AN EXPERIMENTAL STUDY OF NEURAL FEEDFORWARD CONTROLLER WITH GENERALIZED DISTURBANCE ERROR LEARNING

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To overcome the limitation of linear feedforward controllers in nonlinear chemical processes, Lee and Park proposed the feedforward control scheme using a neural network and a dynamic matrix control (DMC). The neural feedforward controller (NFFC) using a neural network and a general linear controller is proposed to extend Lee and Park's control scheme. The generalized disturbance error learning method using the pseudo desired output is also proposed to train the neural network in the NFFC. Results are given for the implementation of the NFFC on a pilot-scale distillation column. The control performance of the NFFC is compared with conventional linear feedforward-feedback and feedback-only controllers such as the PI and the DMC controllers through various experiments. The trained NFFC shows excellent control performance compared with the linear controllers. The results indicate that the NFFC copes well with high nonlinearities and interactions, and may be useful in practice.

Introduction

Recently developed neural network techniques provide a new possibility for solving these problems (Hunt and Sbarbaro, 1991). For this reason, extensive studies on the application of the neural networks to chemical process control have been recently explored (Eikens and Karim, 1994; Lee and Park, 1992; Montague *et al.*, 1992; Nahas *et al.*, 1992; Pshichogios and Ungar, 1991, 1992; Saint-Donat *et al.*, 1991; Scott and Ray, 1993; Song and Park, 1993; Ungar, 1995; Willis *et al.*, 1993; Ydstie, 1990; Ye and McAvoy, 1994).

Lee and Park (1992) proposed the disturbance error learning method to train the neural network in the feedforward control scheme combined with a dynamic matrix control (DMC). Using relevant features of neural networks, their control scheme copes with nonlinear and complex dynamics of measured disturbances well. In their work, the simulation studies for the nonlinear continuous stirred tank reactor were done to examine the performance of their scheme.

In this work, the neural feedforward controller (NFFC) and the generalized disturbance error learning (GDEL) method are proposed to extend Lee and Park's control scheme. The NFFC consists of a neural network and a general linear controller, and the

GDEL method trains the neural network in the NFFC. The experimental studies were carried out on a pilot-scale distillation column to evaluate the control performance of the NFFC. First, we explain the GDEL method. Next, the pilot-scale distillation column used in this study is described. Finally, we show how to apply the NFFC with PI and DMC controllers. The main results applying the NFFC are followed by the conclusions. The structure and the weight update of a multi-layer feedforward neural network is not described since those are fully explained in Lee and Park's work.

1. Neural Feedforward Control and Generalized Disturbance Error Learning

The block diagram of the NFFC is shown in Fig. 1. The feedforward control action (u_N) of the neural network is added to the control action of the linear feedback controller, and compensates the nonlinear effects of the measured disturbance. Note that in this scheme, the network training can be performed while control is done simultaneously by a linear feedback controller. Current and past values of disturbances are used as input variables for the network after being treated through the buffer and pre-processor (BPP). After training the network, the linear controller mainly handles servo problems, and also takes care of regulatory problems for unmeasured or unpredictable disturbances.

The GDEL method is proposed to perform the

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Fig. 1 Block diagram of the neural feedforward controller

training of the neural network in the NFFC of which the objective is to find the weights to minimize the square error $\|r-y\|_2$ against the effects of the measured disturbances. In the GDEL method, the network is trained not by using the actual desired output which is unknown a priori, but by using the pseudo desired output. The pseudo desired output is chosen by the sum of the current output of the neural network and the learning direction to the desired output as

$$T_s(k) = u_N(k-1) + \Delta u_e(k) \quad (1)$$

Then the pseudo desired output is compared with output of the network at the $(k-1)$ th sampling time step, $u_N(k-1)$. Thus, δ_j^L at j th node in the output layer of the neural network becomes

$$\delta_j^L = \Delta u_{ej}(k) F' \left(\sum_{i=1}^{N^{L-1}} W_{ji}^{L-1} O_{pi}^{L-1} \right) \quad (2)$$

at the k th time step.

In the above equations, $\Delta u_e(k)$ is the learning direction which points to the desired output at the current output of the network. $\Delta u_e(k)$ is determined from a part of the control action of the linear feedback controller so as to have the following characteristics: (1) it must direct the output of the neural network to the desired output during training periods; (2) as the output of the neural network approaches the desired output, its magnitude must approach zero. Initially the NFFC has little influence over the control actions for the measured disturbances and all control actions are performed by the linear feedback controller for both regulatory and servo problems. As learning proceeds, the neural network tries to configure itself so that the output of the linear feedback controller for the measured disturbances is as small as possible, and the control action is gradually switched from feedback one to feedforward one. Both system identification and process control are done by the network simultaneously during the training periods. When $\Delta u_e(k)$ sufficiently becomes small, the training has been accomplished and only a relatively small feedback signal is necessary to compensate for

random uncertainties that are unpredictable and, thus, cannot be learned. Therefore, once learning is accomplished, most control actions for the specific disturbance domain are carried out by the neural network instead of the linear feedback controller. The detail description about $\Delta u_e(k)$ for a PID controller and a DMC controller will be explained later.

1.1 Selection of $\Delta u_e(k)$ for the DMC controller

The control action of the DMC can be decomposed into two actions caused by modelled and unmodelled effects (Lee and Park, 1992) as follows:

$$\begin{aligned} \Delta u_L(k) &= (A^T \Gamma^T \Gamma A + A^T \Lambda)^{-1} A^T \Gamma^T \Gamma [e_m(k) + e_d(k)] \\ &= \Delta u_m(k) + \Delta u_d(k) \end{aligned} \quad (3)$$

where the control action $\Delta u_d(k)$ results from unmodelled effects, and plays a role of compensating unmodelled disturbances and model mismatch. $\Delta u_d(k)$ satisfies all the conditions for $\Delta u_e(k)$ described earlier. Thus, in the case where the DMC is used as the linear feedback controller, $\Delta u_e(k)$ is set as follows:

$$\Delta u_e(k) = \Delta u_d(k) \quad (4)$$

1.2 Selection of $\Delta u_e(k)$ for the PID controller

When the PID controller is used in a feedback loop, $\Delta u_e(k)$ is set to the sum of the proportional and the derivative control action as follows:

$$\Delta u_e(k) = u_P(k) + u_D(k) \quad (5)$$

because $u_P(k)$ and $u_D(k)$ have the desired properties for the learning direction. Note that integral action in the PID controller must be excluded from the pseudo desired output, because it does not meet the conditions for $\Delta u_e(k)$.

2. Pilot Scale Distillation Column

The experimental distillation column (Fig. 2) is a packed column with raschig rings of 3/8 in., 285 cm height and 4 in. diameter stainless steel pipe. A feed connection stub-in has been provided at 90 cm from the bottom. The condenser installed in the distillation unit is located horizontally with cooling water in the tube side and the condensed top product in the shell side, the vapor and liquid flow counter-currently downward to the receiver drum. The natural recirculation reboiler is connected to the lower part of the column. The feed preheater is used to heat the feed stream from room temperature to just below the bubble temperature. These two heat exchangers are electronic ones controlled by SCRs (thyristor). The column is designed for operation at atmospheric pressure. Three 1/4 HP electronic pumps are in the pilot plant for feeding and conveying

Fig. 2 Schematic diagram of the pilot scale distillation column

Table 1 Steady state conditions

Feed flow	Flow rate = 520 ml/min Composition = 30 mole% of MeOH Temperature = 70° C
Overhead product	Flow rate = 159 ml/min Composition = 95.9 mole% of MeOH Temperature = 66° C
Bottom product	Flow rate = 361 ml/min Composition = 1.0 mole% of MeOH Temperature = 99° C
Reflux flow	Flow rate = 180 ml/min Composition = 95.9 mole% of MeOH Temperature = 38° C
Reboiler	Voltage input = 69%
Column	Top temperature = 71° C Bottom temperature = 88° C Pressure = 100 kPa

the products.

Three types of sensors to measure process variables and two types of final elements to manipulate actuators are installed: ten resistance thermometer devices for the temperature; two differential pressure gages for the pressure and two ones for the level; the turbine flow meters for the flow rate; two SCRs for the preheater and the reboiler; four I/P converters for the pneumatic valves.

The feed is the mixture of methanol and water. The steady state condition of the experiment is listed in Table 1. As seen from Fig. 2, there are four basic regulatory control loops: two for level control; one for feed temperature control; one for feed rate control.

In addition to these loops, the column has two composition control loops. PI controllers are installed in the basic regulatory control loops. The top and the bottom temperatures of the column are controlled to achieve product compositions from the viewpoint of the inferential control. All these controllers were implemented on the IBM personal computer. Data gathering and monitoring was also performed by the computer automatically.

3. Experiments and Results

To characterize the dynamics over the operating range, several step tests were performed. Figure 3(a),

Fig. 3 Open loop responses of the top and the bottom temperatures to the step changes (a) in the reflux flow rate, (b) in the reboiler heat input, and (c) in the feed flow rate

(b), and (c) show the responses of the top and bottom temperatures to a step up and a step down change in the reflux flow rate, the reboiler heat input, and the feed flow rate, respectively. The significantly differing dynamic responses to a step up and a step down changes show that this system has highly nonlinear characteristics. From the figures, it also can be known that the system has complex dynamics, significant interactions, and noise. In this system, the variation of the feed rate acts as the measurable disturbance. The experiments of the NFFC are performed for both cases of the PI controller and the

DMC controller as the feedback linear controller.

3.1 DMC controller case

The dynamic matrix for the DMC controller was obtained based on the average convolution model. This DMC controller was implemented to the column. Tuning parameters for the DMC controller were chosen based on the recommendation of Garcia *et al.* (1986) and Lee (1990); optimization horizon=45; control horizon=5; model horizon=40; move suppression factor=0.01; output weighting=1. The sampling period was chosen as 30 seconds. The feedforward DMC (FFDMC) controller with the same parameters as above was also implemented for the comparison with the NFFC.

The structure of the neural network in the NFFC was determined from the simulation results. The network has three layer. The input layer contains five neurons which receive the signals comprised of $d(k-n)$, where $n=0, 1, 2, 3, 4$. The hidden layer has also five neurons. The output layer has two neurons and produces the controller signals to the reflux flow rate and the reboiler heat input after appropriate scaling. The weights of the network were initially set with small random numbers. The hyperbolic tangent function was used as the activation function. The learning rate η was empirically set as 0.005.

Simple training patterns lasting 90 min, which include 3 consecutive step changes in the feed rate, were repeated until desired performance was accomplished. The training patterns are shown in Fig. 4. Note that feed rate changes cause the feed temperature changes due to the feed temperature control loop. As a result, the disturbance characteristics become more complex. The training patterns have to be chosen such that the measured disturbance effects on the process output are dominant enough compared with the other unmodelled and unmeasured disturbance effects. Figure 5 compares the $\Delta u_d(k)$ or the $\Delta u_e(k)$ responses to the training disturbance patterns before and after learning. As seen from Fig. 5, $\Delta u_d(k)$ by the DMC controller mostly vanishes. This shows that $\Delta u_d(k)$ provides the correct descent direction for the network training. It is also verified that the control action for disturbance rejection is mostly performed by the feedforward action of the NFFC and only small portion for random feedback error is controlled by the DMC controller, although its result is not shown due to the paper limit.

To evaluate the generalization capability of the NFFC, the inexperienced disturbance patterns were introduced by changing the feed flow rate as shown in Fig. 6. Figure 7 compares output responses to the inexperienced disturbance patterns for each case of the NFFC, the DMC, and the FFDMC. Table 2 shows the comparison of the integral of the squared error (ISE) for each case. The NFFC gives excellent regulatory performance compared with the other two

Fig. 4 Changing patterns of the feed flow rate for training

Fig. 5 Comparison of the learning direction of the neural network before and after learning in the reflux flow rate and in the reboiler heat input

Fig. 6 Changing patterns of the feed flow rate for interpolation test

cases. This means that the NFFC can cope well with nonlinearities and interactions of the system against noise.

3.2 PI controller case

The parameters of two PI controllers for the top and the bottom temperatures were determined

Fig. 7 Process responses for the DMC, the FFDMC, and the NFFC (a) in the top temperature and (b) in the bottom temperature

Table 2 Comparison of ISEs for the DMC controller case

Top temperature control			Bottom temperature control		
DMC	FFDMC	NFFC	DMC	FFDMC	NFFC
16.19	9.39	5.24	89.48	28.92	12.70

according to the biggest log modulus tuning method (Luyben, 1986) based on the average step model. By the inversion of the linearized disturbance model, the linear feedforward-PI controllers (FPC) were also implemented for the comparison with the NFFC.

The same structure and parameters of the neural network as used in the DMC controller case were employed. Similar training patterns of the feed flow rate were also used to train the NFFC. Like the DMC controller case, the $\Delta u_e(k)$ satisfies the desirable characteristics for the learning direction well. Additionally, the feedforward action of the NFFC primarily rejects the effect of the measured disturbance and the PI controller compensates only small portion for random feedback error. Output responses for the NFFC to the inexperienced dis-

Fig. 8 Process responses for the PI, the FPC, and the NFFC (a) in the top temperature and (b) in the bottom temperature

Table 3 Comparison of ISEs for the PI controller case

Top temperature control			Bottom temperature control		
PI	FPC	NFFC	PI	FPC	NFFC
24.52	14.64	2.88	35.89	14.63	4.36

turbance patterns were compared with those for the PI controller and the FPC as shown in Fig. 8(a) and (b). The ISE for each case is listed in Table 3. The NFFC gives far better regulatory performance than the other two cases. This means that the NFFC with the PI controller also can cope well with nonlinearities and interactions of the system.

In our experiments, the control performance of the DMC controller is not better than that of the PI controller as seen from Figs. 7 and 8. This results from the inaccuracy of the average convolution model in the DMC controller due to the linearization of the nonlinear system. However, note that the NFFC always improves the control performance in spite of plant-model mismatch.

Conclusion

This paper addresses the implementation of the NFFC on a pilot-scale distillation column which shows high nonlinearities, severe interactions, noise and complex dynamics. The GDEL method using the pseudo desired output is proposed to train the NFFC by extending Lee and Park's DEL method (1992). Neural networks in the NFFC combined with the conventional linear feedback controller such as the PI and the DMC controllers were trained to compensate the changes of the feed flow rate as the measured disturbance. The trained NFFC showed much better control performance than both linear feedforward-feedback and feedback-only controllers. It illustrates that the proposed NFFC can cope well with nonlinearities and interactions. This experimental results indicate that the proposed NFFC can be very useful in practice.

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Nomenclature

A	= dynamic matrix of the DMC
$F(\bullet)$	= nonlinear activation function
L	= number of layers or output layer number
N^l	= number of neurons in l th layer
O_{jl}^l	= output of the j th neuron in the l th layer for pattern p
T_s	= pseudo desired output
W_{ji}^{l-1}	= connection weight between the i th neuron in the $l-1$ th layer and the j th neuron in the l th layer

d	= measured disturbance
$e_m, e_d(k)$	= predicted errors due to modelled and unmodelled effects respectively
u	= manipulated variable or control action
u_D, u_P	= proportional and derivative control actions in PID controller
u_L, u_N	= control actions of the linear controller and the neural network respectively
Δu_L	= increment of the control action of the linear controller
Δu_e	= learning direction in the pseudo desired output
$\Delta u_m, \Delta u_d$	= increment of the control action due to modelled and unmodelled effects respectively
r	= setpoint
y	= controlled variable
Γ, A	= weighting and move suppression vectors
δ_f^L	= training signal
η	= learning rate
$\ \bullet\ _2$	= Euclidean norm

<Abbreviations>

DMC	= dynamic matrix control
FPC	= feedforward-PI controller
FFDMC	= feedforward DMC controller
GDEL	= generalized disturbance error learning
ISE	= integral of the squared error
NFFC	= neural feedforward control
PID	= proportional-integral-derivative controller

Literature Cited

- Eikens, B. and M. N. Karim; "Identification of a Waste Water Neutralization Process Using Neural Networks," *WCNN*, San Diego, 1, 185-190 (1994)
- Garcia, C. E. and A. M. Moshedi; "Quadratic Programming Solution of Dynamic Matrix Control (QDMC)," *Chem. Eng. Commun.*, 46, 279-293 (1986)
- Hunt K. J., D. Sbarbaro, R. Zbikowski and P. J. Gawthrop; "Neural network for control systems-A survey," *Automatica*, 28, 1083-1112 (1992)
- Lee, J. K. and S. Park; "Dynamic Matrix Controller Design for Practical Applications," Master Thesis, KAIST, Korea (1990)
- Lee, M. and S. Park; "A New Scheme Combining Neural Feedforward Control with Model-Predictive Control," *AIChE J*, 38, 193-200 (1992)
- Luyben, W. L; "Simple Method for Tuning SISO Controllers in Multivariable Systems," *Ind. Eng. Chem. Proc. Des. Dev.*, 25, 654 (1986)
- Montague, G. A., M. T. Tham M. J. Willis and A. J. Morris; "Predictive Control of Distillation Column Using Dynamic Neural Networks," *IFAC*, Maryland, 231-236 (1992)
- Nahas, E. P., M. A. Henson and D. E. Seborg; "Nonlinear Internal Model Control Strategy for Neural Network Models," *Computers chem. Engng.*, 16, 1039-1057 (1992)
- Pshichogios D. C. and L. H. Ungar; "Direct and indirect model based control using artificial neural networks," *Ind. Engng. Chem. Res.*, 30, 2564-2573 (1991)
- Saint-Donat, J., N. Bhat and T. J. McAvoy; "Neural Net Based Model Predictive Control," *Int. J. Control*, 54, 1453-1468 (1991)
- Scott, G. M. and W. H. Ray; "Creating Efficient Nonlinear Neural Network Process Models That Allow Model Interpretation," *J. Proc. Cont.*, 3, 163-178 (1993)
- Song, J. J. and S. Park; "Neural Model Predictive Control for Nonlinear Chemical Processes," *J. Chem. Eng. Japan*, 26, 347-354 (1993)
- Ungar, L. H; "Process Modeling and Control using Neural Networks," *Intelligent Systems in Process Engineering '95*, Colorado (1995)
- Willis, M. J. and G. A. Montague; "Auto-tuning PI(D) Controllers with Artificial Neural Networks," *IFAC*, Sydney, 5, 131-136 (1993)
- Ydstie, B. E; "Forecasting and Control Using Adaptive Connectionist Networks," *Computers Chem, Engng.*, 14, 583-599 (1990)
- Ye, N. and J. McAvoy; "An Inferential Approach Using Neural Network Models for Controlling Chemical Processes," *WCNN*, San Diego, 1, 201-206 (1994)