ECE 539 - Introduction to Artificial Neural Network and Fuzzy Systems

Wavelet Neural Network control of two Continuous Stirred Tank Reactors in Series using MATLAB

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Abstract. With the rapid advances in the field of Artificial Neural Networks (ANN) and their innate ability to approximate any nonlinear system, there has been a considerable increase in the usage of control systems based on nonlinear concepts. In this paper, Wavelet Neural Network (WNN) based Direct Inverse Control (DIC) and Internal Model Control (IMC) schemes are proposed to control nonlinear dynamic systems and compared with the traditional Proportional – Integral- Derivative (PID) Controller. WNN combines the advantages of multi resolution capabilities of wavelets and function approximation capabilities of neural networks optimally. The proposed schemes are implemented and tested on a model of two cascaded Continuous Stirred Tank Reactors (CSTR) with coolant jackets using Shannon wavelet filter. The process variable in the test case is the concentration of the product mixture from the cascaded CSTR setup which is controlled by manipulating the inlet coolant flow rate. WNN based DIC displayed increased speed of response. WNN based IMC displayed better disturbance handling capabilities. Keywords: Artificial Neural Network, Wavelet Neural Network, Direct Inverse Control, Internal Model Control, Continuous Stirred Tank Reactor.

1 Introduction
Getting a desired performance from an industrial process is a major concern, especially when the system under control inherits nonlinear dynamic characteristics. It is required to design an intelligent system to identify the process behavior and control it. For last three decades, various neural network based computational control schemes have been exhibiting effective performances than conventional control schemes. Many research outcomes proved that an ANN, which has dynamically interconnected functional elements called neurons, can be used to model any non-linear system. This universal approximation capability of an ANN was combined with the multi resolution capability of wavelet transform to form a WNN [1-3]. This WNN achieves the performance of an ANN with reduced network size. The reduced network size of a WNN also increases the speed of computation in many applications compared to that of a Multi-Layer Perceptron (MLP) based one. Traditionally, neural controllers were developed using MLP based process models to achieve stable response from any non-linear dynamic systems. In this project, two neural controller schemes, WNN based Direct Inverse Control (WNNDIC) and WNN based Internal Model Control (WNNIMC), are proposed by replacing the traditional MLP models with WNN models. In WNNDIC approach, the necessary control signal, for a system with non-linear behavior (1) was accomplished from the inverse model of the system. A Shannon wavelet based neural network was trained to learn the inverse dynamics (2).

\[ y(k+1) = f[y(k), y(k-1), y(k-2), \ldots, u(k), u(k-1), u(k-2), \ldots] \]  

\[ \hat{u}(k) = \hat{f}^{-1}[y(k+1), y(k), y(k-1), \ldots, u(k-1), u(k-2), \ldots] \]  

(1)  

(2)
The WNNIMC, which closely follows WNNDIC, was accomplished with inverse and forward models of the system under study. Both these models were also designed using Shannon wavelet based WNN models.

The proposed neural control schemes were tested on the model of cascaded CSTR with cooling jacket. The objective was to maintain the chemical concentration in the second reactor at the reference by manipulating the coolant flow. Simulation results reveal that the WNNDIC and WNNIMC improve the performance of their counterparts designed using MLP based models. It was also observed that the WNNIMC overcomes the inability of WNNDIC in efficiently handling constant disturbances.

This report is organized to discuss the CSTR process, formation of PID Controller and the theory behind WNN model in the first section. The following sections will cover WNNDIC and WNNIMC design concepts. The last section discusses the results obtained using both WNN and MLP based approaches.

2 Problem Formation

2.1 Process model

The process setup is shown in fig.1. An irreversible, first order reaction of cyclopentadiene forming cyclopentenol occurs in the reactors. The manipulated variable is the coolant flow rate and the dependent variables are the concentrations of reactants and temperatures of the tanks.

\[
\frac{dC_{A1}}{dt} = \frac{q}{V_1} \left( C_{A1} - C_{A1} \right) - C_{A1} \alpha \exp\left( -\frac{E}{RT_1} \right)
\]  

(3)
Component balance expression for Reactor 2:
\[
\frac{dC_{A2}}{dt} = \frac{q}{V_2} (C_{A1} - C_{A2}) - C_{A2} \alpha \exp(-\frac{E}{RT_2})
\]  
(4)

Where
- \(q\) is the inlet feed rate (L/min),
- \(C_{A}\) is the feed concentration of A (mol/L),
- \(V_1, V_2\) are the volumes of reactor 1 and 2 (L),
- \(\alpha\) is the pre exponential factor for \(A \to B\),
- \(E/R\) is the Activation energy (K),
- \(C_{A1}, C_{A2}\) are the concentrations of A in reactor 1 and 2 (mol/L).

Energy balance expression for Reactor 1:
\[
\frac{dT_1}{dt} = \frac{q(T_f - T_1)}{V_1} - \frac{C_{p} \rho_c q_c}{V_1 C_p \rho} \left(1 - \exp(-\frac{U_{A1}}{q_c \rho_c C_{pc}})\right)(T_{cf} - T_1) - \frac{\Delta H \alpha C_{A1}}{C_p \rho} \exp(-\frac{E}{RT_1})
\]  
(5)

Energy balance expression for Reactor 2:
\[
\frac{dT_2}{dt} = \frac{q(T_f - T_2)}{V_2} - \frac{C_{p} \rho_c q_c}{V_2 C_p \rho} \left(1 - \exp(-\frac{U_{A2}}{q_c \rho_c C_{pc}})\right)(T_1 - T_2) - \frac{\Delta H \alpha C_{A2}}{C_p \rho} \exp(-\frac{E}{RT_2})
\]  
(6)

where,
- \(T_f\) is the feed temperature (K),
- \(T_1, T_2\) are the temperatures of reactor 1 and 2 (K),
- \(U_{A1}, U_{A2}\) are the overall heat transfer coefficients of reactor 1 and 2 (J/min-K),
- \(\Delta H\) is the heat of reaction (J/mol),
- \(\rho\) is the density of fluid (g/L),
- \(\rho_c\) is the density of coolant fluid (g/L),
- \(C_p\) is the heat capacity of fluid (J/g-K),
- \(q_c\) is the inlet coolant flow rate (L/min),
- \(C_{pc}\) is the heat capacity of coolant fluid (J/g-K).

2.2  **PID Controller.**
The most commonly used control strategies are based on conventional linear Proportional Integral Derivative (PID) controllers. The process is simulated digitally. The results from the simulation were used to study the dynamic behavior of the process, i.e. to obtain the parameters that will aid in the selection of controller constants. To obtain the gain (\(kp\)), the process time delay (\(\tau_D\)), and the process time constant (\(\tau_i\)) of our process, the CSTR was perturbed using step input of -11% and +11% of the manipulated variable. Response of CA2 and T2 resulting from the step changes in the input variable is shown in figures 2 and 3.
The transfer function parameters are found from figure 2.

<p>| | |</p>
<table>
<thead>
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<tbody>
<tr>
<td>K</td>
<td>0.00046213</td>
</tr>
<tr>
<td>T</td>
<td>0.6356 mol/L</td>
</tr>
<tr>
<td>td</td>
<td>0</td>
</tr>
<tr>
<td>ts</td>
<td>20 sec</td>
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**Table 1 Open loop response parameters**

Using the Cohen Coon method of controller tuning, approximate PID controller values are found.

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<table>
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<tr>
<td>kp</td>
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</tr>
<tr>
<td>τi</td>
<td>0.003279</td>
</tr>
<tr>
<td>τd</td>
<td>0.0005907</td>
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**Table 2 Tuned Parameters**

As ki = 1/τi and kd = τd, the values of ki and kd are 304.9508 and 0.0005907 respectively.

A digital version, also called velocity form is written as

\[ u_k = u_{k-1} + k_i e_k + k_p (e_k - e_{k-1}) + k_d e_k - 2e_{k-1} + e_{k-2} \]
Here \( u_k \) is the flow rate of coolant (control variable) at the \( k \)th instant. This form is obtained by replacing the integral and the derivative term with the finite difference approximations:

\[
\int_0^t e(t^*) dt \approx \sum_{j=1}^k e_j \Delta t
\]

\[
\frac{de}{dt} = \frac{e_k - e_{k-1}}{\Delta t}
\]

Where, \( \Delta t \) is the sampling period (time between successive measurement of controlled variable) \( e_k \) is the error at the \( k \)th sampling instant.

By using this and writing the equation at \( k \)th, \( k-1 \)th and \( k-2 \)th instant, the velocity form is found.

### 2.3 Wavelet neural network model.

An ANN generally consists of 3 layers- input, hidden and output. These layers are connected through weighted paths. The network is trained to produce the required value by adjusting the weights in the model. The ANN combined with the wavelet transform theory forms the adaptive WNN model. Here, each neuron is defined by the function (7), where \( h(\tau) \) is generated by dilation \( a \), and translation \( b \), with \( a > 0 \) The activation function of the neurons is also adjusted according to the error, by changing \( a \) and \( b \), in the training phase of a WNN. Shannon wavelet filter (8) was utilized in the modeling process.

\[
h(\tau_k) = h((t-b_k)/a_k) \quad (7)
\]

\[
h(\tau_k) = (\sin 2\Pi \tau_k \sin \Pi \tau_k)/\Pi \tau_k \quad (8)
\]

where, \( k \) denotes the \( k \)th neuron in the hidden layer.
3 Direct Inverse Control

Inverse modeling involves training a neural network to form a controller which is the inverse of the plant. The block diagram of the same is shown in fig. 4.

The equation for the inverse model is given by:

\[ u = f^{-1}(q_c(t-1), q_c(t-2), C_{A2}(t-1), C_{A2}, C_{A2}(t+1)) \]  

(9)

A pseudo random signal is given as input to the CSTR model and output values are noted. Using these input-output values, the training pattern for the inverse network is extracted according to (9). The training of the network is done by feeding the feed forward net with the training pattern and adjusting the weights until the error reduces to allowable range. The training uses Levenberg Marquardt Back propagation algorithm.

The neural network structure representing the inverse of the system dynamics at the completion of training is shown in fig. 5. Feedforward network has one hidden layer of seven Shannon activated neurons followed by an output layer of a linear neuron.
Internal Model Control is a control strategy which delivers better constant load disturbance handling capability. It combines both forward and inverse model of the process. Fig. 6 depicts the block diagram of internal model control. Internal model controller is incorporated in parallel with the process model. As the inverse model of the process is modeled into a controller, similarly a forward neural network model is used along with the process. When there is an unknown disturbance in the process, the error between the outputs of the process and forward model are calculated and fed back to the inverse model.
The neural network structure representing the inverse of the system dynamics at the completion of training is shown in fig. 5. Feedforward network has one hidden layer of seven Shannon activated neurons followed by an output layer of a linear neuron. The forward network model is shown in fig. 7. It is a feedforward network having one hidden layer of five Shannon activated neurons followed by an output layer of a linear neuron.

![Diagram](image)

Fig.7: WNNIMC network structure

5 Results

The concentration of cyclopentadiene in reactor 2 is controlled. The manipulated variable is the coolant flow rate. The initial steady state conditions of the 4 states are: \( C_{A1} = 0.0882 \text{ mol/L} \); \( T_1 = 441.2193 \text{ K} \); \( C_{A2} = 0.0052 \text{ mol/L} \); \( T_2 = 449.4745 \text{ K} \);

The closed loop response of the system with the feedback controller as PID controller is shown in figure 8. The system is given to track two set points: 0.006 mol/L and 0.004 mol/L. The response of the PID controller is shown below.
Closed loop response of the system with MLP based DIC is shown in fig. 10 and that of WNNDIC is shown in fig. 11. The system is set to track the reference signal as shown in fig. 9. The MLP based DIC having 9 sigmoidal neurons in the hidden layer gave a rise time of 5 sec and peak overshoot of 0.67%. It takes 25 sec to settle at the required concentration. The WNNDIC has a rise time of 3 sec and a peak overshoot of 2%. It takes 24 sec to settle at the required concentration.

**Figure 8 Response of PID Controller**

Fig. 9: Reference concentration level in reactor-2.
A constant load disturbance in the coolant flow rate of 1 L/min was introduced for a finite duration to analyze the disturbance handling capability of the MLP based DIC and WNNDIC strategies. The response of MLP based DIC to disturbance is shown in fig. 13 and that of WNNDIC is shown in fig. 14. Both the DIC strategies were found to be incapable of handling constant load disturbances. Post disturbance, the MLP based DIC took 21 sec to return to the set point while the WNNDIC took 17 sec to return to the set point.
Fig. 12: Disturbance

Fig. 23: Response of MLP based DIC to disturbance

Fig. 14: Response of WNNDIC to disturbance
The closed loop response of the system with MLP based IMC is shown in fig. 15 and that with WNNIMC is shown in fig. 16. The system is set to track the same reference signal as shown in fig. 9. The MLP based IMC having a forward network with 3 inputs, 8 sigmoidal hidden neurons and 1 output gave a rise time of 14 sec but 0% overshoot. It took 24 sec to settle at the required set point. The WNNIMC has a same rise time and 0% overshoot but settles in 22 sec.

A constant load disturbance in the coolant flow rate of 1 L/min was introduced for a finite duration to analyze the disturbance handling capability of the MLP based IMC and WNNIMC strategies. The response of MLP based IMC to disturbance is shown in fig. 17 and that of WNNIMC is shown in fig. 18. The MLP based IMC returns back to the set point in 16 sec during the disturbance period. The WNNIMC returns to the set point in 14 sec. Both the schemes incur offset peaks at the rising and falling edge of the disturbance graph.
Conclusion

In the present work, WNN based DIC and IMC control strategies were implemented and analyzed on a cascaded CSTR model and the result was compared to that obtained from PID tuning. The constant load disturbance handling capability of these control strategies were also investigated. PID controller had the highest rise time. The WNN based DIC and IMC had reduced network size and displayed improved robustness as compared to conventional MLP based DIC and IMC. WNNDIC showed considerably reduced rise time and settling time than MLP based DIC. IMC strategy was implemented to overcome the inherent inability of the DIC control strategy to handle load disturbances effectively. Both WNNIMC and MLP based IMC returned 0% peak overshoot and lessened rise time and settling time than their DIC counterparts. Also, IMC strategy displayed enhanced constant load disturbance handling capability with just two offset peaks of very short duration; one each at the rising and falling edge of the constant disturbance. The time duration of the offset peaks were lesser in the case of WNNIMC than MLP.
based IMC for same constant disturbance over same duration. The WNNDIC and WNNIMC were found to be more robust and faster than conventional MLP with considerable reduction in network sizes.

7 References