Support Vector Regression Based Controller for Non-Linear CSTR Tank Processes

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Abstract - **Support Vector Regression (SVR) based predictive controller is proposed for nonlinear Continuous Stirrer Tank Reactor (CSTR) processes. SVR based prediction control algorithm is recommended for complex non-linear processes, having very high dimensional input spaces. The proposed control algorithm is compared with Neural Network Predictive Control (NNPC) algorithm to show its effectiveness and observed that, local minima are hidden units selection issues involved in Neural predictive controller are solved. The same algorithm is used in nonlinear Continuous Stirrer Tank Reactor (CSTR) tank process to observe the effectiveness. In CSTR, concentration is controlled by manipulating its feed flow rate. From results, it is concluded that SVR ensures robustness and control accuracy under servo and regulatory operations.**

Keywords: CSTR, Nonlinear, NNPC, Predictive controller, SVR

I. INTRODUCTION

Predictive control algorithm [1] is now used in most of the industrial plants and the possibility of implementation of control algorithm in predictive controller is huge. One important advantage of this kind of approach is its ability to deal with restriction on control and internal variables. In many applications of predictive control, a linear model is used for predicting the process response within the horizon of interest. However, most of the real time processes have some non-linear characteristics; therefore non-linear model is identified in order to extend the predictive control techniques to incorporate non-linear models [2].

The model identification is very difficult in the case of non-linear predictive controller. In such instances processes, it is not possible to identify its model; process model can be derived with the help of corresponding neural network model which is trained through the plant input-output data. However neural network model has lot of drawbacks such as presence of many local minima, no guarantee of high convergence speed and no general rule available to select the number of hidden units [3].

LSSVR a new kernel based model identification method has been proposed instead of neural network model to overcome its drawbacks. SVRs [5,8] developed within the framework of statistical learning theory and structural risk minimizations are powerful tools for model identification. SVM solutions are characterized by quadratic programming and it is used where the high dimensional input spaces exist. Kernel based [14-16] non-linear modeling is used generally in LSSVR based model identification. The kernel width and regularization parameter should be properly selected based on the application. Several methods are available for selecting these parameters, such as bootstrapping, cross validation and Bayesian methods.

Support vector machine introduced by Vapnik in 1990's has been considered as advanced tool to perform classification and regression of functions. In this paper, we have proposed an advanced predictive control algorithm based on LSSVR [10] for controlling non-linear CSTR process [9]. The non-linear CSTR is used in process plant applications such as water treatment process, syrup mixing process, etc,. The LSSVR based predictive controller is trained using the training data obtained from CSTR non-linear process. The simulation result shows that LSSVR based predictive algorithm provides good control accuracy and robustness than NN based predictive control algorithm.

A. CSTR Process Description

Continuous stirred tank reactor (CSTR) [9,18] is a highly non-linear process and mostly used in chemical industries [22]. A single input single output CSTR process is shown in Fig.1. For a non-adiabatic CSTR, single irreversible 1st order exothermic reaction is assumed at constant volume [22, 23].

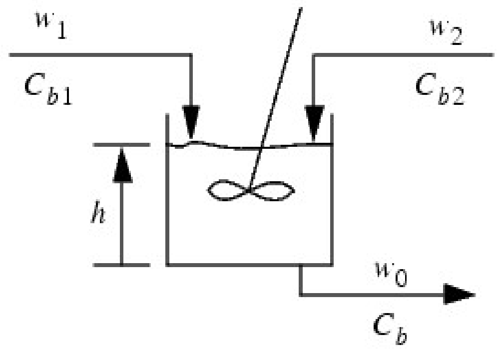

Figure.1 CSTR Process

The reaction rate is assumed to be

$$r = \frac{K_1 C_b}{(1+K_2 C_b)^2} \quad \text{(mole/m}^3\text{s)} \qquad \text{----} \qquad (1)$$

Where K_1 is the reaction rate constant and K_2 is the adsorption equilibrium constant. Exothermic reaction is assumed, the dynamic model of the system is expressed in the equations (2) to (4)

Total Mass balance

$$A\frac{dh}{dt} = W_1 + W_2 - W_0 \qquad \text{----} \qquad (2)$$

Component balance

$$V\frac{dC_{b1}}{dt} = W_1(C_{b1} - C_b) + W_2(C_{b2} - C_b) - rV \qquad \text{----} \qquad (3)$$

$$\frac{dh(t)}{dt} = w_1(t) + w_2(t) - 0.2\sqrt{h(t)}\,\frac{dc_b(t)}{dt}$$

$$= [cb_1(t) - c_b(t)]\frac{w_1(t)}{h(t)} + [cb_2 - cb(t)]\frac{w_2(t)}{h(t)} - \frac{k_1 cb(t)}{[1+k_2 cb(t)]^3} \qquad \text{----} \qquad (4)$$

Where,
h - liquid level,
c – Concentration
w – Feed flow rate

The concentrations C_{b1} & C_{b2} at input side are set to be 24.9 and 0.1 respectively and constants associated with rate of consumption are set to be 1.

The CSTR Parameters are given in the table.1.

Table.2 CSTR Parameters

Inlet concentration C_{b1}	24.9
Inlet concentration C_{b2}	0.1
Volume of the CSTR (V)	100 lit
K_1 and K_2	1
W_2(t)0	0.1
Activation Energy (EbyR)	1e4
Reaction rate constant(K_0)	7.2e10
Feed Temperature(Tf)	350K

B. Neural Network Predictive Controller

Model based Predictive Control (MPC) is an advanced algorithm [6-7], which predicts the control strategy for future output. MPC is a model which is used to predict the future output of the process. MPC is recommended for many processes due to its advantages such as real time prediction, optimization and real time correction. The structure of MPC is shown in the Fig.2.

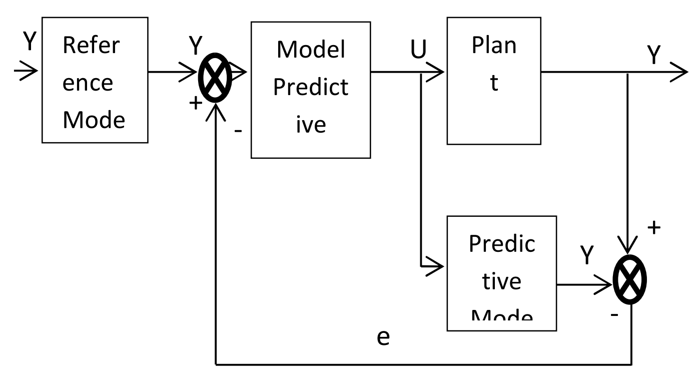

Fig.2 Model Predictive Controller

Where,
Ys - Set point
Yr - Reference
Y - Actual process output
Ym - Predictive model output

Linear Model Predictive Controller (LMPC) [6] predicts future output of process and it develops a predictive model which is in the linear form. For complex non-linear process, the linear form model is not recommended to predict the output and the controller response is also not a satisfactory one. So it is better to identify non-linear predictive model for non-linear process, which can be suitably trained and has the ability to predict the proper output. There are more limitations added to the cost function, because the real time optimization is highly non-linear. The online optimization is very complex, hence some good optimization algorithm is required to get the best control.

Due to the LMPC drawbacks, Non-Linear Model Predictive Controller (NMPC) [17] is developed, in which a proper non-linear model is used for prediction and optimization. Due to the complexity involved in the non-linear process, the non-linear model identification from linear model predictive form or from the general modeling procedure becomes very complex. Empirical approaches such as Hammerstein and Wiener models, Polynomial ARMAX and Artificial Neural Network (ANN) are used to identify non-linear models [17] from real time plant data. Hammerstein and ARMAX models are suitable and restricted only to small processes which are not suitable for highly non-linear process. Hence neural network based non-linear model identification is recommended for non-linear processes.

The plant performance predictions to be done through NNPC, receding horizon of the NN predicts the output performance over a specified time. The outputs of process and NN model is used for the prediciton performance. NNPC has structure selection and training limitations i.e. no.of hidden units and local minima in the prediction algorithm. In order overcomes those, Support Vector Regression based prediction algorithm is proposed to the nonlinear process.

C. Support Vector Regression

A support vector machine (SVM) [5] is a special class of learning algorithm which is used in machine learning applications. SVMs are characterized by kernels, local minima, and sparseness of the solution and support vectors used for control. The function developed through SVMs from the set of training data can be used for classification or regression.

The structural risk minimization (SRM) is employed in SVM to overcome the empirical risk minimization (ERM) principle which is employed in conventional neural networks. Due to the presence of SRM principle the local optimal point problem and structure selection difficulties are completely eliminated. In the SVM algorithm, non-linear input space is mapped into a high dimensional feature space, the linear classification, and regression are performed in that mapped space. SVM based learning algorithm has performed well than the conventional neural networks when smaller size training set, non-linear and high dimensional problem is used [11-12].

In our proposed method SVM is applied for the purpose of regression. The linear regression function is expressed as follows

$$f(x) = \overline{w} \cdot x + b \qquad \text{-------------} \quad (1)$$

Eqn.(1) can be used to match the training data $\{x_i, y_i\}$, i=1,…..,n, $x_i \varepsilon R^d$, $y_i \varepsilon R$, where ε is precision parameter used for matching, which is expressed as

$$\begin{cases} y_i - \overline{w} \cdot x_i - b \subseteq \varepsilon, \\ \overline{w} \cdot x_i + b - y_i \subseteq \varepsilon, \end{cases} \qquad \text{i=1 ,.., n} \qquad \text{-----} \quad (2)$$

If matching errors are permitted, relaxation factors $\xi_i \geq 0$ and $\xi_i^* \geq 0$ can be introduced and equation (2) is expressed as

$$\begin{cases} y_i - \overline{w} \cdot x_i - b \leq \varepsilon + \xi_i, \\ \overline{w} \cdot x_i + b - y_i \leq \varepsilon + \xi_i^*, \end{cases} \quad \text{I = 1,.,n} \quad \text{------} \qquad (3)$$

The cost function is expressed as

$$\frac{1}{2}\left\|\overline{w}\right\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \qquad \text{----------} \ (4)$$

Using Lagrange multipliers, the cost function can be maximized as follows

$$W(\alpha, \alpha^*) = -\varepsilon\sum_{i=1}^{n}(\alpha_i^* + \alpha_i) + \sum_{i=1}^{n} y_i\,(\alpha_i^* - \alpha_i) - \frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)(x_i x_j)$$

-------- (5)

Where $\alpha_i^*\, and\ \alpha_i$ are the Lagrange multipliers, and the regression function is obtained as follows:

$$f(x) = (\overline{w} \cdot x) + b = \sum_{i=1}^{n} \ (\alpha_i^* - \alpha_i)(x_i \cdot x) + b$$

---------------- (6)

Non-linear problems can be transformed into linear problems by using transformation technique in a high dimensional space, and then linear matching is performed by using the above functions. To match the non-linear function the inner product of two training vectors expressed in equation (5) can be substituted by a kernel function $K(x_i \cdot x_j)$. The regression function is modified as:

$$f(x) = (\overline{w} \cdot x) + b = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) K(x_i \cdot x) + b$$

---------- (7)

There are several choices of kernels [15-16] that can be used in LS-SVM models [19-20]. These include linear, polynomial, Radial Basis Function (RBF) and sigmoid type of kernels.

$$k(x_i, x_j) = \begin{cases} x_j^T x_i & Linear \\ (x_j^T x_i + 1)^{\deg ree} & Polynomial \\ \exp(-\gamma |x_j - x_l|^2) & RBF \\ \tanh(kx_j^T x_i + \theta) & Sigmoid(or) \\ & MLP-SVM \end{cases}$$

-------------------- (8)

D. Predictive controller using Support Vector Regression

In this paper, SVR [3,10] is used as predictive model instead of neural network model. The past input and output variables of the process can be taken as the input vector of SVR and the output variable is the predicted future output value of the process. The input and output training data are generated from CSTR process model [9,18], which is used to simulate the process. The obtained model is trained using the identified data and applied in the NMPC strategy.

At each sample time 'k', SVR predictive model calculates the future output which is then compared with the reference output value.

$$y_r(k) = y(t)$$
$$y_r(k + j/k) = \alpha^j y_r(k) + (1 - \alpha^j) y$$

------------------- (9)

Where j=1,…,P. P is the prediction horizon. The predictive error is calculated as:

$$E(j/k) = y_r(k) - \hat{y}(k + j/k)$$

------------------- (10)

The cost function is calculated as

$$J = Q \sum_{i=1}^{P} E(j/k)^2 + R \sum_{j=1}^{M-1} \Delta u(k + j/k)^2$$

------------------- (11)

Where Q and R - Constant weights

P – Prediction horizon

R – Control horizon

At each sample time k, SVR [18] need to predict the control increment $\Delta u(k+1)$ for the next sample point which can minimize the cost function J. After this process, the control signal for the sample point k+1 is obtained by

$$u(k+1) = u(k) + \Delta u(k+1)$$

------------------- (12)

The algorithm of the prediction control based on LS-SVR is expressed as follows:

Step.1: CSTR Process model is obtained based on given input-output data set

Step.2: Obtained non-linear model is linearized at each sampling instant

Step.3: Predicted model output and actual process output are compared

Step.4: Predictive control algorithm is used to determine the output at each sampling instant.

E. Simulation Results

LS-SVM based predictive controller for CSTR process has been implemented in MATLAB using SIMULINK's NN predictive controller block. We collected input/output data from the nonlinear CSTR SIMULINK model implemented according to the first principles equations discussed in section.2. Then we trained an LSSVR model with sigmoidal kernel using LSSVR toolbox and translated the resultant SVM into a feed forward neural network with sigmoidal activation function in the hidden layer. This neural network was imported into SIMULINK's NN predictive controller block for LSSVR based predictive controller simulations. The number of support vectors corresponds to the number of hidden neurons and the Lagrangian multipliers corresponds to weight values between hidden and output layer. Support vectors themselves correspond to weight values between input and hidden layer. The various values of support vectors are chosen to determine the approximate model of the non-linear system based on different set of input-output data. The mean square error values are shown in the Table.2 for different values of number of support vector.

Table.2 Mean Square Error with different sampling Instants (N)

S.No	Sampling Instants	Kernel width and Regularization parameter	Mean Square Error (MSE)
1	300	110, 0.0001	0.0782
2	800	110, .0001	0.0783
3	1000	110, 0.0001	0.0943
4	2000	100, 0.0001	0.0018
5	2100	110, 0.0006	0.0012
6	2500	100, 0.0001	0.0074
7	2800	150, 0.00025	0.0105
8	2800	110, 0.0003	0.0106
9	2900	110, 0.0003	0.0021
10	2950	120, 0.0005	0.0131

The CSTR model actual and predicted output obtained through LSSVR based predictive controller with different values of support vectors are shown in the Figure. (2) to (5). The CSTR process concentration output is shown in Figure. (6).

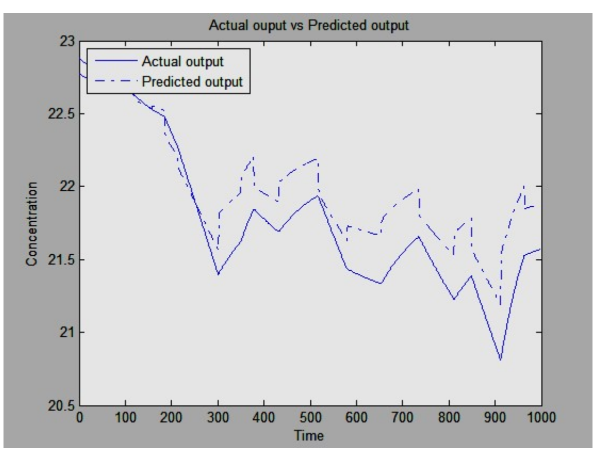

Figure.2 Comparison of actual output Vs predicted output with N=800

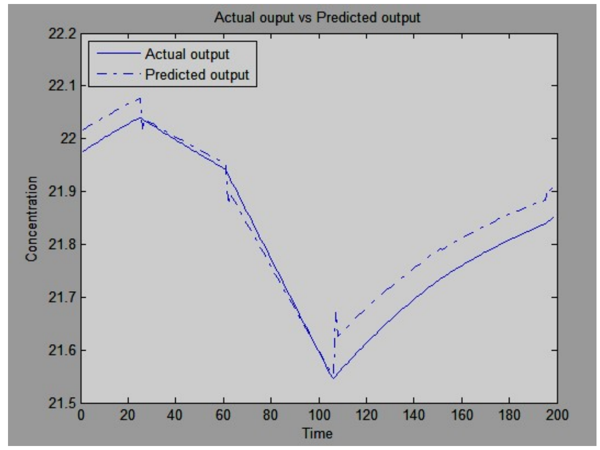

Figure.3 Comparison of actual output Vs predicted output with N=2000

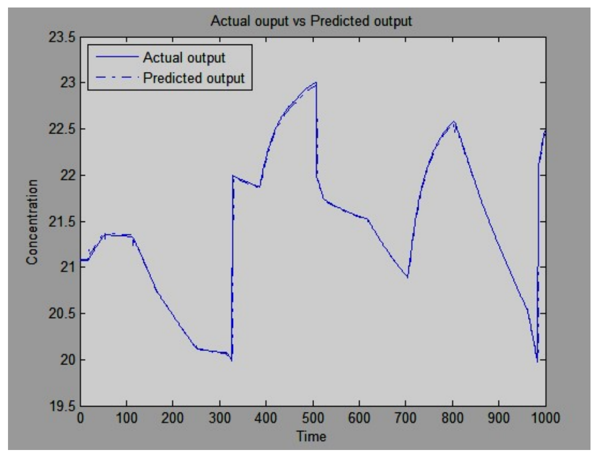

Figure.4 Comparison of actual output Vs predicted output with N=2800

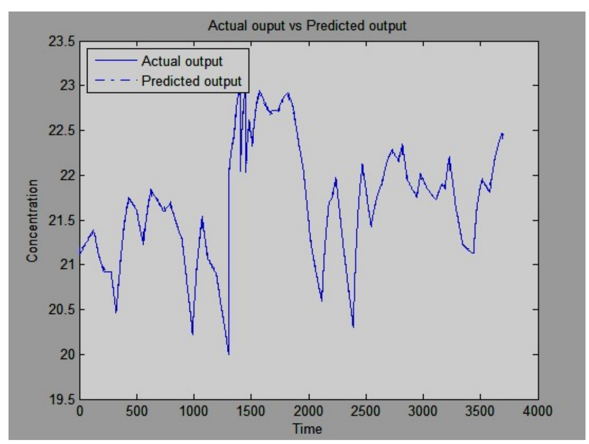

Figure.5 Comparison of actual output Vs. predicted output with N=2900

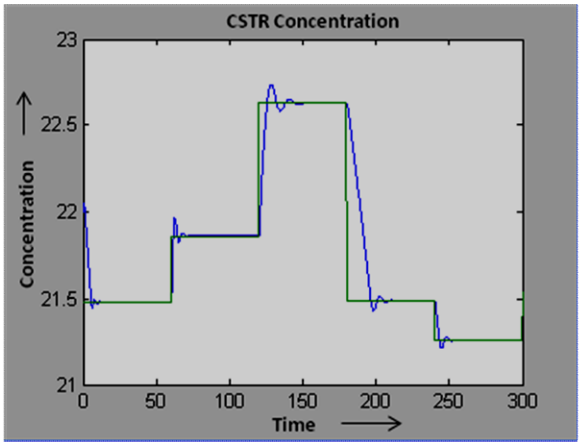

Figure.6 CSTR Concentration ouput with 2900 Support vectots

From these results we can identify that the control performance of SVR based model predictive controller shows better response for the non-linear CSTR process. It is observed that the response of CSTR concentration with 2900 support vectors provides better response with minimum overshoot and faster settling time.

CONCLUSION:

In this paper, predictive control algorithm based on least square SVM has been implemented, in which the proposed LS-SVM is compared with standard SVM. The LS-SVM with sigmoid or MLP kernel based predictive control algorithm used to control the non-linear CSTR process with multiple operating environments. With the help of weighted least square and special pruning techniques, LS-SVM employed robust non-linear estimation and sparse approximation. The CSTR model is identified through kernel based LS-SVM and then predictive control algorithm is used to obtain the closed loop response with respect to reference trajectory. The CSTR concentration output with different support vectors is presented to show the effectiveness of the proposed algorithm. It is observed that the proposed LS-SVM based predictive control algorithm can provide robust performance for complex processes involving operating conditions that can normally vary.

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