Multiple-Model Control of pH Neutralization Plant Using the SOM Neural Networks

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Abstract: A multiple-model adaptive controller is developed using the Self-Organizing Map (SOM) neural network. The considered controller which we name it as Multiple Controller via SOM (MCSOM) is evaluated on the pH neutralization plant. An improved switching algorithm based on excitation level of plant has also been suggested for systems with noisy environments. Identification of pH plant using SOM is discussed and performance of the multiple-model controller is compared to the Self Tuning Regulator (STR) controller.

I. INTRODUCTION

There are many industrial processes which their nonlinear behavior cannot be modeled and controlled by a single mathematical model at least in their full operating range. Various solutions for controlling these systems have been suggested over past decades. Robust and adaptive control is two major approaches toward solving this problem. But these techniques can become quite restrictive in many applications. A more recent approach is the concept of multiple models along with a switching algorithm [1] which has been an area of interest in control theory in order to simplify both the modeling and controller design. Many global controller designs with the aid of multiple models have been reported on different applications [2,3]. Narendra et al. [4] suggested an adaptive MM structure with switching based on a performance function. The key idea to this approach is the ability to approximate the behavior of nonlinear processes within a predefined neighborhood of operating point with a relatively simple linear model with a desired accuracy. By repeating this job in different key operating points of the nonlinear process, a bank of linear models can be created with each model corresponding to one of the operating points. A switching algorithm between these models then should be used to find and select the best approximation of the nonlinear process from this bank as fast and as accurate as possible.

In this paper, a multi-model adaptive strategy with pole placement controllers is considered. Models have the same structure but parameter values are different for each model. To identify the bank of model, the multiple modeling using self-organizing map (MMSOM) [5] is applied to the input output data of the plant. Kohonen’s self-organizing map (SOM) neural networks [6] is used in this algorithm to automatically assign parameters of models in the model bank based on the clustering of identification data from the RLS method. An improved switching algorithm is used to find the best representing model from the generated bank of models. Parameters of the best model are then used in pole placement algorithm to generate the control signal in each cycle. The closed loop stability of the considered control structure is guaranteed [7].

The paper is organized as follows: First, multiple model control strategy is described. A brief description of SOM and its application on MMSOM in generation of model bank is presented in section 3. Simulation results from implementing the described control strategy on a simulated pH neutralization process are presented in section 4 and the paper is concluded in the final section.

II. CONTROL BASED ON MULTIPLE MODELS

A general diagram of the closed loop system is shown in Fig.1. In this approach the understudy nonlinear system will be approximated by a set of linear models which will form a bank of models. The model which best suits the actual system’s behavior will then be searched for in each cycle. For this purpose a performance index is defined based on estimation errors of models. The performance index is given by:

\[ J_i(t) = \alpha e_i^2(t) + \beta \sum_{k=1}^{M} e^{-\lambda (t-k) }e_i^2(t-k) \]

\[ \alpha, \beta > 0, 0 < \lambda \leq 1 \]

\(M > 1\) are three weighting constants and determines the range of effective past data. Relative value of \(\alpha, \beta\) weights the instantaneous and old estimation errors of models and \(\lambda\) is used as a forgetting factor for the past errors. In this manner the model corresponding to the lowest \(J_i\) will be the best describing model at the time \(t\). In order to avoid fast and unnecessary switches, a hysteresis function is added to the switching condition. The switch occurs only if
the performance index for the in-loop model \( J_{\text{in-loop}} \) and new best model \( J_{\text{min}} \) satisfy the condition below:

\[
J_{\text{min}} < \delta J_{\text{in-loop}}
\]  

(2)

where \( \delta \) is an arbitrary constant. This function will block fast switches between models and will decrease the unnecessary switches. But in the presence of measurement noise in the system this condition will not suffice and another complementary condition is introduced in this paper to properly eliminate the remaining unwanted switches which can force oscillations in the system response.

The proposed complementary condition is based on the excitation level of the process and will add a condition to check the level of excitation. The basic idea is to not to allow a switch between models if system is in steady state and is not excited by input. The level of excitation of process is measured using the method proposed by Hugglund et al. [8] using a high pass filter. A predefined threshold will then be used to indicate the required level of excitation in order to allow a switch between the models. This threshold should be selected according to the existing noise characteristics. Care must be taken when introducing this condition to the switching algorithm as high values for this threshold will bring unnecessary delays into the switching algorithm and therefore can make the closed loop system to oscillate and even become unstable.

Note 1: A band-pass filter \( H_f \) is used to filter out the low and high frequency components from the identification data used in the adaptive estimator block [9]. Also, a high-pass filter \( H_{hp} \) is used to impose excitation condition on the switching states.

FIG.1 – GENERAL DIAGRAM OF CONSIDERED MULTIPLE MODEL STRUCTURE

III. MULTIPLE MODELING BY SELF-ORGANIZING MAP

Kohonen [6] developed the SOM with the ability to transform an incoming signal of arbitrary dimension into a lower dimensional discrete representation preserving topological neighborhoods. The SOM network has an input vector \( \psi_k \) with an arbitrary high dimension \( k \). Each node in the network has a reference vector \( w_{i,k} \) with the same dimension as the input vector. Training of SOM is done by finding the index of best matching reference vector of the nodes for each input vector:

\[
i = \arg \min \| \psi_i - w_{i,k} \|
\]  

(3)

The best matching node and its neighbors up to a certain geometric distance will learn from the activating input vector. In this way, the trained SOM will have more nodes in the regions (i.e. close RV’s) where more input vectors existed.

In MMSOM, an input vector of \( \psi_{w \in n} = [a_0, a_1, b_0, \ldots, b_{n-1}] \) is considered as the input to the SOM. This input vector is the identification parameters of the instantaneous model of the plant, which identified using RLS. Therefore, the reference vector of the \( i^{th} \) node \( w_{i,k} \) represents the parameters for the \( i^{th} \) model in the model bank. After training of SOM, models parameters approximate the statistical distribution of the input data [10].

IDENTIFICATION OF pH PLANT USING THE SOM NETWORK

Block diagram of identification and model generation process considered here is shown in Fig.2.

Here we have used SOM to extract the statistical features of offline identification data produced by the RLS method. The nonlinear model of pH neutralization plant has been taken from [11]. A schematic diagram of the pH plant is shown in Fig. 3.
Fig. 3 – Schematic Diagram of pH Plant

The continuous stirred tank neutralizer has three inlet streams: base, acid and buffer. The objective is to control the pH value of the outlet stream.

Nominal operating conditions of the simulated pH system are summarized in Table 1.

<table>
<thead>
<tr>
<th>Operating Parameter</th>
<th>Parameter Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acid concentration ($C_a$)</td>
<td>0.001 mol/lit</td>
</tr>
<tr>
<td>Acid flow rate ($f_a$)</td>
<td>0.3 mlit/sec</td>
</tr>
<tr>
<td>Base concentration ($C_b$)</td>
<td>0.001 mol/lit</td>
</tr>
<tr>
<td>Cross sectional area of tank</td>
<td>70 cm²</td>
</tr>
<tr>
<td>Acid dissociation constant ($K_a$)</td>
<td>1.75e-5</td>
</tr>
<tr>
<td>Water dissociation constant ($K_w$)</td>
<td>1e-14</td>
</tr>
<tr>
<td>Tank level ($h$)</td>
<td>17 cm</td>
</tr>
</tbody>
</table>

Fig. 4 – Operating points on steady state diagram of input flow/pH

In the first step plant is excited by a suitable input sequence of enough persistently excitation (PE) order. A random, binary signal (RBS) pattern was used as the identification input of the pH plant. The input pattern was biased to identify the plant around 5 different operating points. Selected operating points are shown in Fig. 4. Fig. 5 demonstrates the total input signal applied on the base flow pump.

The RLS method was used to estimate the model parameters. A first order ARX model was used as the model structure. A forgetting factor of 0.98 was used to discard the old data and dealing with the problem of time-varying parameters.

In the next step, data from the RLS estimation was given to the SOM network. Input vectors are the estimated parameters of the ARX model which are two in our case. A two dimensional SOM network was then used to cluster the estimation parameter into some clusters based on the statistical properties of them. SOM distributes its RVs across the input space according to the statistical properties of the input data, therefore identification of the system should be done knowing that relative number of identification data in each region acts as a weight for the number of required models in each region. This means that more identification data in a specific operating region of system forces SOM to place more models in that region. Equal identification time intervals were used for each operation region to give equal weights to each region of pH plant.

Fig. 6 shows the graphical representation of U-matrix [12] of the trained SOM.
Although the pH system was excited around 5 operating points, only three different regions can be distinguished from the U-matrix of trained SOM. This matter can be linked to closeness of model parameters in some of the operating points and also the continuity of SOM lattice. Similar results have been obtained by O. Galan et al. [13] using the gap metric method which acknowledges the results from utilizing SOM for generation of models.

IV. SIMULATION RESULTS

In this section, the proposed control strategy is evaluated using the nonlinear model of pH neutralization process. Results have been compared with a self tuning regulator (STR) controller.

A total of 26 models were used in order to control the pH plant in this paper. Bank of models consists of 25 fixed models generated by the SOM and one free running adaptive model which guarantees the closed loop stability of system [7] in addition to giving the flexibility of working in unexplored regions to the control system.

Weighting constants of the performance index were selected as $\alpha, \beta = 1, \lambda = 0.65$ and $M = 30$. Hysteresis constant was selected as $\delta = 0.8$. The desired closed loop pole was placed at 0.95.

Note 2: If the applied control technique does not include an integral action, use of only fixed models in the bank will lead to biased tracking and inevitable steady state errors due to slight model mismatches.

Closed loop response of system for a large setpoint change is shown in Fig.7. This results shows that the MCSOM controller have reached a faster and more stable response comparing to the STR controller. Some observations from the simulations are given below:

1) The MCSOM controller has improved the transient response of closed loop system compared to the STR controller. These improvements are resulted from switching to more appropriate models in the transient state of response.

2) Unlike the STR controller the MCSOM controller avoided the oscillations in the high gain area of system around pH = 8.5 by switching to a more appropriate fixed model from the model bank.
V. CONCLUSION

In this paper, a multiple model pole placement control strategy via SOM which divides the operating region of plant into sub-regions is presented. Simulation results indicated superior performance compared to the STR controller.

An improved switching algorithm based on the excitation level of the process is suggested for systems with noisy environments. Simulations indicated better performance of the multiple-model controller due to adding this condition to the switching algorithm.

REFERENCES


