Temperature Control for Chemical Reactor using Adaptive Neural Network Control Strategy

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Abstract: A pilot scaled chemical reactor [1] is constructed and commissioned to study various conventional and advanced control strategies. One of the researches to be due is regarding the use of neural network inverse model based controller to control the temperature of the chemical reactor. 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. Tests in form of load disturbance and set point tracking are carried out to evaluate the neural network controller. The neural network controller exhibits satisfactory performance. Simulation work prior to the planned online implementation is vital and crucial to predict the control strategy performance and behavior. With the expected performance in hand, we have the prior knowledge of the control strategy.

Keywords

Neural network application, adaptive, exothermic chemical reactor.

I. INTRODUCTION

The adaptive control method is utilized in order for the controller to be able to adjust its control action despite the changes in its operating parameters. Introduction of the adaptive capability is to ensure that the controller will maintain its performance objective regardless of the changing environment. Previous study by Liew and Ho (1999), and Hoo and Ng (1999) demonstrated the capability of the adaptive neural network strategy to control fermentation process successfully. [2,3]

The neural network controller based on the inverse model introduces an offset when it comes to the different load conditions and set point changes. In order to improve the controller performance, adaptive property is introduced to the developed neural network controller to reduce the previous offset during load disturbance changes. This is done by collecting beneficial data to train the neural network controller online as needed. The neural network controller have to be retrain in order to map out the correct new target to issue new control actions. The adaptive neural network controller is designed as such in this paper and simulations have been carried out to evaluate its performance.

II. THE PROCESS

The general layout of the chemical reactor used in this study is shown in Fig 1.

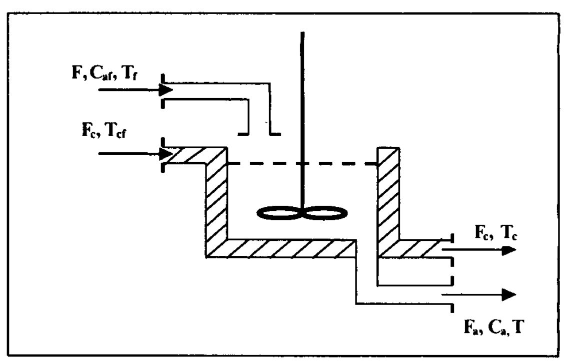

Fig 1: Schematic of a typical CSTR system

This figure shows the schematic of the process, i.e., a continuous stirred tank reactor (CSTR). The coolant jacket temperature, T_c is manipulated to control the CSTR temperature. The CSTR and the coolant jacket are assumed well stirred and the temperature is distributed uniformly within them by the help of the stirrer. In simulation, instantaneous response from the coolant jacket temperature is assumed to take place when setting different set points of coolant jacket temperature, T_c.

A pair of ordinary differential equations represents the mathematical modeling of the chemical reactor used in this simulation [4]. By manipulating the coolant jacket temperature T_c, training data for the neural network modeling and system identification was obtained. T_c is excited in pseudo-random discrete fashion in order to have good system identification properties. This procedure produced various pairs of reactant concentration, C_a and reactor temperature, T. The model equations stated below are as below: -

$$\frac{dC_a}{dt} = \frac{F}{V}\left(C_{af} - C_a\right) - k_o \exp\left(-\frac{E}{RT}\right)C_a$$

$$\frac{dT}{dt} = \frac{F}{V}\left(T_f - T\right) + \left(\frac{-\Delta H}{\rho C_p}\right)k_o \exp\left(-\frac{E}{RT}\right)C_a - \left(\frac{UA}{V\rho C_p}\right)\left(T - T_c\right)$$

The parameters used in the study are described in the nomenclature and as listed in the Table 1 below: -

Parameter	Value
F/V	1
K_o	9703*3600
$(-\Delta H)$	-5960 (exo)
E	11843
ρC_p	500
C_{af}	25
UA	150
R	1.987
T_I	311.1710
Ca_I	8.5636
T_f	298

Table 1: Nominal Operating Parameters for CSTR

III. INTERNAL MODEL CONTROL STRATEGY

The internal model control consists of the neural network forward, inverse model and the process model. Hussain and Kershenbaum have shown experimentally that the strategy can be implemented to control processes, such as a partially simulated exothermic reactor [5]. This work demonstrated the use of the neural network inverse model as the controller. The neural network forward model is applied to compare with the process model during strategy implementation. This is to cater for the plant mismatch error during control implementation.

A. Forward Model

The forward model of the system presents the forward dynamic of the system. The two-layer feedforward network used consists of 6 input nodes, 8 hidden nodes and 1 output node. The tansig transfer functions have been utilized in the hidden nodes and linear transfer function in the output node. The inputs are currents and past values of coolant temperature (T_c), reactant concentration (C_a) and reactor temperature (T) respectively. The forward model can be expressed mathematically in functions of T_c, C_a and T as shown below: -

$$T(t+1) = f\left(T_c(t), T_c(t-1), C_a(t), C_a(t-1), T(t), T(t-1)\right)$$

The objective of this forward model is to predict the reactor temperature (T). The network is trained [6] using Levenberg-Marquardt algorithm and validated until it satisfied the performance mean square error (MSE) of 1 X 10^{-5}. The defined error is the difference between output from the trained network and the actual values.

B. Inverse Model

In determining the inverse model to be used as the controller, once again the two layered feedforward network that have 6 input nodes, 12 hidden nodes and 1 output node is used. The transfer functions used are similar to the forward model network. The training is carried out similar to the previous method but this time the input to the network are the past value of coolant temperature (T_c), current and past values of reactant concentration (C_a), reactor temperature (T) and the required reactor temperature set point. The output of the network is the current value of the coolant temperature (T_c). This can be expressed mathematically as below: -

$$T_c(t) = f^{-1}\left(T_c(t-1), C_a(t), C_a(t-1), T(t), T(t-1), T(t+1)\right)$$

The network is trained and validated until the MSE error reached to the specified value of 1 X 10^{-5}.

For both of the inverse and forward neural network training there are two training data sets used. They are switched between each other during training to improve the neural network system identification capability. In obtaining the forward and inverse model using neural network, the number of the hidden nodes play a very important role in network performance. Currently, there are no specified methods in obtaining the correct number of nodes. In this study, the hidden nodes are chosen by trial and error where the network having the minimum-trained error with the corresponding hidden nodes will be chosen as the correct number of hidden nodes to be used. Larger number of hidden nodes will result in longer training period and an over parameterized network while lower hidden nodes will reduce the capability of the trained network to produce reasonable desired outputs.

IV. THE ADAPTIVE NEURAL NETWORK CONTROL STRATEGY

The Fig 2 shows the schematic of the adaptive neural network control strategy. The control action is coming from the neural network inverse model; the forward model is used here for compensating the plant mismatch that may occur during the process simulation. A filter [7] is placed in cascade prior to the inverse model, i.e. the controller, to improve robustness of the control system performance. As the simulation is carried out, the strategy constantly monitor the error between the desired set point and the process variable. If the error between them exceeds the limitation, the system will collect sequential pair of data to retrain the neural network. The numbers of data set collected are chosen by trial and error and we have collected 20 pairs of data for retraining purpose. When load disturbance occurred, the target for the forward and inverse model is not valid anymore. The models require new assigned target in order to operate properly hence reject the load disturbance. The new target for retraining are the reactor temperature set point (T_{sp}) and the input data sets chosen for the online training are the 20 most previous data sets.

As for the inverse model, slight modifications have to be made to the target value during retraining. The new target, $\tilde{T}_{new}$ values are obtained by using the equation $\tilde{T}_{new}(k) = \tilde{T}(k-1) + C \times \tilde{Z}$ where $\tilde{T}$ is the collected 20 pairs of training data matrices, C = 0.015, a constant and $\tilde{Z}$ is a column matrices of constants depending on the action i.e. reverse or forward acting. By using $T_{diff} = T - T_{for}$ where T_{diff} is temperature difference between the process output, T and the forward model output, T_{for}. The $\tilde{Z}$ is constructed by taking account of T_{diff} as listed below: -

$$
\begin{aligned}
Z &= -1 \quad when\, T_{diff} \langle 0 \\
Z &= 0 \quad when\, T_{diff} = 0 \\
Z &= +1 \quad when\, T_{diff} \rangle 0
\end{aligned}
$$

Constant C here is chosen by trial and error and different system may require different value of constant C.

The neural network is retrained using the same Lavenberg-Marquardt algorithm for a maximum of 10 epochs to minimize the retraining time during simulation of the controller, which is vital in adaptive control of the system.

V. SIMULATION RESULTS

For both the IMC and the adaptive NN control strategy, the set point tracking and load disturbance have been carried out.

Set point tracking result is shown in the Fig 3. The set point is changed to +10% from the previous value at t=600 for both strategies. After t=600, the IMC NN quickly response to the set point changes but introduced an offset. The adaptive NN re-adjusted its weights and biases and brought the process variable to its new set point. Set point tracking test exhibited that the adaptive strategy successfully removed the offset when using the IMC strategy alone.

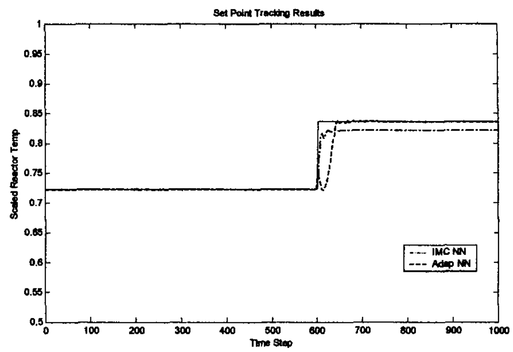

Fig 3: Set Point Tacking Result

To increase the performance of the IMC control strategy during load disturbance, adaptive neural network is implemented and it introduced some good results as can be seen in the Fig 4 and 5. Using IMC alone, offsets have been observed when load disturbance test is carried out. The load disturbance is simulated by taking out the control action at t=400 where the system responded to the load disturbance introduced. Changing the feed reactant concentration C_{af} from nominal value of 25 mol/litre to 20 mol/litre simulate the load disturbance to the system. After t=600, the control action from the neural network controller is injected back to the system and some offset is observed. The offset is greatly reduced when the adaptive NN is implemented. This can be seen in the Fig 4.

Another load disturbance rejection test have been carried out by changing the reactor feed temperature, T_f from 298 K to 303 K. The result can be seen in Fig 5. It showed that the adaptive NN strategy has remove the offset and brought back the system to its previous operating set point compared to the IMC strategy alone.

VI. CONCLUSIONS

It is observed that the adaptive control capable of giving better control compared to the IMC alone due to its capability in responding to changes in the process parameters. By taking account of the changes in the environment, the adaptive algorithm will alter the "memory" of the previous developed neural network and adjust its weights and biases to suites the new changes. In the other hand, it will still maintain its performance objective, which is to control the reactor temperature, T at the desired set point.

VII. REFERENCES

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NOMENCLATURE

F = Flow rate in liter/hr
V = Reactor Volume in liter
C_{af} = Feed Concentration in mol/liter
C_a = Tank Concentration in mol/liter
k_o = pre-exponential factor in per hr
$(-\Delta H)$ = Heat of Reaction in kcal/mol (exothermic)
E = Activation Energy in kcal/hr
R = Ideal gas constant in cal/°C.mol
T = Reactor Temperature in K
T_c = Coolant Jacket Temperature in K
UA = Overall Heat Transfer Coefficient in kcal/hr.K
C_p = Specific Heat of water kJ/kg/°C
ρ = Density of water in kg/m^3

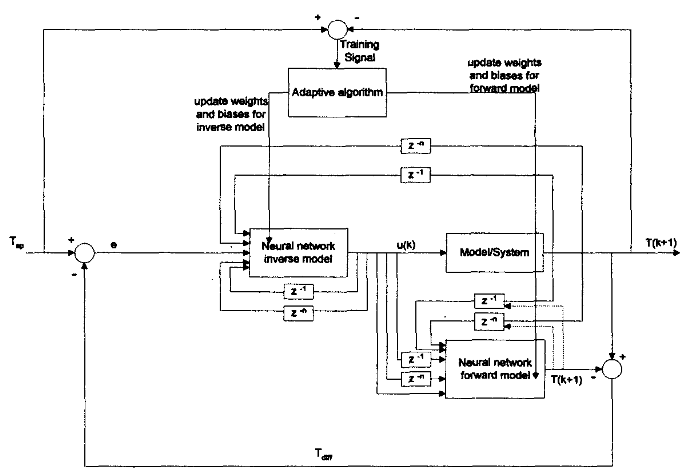

Fig 2: Adaptive Neural Network Control Strategy

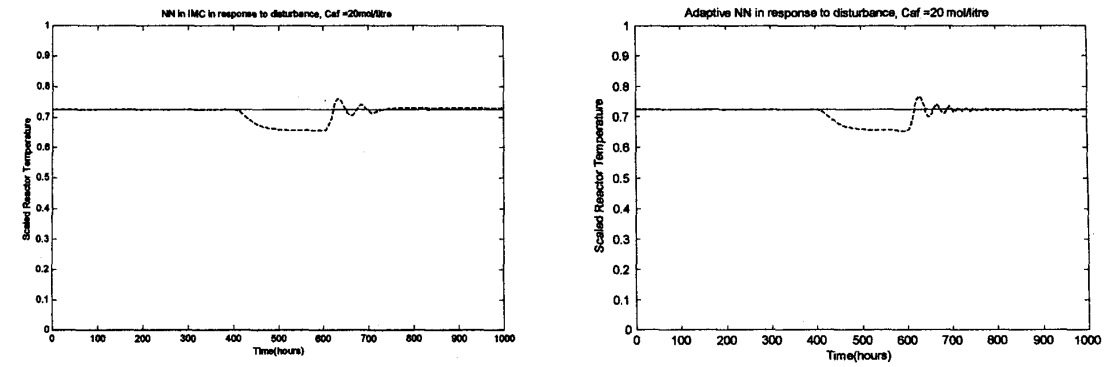

Fig 4: IMC and Adaptive NN Load Disturbance Rejection in Feed Concentration, C_{af} (25 mol/litre→20 mol/litre)

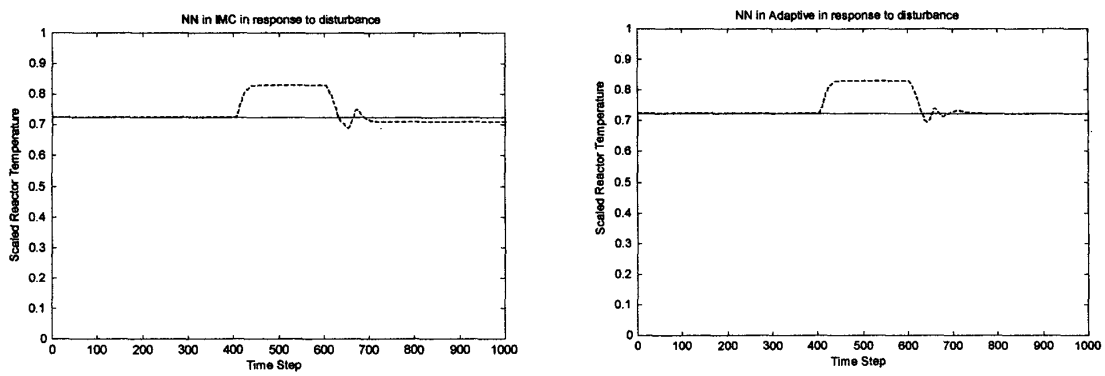

Fig 5: IMC and Adaptive NN Load Disturbance Rejection in Feed Temperature, T_{af} (298 K → 303 K)