Nonlinear Model Predictive Versus Sliding Mode Controller Design for a Class of Nonlinear Non-affine Chemical Batch Reactor Dynamics

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Abstract: In this paper, both nonlinear model predictive control and sliding mode control algorithms are used to control the temperature of the chemical batch reactor utilizing the cooling coil system. The main purpose of the model predictive control is to minimize the difference between the amount of next output prediction and reference values, by considering some constraints on both the states and the inputs. The Sliding mode as a second controller is also considered as an efficient method because of high robustness of the closed-loop system against uncertainties and external disturbance in addition to simplicity in design and practical implementation. With regard to the immeasurability of all state variables, designing high gain observer and sliding mode controller based observer is discussed to track the system states and adjust the temperature of the reactor. The simulation results show the high performance of the proposed algorithms in controlling the reaction implementation in addition to avoid exceeding the temperature limit.

Keywords: Nonlinear Model predictive control; Sliding mode controller; Batch reactor; temperature Control

1-Introduction

In the past, water was used as the internal parts of the engine coolant because of its heat transfer properties and its cheap price. In the following years, the use of substances such as methanol, ethyl alcohol and alcohol-based antifreezes increased and finally they were outdated due to their weaknesses. In 1925 for the first time, propylene glycol was revived as engine coolant.

At first, the use of this substance was low, but gradually become more because of the benefits of the product and now it is used as a major substance in the engine cooling fluid. With the increasing use of propylene glycol and the suitable applications for engine cooling fluid, gradually the use of methanol, ethanol and other chemicals to produce antifreeze decreased. The use of these materials in the engine coolant formulation in general was abolished in 1950 so that the production rate and the consumption rate of propylene glycol is obtained from 49 million liters to 71 million liters per year.

Propylene glycol is produced by the hydrolysis reaction of propylene oxide in a batch reactor. For optimal production of this substance is the need to raise the temperature (the reaction starts at the 535 Rankin), however, with the temperatures over 585 Rankin, by evaporation of propylene oxide, the reaction will be difficult. We are trying to change the temperature of the cooling coil to control the reactor temperature during the reaction. Using the change of temperature of the coil reactor for control of reactor temperature is one of the differences and benefits of the method used in this study than in the other articles. Temperature controls were already discussed in a continuous stirred tank reactor (CSTR), and their consideration is useful due to the similarity of dynamical equations of continuous and discontinuous reactors.

Reactors are widely used equipment that their control has been a problem for the chemical industry because of their high sensitivity and highly nonlinear dynamics. In the past, research on reactor control is carried out using different methods. Among them, a controller base on the dynamic state feedback is designed for CSTR reactor where the steady state error increased with time and the control signal becomes large. In another research [2], a geometric method was used for minimum phase systems to study dynamical models of CSTR. The problem with this approach is that the system and the environment will be strongly influenced by the disturbances. In [4], the authors studied the polystyrene batch reactor control using fuzzy logic and in [5], the number of robust control methods was used to control the batch polymerization reactor. Another article [6] used a combination of robust control and input-output linearization for temperature control, stability and performance improvements by designing system.

In [7] model predictive control is used to control the building cooling system and nonlinear model predictive control is used to control the temperature of greenhouse gases in [8]. In [15], NMPC is used to control the polymerization process industries and in [16], the robust nonlinear predictive control is used to control a semi-batch polymerization reactor. [17] utilized a combination of linear predictive control and wiener neural network, [18] uses a NMPC based on neural network for continuous intensified reactor control. The stochastic nonlinear predictive control is used to control the uncertainty batch polymerization reactor in [19]. In [20], the combination of the NMPC, neural network and adaptive control is used to adjust an industrial process. In [21, 22] also numerical methods are used to implement nonlinear model predictive control.

In [23], the dynamic state feedback controller is designed for a CSTR reactor that steady state error increases with time and the control signal is large. In [24], a geometric method has been used for minimum phase CSTR systems. The problem with this approach is that it is strongly influenced by system disturbances. [33] discusses about designing DMC-optimization PID controller for batch reactor temperature control. The sliding mode control is discussed for rapid thermal process control systems [34]. Also in [35], the sliding mode control is used to control the continuous stirred tank reactor temperature. [36] Has used the sliding mode control with a super twisting algorithm to control the temperature of PEM fuel cells. In [37], a combination of sliding mode control with the adaptive controller is used to control the water temperature using fuzzy logic.

In this paper, at first we obtain the dynamic model of the system by considering the methods that explained in [9]. At second step we try to design the nonlinear model predictive controller with optimal approach that explained in [10]. The advantage of this method is that the stability of the controller is guaranteed. Considering the hints that explained in [13] for implementation of linear and nonlinear model predictive controller helps us to obtain the best results. In [15] also the implementation of MPC in MATLAB is completely explained.

In following the sliding mode controller design will be done and after that the high gain observer is designed by considering [28] that in [38] authors discussed on robustness of this observer and next step is tuning the controller based on the high gain observer.

Finally, we compare the results of NMPC and sliding mode controllers by each other and also with PID controllers. The results show the best performance of the proposed algorithms.

The rest of the paper is organized as follows: section 2 discusses about problem statement, section 3 derives control inputs based on nonlinear model predictive control, section 4 proposed the sliding mode controller design, high gain observer and SM controller based observer. Section 5 shows the simulation results and we conclude the paper in section 6.

2-Problem statements

Propylene glycol is produced by the hydrolysis of propylene oxide. Propylene glycol makes up about 25% of the major derivatives of propylene oxide. The reaction takes place readily at room temperature when catalyzed by sulfuric acid. The feed stream consists of (1) an equivolumetric mixture of propylene oxide and methanol, and (2) water containing 0.1wt% H2SO4. The temperature of both feed streams is 58°F prior to mixing, but there is an immediate 17oF temperature rise upon mixing of the two feed streams caused by the heat of mixing. The entering temperature of all feed streams is thus taken to be 75°F. Under conditions similar to those mentioned above, the reaction is first-order in propylene oxide concentration and apparent zero-order in excess of water. There is an important constraint on the operation. Propylene oxide is a rather low-boiling substance (b.p. at 1 atm, 93.7 oF) and we cannot exceed an operating temperature of 125 oF, or we will lose too much oxide by vaporization through the vent system. To solve the problem, cooling coil with the area of 40 ft2 is used for temperature control. The overall heat transfer coefficient for the coil is equal to $U = 100\ Btu / h.ft^2.°F$.

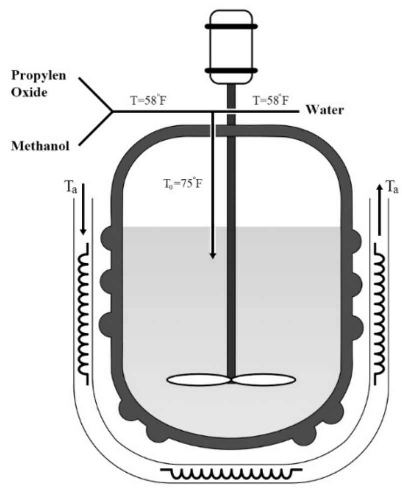

Figure 1 - hydrolysis of propylene oxide in chemical batch reactor

The model used to design the controller can be achieved by following rate law and stoichiometry. The design is based on the following form in which N_{A0} is the initial moles of propylene oxide and r_A is the reaction rate.

$$N_{A0} \frac{dx}{dt} = -r_A \qquad (1)$$

Rate law is defined as below in which c_A is the initial concentration and k is a constant with the unit of '1/hr'.

$$-r_A = kc_A \qquad (2)$$

Stoichiometries relationship obtained from the reaction is in the form of $c_A = (\frac{N_{A0}}{v})(1-x)$ which can be rewritten as:

$$\frac{dx}{dt} = k(1-x)\ ,\ k = 16.96 \times 10^{12}(e^{-\frac{E}{RT}})\ h^{-1} \tag{3}$$

The temperature is in term of Rankin. The following equation represents temperature changes during the conversion of propylene oxide to propylene glycol in a batch reactor.

$$\frac{dT}{dt} = \frac{\dot{Q} + (-\Delta H_{RX}(T_0))(-r_A v)}{N_{A0}(C_{ps} + \Delta C_{ps} x)} \tag{4}$$

Where

$$\dot{Q} = UA(T_a - T) \tag{5}$$

Table 1 - Values of system equations parameters

parameter	symbol	quantity	unit
Cross section of the cooling coil	A	40	ft^2
Overall heat transfer equation	U	100	$Btu / h.ft^2.°F$
Heat of reaction	$\Delta H_{RX}(T_0)$	-36450	$Btu / lb.mol$
Initial mole of propylene oxide	N_{A0}	1.764	$lb.mol / ft^3$
Specific heat capacity	C_{ps}	403	$Btu / lb.mol.A.°F$
Specific heat capacity changes	ΔC_{ps}	0	$Btu / lb.mol.A.°F$

Considering the constant values given in Table 1, the state space model of the system will be given as follows:

$$\begin{cases} \dot{x} = 16.96 \times 10^{12}(e^{-\frac{32400}{1.987 \times T}})(1-x) \\ \dot{T} = 5.627(T_a - T) + 1533.975 \times 10^{12}(e^{-\frac{32400}{1.987 \times T}})(1-x) \end{cases} \tag{6}$$

In the above equation, T_a is as a control term (u) the refrigerantently, by adjusting the temperature of refrigerant, the reactor temperature is controlled.

3-Nonlinear Model Predictive Control

Nonlinear predictive control (NPC) is an advanced control process that began in the 1980 in the process industries, is used in the chemical industry and oil refineries. The reason for using this type of controller in the industry is because of a sensitive and nonlinear dynamics, lack of steady work, despite the uncertainties, high turbulence and noise in the circumstances. The main purpose of applying nonlinear model-based predictive control is to minimize the difference between the amount of output and reference values taking into account constraints on input or on modes. In this way, the future behavior is forecast based on model output and with the definition of the cost function and constraints imposed on the system input or modes, optimal control is gained to minimize the cost function. The advantage of this method is to express the nonlinear state-space model, to optimize the current situation with regard to the future, simply setting controller, constraints applied to solve the optimization problem, including a forward controller to compensate for the effect of the measurable disturbance, predicting future events and taking appropriate control actions with them. This method is much stronger than conventional controllers such as PID and LQR.

This may be structural or parametric uncertainties that are created because of inaccuracies in the statement and system parameters. Uncertainties of unstructured or unmodeled dynamics appear to simplify the system targeted.

Batch reactor systems include uncertainties due to non-linear and exponential terms that robust control methods, including sliding mode control can control the dynamics of the system to eliminate the effects of these uncertainties.

Model-based predictive control is a wide range of control methods that uses explicit model and optimized cost function to obtain a control signal. The diagram of predictive control based on the model is shown in Figure 2.

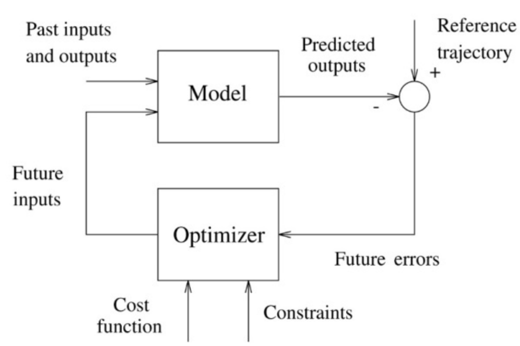

Figure 2 - The diagram of a model based predictive control

In this type of control, using the model of the process, the input and output signals in the past, reference signals in the future, and optimization process, control input determined in a manner that the difference between the output prediction and system reference signal is minimized. Figure 3 shows the predictive control strategy.

Assuming that we are at the time of it and that we have all system information, including inputs and outputs until the time at it, we want to predict the behavior of the system based on a model using the signals of future control to be closed to the output signals of the future plant $y(t),\ y(t+1),\ \ldots\ ,\ y(t+N)$ to the appropriate values. N is prediction horizon and k is control horizon.

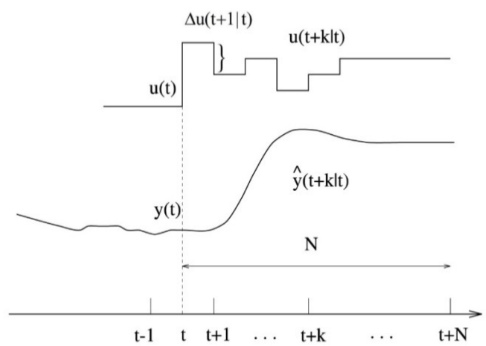

Figure 3 - Predictive control strategy

The selection criteria of plant input signal at the time of future is based on a cost function that can be defined with the aim of tracking the reference signal in the forecast horizon and of minimizing control efforts Δu . This cost function is usually defined as the square and includes the sum of weighted squared error of prediction with the sum of the weighted squares of the development control signals as below. This cost function is minimized by using optimization algorithm. In this cost function, N_1 and N_2 are the minimum and the maximum forecast horizon and N_u is control horizon.

$$J(N_1,N_2,N_u) = \sum_{j=N_1}^{N_2} \delta(j)\left[\hat{y}(t+j\,|\,t)-w(t+j)\right]^2 + \sum_{j=1}^{N_u} \lambda(j)\left[\Delta u(t+j-1)\right]^2 \tag{7}$$

Another important issue is boundary to apply constraints to the system design that these constraints can be considered both in the domain and on the variation domain. These constraints can be applied to the system in a variety of structural factors (liquid level or flow stream), circumstance factors (the maximum temperature in the reactor) and safety factors. A variety of constraints, including input domain, input and output changes are defined as follows:

$$
\begin{aligned}
&u_{\min} \le u(\mathrm{t}) \le \mathrm{u}_{\max} \quad \forall t > 0 \\
&du_{\min} \le u(\mathrm{t}) - \mathrm{u(t-1)} \le \mathrm{du}_{\max} \quad \forall t > 0 \qquad (8) \\
&y_{\min} \le y(\mathrm{t}) \le y_{\max} \quad \forall t > 0
\end{aligned}
$$

As mentioned, predictive control is defined such that cost function J , which is function of the system state variables and inputs ($x(t),\overline{u}(.)$), is minimized

$$\min_{\overline{u}} J(x(t),\overline{u}(.)) \qquad (9)$$

$$J(x(t),\overline{u}(.)) = \int_t^{t+T_p} (\|\overline{x}(\tau;x(t),t)\|_Q^2 + \|\overline{u}(\tau)\|_R^2)\, d\tau + \|\overline{x}(t+T_p;x(t),t)\|_P^2 \qquad (10)$$

Where $\|x\|_p^2$ is defined as

$$\|x\|_p^2 := x^T P\, x \qquad (11)$$

Constraint in the optimization process can be considered to three forms as follows:

$$A * x \le B,\ A_{eq} * x = B_{eq} \qquad (12)$$

$$C(x) \le 0,\ C_{eq}(x) = 0 \qquad (13)$$

$$LB \le x \le UB \qquad (14)$$

(12), (13) and $\|x\|_p^2 := x^T P\, x$ (11) are linear and nonlinear constraints and (14) bounded the states and outputs. The cost function (10) must be optimized subject to:

$$\dot{\overline{x}} = f(\overline{x},\overline{u}),\ \ \overline{x}(t;x(t),t) = x(t) \qquad (15)$$

$$\overline{u}(\tau) \in U,\ \ \tau \in [t, t+T_p] \qquad (16)$$

$$\overline{x}(t+T_p;x(t),t) \in \Omega \qquad (17)$$

Where $Q \in R^{n \times n}$ and $R \in R^{m \times m}$ denote positive definite, symmetric weighting matrices; T_p is a finite horizon; $\overline{x}(.;x(t),t)$ is the trajectory of (15) driven by $\overline{u}(.):[t,t+T_p] \to U$. Note the initial conditions in (15): The system model used to predict the future in the controller is initialized with the actual, measured

Finally, cost function limits infinite horizon of nonlinear system.

$$\left\|\bar{x}(t+T_{p;}x(t),t\right\|_{p}^{2} \geq \int_{t+T_p}^{\infty}(\left\|\bar{x}(\tau;x(t),t\right\|_{Q}^{2}+\left\|\bar{u}(\tau)\right\|_{R}^{2})d\tau \tag{18}$$

$$\bar{u}=k\bar{x},\ \ \forall\bar{x}(t+T_p;x(t),t)\in\Omega \tag{19}$$

By substituting (19) and (20) in in the above equations, we have:

$$J(x(t),\bar{u})\geq\int_{t}^{\infty}(\left\|\bar{x}(\tau;x(t),t\right\|_{Q}^{2}+\left\|\bar{u}(\tau)\right\|_{R}^{2})d\tau \tag{20}$$

$$\bar{u}(\tau)=K\bar{x}(\tau;x(t),t)\ \text{ for }\ \tau\geq t+T_p \tag{21}$$

The optimal solution of $\min_{\bar{u}} J(x(t),\bar{u}(.))$ taking into account the cost function and defined constraints in time t is as below:

$$\bar{u}^{*}(.;x(t0,t)\ :\ [t,t+T_p]\ \rightarrow\ U \tag{22}$$

The optimal cost function is as follows:

$$J^{*}(x(t)):=J(x(t),\bar{u}^{*}(.)) \tag{23}$$

The model predictive control implementation is applied to the system when the measurement is taken the next step and be available. It is assumed that the repeat of this action is done per unit of time δ that is called sampling time. Finally, the closed loop of the input efforts will be defined as follows:

$$u^{*}(\tau):=\bar{u}^{*}(\tau;x(t),t)\ ,\ \ \tau\in[t,t+\delta] \tag{24}$$

By measuring the output, the optimization problem will be repeated to be solved. In fact, what has been considered here is the optimal solution and ultimately offers the appropriate control efforts.

Note that in this manner, a discrete system should be defined. Here the system dynamic equations are defined as differential equations in which the derivative is defined as follows:

$$\dot{x}(t)=\frac{x(k+1)-x(k)}{T}\ \ \rightarrow\ x(k+1)=x(k)+T*\dot{x}(t) \tag{25}$$

From equation (24), dynamical systems are defined as follows:

$$\begin{cases} \mathrm{x}(\mathrm{k}+1)=x(\mathrm{k})+T\times a\times e^{-\frac{b}{\mathrm{y(k)}}}(1-x(\mathrm{k})) \\ y(\mathrm{k}+1)=y(\mathrm{k})+T\times[c(u-\mathrm{y(k)})+d\times e^{-\frac{b}{\mathrm{y(k)}}}(1-x(\mathrm{k}))] \end{cases} \tag{26}$$

The first and second states are shown as $x(1)$ and $x(2)$ respectively. Cost function should also be defined as follows

$$J = 1000 \times (x(\mathrm{k}) - 1)^2 \tag{27}$$

To pay attention that coefficient applied in cost function is for better effectiveness that shows the importance of the final set points value for tracking. By reducing this factor, final response reaches the set point later and it may also have a steady state error.

Consider that in this problem we have no linear constraint on bounding the states. The only case that must be imposed is a nonlinear constraint on the second state (temperature of the reactor) that is of inequality type and defined as follow

$$C(1) \le 0 \ , \ C(1) = x(2) - 580, C_{eq} = 0 \tag{28}$$

So the final constraint is defined as follows

$$x(2) - 585 \le 0 \ \rightarrow \ x(2) \le 585 \tag{29}$$

Pay attention that NMPC is an optimal approach for designing controllers and its difference from optimal control is that the optimization is done in the prediction horizon. For obtaining the optimal control effort in (24) that satisfies (23), the cost function in (9) must be optimized.

4-Sliding Mode Controller Design

Uncertainties may come into modeling because of the simplification in modeling, disturbances and noises. The uncertainties can be categorized as the structural and unstructured that are created because of inaccuracies or simplification modeling or the parameter uncertainties.

Batch reactor system dynamics also due to nonlinear and exponential terms, include uncertainties that can be eliminated by the robust control techniques including sliding mode control. The sliding surface can be defined as follows.

$$s = (x - 1) + \lambda T \tag{29}$$

According to the mentioned sliding surface, the control input can be considered as follows:

$$u = u_r + u_{eq} \tag{30}$$

In the above equation,

$$u_{eq} = \frac{-1}{\lambda Cx - \lambda C + \lambda^2 CT} \times \begin{pmatrix} ABx - ABx^2 - \lambda CTx + \lambda DBx - \lambda DBx^2 \\ -AB + ABx + \lambda CT - \lambda DB + \lambda DBx + \lambda ABT \\ -\lambda ABxT - \lambda^2 CT^2 + \lambda^2 DBT - \lambda^2 DBxT \end{pmatrix} \tag{30}$$

$$u_r \leq -(\zeta + \mu)\operatorname{sign}(s) \tag{31}$$

u_{eq} Is to remove certain term (f_{nom}) and u_r is to remove uncertainties (f_{un}).

Theorem: Consider the dynamic system given in (5). By defining the slides surface as (29) the suggested controller structure given in (30), (31) and (32) makes the tracking error converge to zero and all signals in the closed loop system bounded as well.

Proof: To prove the stability of the closed loop system, the time derivative of the slide variable is as follow replacement

$$\dot{s} = \dot{x} + \lambda\dot{T} = A(e^{-\frac{B}{T}})(1 - x) + \lambda(C(u - T) + D(e^{-\frac{B}{T}})(1 - x)) \tag{32}$$

Where

$$A = 16.96 \times 10^{12},\ B = 16305,\ C = 5.627,\ D = 1533.975 \times 10^{12} \tag{33}$$

Because the control input is appeared in the first derivative of variable S, the Lyapunov function candidates as

$$v = \tfrac{1}{2}s^2 \tag{34}$$

By derivative of Lyapunov function, we have

$$\dot{v} = s\dot{s} = (x - 1 + \lambda T)(\dot{x} + \lambda\dot{T}) \tag{35}$$

For finite time stability, the following condition should be satisfied

$$\dot{v} = s\dot{s} \leq -\zeta\left|s(t)\right|,\ \zeta > 0 \tag{36}$$

The above equation can be rewritten as follows.

$$s\dot{s} \leq -\zeta|s| \rightarrow \frac{s}{|s|}\dot{s} \leq -\zeta \rightarrow \int_{s(0)}^{0} \frac{s}{|s|}ds \leq \int_{0}^{t_r} -\zeta\, dt \tag{37}$$

So the controller is finite time and it is proofed according to (37) that this time must satisfy the following inequality equation

$$t_r \leq \frac{|s(0)|}{\zeta} \tag{38}$$

By replacing state space equations into derivative of Lyapunov function we have

$$\begin{aligned}\dot{v} &= (x - 1 + \lambda T)(AB - ABx - \lambda CT + \lambda DB - \lambda DBx + \lambda Cu + d(t)) \\ &= M + Gu + d_2(t)\end{aligned} \tag{39}$$

Where M , G and $d_2(t)$ have been defined as follows:

$$M = ABx - ABx^2 - \lambda CTx + \lambda DBx - \lambda DBx^2 - AB + ABx + \lambda CT \\ -\lambda DB + \lambda DBx + \lambda ABT - \lambda ABxT - \lambda^2 CT^2 + \lambda^2 DBT - \lambda^2 DBxT \tag{40}$$

$$G = \lambda Cx - \lambda C + \lambda^2 CT \tag{41}$$

$$d_2(t) = (x - 1 + \lambda T)d(t) \tag{42}$$

By imposing the control input (30) and (31), we have

$$f_{un}\frac{s}{|s|} + u_r\frac{s}{|s|} + \zeta \le 0 \tag{43}$$

If $|f_{un}| < \mu$, then u_r is obtained by the following equation

$$u_r \le -(\zeta + \mu)sign(s) \tag{44}$$

The second part of the control input for elimination of uncertainties can be considered as follows:

$$u_r = -k\,\mathrm{sgn}(s) \tag{45}$$

By replacing the *u* in derivative of Lyapunov function

$$\dot{v} = M + G(u_{eq} + u_r) + d_2(t) = Gu_r + d_2(t) \le -\zeta|s| \tag{46}$$

By simplification we have

$$s(-\lambda Ck\,\mathrm{sgn}(s) + d(t)) \le -\zeta|s| \to \mathrm{sgn}(s)(-\lambda Ck\,\mathrm{sgn}(s) + d(t)) \le -\zeta \tag{47}$$

Finally, we have

$$-\lambda Ck + \mathrm{sgn}(s)d(t) \le -\zeta \tag{48}$$

Now by imposing the controller to system it is guaranteed that slides surface converges to zero in finite time.

Here the proof is completed.

Remark: boundary layer method can be used to eliminate the chattering in sliding mode controller. So the second part of controller defined as follows

$$u_r = -(\zeta + \mu)\mathrm{sat}(\frac{s(t)}{\varphi}),\ \mathrm{k} = \zeta + \mu \tag{49}$$

Where φ determines the width of the boundary layer. In addition, we can use the continuous function $\tanh({}^{s}\!/_{\varepsilon})$ for better elimination of chattering.

Parameter k in (45), obtained for worst condition that depends on the disturbance *d(t)*. By adding a Sinusoidal perturbation $d(t) = a\sin(t)$ to the first state of the system in (5), worst condition is equal to *a*. So we have

$$k = -(a+\zeta) \tag{50}$$

In the next step we will design high gain observer for the system. Consider the state space equations of the system as follows

$$\dot{x} = A(e^{-\frac{B}{T}})(1-x) \tag{51}$$

$$\dot{T} = C(u-T) + D(e^{-\frac{B}{T}})(1-x) \tag{52}$$

The only linear term in the equations is *CT* in (52). By considering that couple (A,C) must be observable, the Matrix *A* defined as follow

$$A = \begin{bmatrix} 0 & 0.01 \\ 5.627 & 0.01 \end{bmatrix} \tag{53}$$

So the observer structure and estimated state space equation are

$$\dot{\hat{x}} = \begin{bmatrix} 0 & 0.01 \\ 5.627 & 0.01 \end{bmatrix}\hat{x} + g(x,u) + H(y - C\hat{x}) \tag{54}$$

Where the output of the system is

$$y = Cx = \begin{bmatrix} 1 & 0 \end{bmatrix} x \tag{55}$$

Matrix *H* must be defined such that *(A-HC)* be Hurwitz and the observer be stable. By using pole placement method, and placing system poles at (100,200) this matrix obtained as

$$H = [301 \quad 20307] \tag{56}$$

By considering above equations, the observer will be stable and estimated states will track the real states as well.

5- Simulation Results

In this section, first the nonlinear model predictive control designed in section 3 practically implemented. The prediction horizon and control horizon considered respectively equal to 400 and 5. Sampling time also is set to 0.01. The initial values of the states of the system are set (0, 535).

Figure 4 presents the conversion trend of propylene oxide to propylene glycol and Figure 5 shows the changes in the temperature inside the reactor. As it stands, despite achieving best in the conversion of raw materials into the final product, the reactor temperature does not exceed the allowed limit.

Figure 6 indicates control efforts related to design nonlinear model predictive control. In fact, with increasing frequency, it can be seen that the figure will be continually trying to control the process.

In section 4, the design of the sliding mode controller and high gain observer was discussed. Consider the parameters for the controller as $\lambda = -5$ and $k = 1$, the simulation results have been recorded as the following figures.

Figure 7 shows the conversion of propylene oxide to propylene glycol and Figure 8 indicates the reactor temperature changes. Furthermore,

Figure 9 represents the design control efforts. As it stands, the first state converges to 1. In fact, with conversion of all raw materials to the final product, the temperature does not exceed the limit of the 575 degree Rankin.

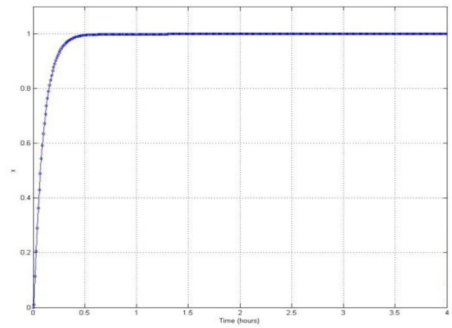

Figure 4- reaction performance after imposing NMPC

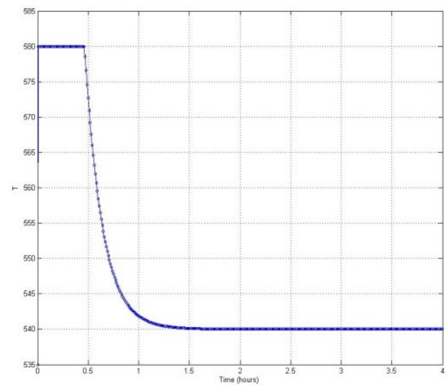

Figure 5 – reactor temperature changes after imposing NMPC

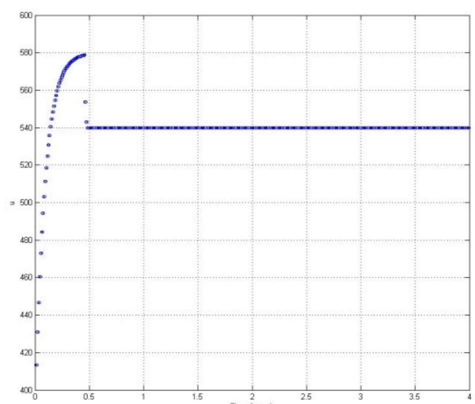

Figure 6 – control input obtained by NMPC algorithm

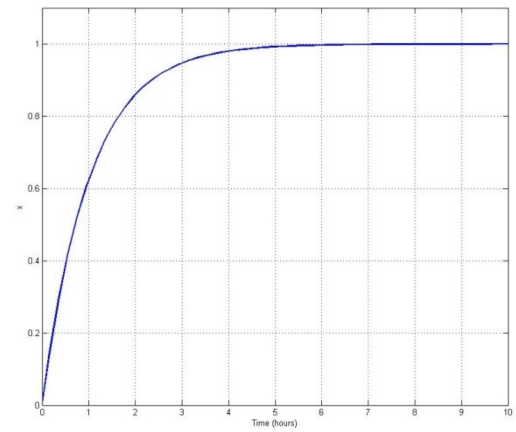

Figure 7 – reaction performance after imposing SMC

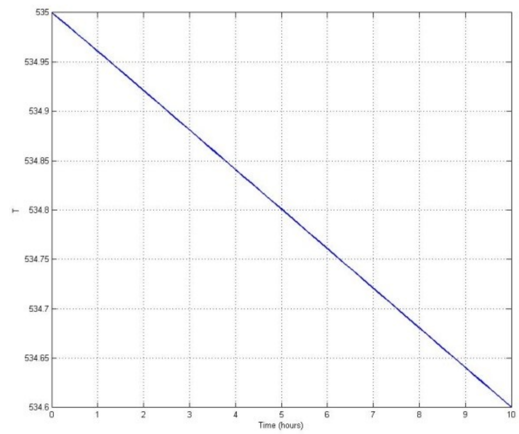

Figure 8 – reactor temperature changes after imposing SMC

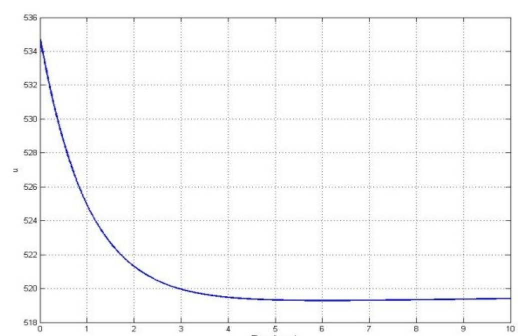

Figure 9 – input control obtained by SMC algorithm

The slide surface is shown in the following figure.

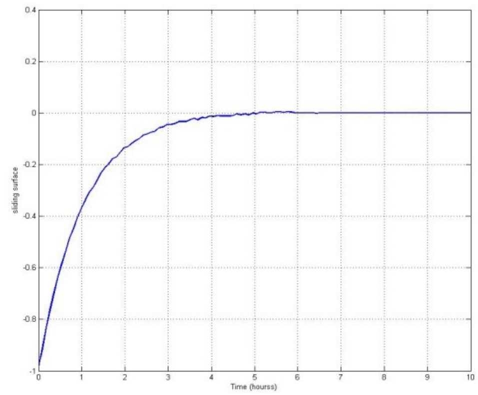

Figure 10 – slide surface

In the next step, high gain observer designed and sliding mode controller tuned based on this observer. Figure 11 indicates the conversion of propylene oxide to propylene glycol. Designed controller based on observer lead first state variable to the desired value.

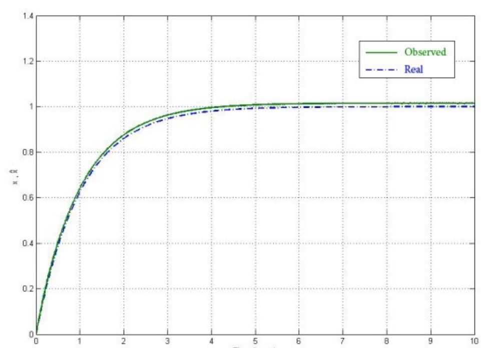

Figure 11 – comparing SMC and SMC based high gain observer of the system on first state of system

Figure 12 indicates the second state variable, namely temperature inside the reactor. As it shows, designed controller on the basis of observer has also a promising performance. This brings the variable state to the desired level.

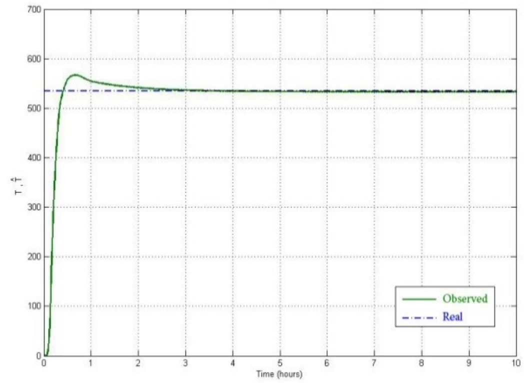

Figure 12 - comparing SMC and SMC based high gain observer system on second state of system

The simulation results show the promising performance of the controller and the observer in both convergence of the tracking error to zero and boundedness of the signals involved in the closed loop system.

It can be seen the comparison the performance of PID and NMPC in Figure 11 and Figure 12.

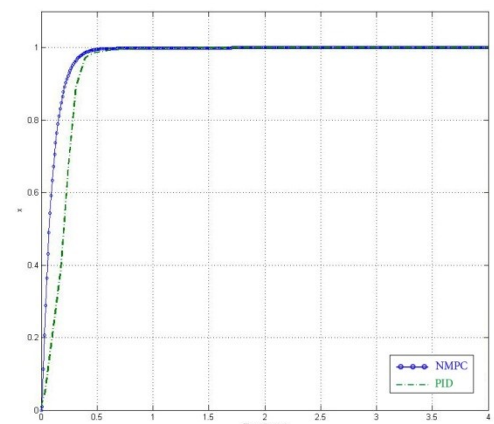

Figure 13 – comparing PID and NMPC in controlling the reaction performance

As these figures shows, both controllers have approximately the same performance in controlling the reaction. But the main difference is in controlling the reactor temperature. As the results show, PID could not keep the reactor temperature in the allowed range.

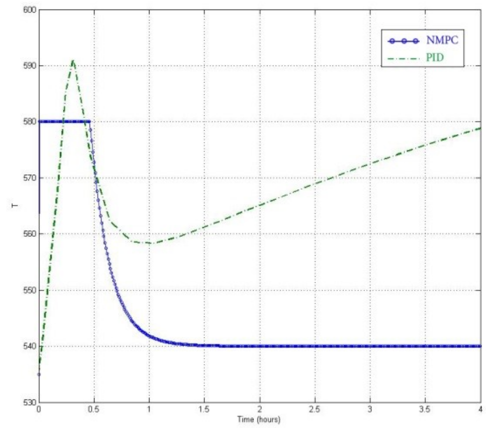

Figure 14 – comparing PID and NMPC in controlling the reactor temperature

Also for MIMO systems, it needs to have a large number of controllers for different loops. The main merits of the nonlinear MPC are optimal performance of the controller, exerting the linear and nonlinear constraints.

These are shown comparing the performance of PID and SMC in Figure 15 and Figure 16.

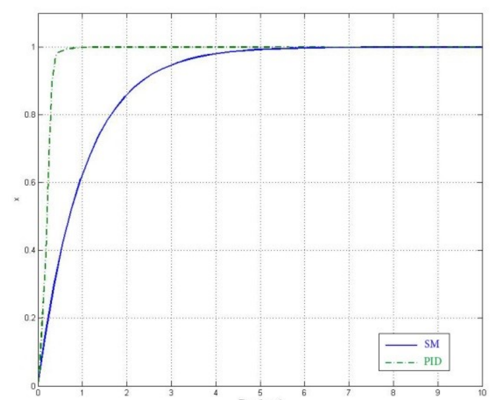

Figure 15 - comparing PID and SMC in controlling the reaction performance

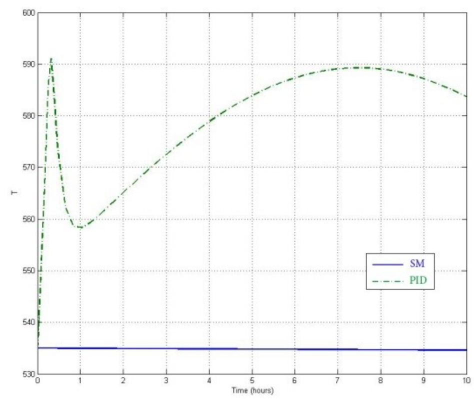

Figure 16 - comparing PID and SMC in controlling the reactor temperature

As the results shows, although by imposing PID, the reaction complete faster, but this controller can't keep the reactor temperature in the allowed range. But SMC by its robust structure could control the reactor temperature as well.

Finally, in Figure 17 and Figure 18, we can see the comparison of NMPC and SMC performance.

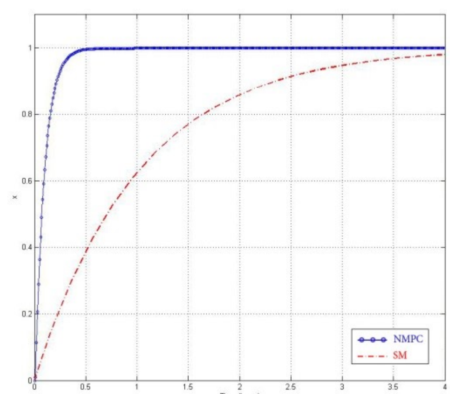

Figure 17 - comparing NMPC and SMC in controlling the reaction performance

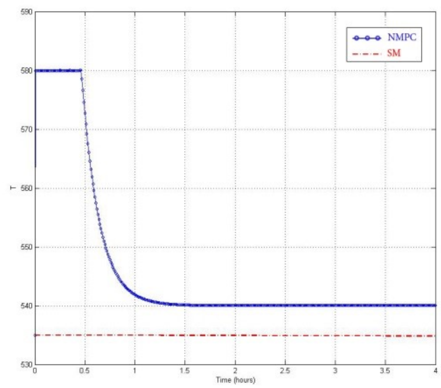

Figure 18 - comparing NMPC and SMC in controlling the reactor temperature

At the these figures shows, in both cases, in addition to performing reaction and conversion of all raw materials to the final product, the reactor temperature remained in allowing ranges and there is also not any uncertainty in the dynamics of the system.

Conclusion

This paper discusses about both the nonlinear model predictive control and observer based sliding mode controller. The optimal convergence of the tracking error to zero in presence of the disturbance, considering the constrains in designing procedure and applicability in chemical process are the illustrious characteristics of the NMPC. Sliding mode control is more efficient rather than traditional method, due to both the robustness against uncertainties and external disturbances and simplicity in the designing and implementation in practice. Robustness against uncertainties and disturbances, convergence of the tracking error to zero and promising performance are the merits of the proposed controllers. The simulation results show the promising performance of the proposed methods.

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