Nonlinear Model Predictive Control based on Neural Network Model for Controlling CSTR System

Daryoosh Mansouri, Behrooz Rezaie

Abstract**—**In this paper, a neural-network-based model predictive control method is proposed for controlling a nonlinear CSTR system. In the proposed method, a neural network model of the system is utilized to predict future behavior of the system. Then, the control signal is calculated using a nonlinear optimization tool. Calculation of the control signal is based on the neural network model of the system to optimize the system performance over a finite time horizon. To evaluate the efficiency of the proposed method, it is compared with a nonlinear fuzzy controller and also with a linear proportional-integral-derivative controller as a common industrial controller. Performance of the controllers is studied through simulations for the CSTR system in normal conditions and in the presence of disturbances. Simulation results show the superiority of the proposed method in both cases.

Keywords**—**Neural network, model predictive controller, continuous stirred tank reactor.

I. Introduction

Linear controllers are widely utilized in process control problems. Generally these systems show a highly nonlinear behavior and therefore control techniques, which are directly based on nonlinear concepts, are expected to show better performance. Model predictive control (MPC) has become a popular method in industrial processes because of its explicit capability to handle the system constraints. Choosing a proper model of the system is one of the most important issues in model based control methods like MPC. Many versions of MPCs are proposed such as Model Algorithmic Control (MAC) [1], Dynamic Matrix Control (DMC) [2], and Internal Model Control (IMC) [3] which despite of some differences, have the same structure and use a linear model of the plant. Although using a nonlinear model will increase the computational complexities, it will significantly improve the performance of controlled system.

In recent years, intelligent methods such as neural network (NN) and fuzzy logic control (FLC) have been combined with MPC [5]-[8], [11]. Due to inherit ability of NNs to approximate any nonlinear systems it has been widely used in the field of prediction and process control [4]. Also, FLCs have been increasingly applied to nonlinear systems in different areas of engineering. This control method is based on modeling of human language and has many advantages such as simple calculation, high robustness and lack of need to find the transfer function [8]. This paper focuses on the MPC method in which NN is used as model of the plant. Such NN-based MPC (NNMPC) has been successfully applied to many processes such as paper mill wastewater treatment [4], chemical reactor systems [6], air–fuel ratio of engines [5], steel pickling process [7] etc. In this paper, we consider the proposed NNMPC for a continuous stirred tank reactor (CSTR) system.

In addition to the proposed NNMPC, a nonlinear FLC is also designed for comparison. Moreover, a proportional-integral-derivative (PID) controller is also designed. PID as the most common used controller in industrial processes is based on the linear model of the system. These methods are applied to a continuous stirred tank reactor (CSTR) system and their performance is compared.

In the following, first, model of the CSTR is described in Section II. Then, in Section III formulation and designing procedure of the NNMPC and FLC is explained. In Section IV, performance of three designed controllers including NNMPC, FLC and PID controller is compared through simulation result performed for two scenarios: normal condition and in presence of disturbance. In the last section conclusion of the paper is given.

II. The Model of CSTR

CSTR systems are commonly used in chemistry field and the control problem of this type of reactors has been investigated in many papers [9]-[10], [15]. A schematic of a CSTR system is depicted in Fig.1.

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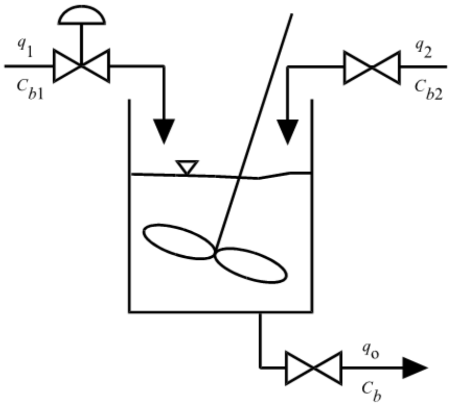

Fig. 1. Schematic of a continuous stirred tank reactor [10]

Model of the reactor studied here is taken from [9]-[10]. State equations for CSTR system are:

$$\begin{aligned}\frac{dh}{dt} &= q_1 + q_2 - 0.2\sqrt{h} \\ \frac{dC_b}{dt} &= (C_{b1} - C_b)\frac{q_1}{h} + (C_{b2} - C_b)\frac{q_2}{h} - r_b \\ r_b &= \frac{K_1.C_b}{(1 + K_2.C_b)^2}\end{aligned} \tag{1}$$

where r_b is rate of consumption of C_b, $h(t)$ is the liquid level, $C_b(t)$ is the product concentration at the output of the process, q_1 is the flow rate of the concentrated feed C_{b1}, and q_2 is the flow rate of the concentrated feed C_{b2}. As mentioned in [9] and [10], q_2 is assumed to be constant. Thus, the system is controlled as a single input single output system with q_1 as input and C_b as output. The acceptable range for the input of the reactor is $[0 \quad 4]\ mol/cm^3$. The controller task is to maintain value of C_b at a desired set point by adjusting q_1.

III. Controller Design

A. NNMPC

MPC is an optimal control strategy based on numerical optimization. Future control inputs and plant responses are predicted by the use of a system model and optimized over a specified finite time horizon regarding performance objective and constrains. In NNMPC, a NN model of the system is developed and used to predict the future responses of the plant. Various types of NNs such As multi-layer perceptron (MLP) [5]-[7], [13], [14], radial basis function (RBF) networks [11], [12] have been used in literature. In this paper a MLP network is trained to simulate the behavior of the CSTR.

As shown in Fig. 2, a NNMPC consists of four main parts: the controlled plant, the desired performance of the plant, a NN model of plant and an optimization part which calculates the future optimal control inputs.

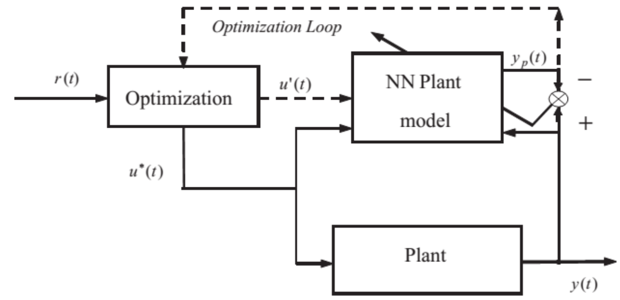

Fig. 2. Block Diagram of NNMPC [4]

1) MLP Model of CSTR

NNs have been applied successfully for the identification and control of dynamical systems. The universal approximation capability of MLP makes it a popular choice for modeling of nonlinear systems. Two-layer MLP networks with sigmoid transfer functions in the hidden layer and linear functions in output layer are proven to be universal approximators [15]. Structure of a typical two-layer MLP network is shown in Fig. 3.

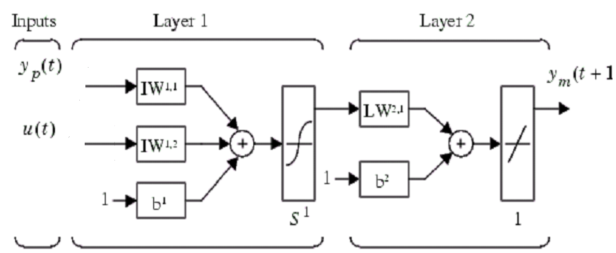

Fig. 3. Two Layer MLP Network [9]

The procedure of selecting the network parameters, i.e., training is of great importance in designing NN. Training of the MLP model can be performed off-line. Back propagation (BP) is a commonly used algorithm to train MLP networks. It is a gradient descent optimization procedure where a mean square error index is minimized [15].

MLP model of the plant take the present and past input and outputs of the plant as input and predicts the plant's output.

2) Optimization

The optimization process is generally based on minimizing a cost function over a defined prediction horizon under several constraints. The cost function will have different forms under different control requirements. If the constraints are linear the cost function can have quadratic formation as (2).

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$$\underset{u(t)}{Min} \quad J = \underset{u(t)}{Min} \left\{ 1/2 \sum_{i=N_1}^{N_2} \left\| y_r(t+i) - y(t+i) \right\|^2 \right.$$
$$\left. + 1/2 \sum_{i=0}^{N_\mu} \lambda_i \left\| u(t+i) \right\|^2 + 1/2 \sum_{i=0}^{N_\mu} \lambda'_i \left\| \Delta u(t+i) \right\|^2 \right\} \quad (2)$$
$$s.t. \begin{cases} u_{\min} \le u(t+i) \le u_{\max} & (i = 0, \dots, N_\mu) \\ y_{\min} \le y(t+i) \le y_{\max} & (i = N_1, \dots, N_2) \\ \left\| \Delta u(t+i) \right\| \le \Delta u_{\max} & (i = 0, \dots, N_\mu) \\ \Delta u(t+i) = 0 & (i > N_\mu - 1) \end{cases}$$

In this equation, λ_i, λ' are weight matrices (positive deterministic and symmetric), N_1, N_2 are the minimum and maximum output horizons respectively, N_μ is the control horizon, $\Delta u(t+i) = u(t+i) - u(t+i-1)$ is the control increment at time $t+i$, $y_r(t+i)$ is the desired output and $\|.\|$ denotes the Euclidean 2-norm.

The minimization process of function J is performed repeatedly at each time step. The calculated control signal is a time series vector but only the first element is applied to the plant as real input.

$$U = [u(t+1), u(t+2), \dots, u(n+N_\mu)]^T \quad (3)$$

In this equation, λ_i, λ' are weight matrices (positive deterministic and symmetric), N_1, N_2 are the minimum and maximum output horizons respectively, N_μ is the control horizon, $\Delta u(t+i) = u(t+i) - u(t+i-1)$ is the control increment at time $t+i$, $y_r(t+i)$ is the desired output and $\|.\|$ denotes the Euclidean 2-norm.

Since J depends on sequence of control actions, an iterative process can be used to determine the best control signal. The calculation and, mathematical formulation of the minimization process can be found in [4], [17].

The NNMPC controller is compared with a nonlinear FLC and also a linear PID controller. In the next sub-sections these controllers are described.

B.FLC

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A typical fuzzy controller can be considered as:

- If error is negative and change in error is negative then output is negative big

- If error is negative and change in error is zero then output is negative medium

Block diagram of a typical FLC is shown in Fig. 4. The fuzzification block converts the input data to degrees of membership in one or several membership functions. The rules are stored in rule base. Fuzzy rules are commonly in the form of if-then sentences. The controller calculates the control input by use of inputs and a reasoning algorithm based on the rules defined in the rule base. In the last step, the calculated fuzzy control signals are defuzzified so can be applied to the plant.

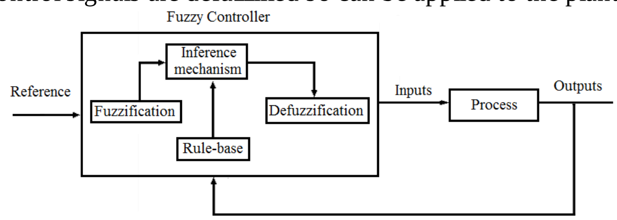


Fig. 4. Block Diagram of a Fuzzy Controller [15]

Selecting the membership functions and fuzzy rules are the most important part in designing a FLC that requires a detailed knowledge about the system dynamics and behavior. Parameter selecting of FLC is usually done using trial and error manner. Sometime the FLC is developed using the result of another designed controller. In other words, first a common controller like PID is designed for the plant and then it is fuzzified and improved using a well-known Takagi-Sugeno (T-S) fuzzy system namely adaptive neuro-fuzzy inference system (ANFIS).

Output of a fuzzy controller can be a combination of the inputs. For example suppose the rule of T-S fuzzy system is as follows:

$$If \ x_1 \ is \ A_i \ and \ x_2 \ is \ B_i \ then \ y = p_i . x_1 + q_i . x_2 + r_i \quad i = 1, .., N \quad (4)$$

The "if" part of the rule describes fuzzy regions in the space of input variables (error and derivative of error in this paper). The "then" parts are linear with consequent parameters (p_i, q_i, r_i) and y is and output variable and A_i, B_i are the fuzzy sets [15].

C. PID Controller

PID controller is the most common controller used in the industrial applications. To design a PID controller for a nonlinear system, first the linear approximation model of the system is calculated and PID controller is designed for the resulted linear system. Transfer function of a PID controller has the form of (5).

$$G_c(s) = K_c \left(1 + \frac{1}{T_I s} + T_D s \right) \quad (5)$$

A PID controller does not take into account the constraints on the control signal (as it is necessary for the CSTR system), so the range of controller output should be limited in some way.

IV. SIMULATION RESULTS

Performance of the proposed controller is evaluated via simulations for two scenarios in MATLAB/SIMULINK software. In the first scenario, CSTR system is working in normal conditions with no disturbances. In the second scenario, CSTR system works in the presence of disturbance which is considered to have changes in the second input (q_2).

Parameters of CSTR and initial conditions are mentioned in Table I.

TABLE I
PARAMETERS OF CSTR

Parameters	Value
K_1	1
K_2	1
C_{b1}	24.9 mol/cm^3
C_{b2}	0.1 mol/cm^3
q_1	0.1 cm^3/s
$C_b(0)$	22 mol/cm^3
$h(0)$	30 cm
Input Range	[0 4] mol/cm^3

For the NNMPC, the MLP model of system is a two layer network with 7 neurons in the hidden layer. Inputs to the MLP include three last samples of the input and two last samples of output. N_1, N_2 and N_μ are chosen 1, 8, 3 respectively.

In the designed fuzzy controller, error ($e = y_{ref} - y$) and its derivative (de/dt) are considered as the inputs. For each input, five membership functions are defined, so the rule base consists of 25 rules and output is a linear combination of the input values.

Membership functions are chosen to be symmetric Gaussian functions as it is seen in (6).

$$f(\mathrm{x};\sigma,\mathrm{c}) = \mathrm{e}^{\frac{-(x-c)^2}{2\sigma^2}} \tag{6}$$

In this equation, c is the mean of distribution and σ is standard deviation.

Since the PID controller and fuzzy controller may violate the acceptable range [0 4] for the control signal, their outputs are limited by means of a saturation block in MATLAB/SIMULINK.

A.Scenario 1

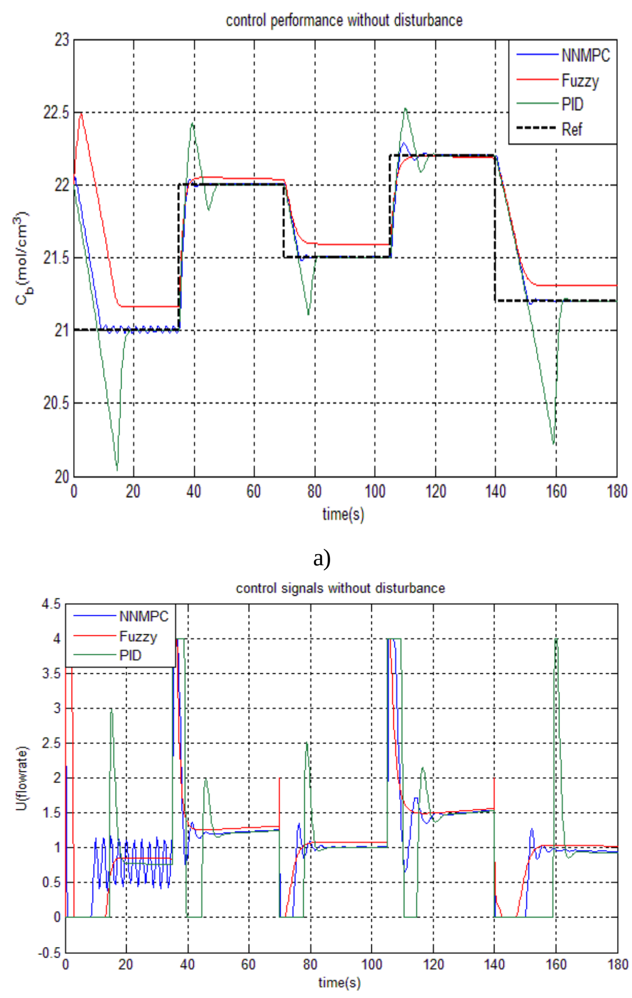
In this case, task of the controller is to track the reference signal for C_b. The reference signal is a step signal with magnitude of 21, then a step changes to 22 at t=35, step changes to 21.5 at time t=70 and to 22.2 at t= 105 and to 21.2 at t=140. Fig. 5 shows the changes in C_b and control signals for scenario 1.

As can be seen, system response for fuzzy controller reaches the steady state response smoothly and with no overshoot and response of PID shows high overshoots and undershoots. PID and NNMPC follow the reference signal with a small steady state error while the FLC suffers quite high error in steady state condition. PID controller needs much longer time to settle down.

B.Scenario 2

In this case, performance of the controllers in the presence of disturbance is studied. Disturbance in the CSTR system is considered as changes in q_2 (Fig. 6). System output and control signals are depicted in Fig. 6.

As shown in the figure, NNMPC shows a robust behavior against the disturbance and its response is still fast and precise. Fuzzy controller rejects the disturbance rather fast but steady state error is remarkable. Performance of the PID controller is highly affected when disturbance occurs. Magnitude of overshoots and settling time are significantly increased and the controller is not able to track the reference properly.



a)

b)

Fig. 5. Performance of controllers in normal condition: a) system

outputs, b) control signals

V. CONCLUSION

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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