Neural Network – Based Control Strategies Applied to a Chemical Reactor Process

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ABSTRACT

This paper is focused on issues of process modeling and model based control strategy of chemical reactor process applying the concept of artificial neural networks (ANNs). The control objective is to force the operation into optimal supersaturating trajectory. It is achieved by; manipulating coolant flow rate, the influent concentration of compound is control. Model predictive control (MPC) alternative is considered. Adequate ANN process models are first built as part of the controller structures. MPC algorithm outperforms satisfactory reference tracking and smooth control action while for the IMC an analytical control solution was determined.

Keywords

artificial neural network, nonlinear model control, process identification, chemical reactor process.

1. INTRODUCTION

A piolet scaled chemical reactor [1] is constructed and commissioned to study various conventional and advanced control strategies. Most successful data driven modeling techniques are the artificial neural networks (ANNs). Their ability to approximate complex non-linear relationships without prior knowledge of the model structure makes them a very attractive alternative to the classical modeling techniques [2][3]. Neural network control was chosen due to its capabilities to overcome the hassle in periodically tuning the conventional controller in obtaining good process response for certain set point. The purpose of this is twofold. We introduce two control alternatives based on an ANN nonlinear model to regulate the process. Model predictive control (MPC) and Internal model control (IMC) are comparatively considered and evaluated with respect to closed loop performance, certain feasibility and computational efforts.

2. PROCESS OPERATION

A chemical system, known as a Continuous stirred tank reactor (CSTR), was utilized as an example to illustrate the use of proposed MPC and IMC tool. In the CSTR, two chemicals are mixed, and react to produce a product compound with concentration $C_A(t)$. The temperature of the mixer is T (t). The reaction is exothermic, producing heat that acts to slow the reaction down. By introducing a coolant flow rate qc (t), the temperature can be varied and hence the product concentration controlled. This system can be described by the following two nonlinear simultaneous differential equations:

Rate of change of concentration:

$$\frac{dC_A}{dt} = \frac{q}{V}\left(C_{AF} - C_A\right) - k_0 C_A e^{\left(-E/RT\right)} \quad (1)$$

Rate of change of temperature:

$$\frac{dT}{dt} = \frac{q}{V}\left(T_F - T\right) + \frac{(-\Delta H) k_0 C_A}{\rho C_p} e^{\left(-E/RT\right)} + \frac{\rho_c C_{pc}}{\rho C_p V} q_c \left(1 - e^{\frac{-hA}{q_c \rho_c C_{pc}}}\right) \cdot \left(T_{cF} - T\right)$$

(2)

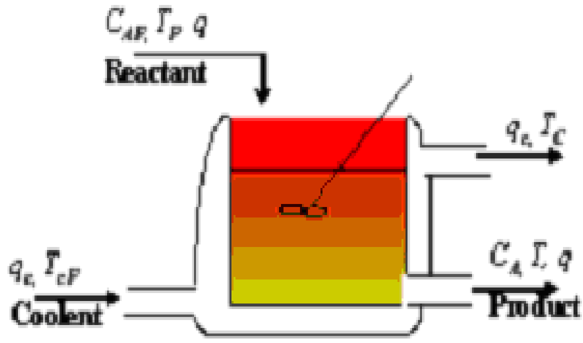

Fig. 1 Continuous stirred tank reactor (CSTR)

3. ANN –BASED MODEL PREDICTIVE CONTROL

3.1 Problem formulation

Nonlinear model predictive control (NMPC) is an optimization based multivariable constrained control technique that uses a nonlinear dynamic model for the prediction of the process outputs [4] [10]. At each sampling time the model is updated on the basis of new measurements and state variables estimates. Then the open loop optimal manipulated variable moves are computed over a finite (predefined) prediction horizon with respect to some performance index, and the manipulated variables for the subsequent prediction horizon are implemented. Then the prediction horizon is shifted or shrunk by usually one sampling time into the future, and the previous steps are repeated. The optimal control problem in the NMPC framework can be mathematically formulated as:

min J = Ø (x (t),u(t),p), (3)

umin<u (t) <umax

Where (3) is the performance index.

3.2 Identification stage – ANN learning algorithms

ANN has been successfully applied in the modeling, estimation, monitoring and control of dynamical systems. Their approximation capabilities make them a promising alternative for modeling nonlinear systems and for the implementing general purpose nonlinear controllers [2] [5] [6].There is typically two stages involved when using ANN for control: Process identification and control design. At the identification stage, an ANN model of the process dynamics is developed. ANN model uses previous inputs and previous process outputs to predict future values of the process output. The prediction error between the process output and the ANN output is used as an ANN training signal. The network is trained usually offline in batch mode, using data collected from the operation of the plant or generated by a reliable model. At the control design stage the ANN plant model is used to design the controller. Among various ANN training algorithms the back propagation algorithm (BP) algorithm is the most widely implemented for modeling purposes [7]. 3.3Closed loop ANN- MPC structure.

The particular closed MPC structure considered in this work is illustrated in fig. 2.

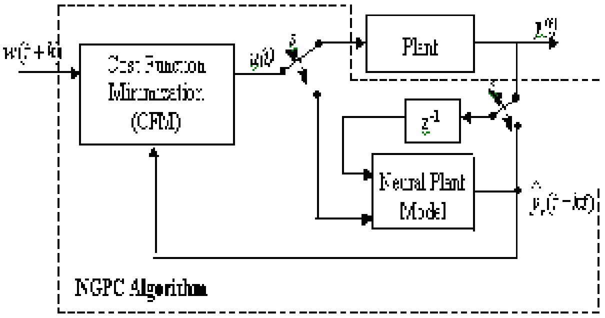

Fig.2 ANN MPC- simulation scheme

For the simulation purposes the CSTR process model implemented as the simulation model The ANN model predicts future process responses to potential control signals over the prediction horizon. The predictions are supplied to the optimization block to determine the values of the control action over a specified (control) horizon that minimizes the performance index. The MPC controller requires a significant amount of online computation, since the optimization is performed at each sample time to compute the optimal control input. At each step only the first control action is implemented to the process.

3.3 Numerical implementation of ANN-MPC

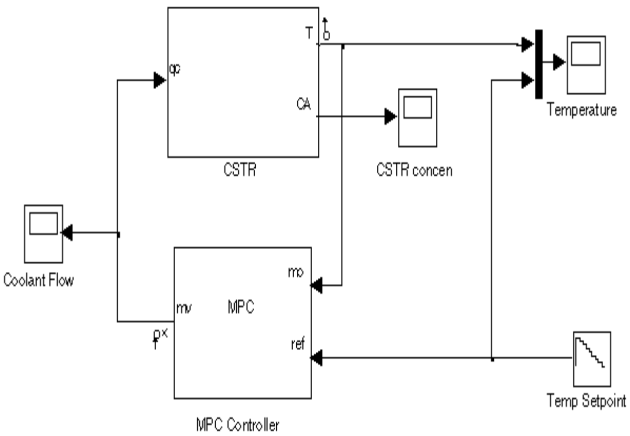

Fig. 3 ANN MPC-simulation scheme

The Numerical implementation of ANN-MPC model control is schematically presented in fig. 3. The control problem is simulated in Matlab/Simulink framework as a set of modules. The matlab NN Toolbox is also required the controller is designed as an independent block and the process is simulated as a CSTR model. The CSTR model is coded as a function required by simulink. First the ANN process model is identified in a specific plant identification window. This window is specified the network architecture (number of inputs, outputs, layers, type and number of neurons in layer), training data limitations and training parameters (number of epochs, training algorithm).

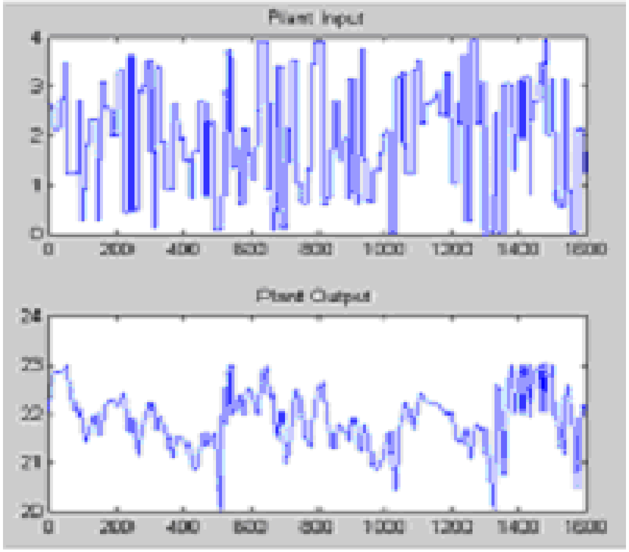

Fig.4 Training (input-output) data

The ANN is trained in a batch mode. An example of data generated by applying a series of random step inputs is shown in fig. 4. Data is divided into training, validation and simulation portion. On the same fig. 5 one can observe the ANN response and error to the different data sets.

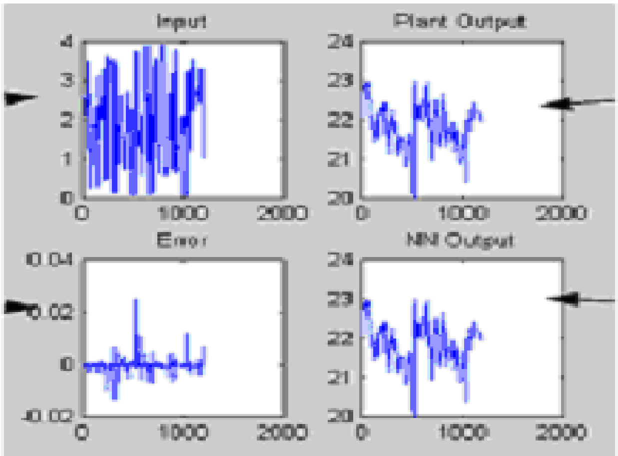

Fig.5 Validation (input-output) data; ANN error and output

4. SIMULATION STUDIES:

In this section MPC strategy developed is evaluated via simulation for highly nonlinear process i.e.CSTR

Table-I: Nominal CSTR operating conditions

$q = 100\ lmin^{-1}$	$E/R = 9.95 \times 10^{3}\ K$
$C_{Af} = 1\ mol^{-1}$	$-\Delta H = 2 \times 10^{5}\ cal\ mol^{-1}$
$T_f = 350\ K$	$\rho, \rho_c = 1000\ gl^{-1}$
$T_{cf} = 350\ K$	$C_p, C_{pc} = 1\ cal\ g^{-1}.K^{-1}$
$V = 100\ l$	$q_c = 103.41\ lmin^{-1}$
$hA = 7 \times 10^{5}\ cal\ min^{-1}\ K^{-1}$	$T = 440.2\ K$
$k_0 = 7.2 \times 10^{10}\ min^{-1}$	$C_A = 8.36 \times 10^{-2}\ mol\ l^{-1}$

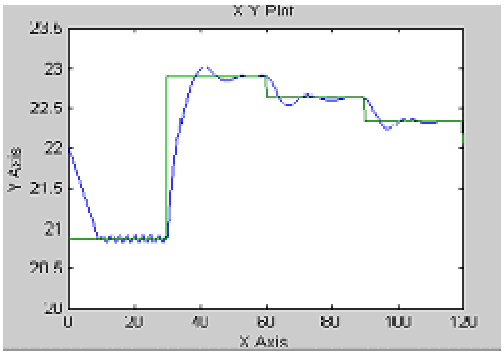

Fig. 6 ANN-MPC simulation

Fig. 5 summarized the learning process. While training and validation errors are significantly different, the generalization properties of the network are not reliable and the training has to continue. The learning is stopped when the training and the validation errors are sufficiently close. Simulation result is summarized in fig.6. Here disturbance occurs from t=20 to t=60. In case the controller explicitly considered the measurable disturbances it is able to reject them. A smooth transition between the two levels was determined to overcome possible overreaction of the tracking controller. The graph show satisfactory reference tracking with an acceptable smooth behavior of the control input.

5. CONCLUSION

The application of ANNs at two stages of CSTR process namely modeling and control is presented in this paper. ANN-based control algorithms were studied for model predictive control (MPC).MPC algorithm outperforms approach to satisfactory reference tracking and smooth control action It is observed that, for all set point changes, the NIMC controller yields a fast response with very little overshoot. Since the ANN model capture the nonlinear process nature, this methods have the potential advantages over the control methods based on linear models.

6. REFERENCES

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