ScienceAsia 27 (2001) : **41-50**

Implementation of Neural-Network-Based Inverse-Model Control Strategies on an Exothermic Reactor

Mohamed Azlan Hussain[a], Paisan Kittisupakorn[b] and Wachira Daosud[b]
[a] Department of Chemical Engineering, University Malaya, 50603 Kuala Lumpur.
[b] Department of Chemical Engineering, Chulalongkorn University, Bangkok 10330.

Received 22 Dec 1999
Accepted 3 Aug 2000

ABSTRACT In recent years there has been a significant increase in the number of control system techniques that are based on nonlinear concepts. One such method is the nonlinear inverse-model based control strategy. This method is however highly dependent on the availability of the inverse of the system model under control, which are normally difficult to obtain analytically for nonlinear systems. Since neural networks have the ability to model many nonlinear systems including their inverses, their use in this control scheme is highly promising. In this work, we investigate the use of these neural-network-based inverse model control strategy to control an exothermic reactor. The use of the specialised method of training the inverse neural network model is demonstrated. The utilization of two different inverse-model schemes namely the direct inverse control and the internal-model control methods are shown for both set point and disturbance rejection cases. The overall results for set point tracking are good in both control strategies but the direct inverse control method had limitations when dealing with disturbances. Other important aspects relating to the use of neural networks for identification and controls are also discussed in this paper.

KEYWORDS: control, neural network, reactor.

INTRODUCTION

Although the use of linear control methods have been prevalent in the chemical process industries, they have their limitations especially when dealing with nonlinear plants in a wide operating region as commonly found in these industries. Many economically important operations, such as reactors and high-purity distillation columns, can be very nonlinear and very difficult to control adequately with linear controllers. In fact chemical reactors create some of the most challenging feedback control problems faced by chemical process control engineers. Complex steady state and dynamic behaviour, such as ignition/extinction behaviour and parametric sensitivity create challenges that are tough for traditional linear controllers to handle. However progress in nonlinear control theory, combined with computer hardware advances, now allow advanced, nonlinear control strategies to be successfully implemented on chemical processes Bequette BW(1991). One such technique is the nonlinear based inverse-model control strategy. The ease and speed of applying this method relative to other possible methods (such as the predictive schemes) for many applications is clearly evident. However this method relies heavily on the availability of the inverse of the system's model, which acts as the controller in this scheme. Unfortunately the inverse of a system may be difficult to obtain analytically for many nonlinear systems, which is one of the reason why its use is not presently widespread in the control of process systems.

However since neural networks have the potential to model any system, the use of neural network for modelling these inverses and hence utilised them in these inverse-model-based strategies is highly promising. These connectionist models also have the ability to learn the frequently complex dynamic behaviour of a physical system. In fact many researches e.g. Cybenko G (1989), Hornik K, Stinchcombe M. and White H (1989) have recently proven that any continuous functions can be approximated to an arbitrary degree of exactness on a compact set by a feedforward neural network comprising two hidden layers and a fixed, continuous non-linearity. In general some of the reasons for the recent upsurge in the use of neural networks in chemical engineering are as follows:

1. The tremendous hardware advances in digital technology over the past decade have enabled simulations of neural nets to be made both

economically and with relative ease and speed. Although neural networks are parallel devices, the majority of their simulations at present are being simulated sequentially on serial computers. However, neural networks can be more efficiently used as parallel computing technology becomes more readily available.

2. Application of neural network for sensor pattern classification have been found to be superior to the traditional techniques or the expert system approaches.

3. Neural networks offer the promise of being able to extract information from plant in an efficient manner with normal availability of rich data. In some cases, it may not be cost effective to develop models from first principles at all times especially those dealing with severe/unknown on-linearity's. Neural networks offer a simpler and efficient alternative.

4. Some practitioners contend that neural networks may be easier to use and apply in the real plant, with difficult to handle nonlinearities, as compared to the modelling approach which can be subjected to various modelling errors.

5. Finally the versatility in structure and application of neural networks enables them to be utilised in the middle ground between conventional model-based approaches and black box approaches for solving many classes of problems and they can also be easily accommodated in various conventional model based control strategies such as the inverse, adaptive and predictive control methods.

These factors motivates us to study the use of these inverse-model neural-network-based controllers on a complex nonlinear system such as the two-state variables continuous stirred tank exothermic reactor. This article describes the use of such controllers for the control of a reactor exhibiting strong parametric sensitivity. Two control schemes based on the inverse models are utilised. Before utilising them in these schemes various important features on the forward and inverse models are discussed. The usual approach for identification of plant dynamics is followed, where it is assumed that the output of the plant can be reconstructed from a finite number of past inputs and outputs. The control simulation studies involve set point tracking and disturbance rejection cases, where the concentration (dimensionless) is controlled using the coolant temperature (dimensionless) as the manipulated variable.

Case Study

Continuous Stirred Tank Reactor

The nonlinear chemical process studied in this work is the exothermic stirred tank reactor system with first order reactions. The reactor is assumed to be perfectly mixed and no heat loss occurs within the system Limqueco LC and Kantor JC (1990). Other assumptions made in formulating the model include: All model parameters and physical properties are constant at nominal operation, all temperatures and concentration values are measurable either directly or indirectly, the temperature of cooling water can be directly manipulated without delay i.e the cooling water jacket dynamics can be neglected and the feed concentration is assumed to be a known constant in this case.

The irreversible, first order reaction in the system takes the form

$$A \xrightarrow{k0} B$$

The model of the CSTR and its reaction system in continuous time is given by:

$$\frac{dC}{dt} = -k_o C e^{-\frac{E}{RT}} + \frac{Q}{V}\left(C_f - C\right) \qquad (1)$$

$$\frac{dT}{dt} = \frac{-\Delta H}{\rho C_p} k_o C e^{-\frac{E}{RT}} + \frac{Q}{V}\left(T_f - T\right) + \frac{U_r A_r}{\rho C_p V}\left(T_c - T\right) \qquad (2)$$

where C and T are reactants concentration and reactor temperature respectively. The feed concentration C_f is assumed to be constant and known. The model can be made dimensionless by introducing the parameters:

$$\beta = \frac{-\left(\Delta H\right) C_f}{\rho C_p T_{fo}} \gamma \qquad (3)$$

$$\delta = \frac{U_r A_r}{\rho C_p Q_o} \qquad (4)$$

$$\gamma = \frac{E}{R T_{fo}} \qquad (5)$$

$$\phi = \frac{V}{Q_o} k_o e^{-\gamma} \qquad (6)$$

$$q = \frac{Q}{Q_o} \qquad (7)$$

where Q_0 and T_{f0} are the known nominal values of the volumetric flowrate and feed temperatures respectively. The meanings of the other variables and parameters can be found in the nomenclature. The corresponding dimensionless variables are defined by:

$$\tau = \frac{Q_o}{V} t \tag{8}$$

$$u = \frac{\gamma\delta}{T_{fo}}\left(T_c - T_{fo}\right) \tag{9}$$

$$v = \frac{\gamma q}{T_{fo}}\left(T_f - T_{fo}\right) \tag{10}$$

$$x_1 = \frac{C}{C_f} \tag{11}$$

$$x_2 = \frac{T - T_{fo}}{T_{fo}}\gamma \tag{12}$$

The resulting reduced dimensionless model is then given by:

$$\frac{dx_1}{d\tau} = -\phi x_1 K\left(x_2\right) + q\left(1 - x_1\right) \tag{13}$$

$$\frac{dx_2}{d\tau} = \beta\phi x_1 K\left(x_2\right) - \left(q + \delta\right)x_2 + u + v \tag{14}$$

where $K(X_2)$ is given by $\exp\left(\frac{x_2}{1 + x_2/\gamma}\right)$. Here x_1 (or output, y) is the dimensionless concentration, x_2 is the dimensionless reactor temperature, u (the control variable) is the dimensionless temperature of the cooling medium and v is the dimensionless feed temperature (disturbance).

The parameters chosen in this case study can be seen in Table l. In this case study, the initial feed temperature, T_f and the nominal feed temperature, T_{fo} are both equal at 300 K. The system has been shown to exhibit strong parametric sensitivity for these range of parameters and conditions where a dramatic change in the outlet temperature and concentration can be caused by a small disturbance in feed temperature. This can be clearly seen from the steady state operating plot for the CSTR in dimensional form i.e. plots of the steady state rate of heat generation, QRrel and removal, QRrem versus the reactor temperature. The intersection of these two plots points to the steady state condition of the reactor (steady state reactor temperature), assuming constant cooling water temperature. As seen in Figure 1 an increase in feed temperature of 5 K, from the nominal temperature of 300 K, dramatically changes the steady state point to a new one (changes in both the dimensionless concentration and temperature under open-loop).

Table 1: Parameter values for case study

Dimensionless activation energy	γ	20
Damkohler number	ϕ	0.11
Dimensionless heat of reaction	β	7
Dimensionless heat transfer coefficient	δ	0.5
Dimensionless volumetic flowrate	q	1

Neural Networks in Inverse-Model Control Strateges

Neural networks can be incorporated in the inverse-model control scheme in two different ways i.e. direct inverse control and the inverse model control methods. The direct inverse control strategy utilises these neural networks in a simple form. In this case the neural network acting as the controller, has to learn to supply at its output, the appropriate control parameters, u for the desired targets, ysp at its input. The network inverse model (the training or identification of which will be explained in later sections) is then utilised in the control strategy by simply cascading it with the controlled system or

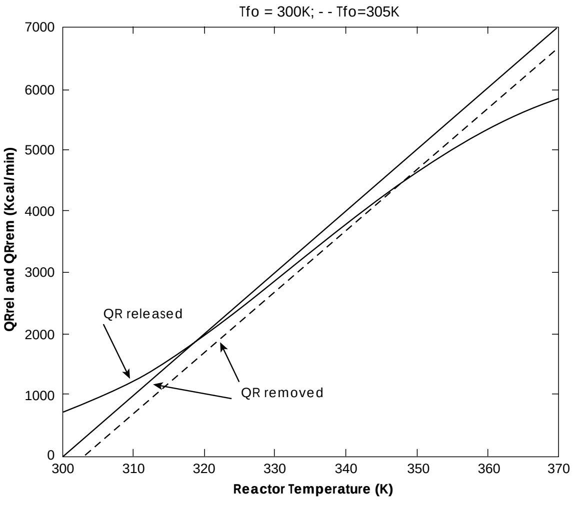

Fig 1. Steady state operating condition with changed in feed temperature.

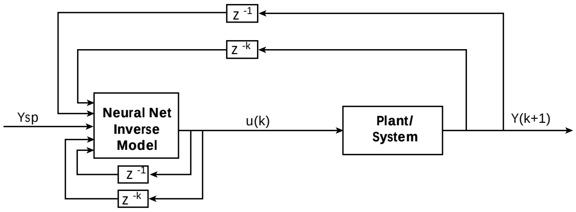

Fig 2. Neural network in direct inverse control strategy.

plant as seen in Figure 2. In this control scheme the desired set point, ysp acts as the desired output which is fed to the network together with the past plant inputs and outputs to predict the desired current plant input Pao YH Phillips SM and Sobajic DJ (1992). This method depends heavily on the accuracy of the inverse model mapping and is commonly used in applications such as robotics Kawato M, Furukama K and Suzuki S (1987), Yamada T and Yabuta T (1990).

The other strategy is that of the nonlinear internal model control technique, which is basically an extension of the linear IMC method Hornik K, Stinchcombe M. and White H (1989). In this method both the forward and inverse models are used directly as elements within the feedback loop. The IMC approach is similar to the direct inverse approach above except for two additions. First is the addition of the forward model placed in parallel with the plant, to cater for plant or model mismatches and second is that the error between the plant output and the neural net forward model is subtracted from the set point before being fed into the inverse model. The other inputs to the inverse model is similar to the direct method. Furthermore in this case the forward model is fed with the input to the plant (i.e. output of inverse model) as well as the past inputs and past outputs of the plant. The forward model can also be fed with its past outputs instead of the plant outputs, especially in cases of noisy plant output data (as seen from the dotted line of Figure 3). A filter, F can be introduced prior to the controller in this approach to incorporate robustness in the feedback system, especially where it is difficult to get exact inverse models. The IMC strategy however has a few drawbacks such as not being able to handle unstable processes and nonminimum phase systems.

An alternative method used by researchers to compute the control signals Psichogios DM and Ungar LH (1991), Nahas EP, Henson MA and Seborg DE (1992) is to numerically invert the neural network forward model at each interval by Newton's method or substitution methods based on the contraction mapping theorem. The first derivative with respect to the control input can be computed in these techniques by the usual backpropagation method. These numerical techniques are time-consuming, very sensitive to the initial estimates and they may not necessarily give the global and unique solution. They are also computationally intensive as compared to using the neural network inverse model directly, as in our work here.

Neural network models

Before applying these inverse-model neural network control strategies on the stirred tank reactor, we will initially discuss the development and configuration of the forward and inverse models, fundamental to these model-based control strategies.

Forward models

The procedure of training a neural net to represent the forward dynamics of a system (i.e. Obtain outputs given the inputs) is referred to as forward modelling and the models obtained from this procedure are called the...forward models. The most popular and straightforward approach is to augment the network inputs with corresponding discrete-time past inputs and past output data signals in real number form, from the model or system being identified as seen in Figure 4. Other fundamental state variables such as the reactor temperature in this case study can also be fed into the network and considered as part of the inputs. In this procedure, the network is fed with the present input, past inputs as well as the past outputs to predict the necessary output. The neural network is placed in parallel with the model or system and the error between the system output and

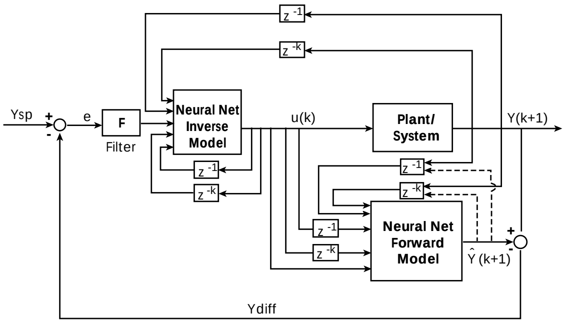

Fig 3. Neural network in internal model control strategy.

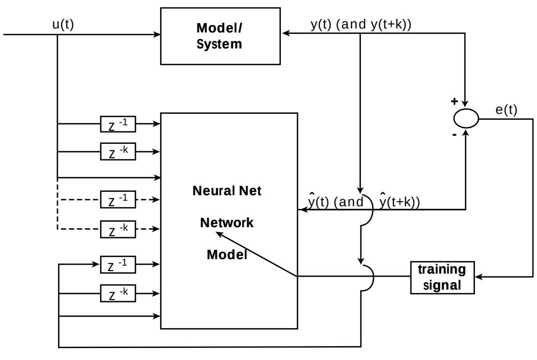

Fig 4. Forward dynamic modelling with neural networks.

network output (i.e. prediction error) is used as the training signal for the neural network. Various important steps to be followed for performing this identification includes: proper selection of model structure and size, selection of data set, selection of suitable input excitation signal, adequate weight initialization, proper training method and model validation.

We could also have used both of the state variable as the outputs but we would like to avoid the complexity of dealing with multivariable, multi-output networks in this study especially when it comes to training and validation. Since this system is also second order,both in model (linearized) and relative order, and with the assumption that the structure of the network inputs and output are the same as that of the plant, the output of the network is then the one-step ahead prediction of the dimensionless concentration while the inputs consists of the present and one past values of dimensionless concentration, dimensionless temperature and control respectively (see Figure 5). Experimentation on various other input configurations reveals that this configuration is adequate to achieve the dual objective of utilising parsimonious models as well as for control purposes.The final forward model representation is given as:

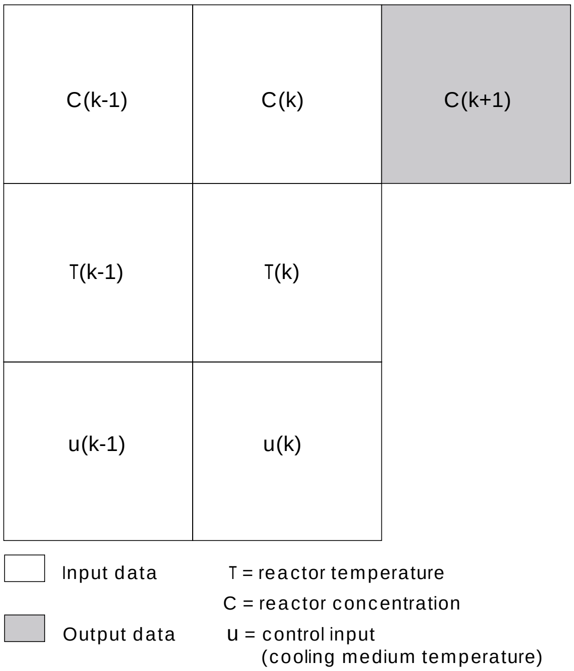

Fig 5. Input and output data node assignment for the CSTR forward models.

$$\hat{y}_m(k+1) = \hat{f}\left[y_p(k), y_p(k-1), x_2(k), x_2(k-1), u(k), u(k-1)\right] \quad (15)$$

where $\hat{f}$ represents the nonlinear neural network input/output map, output y_p represents the dimensionless concentration, state x_2 represents the dimensionless temperature and input u the control action (i.e. dimensionless cooling water temperature).

We also assume here that there is no time delay between input and output, as formulated in the model equations. The input signals used to train and test the network consist of pseudorandom multistep signals i.e. One with random amplitude in the range -1.5 to 1.5 (dimensionless values) with random frequency and the other with random amplitude in the range-l.O to 1.5 but constant frequency. The data is sampled at every 1 dimensionless time interval, which applies for both the forward and inverse models. The dimensionless temperature and input variable, u are scaled to between O and 1 for utilization in the network. The values for the dimensionless concentration are in the range O to 1 and are no need to be scaled. A total of 100 data were corrected for each of the training and test data set generated.

In this case study, training was switched between the train and the first test data set. The training was performed initially in the normal way on the training set until a reasonable rms error was achieved. Then training was repeated using the 1st test data set instead until the rms error decreased again to another reasonable minimum. The training was then switched back using the first training data set to check if the error was still reasonable and decreasing. If it is not then the whole procedure is repeated again either withdifferent initial weights or different number of hidden nodes in the hidden layer. Once a reasonable and continually decreasing rms error was achieved for both sets of data, the training was stopped and the network topology and configuration taken to be the optimum required. If the error was increasing for any of the data set then it was well known that the network At was not generalising over the data set but performing a pointwise data-to-data fitting which means that the network is over-parameterised. On completion of training the network is validated by applying it on the validation data, which is generated by a mixture of ramp input signals and steady state values in the range -1 to 2. These input excitation signals (scaled) for training and testing are similar to that used for inverse modelling which is described in the next section.

The final network configuration chosen to represent the forward model is a 6 input-node, 20 hidden-node and 1 output-node network.

Inverse models

Inverse models are basically the neural net structure representing the inverse of the system dynamics at the completion of training. The training procedure in this case is called inverse modelling. In the incorporation of all inverse models in the control strategies later, $y(k+1)$ corresponds to the required set point or reference signal. The final network representation of the inverse is given as:

$$u(k) = \hat{f}^{-1}\left[y_p(k+1), y_p(k), y_p(k-1), x_2(k), x_2(k-1), u(k), u(k-1)\right] \tag{16}$$

where $\hat{f}^{-1}$ represents the inverse map of the forward model.

The prediction of the control input, *u(k) is* performed for a one-step ahead prediction, in conformity with that of the forward model and the application of a one-step ahead control action in the control strategies to be shown later. The training, test and validation data set generated for the networks are similar to that used for forward modelling but with the input and output configuration as of Figure 6. Training is performed by switching between the train and test data as for the forward model. The control inputs (dimensionless cooling water temperature) and the ù state variable (dimensionless reactor temperature) are also scaled in the region 0 to 1.

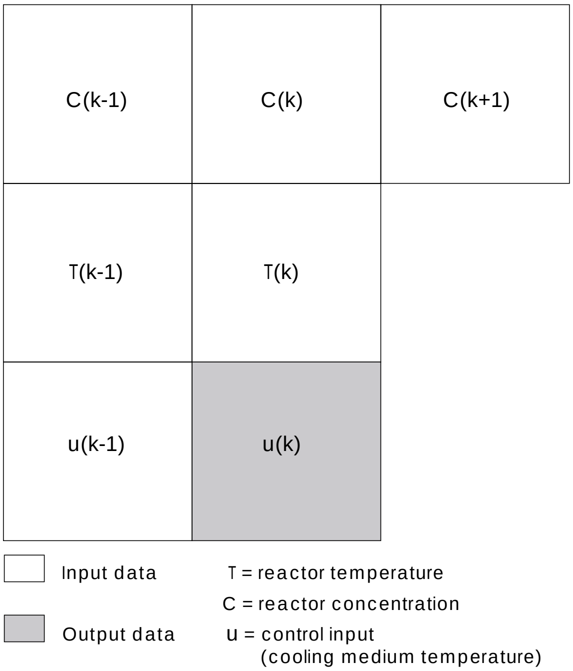

Fig 6. Input and output data node assignment for the CSTR inverse model.

The inverse model is obtained from an approach known as the specialized method. In this approach (see Figure 7) the network inverse model precedes the system and receives as input the system reference or command signal i.e. set points, together with the past system output and past inputs. The error signal used to train the network is the difference between the reference signal and the system output. In comparison with other methods this approach is goal directed *ie* the system receives inputs during training corresponding to operational inputs it expects to encounter in practice and in cases where the forward mapping is not one-to-one, a particular useful inverse can still be found Hunt KJ and Sbarbaro D (1992).

It is also closed loop in structure and relevant for application in the neural network inverse model based closed loop control strategies, as shown here.

In utilising the specialized inverse learning method, the plant or model is situated between the' neural network and the training error signal. Hence it is necessary to propagate this error through the plant and feedback to the output of the neural network to provide a suitable descent direction for the backpropagation algorithm, which results in an increase in the training period when using this method. Psaltis and Sideris Psaltis D, Sideris A and Yamamura A (1988) introduced a concept of using the plant Jacobian or sensitivity derivative to achieve this and considered the plant as an additional but unmodifiable layer of the inversemodel neural network. In this case the output error, E to be minimised is given in general by

$$E = \frac{1}{2}\sum_q \left(y_q - y_q^d\right)^2 \tag{17}$$

and

$$\frac{\delta E}{\delta y_q} = \left(y_q - y_q^d\right) \tag{18}$$

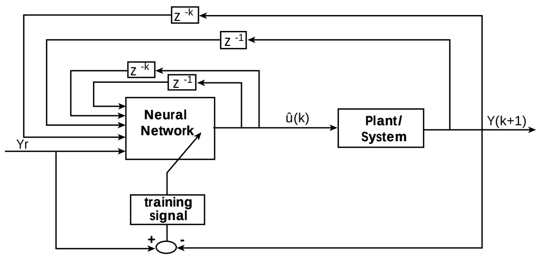

Fig 7. Specialised method of training inverse model.

where y_q is the output of the plant, y_q^d the desired output of the plant and q is the number of outputs. From the backpropagation algorithm Rumelhart DE and McClelland JL (1986), the needed derivative to manipulate the weights at the output layer is $\frac{\delta E}{\delta O_k}$ where O_k the actual output from the neural network i.e. input or control signal, n. However since E is not in terms of O_k we can evaluate $\frac{\delta E}{\delta O_k}$ by the product of two terms i.e

$$\frac{\delta E}{\delta O_k} = \sum_q \frac{\delta E}{\delta y_q}\frac{\delta y_q}{\delta O_k} \qquad (19)$$

But from Equation 18 above, we get

$$\frac{\delta E}{\delta O_k} = \sum_q \left(y_q - y_q^d\right)\frac{\delta y_q}{\delta O_k} \qquad (20)$$

and hence the output layer error signal is propagated back from the output layer to the hidden layer in proportion to δ_k which is given by

$$\delta_k = f\left(\mathrm{net}_k\right)\sum_q \left(y_q - y_q^d\right)\frac{\delta y_q}{\delta O_k} \qquad (21)$$

However since it is difficult to obtain an explicit analytical expression for the plant Jacobian, $\frac{\delta y_q}{\delta O_k}$ in this case study (and in many other cases as well); we have used the sign of the Jacobian instead of its real value as suggested by Saerens and Soquet Saerens M and Soquet A (1990). It should be noted that the product between the gradient produced by the exact method and that produced by this approximation is always positive and will hence ensure error minimization, although at the expense of longer training time.

The final model configuration for the inverse models is a 6 input-node, 20 hidden-node and 1 output-node network.

Control Implementation

This section demonstrates the application of the direct inverse control and IMC strategies on the CSTR system for both set point tracking and disturbance rejection studies. For this second order system being considered, the control manipulated input, u represents the jacket cooling water dimensionless temperature while the controlled output, y represents the reactor dimensionless concentration. In all these strategies the one-step ahead prediction and implementation is used for both the forward and inverse models respectively and in accordance with the way of training these forward and inverse models. The control sampling time is chosen to be equivalent to the data acquisition sampling time of 1 dimensionless time interval i.e. synchronized data sampling and control implementation time. Hence each time step shown in the plots for this case study represents this period of time in implementation.

Set Point Tracking - Inverse Model from Specialised Training

Direct Inverse Control Strategy

The neural network inverse model obtained from this training method was implemented in the direct inverse control strategy. The results for set point tracking (increase and decrease from the nominal steady state value of 0.75 for y) can be seen in Figure 8. The controlled system could follow the set point trajectory very well overall with minimal offsets at all points, as summarised in Table 2.

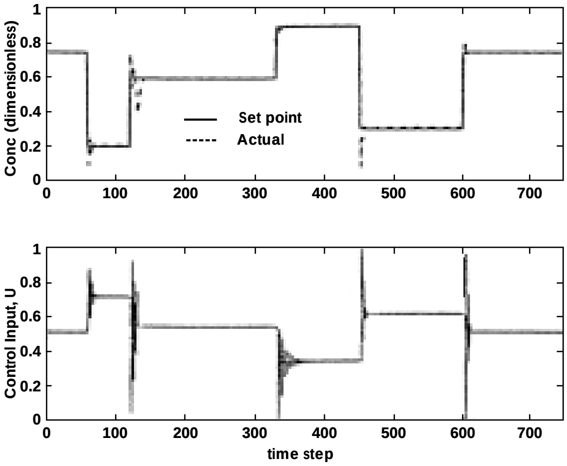

Fig 8. Direct inverse control strategy, specialed training - set point tracking.

Table 2. Specialised training results - CSTR system.

Direction inverse control		IMC with yp as inputs	
st pt	yplant	St pt	yplant
0.7500	0.7498	0.7500	0.7474
0.2000	0.2031	0.2000	0.2077
0.6000	0.6041	0.6000	0.6026
0.9000	0.09055	0.9000	0.9040
0.3000	0.3094	0.3000	0.3114
0.7500	0.7498	0.7500	0.7474

Internal Model Control Strategy

The inverse neural network model, from the specialized training method, and the existing forward neural network model were then incorporated in the IMC strategy for this case. The results as seen in Figure 9 again show good set point tracking with minimal offsets, comparable to the direct inverse control method (see Table 2). Some oscillatory behaviour of the control at the step change can be seen in both cases, which is not surprising since we are implementing the one-step ahead action without filtering in these control schemes.

Disturbance Rejection

This represents a case for disturbance rejection in both control strategies. As shown before in the previous sections, the CSTR system exhibits strong parametric sensitivity in the sense that a small feed temperature disturbance can cause a dramatic change in outlet temperature and concentration. The objective of our simulation in this section is to utilise these control strategies to keep the dimensionless concentration at its nominal steady state value even when the system would be forced open-loop into another steady state dimensionless concentration due to the disturbance in feed temperature. In this scheme for both control methods, the system output is initially controlled at its nominal dimensionless steady state value, of 0.75, until the 50th time step. At this point the disturbance consisting of an increase in the feed temperature from 300 K(27 C) to 305 K (32 C) is introduced. The controller is kept to its initial value (kept inactive) until the 120~ time step before being; turned on again. During this open-loop period the dimensionless concentration decreased to a new steady state value.

In the direct inverse control approach, no change in control action was produced to offset this disturbance and the system could not be brought back to its original set point value as seen in Figure 10. In the IMC approach the control action immediately reacted when initiated at the 120th time step and brought the system back to its nominal set point value within 10th time steps, as seen in Figure 11. This shows the ability of the IMC method to reject disturbances in the presence of the error (and plant/model mismatch) feedback mechanism which does not exist in the direct inverse control method.

Summary and Discussions

The overall results showed the capability of employing these inverse-model-based neural network control strategies to control a nonlinear system such as the exothermic reactor used in this case study. The work also deal with the various ways

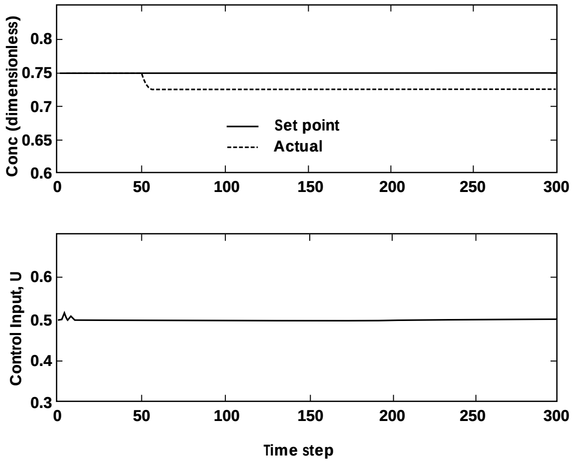

Fig 10. Direct inverse control-disturbance rejection.

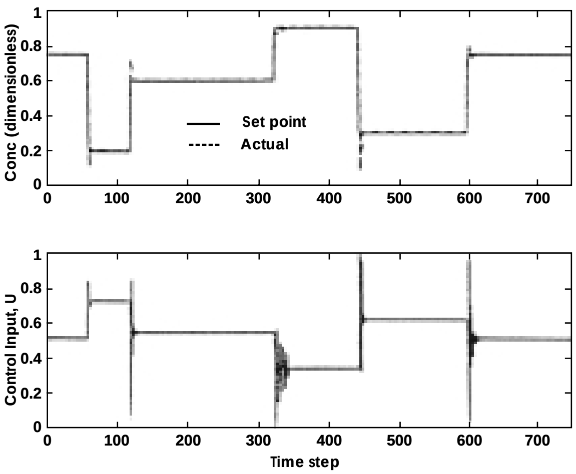

Fig 9. IMC strategy, specialised training set point tracking.

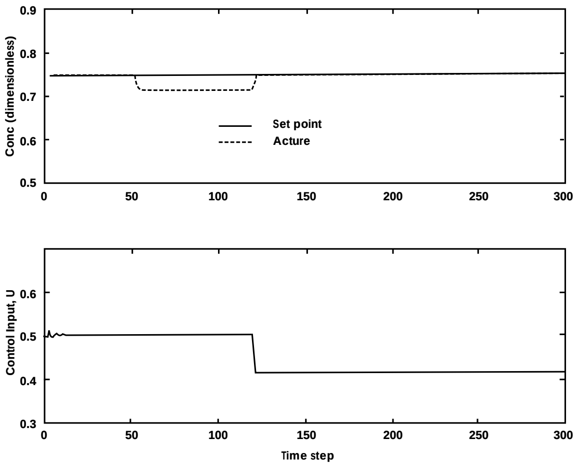

Fig 11. IMC strategy - disturbance rejection.

of employing these neural network models in these inverse-model based control schemes. However many other important and valuable observations have been obtained from this study and they are discussed below.

Firstly, the importance of choosing the right magnitude and range of input excitation signals, which suits its intended application, when training the inverse models is clearly seen. This was taken into account when training the neural networks by switching the training between the train and test data set, hence covering a higher magnitude range with varying frequency. The other important consideration when choosing the right sort of training data, is to incorporate steady state as well as transient data in the training data set for the neural networks. This means that the input excitation signal has to be of sufficient duration and frequency to be able to produce both transient as well as steady state conditions. This is the reason that ramp only data signals are not suitable for training the inverse models and are only utilised for validation purposes. Due to the significant nonlinearity of the systems (especially the CSTR system), the use of transient data only may not give any unique one-to-one relationship between outputs and inputs which may result in an unstable system when applied in these control strategies. This could be the main reason why some researches experienced instability when implementing the directly trained neural network inverse model in this IMC approach Psichogios DM and Ungar LH (1991) .In fact many researches have incorporated neural network controllers in the 1MC approach by solving for the control inputs, through numerical inversion of the forward neural network models, using techniques such as Newton's method. Although these numerical methods produce offset-free results Nahas EP, Henson MA and Seborg DE (1992), they are very computer intensive and time consuming and defeat the purpose and advantages of using these inverse-model-based methods over the predictive control methods.

As stated in the theory for IMC formulation Economou C Morari M and Palsson B.0 (1986), offset-free controlled systems is only ensured when the controller is an exact inverse of the forward model. However this is difficult to achieve in this method shown in our simulation studies, since there is no guarantee that the inverse model obtained is able to invert the steady state gain of the system perfectly. However if the training is performed properly and adequately as in our work here, the offset obtained is minimal and is sufficient for most process systems control application. Furthermore its implementation is fast and amenable for online application. The offset-free method of utilising numerical techniques to solve the neural network inverse controller would be too cumbersome and too slow to be able to implement it practically.

Another observation made in this study is that in all the cases for set point tracking, the performance of the direct inverse control and the IMC method are similar with very little difference in the steady state offsets. This is clearly due to the small difference between the plant and the neural forward model. Since the inverse models are identical in bothmethods, this small difference makes these two strategies similar in implementation and hence both methods give closely similar results. This small difference between plant and network forward model also enables the network output to be fed back to the forward and inverse models instead of the plant outputs in a recurrent network fashion. This approach would be extremely useful when applying this control strategy in actual systems with noisy measurements which allows the neural networks to be working with noise-free input signals and hence produce more reliable performance.

However the superiority of the IMC over the direct inverse control method becomes evident in the disturbance rejection case. In both case studies, the 1MC approach was able to reject the disturbance, in the form of a change in the feed conditions, precisely and keep the system at its set point value while the direct inverse control method could not act on these disturbances and suppress them. This clearly demonstrates the importance of feeding back plant measurements as well as the plant - model error signal to the controller to handle such situations. Since most process systems experience such disturbances in their day-to-day operation, we can conclude that the IMC approach would be the more suitable method for the control of all practical process systems applications.

Finally an important point to note is that the successful implementation of the IMC approach relies heavily on the simultaneous accuracy of the forward and inverse models. However since this is not easily achieved for many non linear systems, a filter is added prior to the controller to compensate for this inaccuracies and sustain robustness in the control implementation. However as shown in our simulation studies here, the inverse neural network models obtained for both case studies are a fairly good representation of the inverses of the forward models, in which case no filtering action was necessary (filter tuning constant set to zero). However large spikes and oscillations in the control inputs could be clearly observed at every instance of set point changes in the set point tracking studies using both control strategies in this case study. This could be primarily attributed to the use of the one-step control implementation without filtering, which normally demands this drastic changes in control inputs and results in the momentarily rapid oscillations observed. Although this requirement brings about a fast set point tracking response, this highly oscillatory behaviour in control action, which can easily exceed its hard limits, is not desirable for real time hardware implementation. The effect of using filters will be followed up later in our future work.

NOMENCLATURE

A	Component "A"
A_r	Heat transfer area (m^2)
B	Component "B"
C	Reactor concentration *(mol/m³)*
Cp	Specific Heat Capacity *(J/(kg.K))*
C_f	Feed Concentration of reactor *(mol/m³)*
E	Activation energy *(J/mol)*
$\hat{f}$	Nonlinear neural network input/output map
ΔH	Heat of Reaction *(J/mol)*
k_o	Arrhenius pre-exponential constant *(min^{-1})*
Q	Volumetric flowrate *(m^3/min)*
Q_o	Nominal volumetric flowrate *(m^3/min)*
QR	Heat released within reactor (kcal/min)
R	Universal gas constant *(J/(mol.K))*
t	Time
T	Reactor temperature(K)
Tf	Temperature of feed (K)
Tc	Coolant temperature (K)
u	Dimensionless process input
v	Dimensionless disturbance
u(k)	Input variable / control input
U_r	Heat Transfer coefficient *(J/(s.m^2.K)*
V_r	Volume of reactor (m^3)
x_1	Dimensionless reactant concentration
x_2	Dimensionless reactant temperature
y,yp	Outputlplant variable
$\hat{y}_m(k)$	Neural network output

Subscripts

f	feed condition
o	initial condition or nominal condition

Greek symbols

ρ	Reactant density (kg/m^3)
β	Dimensionless heat of reaction
δ	Dimensionless heat transfer coefficient
γ	Dimensionless activation energy
ϕ	Damkohler number
τ	Dimensionless time

REFERENCES

1. Bequette BW(1991) Nonlinear control of chemical processes: A review. In: *Ind EngChem,* pp 1391-1413.
2. Cybenko G (1989) Approximation by superposition of a sigmoidal function, Math. In: *Control Signals System 2nd ed,* PP 303-314.
3. Economou C Morari M and Palsson B 0 (1986) Internal model control. Extension to nonlinear systems. *Ind Eng Chem Process Des Dev* 25, pp 403-411.
4. Hornik K, Stinchcombe M and White H (1989) Multilayer feedforward networks are universal approximators. In: *Neural Networks, 2nd ed,* PP 359.
5. Hunt KJ and Sbarbaro D (1992) IKE Control Engineering Series, London.
6. Kawato M, Furukama K and Suzuki S (1987) A hierarchical neural- network model for control and.learning of voluntary movement. In: *Biological Cybernetics* 57, pp 169-185.
7. Limqueco LC and Kantor JC (1990) Nonlinear output feedback control of an exothermic reactor. In: *Computers Chem Eng,* vol 14(5), pp 427-437.
8. Nahas EP, Henson MA and Seborg DE (1992) Nonlinear internal model control strategy for neural network models. *Computers Chem Eng* 16, 1039-57.
9. Pao YH Phillips SM and Sobajic DJ (1992) Neural net computing and the intelligent control of systems. *Int J Control* 56, 263-89.
10. Psaltis D, Sideris A and Yamamura A (1988) A multilayered neural network controller *IEEE control systems* magazine 8, 17-21.
11. Psichogios DM and Ungar LH (1991) Direct and indirect model based control using artificial neural-networks. In: *Ind Eng Chem Res* 30, 2564-2573.
12. Rumelhart DE and McClelland JL (1986) Explorations in the microstructure of cognition. *Parallel Distributed processing Chapter* 8, MIT PressCambridge, U.S.A.
13. Saerens M and Soquet A (1990) A neural controller. In: *Proc Ist IKE Conf: on neural networks,* pp 211-215.
14. Yamada T and Yabuta T (1990) An extension of neural network direct controller In: *IEEE Int. Workshop on intelligent robots and systems,* pp 619-626. Japan.