are presented over past decades. Two major methods are robust control and adaptive control methods, but using this methods makes many restrictions and sometimes quite useless. One of the more recent approaches which can be simply implemented in real industrial processes is the notion of multiple models (MM) based control (Murray Smith, et. al, 1997) In this method global control execution breaks down into small linear control problems in different operation conditions and appropriate pair of model-controller is designed. The considered supervisor is responsible for switching between pairs or combining appropriate pairs. The idea of MM is widely used in modelling of nonlinear systems, identification of multi level plants and control of hard nonlinear plants (Fatehi, et. al, 2008, Yanakiev, et. al, 2012, Camerona, et. al, 2012, Karimi, et. al, 2000). Many global controller designs with the aid of MM have been reported on different applications (Dougherty, et. al, 2003, Galán, et. al, 2004).

In multiple model controllers precision of models that exist in model bank significantly affects control performance. The model bank should cover all possible operating conditions but there is some kind of trade off in number of models in model bank, increasing the number of models of the model bank improves the precision of model bank but can cause some problem like augmentation of computational cost and incremental numbers of switching which finally can deteriorate control performance (Fatehi, et. al, 2008).

Identification of members of the model bank, the multiple modelling using self-organizing map considered. Automatically estimation of models parameters has been done with clustering of data acquisitioning data bank from the RLS method based on Kohonen's self-organizing map (SOM) neural networks (Kohonen, et. al, 1995). After generation of a model, the best model which describes the process behaviour in each sample recognized and selected using supervisory strategy. Then the parameters of the best model are used in fundamental control method. According to (Karimi, et. al, 2000), the closed loop stability of the multiple model based control is guaranteed if each model\controller pair is individually robust to un-modelled systems dynamics and bounded unmeasured disturbances. Since the Generalized Predictive Control with Independent model (GPCI) and Dynamic Matrix Control (DMC) strategies are inherently robust therefore the overall stability is guaranteed.

Model predictive controller (MPC) is well known for its robustness and has a rich theoretical background. Two widely used MPC methods are: 1) DMC which is the most popular MPC algorithm used in the chemical process industries (Dougherty, et. al, 2003) and 2) Generalized Predictive Control (GPC) method which has become in both industry and academia as a famous process controller. In this paper, multivariable DMC and GPC algorithms based on the state-space model are used as a fundamental controller of desired Multiple Model Predictive Control (MMPC) strategy.

Most of the industrial processes have nonlinear dynamics and can not be modelled or even controlled by one mathematical model at least in their full operating range. One of the important instants of these industrial processes is pH which plays a central role in biotechnology, wastewater treatment, medical drugs production, food industry and electrochemistry. Most difficult control problem among different application of pH control is wastewater neutralization which is performing in continues form.

Some characteristics of pH neutralization processes are; 1) high sensitivity for small amounts of titrating reagent which can result in change of pH up to one unit especially in equivalence point; 2) at each time the process static gain is complicated function of physical and chemical components and so titration curve is unknown for multi component and poor streams these problems are intensified in real-world processes because of unpredictable and immeasurable noises and disturbances; 3) this process is unobservable and uncontrollable because of chemical buffering and there is no unique relationship between required portion of titration reagent and pH; 4) reagent flow accuracy must be in a range of 1000:1 or more this means high there is high need for precise actuators and reagent metering devices. These extreme nonlinear attributes of pH process caused them to be known as test bench for comparison and evaluation of different control methods.

During the last decade, modern process control applicants had investigations on improvement of product quality by optimizing operation conditions. In this concept, design of advanced control strategies and efficient monitoring tools for supervising are two wings of bird. One of the most recent methods in monitoring of process is using data-driven soft sensor models (Narendra, et. al, 2000, Desai, et. al. 2006). The designed soft sensor is used to produce estimation of process signals and extracting product information that are useful for controller design. This control scheme is known as inferential control (Kano, et. al, 2004). In order to extracting nonlinear model of pH process Multi-layer perceptron (MLP) as a paradigm of artificial neural networks (ANNs) has been used . The MLP-based soft-sensors are calibrated and optimized using a standard cross-validation and the Levenberg−Marquardt (LM) method (Nelles, et. al, 2001).

Various approaches to cope with possible unmeasured disturbances are presented in literatures, in this paper a new disturbance rejection supervisor for Self Tuning Adaptive Multiple Model Predictive Control (STAMMPC) presented and closed loop stability is guaranteed. There are great numbers of researches on the pH control strategies in recent years (Garcila, et. Al, 1986, Yanakiev, et. al, 2012). Most of these strategies desiged for single input single output (SISO) pH processes and few researches has been done for the multivariable pH processes especially in experimental form.

This paper organized as follows; in section 2 fundamentals of multivariable GPCI and DMC methods are presented. In section 3 a real time soft analyzer design procedure for pH pilot plant presented. Section 4 is allocated to generation of model bank using SOM. After that in section 5, multivariable MMPC strategy based on SOM and Soft Sensor presented. In section 6 the disturbance rejection supervisor is designed. Section 7 dedicated to specifications of pH neutralization pilot plant, overall design procedure of the STAMMPC and experimental results. Finally, the paper is concluded in section 8.

2. MODEL PREDICTIVE CONTROL

In this section two most popular MPC control strategy in industrial process control are presented. First multivariable GPC method using Independent Model (GPCI) presented (Rossiter, et. al, 2005) and then Multivariable DMC which has been discussed extensively in (Shridhar, et. al, 1998, Townsend, et. al, 1998) is summarized here.

2.1 Multivariable GPCI

A brief description of multivariable state space GPC algorithm based on independent model (GPCI) (Rossiter, et. al, 2005) for convenience of the reader presented here. Considering a state space model as following:

$$\hat{x}_{k+1} = A\hat{x}_k + Bu_k \qquad (1)$$
$$\hat{y}_k = C\hat{x}_k$$

Where $\hat{x}$ is the model state vector, $\hat{y}$ and u respectively denote model output and process input. A,B,C are matrixes which are defining state-space model. The model (1) can be considered as Independent Model (IM), and as "(1)" the real process and IM model use the same input (u). In truth the IM operate simultaneously and parallel to the real process. The design procedure of a GPCI control strategy is as following. Consider the cost function:

$$J = [\bar{y} - \bar{r}]Q[\bar{y} - \bar{r}]^T + [\bar{u} - \bar{u}_{ss}]R[\bar{u} - \bar{u}_{ss}]^T \qquad (2)$$

Where $\bar{y},\bar{u}$ is the future value vector of y and u respectively, u_{ss} is the steady state input, Q and R are weighting matrixes and values of these matrix determines location of desired closed loop poles. Therefore changing of these matrixes would result in control strategy with different speeds and idea of this paper in MMPC based on GPIC control strategy. Contemplation cost function (2) zero steady-state error is guaranteed trough solving of inequality "(3)":

$$\bar{y} = P\hat{x} + H\bar{u} + L[y_k - \hat{y}_k] \qquad (3)$$

In which $L[y_k - \hat{y}_k]$ is bias correction term and P, H and L are the vector of future prediction up to n_y output horizons can be calculated from "(4)":

$$\begin{bmatrix} y(k+1) \\ Y(k+2) \\ \vdots \\ Y(k+n_y) \end{bmatrix} = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ \mathrm{CA}^{n_y} \end{bmatrix} \hat{x}(k) + \qquad (4)$$
$$+ \begin{bmatrix} CB & 0 & \cdots \\ \mathrm{CAB} & \mathrm{CB} & \cdots \\ \vdots & \vdots & \vdots \\ \mathrm{CA}^{n_y-1}B & \mathrm{CA}^{n_y-2}B & \cdots \end{bmatrix} \times \begin{bmatrix} u(k) \\ u(k+1) \\ \vdots \\ u(k+n_u-1) \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} D(k)$$

As seen in "(4)" the disturbance value $D(k)$ is used for correction of the difference between the current measurement of the process variable and the current value of the predicted process variable at the present sample time. The steady state input can be estimated as "(5)":

$$u_{ss} = M \times (r - D)$$
$$D = y - \hat{y} \qquad (5)$$
$$M = (C(I - A)^{-1}B)^{-1}$$

By putting "(4)" and "(5)" in the cost function "(3)", and solving that, the following optimal control law extracted:

$$u = -k\hat{x} + P_r(r - D)$$
$$k = S^{-1}X_1, S = H^TQH + R, P_r = -S^{-1}X_2 \qquad (6)$$
$$X_1 = H^TQP, X_2 = -H^TQL - RM$$

Therefore optimal control law with respect to desired Q and R in each sample can be calculated.

2.2 Multivariable DMC

In DMC strategy the quadratic performance objective function for a multivariable system (Dougherty, et. al, 2003, Shamsaddinlou, et. al, 2013a) with S controller output and R measured process variables considered as "(7)"

$$
\begin{aligned}
&J = \left[\bar{e} - A\Delta\bar{u}\right]^T \Gamma^T \Gamma \left[\bar{e} - A\Delta\bar{u}\right] + \left[\Delta\bar{u}\right]^T \Lambda^T \Lambda \left[\Delta\bar{u}\right] \\
&\hat{y}_{r,\min} \le \hat{y}_r \le \hat{y}_{r,\max} \\
&\Delta\bar{u}_{s,\min} \le \Delta\bar{u}_s \le \Delta\bar{u}_{s,\max} \\
&\bar{u}_{s,\min} \le \bar{u}_s \le \bar{u}_{s,\max}
\end{aligned}
\qquad (7)
$$

Where $\hat{y}_r$ is r^{th} measured process predicted profile; $\bar{e}$ is the vector of predicted errors over prediction horizon (next P sampling time); $\Delta\bar{u}$ is process input that computed by controller for M sampling time (control horizon); A is the multivariable dynamic matrix and formed from P unit step response coefficients of each controller\process variable pair. Formulation of matrix A for two-by-two system in P step response is:

$$
A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}_{2P\times 2M} \qquad (8)
$$

where A_{11} is step response of variable 1 which is exited with controller output 1. A_{ij} is given by:

$$
A_{ij} = \begin{bmatrix}
a_{ij,1} & 0 & 0 & \cdots & 0 \\
a_{ij,2} & a_{ij,1} & 0 & & 0 \\
a_{ij,3} & a_{ij,2} & a_{ij,1} & \ddots & 0 \\
\vdots & \vdots & \vdots & & 0 \\
a_{ij,M} & a_{ij,M-1} & a_{ij,M-2} & & a_{ij,1} \\
\vdots & \vdots & \vdots & & \vdots \\
a_{ij,P} & a_{ij,P-1} & a_{ij,P-2} & \cdots & a_{ij,P-M+1}
\end{bmatrix}_{P\times M} \qquad (9)
$$

A closed form solution of “(7)” for unconstraint systems following unconstrained multivariable DMC control law:

$$
\Delta\bar{u} = (A^T \Gamma^T \Gamma A + \Lambda^T \Lambda)^{-1} A^T \Gamma^T \Gamma \bar{e} \qquad (10)
$$

$\Gamma^T \Gamma$ is the $PR \times PR$ controlled variable weights matrix which has leading diagonal elements as $\gamma_i^2, (i = 1, 2, \ldots, R)$ and off diagonal elements are zero. $\Lambda^T \Lambda$ is the square diagonal matrix of dimensions $MS \times MS$ and its leading diagonal elements are move suppression coefficient ($\lambda_i^2, (i = 1, 2, \ldots, S)$). Solving equation (7) for constrained DMC or equation (10) for unconstrained systems controller output vector moves is computed over the control horizon:

$$
\Delta\bar{u} = \begin{bmatrix}
\Delta u_1(n) \\
\Delta u_1(n+1) \\
\vdots \\
\Delta u_1(n+M-1) \\
\Delta u_2(n) \\
\Delta u_2(n+1) \\
\vdots \\
\Delta u_2(n+M-1)
\end{bmatrix}_{2M\times 1} \qquad (11)
$$

Similar to GPCI method in implementation of the DMC for a process, disturbance profile should be added as correction factor of difference between current values of process value and predicted process value in present sample. Only the first element of the controller output vector is implemented and the entire computation procedure is repeated at each sample.

There are various tuning strategies for DMC, two of the most popular tuning methods are; 1) Smith method which using first order plus dead time model (FOPDT) and variance analysis affect of each parameters on proposed cost function evaluated and finally reached the closed formula (Iglesias, et. al, 2006); 2) Cooper method in which using presented FOPDT model first the value of the suppression coefficient is normalized with respect to DC gain of model and the after some algebraic operations the closed formula is extracted for optimal value of λ (Shridhar, et.

al, 1998). The goal of this paper is presentation of practical effective, easy to understand and simply implementable control strategy so the cooper method is chosen as tuning method. Step by step guideline for determining the tuning parameters for multivariable DMC are as following:

- Approximate FOPDT models for each pair of controller output\measured process variable:

Sample time should chosen close to

$$T = Min(T_{rs} = Max\,(0.1\tau_{rs}, 0.5\theta_{rs}))$$
$$(r = 1,\ldots,R;\; s = 1,\ldots,S)$$

Compute prediction horizon, P, model horizon, N, control horizon ,M

$$P = N = Max\,(\frac{5\tau_{rs}}{T} + k_{rs}) \qquad k_{rs} = (\frac{\theta_{rs}}{T} + 1)$$
$$M = Max\,(\frac{\tau_{rs}}{T} + k_{rs}) \qquad (r = 1,\ldots,R;\; s = 1,\ldots,S)$$

- Select controlled value weights γ_r^2
- Compute move suppression coefficient

$$\lambda_s^2 = \frac{M}{10}\sum_{r=1}^{R}\left[\gamma_r^2 K_{rs}^2\left\{P - k_{rs} - \frac{3}{2}\frac{\tau_{rs}}{T} + 2 - \frac{M-1}{2}\right\}\right]$$

3. REAL TIME SOFT ANALYZER

Designing efficient monitoring tools is the first step toward precise automation of industrial processes (Corona, et. al, 2012). The majority of control executions suffer from noise and many of them present poor performance or even are useless because of low values of signal to noise ratio. Shamsaddinlou (2013b) concluded that a type of proposed supervisors of MMPC could not be used because of the hard and strong noises have negative effect on small signals that pass from filters and used in computational part of supervisor.

Delay is inseparable component of processes so that high number of chemical and industrial processes often can be characterized by delays. The systems which are stable without delays have the maximal range of delay that preserves stability. The estimation of effective number of time delay for process variables is the first step in real time identification and control. There are numerous methods of delay estimations in literatures. In the step response method for delay estimation (Ahmed, et. al, 2006), the efficient delay is estimated by measuring the time-delay in the rising part of the step response of the system. Despite simplicity of this method in estimation of most effective delay without need to rich data of process behaviour but some of disadvantages limited use of step response method; 1) resolution of the results is affected by the output signal sample time 2) can be used only in proper high signal-to-noise ratio (SNR) step signals 3) performing this test is not possible for most closed loop process 4) Results are highly related to visual inspection of the operator to recognize the efficient time delay.

Generally Lipschitz number method is used in input-output order estimation of nonlinear systems. Prospering use of this method extended to delay estimation in (He, et. al, 1993). Prominent advantages of this method which made it applicable in real implementations are its independency to the sampling time and ability to be used in low SNR signals. Considering model $f(x)$ is Lipschitz and (x_i, y_i) as a input-output pair, the Lipschitz quotient is:

$$q_{ij}^{(n)} = \frac{|y_i - y_j|}{\|x_i - y_j\|_2}, (i \neq j) \qquad (12)$$

$q^{(n)}(k)$ is the kth largest Lipschitz quotient among all q_{ij}^{n} calculated for n input variables. The Lipschitz number will increased considerably if delayed variable excluded from x so gives numerical inspection of the time delay.

The soft sensor which forms measurement section of self tuning method designed based on nonlinear model with one MLP structure. 12 hidden neuron numbers (HNN) has been selected by semi cross validation technique in which model response accuracy is investigated for validation data set. During training phase mean square error between network error and output error iteratively adjusted. The LM algorithm selected as training algorithm which is well-known for its fast convergence and small residual error. The pseudo random binary sequence (PRBS) signal is used in order to have full exciting dataset for identification purpose. A band-pass filter H_{bp} is used to filter out the low and high frequency components and noises from the identification data used in the soft sensor.

4. MODEL IDENTIFICATION USING SOM NETWORK

In non-self tuning and manual tuning control strategy there are many parameters which can be tuned and in the same time have direct affect on system stability and performance. In systems with variable operating conditions if these parameters stay in fix value, the control will be degrade or even unstable. Here automatic generation of process models using the RLS method based on Kohonen's self-organizing map (SOM) neural networks for models with first order ARX structure presented. Indeed explicit self tuning control is duty of this section. According to SOM transformation of an incoming signal to lower dimension preserves topological neighbourhood. In the SOM network each input vector, ψ_k , has a reference vector , $w_{i,k}$, which have the best match on it. Training of SOM is done using best matching of reference vector and input vectors:

$$i = \arg\min_i \left|\psi_k - w_{i,k}\right| \qquad (13)$$

The best matching node and its neighbours in the certain geometric distance will learn from the activating input vector therefore trained SOM in the regions where more input vectors existed will have more nodes. Since proportional to identification data of each operation region number of required models in each region determined therefore to have equal attention to each operating region equal identification time is considered for each region. In model generation using SOM, the ARX models parameters $[a_0,\ldots,a_{n-1},b_0,\ldots,b_{n-1}]$ which are identified using RLS are considered as input vector. Therefore reference vector $w_{i,k}$ shows the parameters of i^{th} model. Overall procedure of considered system identification using SOM is; 1) Plant is excited by a suitable enough persistently excitation (PE) input sequence. A random binary signal (RBS) pattern was used as the identification input 2) Process Data which are passed through High-Pass filter is given to RLS 3) RLS Data is given to SOM network 4) Using two dimensional SOM parameters are clustered 5) Using statistical properties of the input data SOM compute the relative values and model parameters of each operation region.

5. PRINCIPALS OF ADAPTIVE MULTIPLE MODEL PREDICTIVE CONTROL

In this paper, Adaptive Multiple Model Predictive Control (AMMPC) strategy (Dougherty, et. al, 2003) used as implicit self tuning controller for estimation of controller parameters. The basic idea behind the MMPC (Lupu, et. al, 2008) is to choose the best model, describing the current dynamics of operation of the process from pre-designed model data based on numerical criterion, and finally selection and placing its corresponding controller in the feedback loop. Multiple-model based control strategy formed from 3 major parts. The first part is model bank which is most important part in multiple model control and affect directly on all design procedure. The second part is the control design strategy which is based on MPC. The last section is decision making unit which orchestrates the model\ controller operations in feedback loop.

Increasing richness of the model bank results in more efficient control strategy. Each model in the bank determines the designer consideration about that new condition of the process but selection of number of models which are describing dynamics of plant and should be put in the bank to cover all different operating modes is a critical problem. There is some kind of trade off in arranging models in model bank; since all operating points are not known a priori, one solution is increasing the number of members of model bank members but this solution can cause some problem like intensifying computational burden, excessive numbers of switching and deterioration of the performance of the control system (Li, et. al, 1996). In the other hand model bank with low numbers of models can be imprecise, and the control system leads to a low performance for unpredicted conditions. Therefore determination of the model bank is a difficult, imperative and time consuming problem. There are various methods in separating whole operation region, such as Self-Organizing Map (SOM) neural network and gap metric methods (Galán, et. al, 2003). The goal of this paper is presentation of fully automatic control strategy from identification of process to controlling it. Therefore in order to model bank generation Kohonen's self-organizing map (SOM) neural networks is used.

In (Luo, et. al, 2006), supervisor for switching MMPC (SMMPC) designed so that gets the difference between of predicted outputs the models, $\hat{y}$, and real-time soft analyzer output of the process, $\bar{y}$, which is passed through high pass filter, and calculates predictive prediction error performance indexes (PPI):

$$J_S(t) = \alpha e_S^2 + \beta \sum_{k=1}^{M} \gamma^k e_S^2(t-k) + \Omega \sum_{r=1}^{T} \zeta^r e_p^2(t+1) \qquad (14)$$
$$\alpha, \beta, M, \Omega, T > 0 \ , \ 0 < \gamma \le 1, 0 < \zeta \le 1, s \in [1, Z]$$

where α, β, Ω, M are free-design parameters, γ and ζ are forget factors, T is chosen in some range of prediction horizon $0 < T < prediction\,horizon$, Z is number of model, and $e_p = y_p - y_d$, y_p is predicted output in prediction horizon and y_d is a desired output. The supervisor calculates $\bar{J} = \min_i \{J_i\}$ and $l = \arg\min\{J_i\}$, $i = [1, Z-1]$ at each sampling time. To limit hard switching speed, a hysteresis cycle gain h_1 is used. The previous model will be changed if $J_B < h_1 J_A$, Subscripts 'A' and 'B' point to the current active model and the current best model respectively.

Depends on type of the process and control execution expectancy free design parameters are selected. Higher values for $\alpha, \beta, \zeta, \Omega$ parameters and in the same time small values of M, T, h_1 result in fast global controller but with low performance, and they make the overall system sensitive to measurement noise. The further feature of this type of supervisors is that the integral characteristic of the performance index and hysteresis cycles, decrease the effect of measurement noise. The schematic diagram of proposed STAMMPC is presented in Fig. 1.

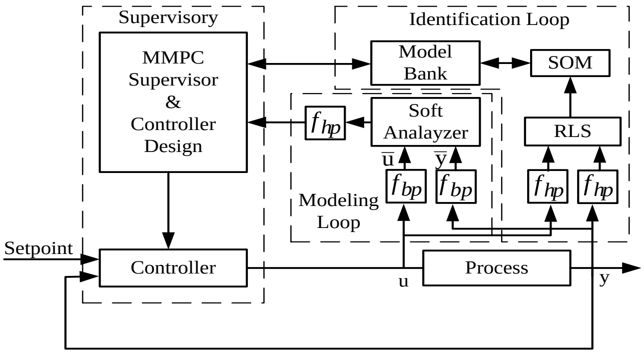


Fig . 1. Schematic diagram of STAMMPC

6. DISTURBANCE REJECTION SUPERVISOR

In process control the major source of excitations are disturbances because setpoints change rarely (Hägglund, et. al, 2000). The procedure of excitation of disturbance can be divided for two phase. In the first phase the disturbance changes the output and in this phase identification of models using SOM should released because there is not any rational relation between inputs and outputs and system works in worse case. In the second the controller compasses the system and there are meaningful between the input and the output data which are useful for identification and SOM is on in this period. So in automatic control the correct identification of process depends on to detect when a load disturbance occurs. From productivity point of view controllers with high rate of disturbance rejection have excellence to the others so estimating the disturbance is vital for performance preservation.

A practical idea for detection of disturbance occurrence instance is the sign of $u_f y_f$ (Kaminskas, et. al, 2006). In this method considering y_f and u_f as filtered soft sensor output and input, assuming the system is positive definite gain, the positive sign of $u_f y_f$ demonstrates the set-point change and negative value means disturbance has been occurred. The supervisor should restrict the use of the tuning mode until period of time. Throughout this period, adjusting of the SOM model is not allowed until condition meet to the end. In the second period adaptation is starts when the excitation is suitable, For chattering free disturbance rejection supervisor, hysteresis factor h_d is chosen such that if $|u_f y_f| \ge h_d$ then sign of it will be checked. In this way the noise effects will weaken in a large extent. In some conditions the deviation from set-point is large, slowest model and its corresponding fastest controller chosen in these conditions to force the output to settle rapidly. This deviation can be calculated from following formula:

$$J_{Dis}(t) = \sum_{k=1}^{L} \left|(y(t-k) - y_d(t-k)\right| \qquad (15)$$

In “(4)” y is the output of the process and y_d is the reference or desired output and L is the memory of the Disturbance index respectively. If $J_{Dis}(t) > h_2$, the fastest controller in bank located in loop. Fig. 2 shows disturbance rejection supervisor for AMMPC. The flowchart of novel disturbance rejection supervisor for STAMMPC is presented in Fig. 3.

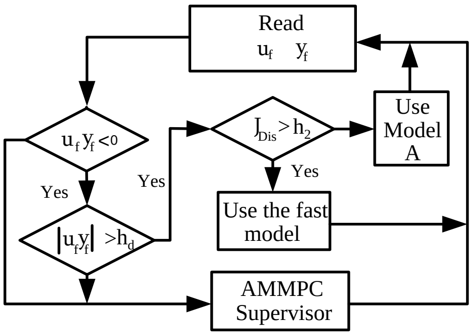


Fig. 2. Disturbance Rejection supervisor of AMMPC

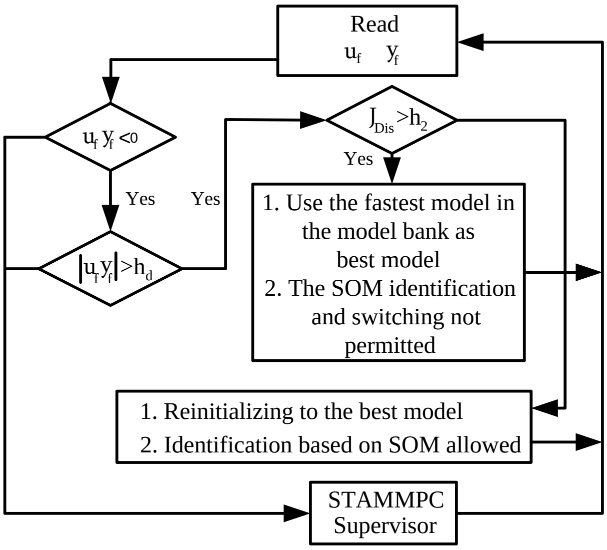


Fig. 3. Disturbance Rejection supervisor of AMMPC

7. EXPRIMENTAL RESULTS

In this section, a typical multivariable pH process (Hall, et. al, 1989), is described in some details and important properties of that is explored using system identification tests. After that the laboratory scale pH neutralization pilot plant presented. Finally the implementation considerations of STAMMPC method are explained and applied to the pH pilot plant and compared with each other.

7.1 pH Process Description

pH is the measurement of the activity of the hydrogen ion in a solution and mathematically pH is the negative logarithm of the hydrogen ion of the solution, $pH = -\log_{10}[H^+]$. Static chemical equation of a multivariable pH process is:

$$\left[H^+\right]^4 + \left[H^+\right]^3 (k_{a1} - w_b) + \left[H^+\right]^2 (k_{a1}(k_{a2} - w_a - w_b)) +$$
$$+ \left[H^+\right](-k_{a1}(k_w + k_{a2}(w_a + 2w_b))) - (k_{a1}k_{a2}k_w) = 0 \qquad (16)$$

where $[H^+]$ is hydrogen ion concentration, w_a is acid stream flow and w_b is base stream flow inlet to the CSTR and relationship between them expressed as titration function, definition of other parameters can be found in (Nie, et. al, 1996). Two-by-Two pH process considered here in which acid and base streams are system inputs and pH and level of solution in CSTR are system output. The dynamic chemical equations of the ph neutralization pilot plant are:

$$pH = -\log_{10}\left[H^+\right]$$
$$\frac{dh}{dt} = \frac{1}{A}\left(-C_\upsilon\sqrt{h} + F_a + F_b + F_{bf}\right) \quad (17)$$
$$\frac{dw_a}{dt} = \frac{1}{Ah}\left((w_{aa} - w_a)F_a + (w_{ba} - w_a)F_b + (w_{bfa} - w_a)F_{bf}\right)$$
$$\frac{dw_b}{dt} = \frac{1}{Ah}\left((w_{ab} - w_b)F_a + (w_{bb} - w_b)F_b + (w_{bfb} - w_b)F_{bf}\right)$$

In this structure of multivariable pH process decoupling of outputs is possible if the suitable type of controllers is designed. The First Order Pulse Dead Time (FOPDT) linear model of pH plant at each operating points is:

$$pH = \frac{a_{11}}{z-b_1}Acid + \frac{a_{12}}{z-b_1}Base + \frac{a_{13}}{z-b_1}Buffer$$
$$h = \frac{a_{21}}{z-b_2}Acid + \frac{a_{22}}{z-b_2}Base + \frac{a_{23}}{z-b_2}Buffer \quad (18)$$

Since each of inlet streams have identical affect on level of CSTR so $a_{21} = a_{22} = a_{23}$. In the fixed level of solution, variations of pH extremely affects on the $a_{11} = a_{12} = a_{13}$ while small changes take place in $a_{21} = a_{22} = a_{23}, b_1, b_2$. Unlike constant level value, in fixed pH, level changes only affect on time constant of the process b_1 and other values have small changes.

7.2 Experimental pH Neutralization Process

The experimental implementation of the proposed advanced control strategies are accomplished at APAC research group of K.N.Toosi University of Technology using a continuous pH neutralization pilot plant (Fig. 4). It formed from a continuous stirred tank reactor (CSTR) with a manual valve in bottom which directly affects delay and model parameters of the process and a motorized mixer on top to blend the component of CSTR. A pH sensor is located in middle of the CSTR. The level of solution measured trough a diaphragm level transmitter which is located in the bed of CSTR. Using two precise dosing pumps acid and base which are held in tanks pumped into the CSTR. The control objective is to regulation in different pH values and keeping the pH in neutrality in the presence of unmeasured and intentional disturbances for evaluating the abilities of controllers. A PLC S7-315 is considered for data acquisition and communicates with advanced controller in computer using profibus protocol. The real time soft analyzer, SOM neural network and advanced controller are performed by MATLAB software. The control system can be enhanced by correct selection of pH sensor and inlet and outlet streams locations. The operating conditions of components of pilot are presented in Table 1.

Table 1. pH pilot plant Parameters setting

Parameter		Operating value
CSTR	Cross area	78.2 cm2
	height	25 cm
Acid concentration		80 mlit /30 lit city tab water
Base concentration		84 mlit /30 lit city tab water
Acid flow rate (f_a)		36 mlit/min
Base flow rate (f_b)		48 mlit/min

Titration reagents of pilot plant are aquatic solution of acid acetic which is a weak acid and sodium hydroxide a strong base. No buffer stream is considered in this process, so the dynamics of system is highly sensitive especially in operation range of $pH = [7.8, 8.4]$. Therefore the FOPDT model of pilot plant in each operation condition and a model of the system according to identification test in $ph = 7\ \&\ h = 12cm$ are:

$$\begin{bmatrix} pH \\ Level \end{bmatrix} = G(z) \begin{bmatrix} Acid \\ Base \end{bmatrix} = \begin{bmatrix} g_{11}(z) & g_{12}(z) \\ g_{21}(z) & g_{22}(z) \end{bmatrix} \begin{bmatrix} Acid \\ Base \end{bmatrix}$$

$$\begin{matrix} ph=7 \\ h=12 \end{matrix} \rightarrow G(z) = \begin{bmatrix} \dfrac{-0.47}{z-0.9} & \dfrac{-0.45}{z-0.9} \\ \dfrac{0.063}{z-0.937} & \dfrac{0.063}{z-0.937} \end{bmatrix} \qquad (19)$$

Figs. 5-A and 5-B presents the titration curve and variation of static gain of pilot plant in various operating points of pH solution in the batch form. It shows that the highest static gain is at region of pH= [7.8, 8.1] and is about 24. Highest chemical buffering which lead to the lowest static gain take place in pH= [4,4.5] and pH=[11.3,12] is 0.22. Thus, in the whole operating point the static gain of the process changes 109 times.

Fig. 4. Laboratory scale pH Pilot Plant

The pH pilot process is subject to various sources of unpredictable disturbances such as; 1) the city tab water which is used in dilution of acid and base in the tanks is not neutral and its pH value changes in the range of [7.3-7.9]; 2) CO_2 absorption of sodium hydroxide from ambient which detract the alkaline specification of base reagent and cause unwanted buffering effect; 3) imperfect mixing of solution create inevitably changes in pH pilot value.

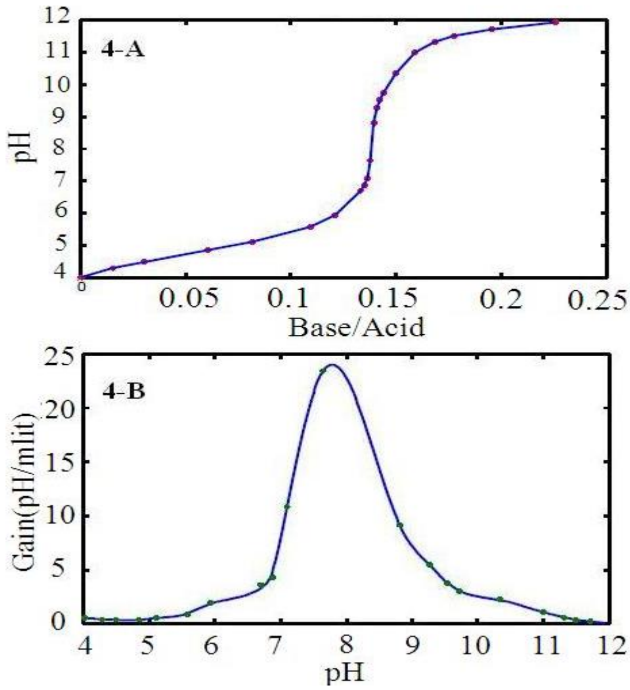


Fig. 5. 5-A Titration cure, 5-B Static gain.

In addition to the immeasurable disturbances the pH pilot plant suffers from suffer from hard noises and in some regions imposed to the noises up to 5% of the process pH value. Main noise generating sources are Mixer, sensor and pumps. Globally there are two methods for decreasing the noises effects. One solution is locating the pH sensor after the CSTR outlet valve to measure effluent stream. In this way the noise affects of mixer and pumps considerably reduced but the large value of delay would be added to the system and the system dynamics extremely will be dependent on output valve situation. Another method is using real time soft analyzer which after learning of the system dynamic can generate the pH values without noise effects. In this paper real time soft analyzer based on multi layer perceptron is designed and implemented in the structure of automatic control strategy.

7.3 Self Tuning Adaptive Multiple Model Predictive Control Implementation on pH Pilot Plant

In this section the step by step design procedure of STAMMPC and different scenarios for evaluation of this advanced controller on the laboratory scale pH neutralization process is presented. Schematic of the proposed self tuning automatic method is shown in Fig. 6. The innovation of this paper is integration and unification of various automation concepts in the cast of self tuning automatic AMMPC.

7.3.1 Soft Sensor Design

High amplitudes of noise deteriorate the control performance and even make instablility especially in processes with extreme sensitivity such as pH process. Here a soft analyzer using neural networks is designed for reduction of noises affects in the pilot plant. Lipschitz number method is used to delay estimation. According to this method delay of streams with respect to plant outputs are:

$$\text{Acid Stream Delay for } \begin{cases} pH = 55 \text{ Sec} \\ Level = 25 \text{ Sec} \end{cases}$$

$$\text{Base Stream Delay for } \begin{cases} pH = 50 \text{ Sec} \\ Level = 25 \text{ Sec} \end{cases}$$

One layer MLP is used for nonlinear modeling and estimation of output values. Based on semi cross validation technique 12 optimal HNN is selected. The training algorithm of LM is used for fast convergence. In order to generation of rich data base for identification, the PRBS signal introduced to the process. Validation of designed soft sensor model performance has been done trough validation figure is shown in the Fig. 7., where normal probability plot is visually monitored. As demonstrated the residual characteristics are similar to Gaussian noise characteristics in the projection of it depicted to negative values, which means the model response error is as the result of the process noise and designed nonlinear model have a good estimation of desired process.

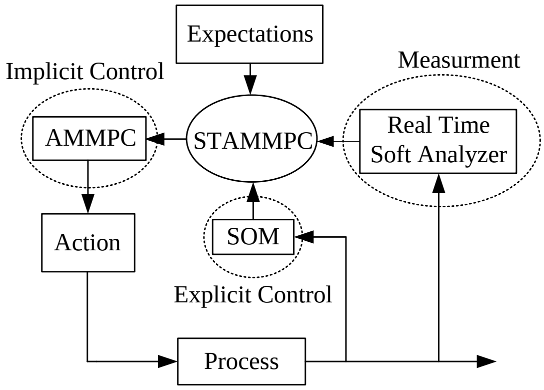


Fig. 6. Schematic of self tuning automatic controller

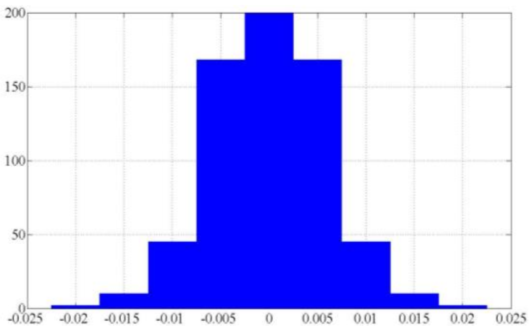


Fig. 7. Schematic of Self tuning automatic controller

7.3.2 Identification Using SOM

Two dimensional SOM is used to extract the statistical features of online identification data which are produced by the RLS. Plant exited by random binary signal (RBS) as identification input in various level of solution in CSTR. In this paper the level changes considered in the range of [10cm-20cm]. Estimated parameters of the ARX are input vector. Relative values of the SOM distributed across the input space and identification data in each region specify the number of models in that region. Except in the region pH=8, which process have high degree of sensitivity and its interval time is 3/2 others, in going regions equal weight is given for each region so the same interval time is used in each operation region. The U-Matrix (Kraaijveld, et. al, 1992) of trained SOM for level=16cm is presented in Fig. 8.

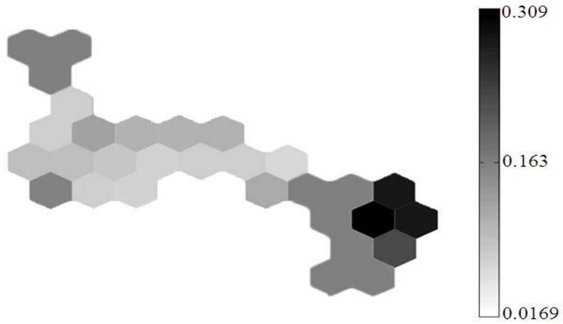


Fig. 8. U-Matrix of network, level=16

7.3.3 Self Tuning Controller Design

Basic controllers of proposed STAMMPC strategy are GPCI and DMC which are inherently robust and also are the most popular process control method. The robustness of each local controller guarantees the close loop stability in global region (Narendra, et. al, 1997). Breaking down of operation regions and using more linear controller, the better adaptive controller will perform but there is no theoretical guide which show how many models should be considered to reach to the optimal performance (Yu, et. al, 1992). Here model bank generated using SOM and total 35 models are selected by that to describe the whole operation range of pH pilot plant.

An expansion of tuning of DMC method for multiple model case is built on formal tuning rule and DMC move calculation. In this method each controller has its own model based predictor and optimizer. Implementation begins with identification of first order models by SOM and delays estimated by Lipschitz operator of soft analyzer. Therefore the FOPDT models for s^{th} controller output and r^{th} measured process values generated. The FOPDT models are used in the tuning correlations as following:

- Smallest Sample time should chosen:

$$T_{rs} = Min(T_{rsl} = Max\,(0.1\tau_{rsl}, 0.5\theta_{rsl}))$$
$$(r = 1,\ldots,R;\ s = 1,\ldots,S, l = 1,\ldots,35)$$

- P, N, M are selected long enough to capture slowest dynamics so like single model DMC.
- The weights considered equal to one, $\gamma_r^2 = 1$
- move suppression coefficient computed on overall control horizon

$$\lambda_{sl}^2 = \frac{M}{10}\sum_{r=1}^{R}\left[\gamma_{rl}^2 K_{rsl}^2 \left\{P - k_{rsl} - \frac{3}{2}\frac{\tau_{rsl}}{T} + 2 - \frac{M-1}{2}\right\}\right]$$

According to identification tests it is determined that base and acid have similar affects on pH value so weighting matrix arrays should be same $R = diag(1,1)$ in GPCI method. Output and control horizons respectively considered $n_y = 35$, $n_u = 6$. Like DMC method the smallest sample time as a sampling time of system should be chosen in multiple model based on GPCI, $T = Min(T_{rsl} = Max\,(0.1\tau_{rsl}, 0.5\theta_{rsl}))$, $(r = 1,\ldots,R;\ s = 1,\ldots,S, l = 1,\ldots,35)$.

Experimental tests show that the range of nonlinearity in the level output is negligible in other hand there is partial changes in poles of models in pH output. Therefore in order to simplification of identification procedure these parameters are considered to be constant for whole operation range:

$$G(z) = \begin{bmatrix} \frac{a}{z-0.9} & \frac{b}{z-0.9} \\ \frac{0.063}{z-0.937} & \frac{0.063}{z-0.937} \end{bmatrix} \qquad (20)$$

Now the only parameter that should be tuned is Q. Since the level output models are fixed, so the second array of Q must be firm. Using try and error proper value of 3 has obtained, $Q = [q_1, 3]$. Formula which is considered for automatic calculation of q_1 based on static gain of each model is $q_1 = \frac{\text{Static Gain}}{8} + 3$. The parameters of h_2, h_d, L are chosen to have same value for disturbance supervisors, $h_2 = 0.80$, $h_d = 0.07$, $L = 4$.The suggested supervisor parameters are shown in Table 2.

Table 2. Controllers supervisors parameters, AMMPC +DMC+Dist Sup=AMMPC based on DMC and in the presence of disturbance rejection supervisor

Parameter	α	β	M	γ	T	Ω	ζ	h_1
AMMPC +DMC	.80	.80	15	.95	12	.60	.93	.95
AMMPC + GPCI	.85	.80	12	.96	12	.60	.90	.95
AMMPC + DMC +Dist Sup	.85	.80	10	.93	8	.80	.95	.90
AMMPC +GPCI +Dist Sup	.75	.90	14	.97	8	.70	.90	.90
STAMMPC+ DMC	.85	.85	10	.95	10	.60	.95	.92
STAMMPC + GPCI	.80	.75	8	.95	10	.60	.95	.92
STAMMPC+ DMC +Dist Sup	.95	.95	10	.98	14	.80	.9	.80
STAMMPC+ GPCI +Dist Sup	.9	.90	18	.98	12	.80	.9	.80

In order to evaluation of the proposed method, two regulating tests with small set point and large set point changes and one disturbance rejection test for acid and base changes are supposed. The reference input can be given to the system several samples in advance. This future programming of set point of predictive control method compensates the delay. Fig. 9. shows the regulation of STAMMPC based on GPCI, AMMPC based on GPCI and single GPCI method for small changes in setpoint. Fig. 10. presents tracking of large changes in setpoint using STAMMPC based on DMC, AMMPC based on DMC and single DMC method. AMMPC controller is designed using three fixed model in three operating regions of pH=5, pH=6.5, pH=8. It can be seen from these figures that STAMMPC has better performance than others in control of pH channel but the level channel response is good and similar in all of the methods. The control strategies results are compared to each other in Table 3. In order to compare the results from different points of view two methods of mean square error (MSE) and mean absolute percentage error (MPAE (%))are used.

In second scenario disturbance rejection capability of controllers deliberated. Pump flow rate (f_a) of acid stream changed from nominal value of 36 mlit/min to 15 mlit/min and then to 48 mlit/min. Disturbance rejection in the presence and absence of disturbance rejection supervisor for STAMMPC and conventional AMMPC are shown in Fig. 11. and Fig. 12. Again, STAMMPC has the best performance. It is obvious that both of the MM methods have most excellent performance in comparison to single DMC or GPCI control strategies. Table 3 presents the performance measure for all of the methods during disturbance rejection. As a result, we can say that STAMMPC especially in the presence of disturbance rejection supervisor improve the performance of controller significantly.

Table 3. Numerical results of controllers in pH Channel, * Shows presence of disturbance rejection supervisor

Test	Method	MSE	MAPE(%)
Regulating of small changes in set-point	Single DMC	0.1824	3.8906
	Single GPCI	0.1975	4.2812
	AMMPC using DMC	0.0166	2.071
	AMMPC using GPCI	0.0127	1.9020
	STAMMPC using DMC	0.0102	1.3379
	STAMMPC using GPCI	0.0112	1.5272
Regulating of large changes in set-point	Single DMC	0.5134	7.6849
	Single GPCI	0.6454	9.078
	AMMPC using DMC	0.0708	3.1369
	AMMPC using GPCI	0.0835	3.6388
	STAMMPC using DMC	0.0413	1.7890
	STAMMPC using GPCI	0.0386	1.5916
Acid flow Disturbance rejection	Single DMC	0.4287	11.6784
	Single GPCI	0.4227	17.0522
	AMMPC using DMC*	0.0176	0.5470
	AMMPC using GPCI*	0.0160	0.7751
	STAMMPC using DMC*	0.0045	0.4000
	STAMMPC using GPCI*	0.0070	0.4790

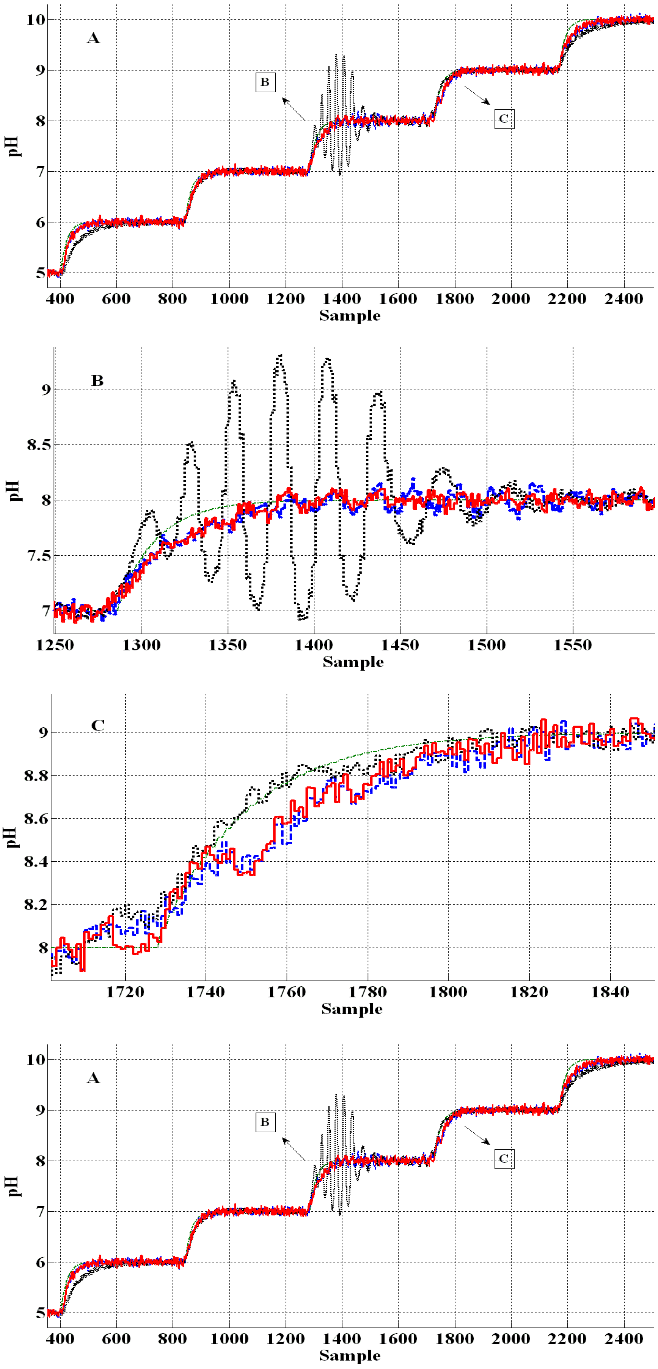
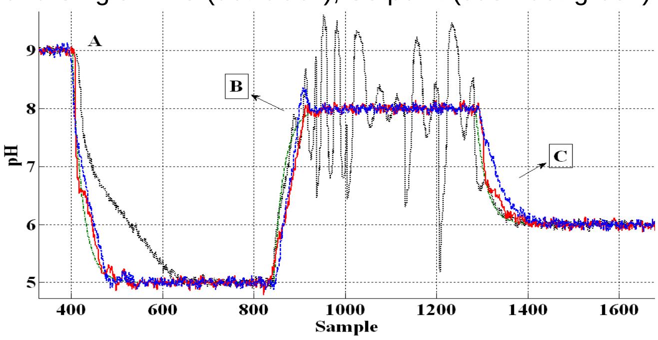


Fig. 9. Regulation of small changes in setpoint, STAMMPC using DMC (solid-red), AMMPC using DMC (dash-blue) and Single DMC (dot-black), Setpoint (dash-dot-green)



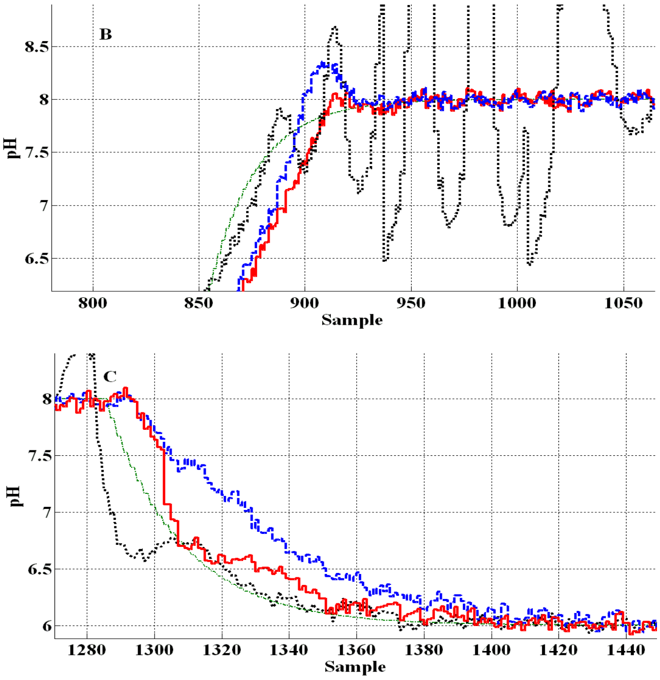


Fig. 10. Regulation of large changes in setpoint, STAMMPC using GPCI (solid-red), AMMPC using GPCI (dash-blue) and Single GPCI (dot-black), Setpoint (dash-dot-green)

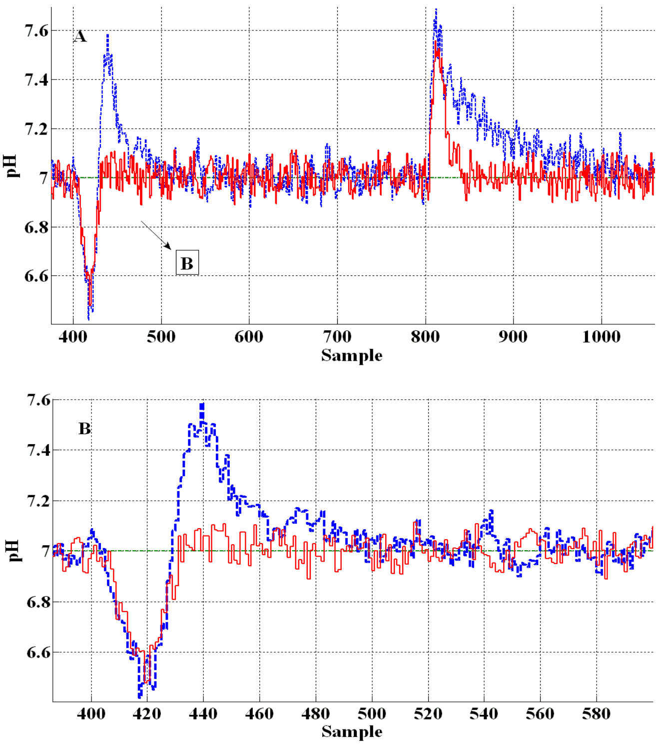


Fig. 11. Disturbance rejection of acid stream flow rate, STAMMPC using DMC (solid-red), AMMPC using DMC (dash-blue) , Setpoint (dash-dot-green)

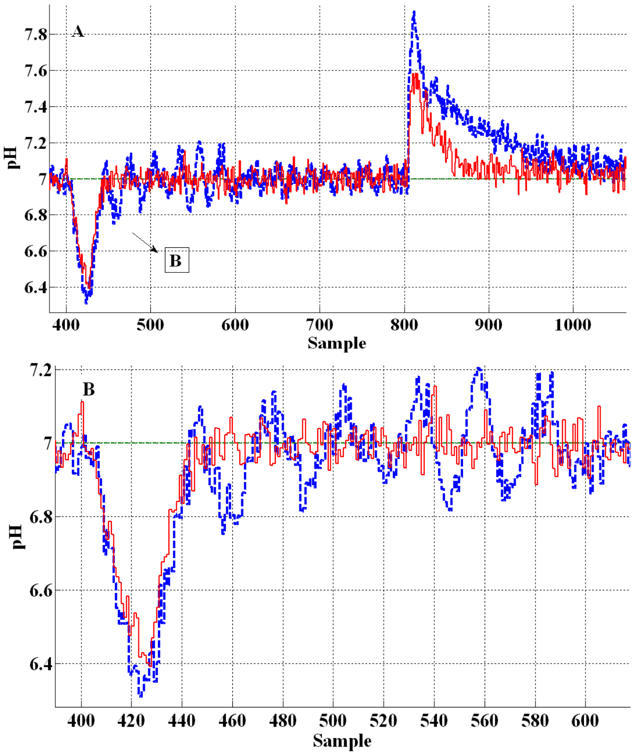


Fig. 12. Disturbance rejection of acid stream flow rate, STAMMPC using GPCI (solid-red), AMMPC using GPCI (dash-blue) , Setpoint (dash-dot-green)

8. CONSLUSIONS

Self tuning adaptive multiple model predictive control strategy successfully designed and implemented on a pH pilot plan. The presented self tuning automatic control strategy prepared a theme in which the operator only set the supervisor parameters and all of the rest of control executions like nonlinear modelling of plant, model bank generation, model identification for each region and controller design will be tuned and done automatically. Since all the local controllers are stable and robust in their own working point the stability and robustness of global control is guaranteed in whole of operation range.

Some advantages of STAMMPC are; 1) Increasing the control quality by optimizing internal running parameters which resulted in outperforming the traditional AMMPC methods performance from both of the regulation and disturbance rejection viewpoints 2) Simple to use and understand for non occupational operators and non professional personnel 3) Facilitates design unification 4) Lowers the instrumentation requirements by designing an optimized soft sensor 5) Shortens the testing and tuning time of personnel 6) Simply can be generalized to the other control methods.

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