The South African Institute of Computer Scientists
and
Information Technologists

Proceedings

of the

1996 National Research and Development Conference

Industry meets Academia

Interaction Conference Centre, University of Natal,
Durban.
26 & 27 September

Edited by
Vevek Ram

ISBN 0-620-20568-7

Cover printed by Natal Printers (Pty) Ltd, Pietermaritzburg
Copying by the Multicopy Centre, University of Natal, Pietermaritzburg
Binding by Library Technical Services, University of Natal, Pietermaritzburg

FOREWORD

This book is a collection of papers presented at the National Research and Development Conference of the Institute of Computer Scientists and Information Technologists, held on 26 & 27 September, at the Interaction Conference Centre, University of Natal, Durban. The Conference was organised by the Department of Computer Science and Information Systems of The University of Natal, Pietermaritzburg.

The papers contained herein range from serious technical research to work-in-progress reports of current research to industry and commercial practice and experience. It has been a difficult task maintaining an adequate and representative spread of interests and a high standard of scholarship at the same time. Nevertheless, the conference boasts a wide range of high quality papers. The program committee decided not only to accept papers that are publishable in their present form, but also papers which reflect this potential in order to encourage young researchers and to involve practitioners from commerce and industry.

The organisers would like to thank IBM South Africa for their generous sponsorship and all the members of the organising and program committees, and the referees for making the conference a success. The organisers are indebted to the Computer Society of South Africa (Natal Chapter) for promoting the conference among its members and also to the staff and management of the Interaction Conference Centre for their contribution to the success of the conference.

On behalf of the Organising Committee
Vevek Ram
Editor and Program Chair
Pietermaritzburg, September 1996

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NEURAL NETWORKS FOR PROCESS PARAMETER IDENTIFICATION AND ASSISTED CONTROLLER TUNING FOR CONTROL LOOPS

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Abstract

The paper introduces a method for identification and assisted controller tuning for industrial process control loops suitable for an 'in-chip' solution. The method is based on utilization of neural network technology. It employs pattern recognition and exploits the nonlinear function approximation feature of neural networks. The method has the advantage of simplicity and sufficient accuracy. It is developed for on-line usage in closed-loop operations.

Introduction

Most process control loops are not well tuned (see Brown 1996). The proper control loop performance depends directly on adequate controller tuning. For that reason many standardized tuning methods are developed and used in practice (see for example Ziegler-Nichols 1942, 1943, Cohen-Coon 1952, Chrones *et al.* 1952, Yuwana and Seborg 1982, Shinskey 1979, Astrom and Hagglund 1988, Hang and Sin 1991, etc). Characteristic of all these methods is that they first attempt to determine some features of the model of the process to be controlled, and then provide appropriate controller tuning. Some of these standardized methods require testing on the open-loop process which is not always suitable as the process can be for example unstable. Another problem with the open-loop testing is that some processes do not allow breaking of the feedback due to operational constraints. Another group of methods uses closed-loop testing. Some of them induce specific oscillations in the system, while others consider the process response to specific test signals. All these methods are based on the analysis of process reaction from which the necessary information about the process is extracted and used in the next step for suitable controller setting.

ANNs have been used in numerous ways for control purposes (see Pham and Liu 1995, Warwick *et al.* 1992). Recently, ANNs have been utilized for different aspects of loop tuning. Several authors proposed their usage as auto-tuners of controllers (see Mamat *et al.* 1995, Ruano *et al.* 1992, Swiniarski 1990, Willis and Montague 1993, McLeod and Bajić 1996). For example, Mamat *et al.* (1995) have used ANNs to assist in the selection of optimal tuning of the controller after the process model has been determined on the basis of a modification of Yuwana and Seborg's (1982) method.

In this paper we will exploit the capability of static ANNs to encode the relationships between 168-element vectors representing 168 samples of the process output waveform and three crucial process model parameters affecting the shape of this waveform. The ANNs for this purpose will use pattern recognition. Once trained, an ANN provides rapid identification based on a single test waveform. When the process model parameters are obtained the optimal tuning of the PID controller is provided from a set of possible choices by ANNs. One approach where pattern recognition is used in connection with ANNs in the process of controller tuning is given for example in Valdebenito *et al.* (1995). The method proposed in this paper seems to be simpler, computationally more effective and more easily applicable to industrial applications. Also, the method proposed is suitable as the complete solution for EPROM implementation, where the trained ANNs will perform the task of process parameter identification and optimal controller tuning.

The method proposed is illustrated by a simulation example.

Preliminaries

The crucial part of the loop tuning in the method proposed in the paper is determination of the parameters of the process. For this purpose consider a classical negative unity feedback system with the PID controller and the plant in series connection in the forward branch (Fig.1).

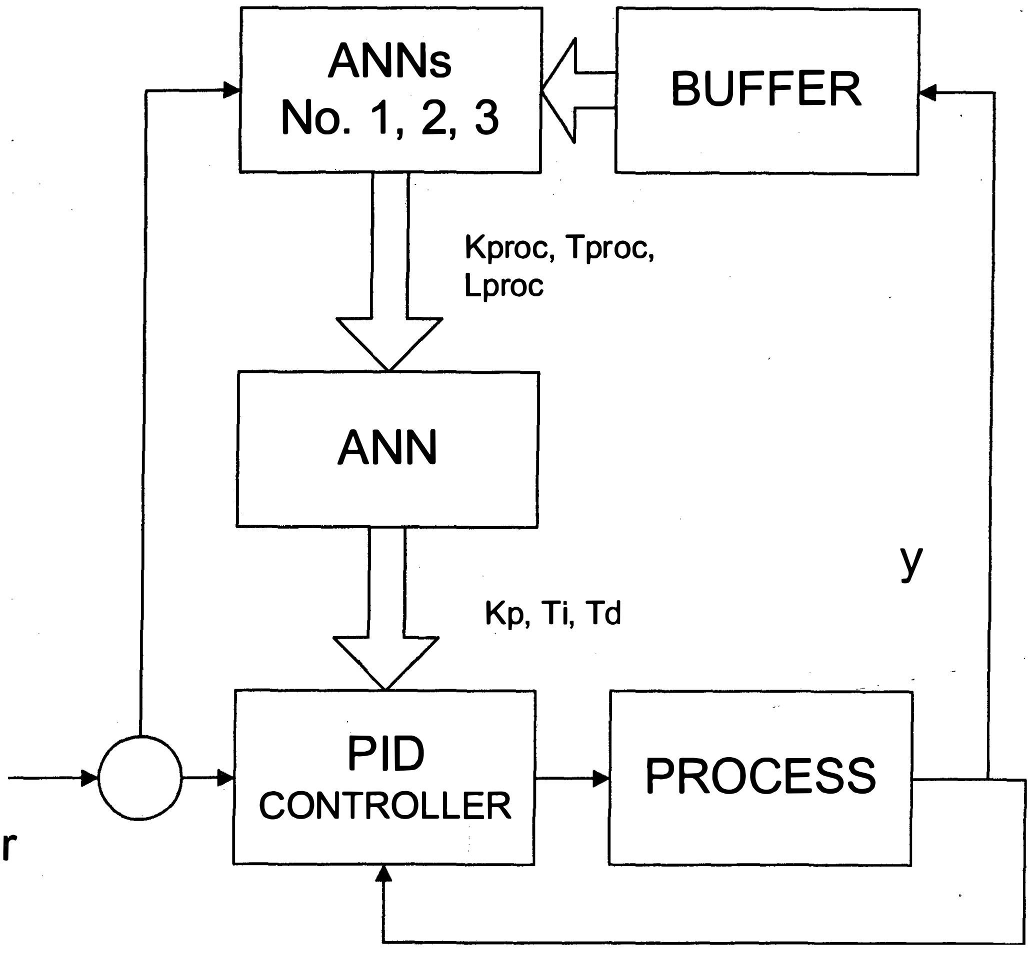

Fig. 1 Structure of the control system

Let r, u and y denote the reference input signal, the controller output signal and the measured plant output signal, respectively. It is assumed that the process model is governed or that it can be reasonably well approximated by the transfer function

$$G_{proc}(s) = \frac{K_{proc}}{T_{proc}s + 1} e^{-L_{proc}s} \tag{1}$$

The motivation for using this type of process transfer function is that many methods for controller tuning are based on such an assumption for the process model. The reason is that the step responses of many industrial processes roughly correspond to the response obtained by (1) as they are monotonic and self-saturating. Although there are many methods that can provide parameters of (1) in the closed-loop testing like the one given in Bologna *et al.* (1995), we will use ANNs to obtain this information. The main reason for this is that once trained, ANNs will provide convenient, computationally fast and sufficiently accurate answer about the process parameters and, based on this, optimal controller tuning. In principle, the whole 'solution' proposed in the paper can be memorized in EPROM and used like an additional one-chip unit attached to the already implemented PID controller. Our assumption is that initially the nominal value K_{proc}^n of K_{proc} is available. This value is usually easy to estimate, but the method proposed allows that it be arbitrarily chosen as a positive gain. The controller used for training of ANNs is a PID one governed by the operator equation

$$u = K_p e + \frac{K_p}{T_i s} e - K_p T_d \frac{N}{T_d s + N} y \tag{2}$$

where $e = r - y$ is the error signal. Controller parameters are K_p - the proportional gain, T_i - the integral time, T_d - the derivative time and N is the filtering constant.

Determination of parameters of (1) via ANNs is performed utilizing an on-line test with the control system in the closed loop. The flow-chart given in Fig.2 indicates the operation of the algorithm. There are three parameters of (1) to be determined, K_{proc}, T_{proc} and L_{proc}. They are determined in two successive phases that will be described later on.

Outline of the method for process parameter determination via ANNs

In applying the proposed method a known input pulse (Fig.3) is used as a calibrated 'stimulus' to produce an output waveform from the process under test in the closed loop with the PID controller (2) set to specifically determined parameters. The recorded response is then applied to one of the three ANNs which have been previously trained to associate the recorded waveform with the appropriate parameter value. This produces the value of a parameter from which the actual value of K_{proc} is determined. Then the PID controller is specifically retuned, and the same test is repeated, but the recorded waveform is presented to the other two ANNs to provide estimation of the parameters T_{proc} and L_{proc}/T_{proc}. The on-line experiment follows the next steps.

Step 1: Phase of K_{proc} determination. For test to start the closed-loop system has to be in the steady-state. The PID controller parameters are then set as given in the following table

K_p	T_i	T_d	N
$0.14798/K_{proc}^n$	10	1.332	10

The test signal shown in Fig. 3 is then presented to the system input (it is added to the signal r). The process response is recorded and presented to the ANN No.1, which produces the estimated value k equal to $0.4743 \cdot K_{proc}/K_{proc}^n$. From this one gets the actual value of $K_{proc} = kK_{proc}^n/0.4743$.

Step 2: Phase of determination of T_{proc} and L_{proc}/T_{proc}. At this stage the PID controller is retuned according to the following table

K_p	T_i	T_d	N
$0.312/K_{proc}$	10	1.332	10

This is a normalization of the process gain used to suit the next two ANNs which were trained with a training set generated with $K_{proc} = 1$. Then the same test signal as in Step 1 is applied to the system input in the same way as in Step 1. The process response is recorded and presented to the ANN No.2 which produces the estimated value T_{proc} and to the ANN No.3 which produces the value of L_{proc}/T_{proc}. In this way all three parameters of the process model (1) are determined.

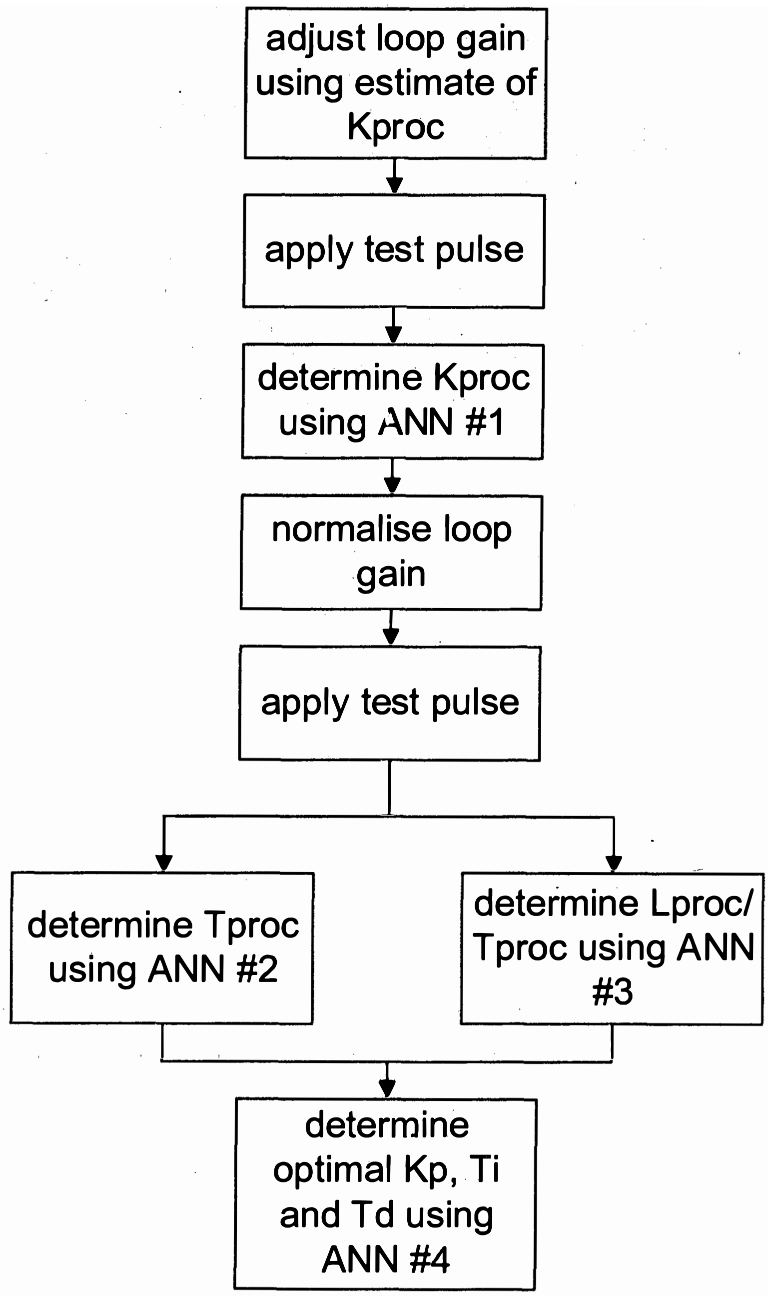

Fig. 2 Flowchart of the method

Preparation of the output signal waveforms for parameter identification

To prepare these waveforms to be used in the training set, the test signal shown in Fig.3 was used in conjunction with a PID controller (2) with the parameters set accordingly, and the parameters of the process model (1) varied in the appropriate ranges. The waveform chosen as the test input signal was selected as likely to generate a response illustrating the effects of varying the three process model parameters. The following setting of a PID controller is used:

$$K_p = 0.312, \ T_i = 10, \ T_d = 1.332, \ N = 10.$$

These values were selected to produce waveforms that were distinctly different but without excessive oscillation as the process parameters were varied. The range of values for parameters of the process (1) used for generation of the testing sets were the following:

$$K_{proc} \in [0.15, \ 1.5], \ T_{proc} \in [1, \ 7.8], \ L_{proc}/T_{proc} \in [0.3, \ 1.5],$$

i.e. the corresponding range for L_{proc} is $[0.3, \ 11.7]$. It was decided to use 168 samples of the output signal with the sampling interval of 0.2[s] for the length of 33.6 [s] for each input training vector. Examples of the typical output signal waveforms obtained are shown in Figs. 4, 5 and 6.

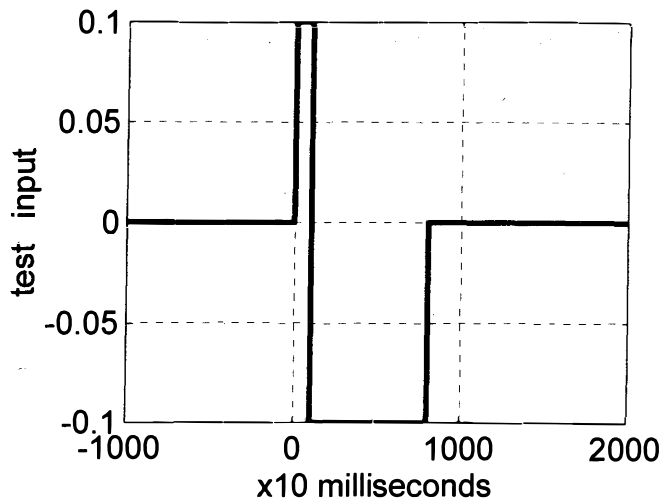

Fig. 3 Test signal

Neural networks for parameter identification - structure and training

Choice of ANN type. The choice of the ANN type was limited by the available software and hardware. Although initially we attempted to use ANNs based on the Levenberg-Marquardt Back-propagation Algorithm (BPLM), experiments showed that BPLM was not viable for this application due to large memory requirements. As we had MATLAB Ver.4.2c and Matlab's Neural Network Toolbox Ver.2.0c running on a PC with 64 MB RAM, the choice of radial basis function networks (RBFNs) seemed natural.

It is, in principle, possible to use one MIMO ANN to produce all three parameters of (1) at once. This approach was found to be beyond the capability of the PC and software being used for these experiments due to memory limitations in the training phase of MIMO RBFN. As a consequence the separate ANNs for determination of each of the three process parameters were used. It should be noted that the memory constraint experienced with MIMO RBFNs existed only in the training phase. Once trained, the ANN can be invoked with a smaller memory requirement. Since the final goal is to utilize them as trained networks, this approach that employed more than one ANN was considered acceptable.

Training sets. Initially an attempt was made to use a training set of 1000 vectors obtained from process response, taking only 10 values of each of the three model parameters ($10 \times 10 \times 10 = 1000$). This training set was found to work only for K_{proc}. It was necessary to use a separate training set composed of 900 vectors obtained using 30 values from the range for T_{proc} and L_{proc}/T_{proc}

(30 × 30 = 900). The problem was therefore taken up in two stages. Firstly, a single radial basis function network (ANN No.1) was trained to output the value of K_{proc} in the range [0.15, 1.5] when presented with a waveform produced by the process model (1) with unknown parameters and controlled by a 'reference' PID controller. Secondly, ANN No.2 and ANN No.3 were trained to output T_{proc} and L_{proc}/T_{proc} respectively, once the process gain K_{proc} had been normalized to unity. The test signal of Fig.3 was applied 1105 [s] after a unit step input signal r, when the steady state of the process output y had virtually been established. Then the test signal was applied. The response waveforms were recorded as 168 data points over 33.6 [s] from the time of application of the test signal. The 'reference' controller parameters were selected so as to produce stable but unique waveforms for all combinations of process parameters.

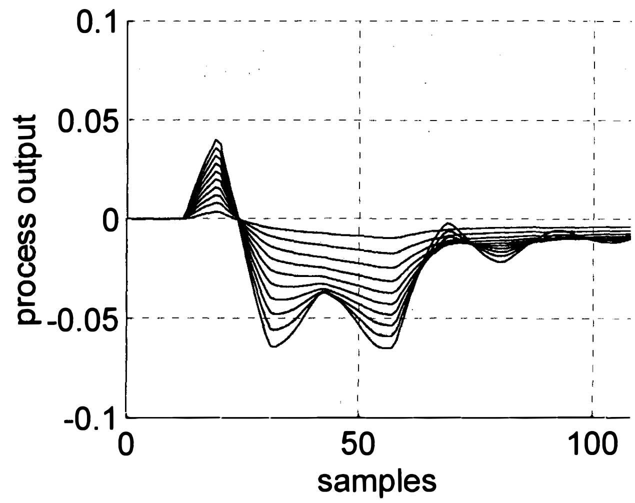

Fig. 4 Response for different values of K_{proc}

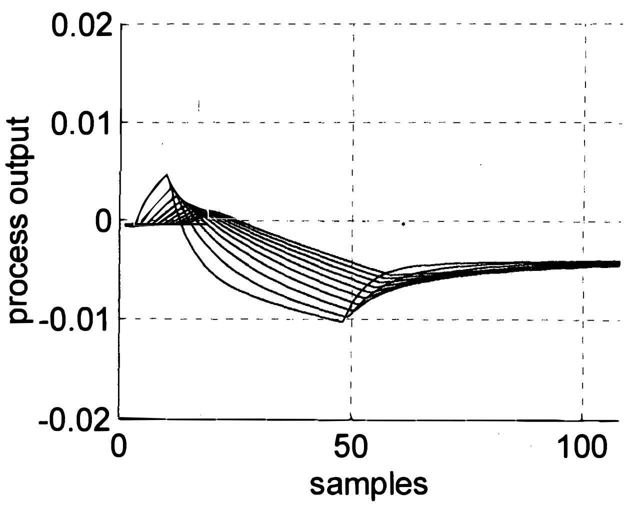

Fig. 5 Response for different values of T_{proc}

Training results of ANN No.1. It was found that the clearly defined amplitude changes as K_{proc} was varied permitted effective training using as few as 10 values of K_{proc} in the range under consideration. Ten values each of T_{proc} and L_{proc}/T_{proc} over the ranges under consideration were combined with the 10 values of K_{proc} to produce a 1000-vector output training matrix. The input training matrix was produced using these values in the closed-loop simulation with the 'reference'

PID controller and recording the process output waveforms. This produced 1000 vectors with 168 elements. The RBFN training took 57 [min] to reach a sum-squared error (sse) of 0.0003. There were 121 hidden layer neurons (HLNs). Subsequent testing using 100 randomly chosen triplets (K_{proc}, T_{proc}, L_{proc}) produced a maximum absolute error (mae) of 0.938% and a standard deviation (std) of 0.249.

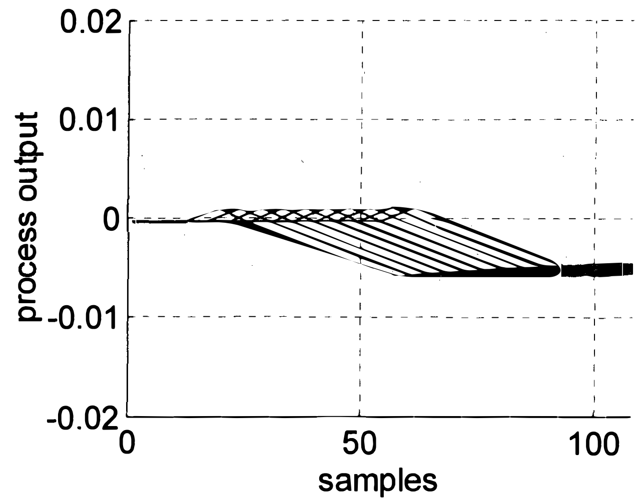

Fig. 6 Response for different values of L_{proc}/T_{proc}

Training results of ANN No.2 and ANN No.3. Because difficulties were experienced in training RBFNs to recognize T_{proc} or L_{proc}/T_{proc} from the waveforms for the $10 \times 10 \times 10$ combinations used in ANN No.1 it was decided to keep K_{proc} constant as $K_{proc} = 1$ and use 30×30 combinations of T_{proc} and L_{proc}/T_{proc}. The results can be summarized as follows:

ANN No.2 (determination of T_{proc}): It required 37 hidden layer neurons, 10 [min], $sse = 0.3$. Test with 100 randomly selected triplets (K_{proc}, T_{proc}, L_{proc}) resulted in $mae = 3.30\%$, $std = 0.676$.

ANN No.3 (determination of L_{proc}/T_{proc}): 246 hidden layer neurons are required in the network, 185 [min], $sse = 0.0003$. Test with 100 randomly selected triplets (K_{proc}, T_{proc}, L_{proc}) produced $mae = 1.13\%$, $std = 0.309$.

All RBFNs used gaussian activation functions in the hidden layer with a linear function in the output layer.

Method for optimal controller tuning via ANN

There are several methods for tuning of a PID controller when the model (1) of the process is known. Some of these are mentioned in the Introduction. However, the ANNs give an opportunity to memorize the optimal tuning for the controller for different optimization criteria and different constraints under the wide range of process parameter values. One such ANN approach is given in Mamat *et al.* (1995) where only one optimization criterion is used for derivation of controller parameters. What we propose is an extension of that approach, where a set of optimum controller settings is generated for the range of parameters of the process model (1) and for a number of different tuning requests commonly used in practice, e.g. optimal disturbance rejection, optimal set-point tracking, combined optimal disturbance rejection and set-point tracking, etc. Then, one or more ANNs are trained to match the controller parameter values to the process parameter values. From the practical viewpoint this should not be a problem. Then the ANN can choose, according to the specific need, the correct controller tuning. The specific need for a particular loop can be selected by the operator from the choices provided. This part of the application does not go beyond the standard application of static ANNs and will not be discussed further.

Example

This example demonstrates the procedure of process model identification and controller setting using ANNs. The quality of disturbance rejection of the neural network tuned PID controller is then compared with the quality of disturbance rejection of a system tuned according the Cohen-Coon method.

For a practical assessment of the method it was necessary to choose an example of an unknown plant. A simulation was set up using a fourth order process described by

$$G_p(s) = \frac{0.5}{(s+1)^4}e^{-s} \tag{3}$$

The nominal value of the process gain is guessed to be $K^n_{proc} = 1$. The 'reference' PID controller was set as outlined in Step 1, the test signal of Fig.3 was applied to the system input and the output of the process was recorded. The recorded waveform was then applied to ANN No.1 yielding $K_{proc} = 0.5006$. Then the PID controller was retuned according to the requirements outlined in the Step 2 and the test signal was applied again. The resulting waveform was applied to ANN No.2 and ANN No.3 to yield $T_{proc} = 2.18$ and $L_{proc}/T_{proc} = 0.974$.

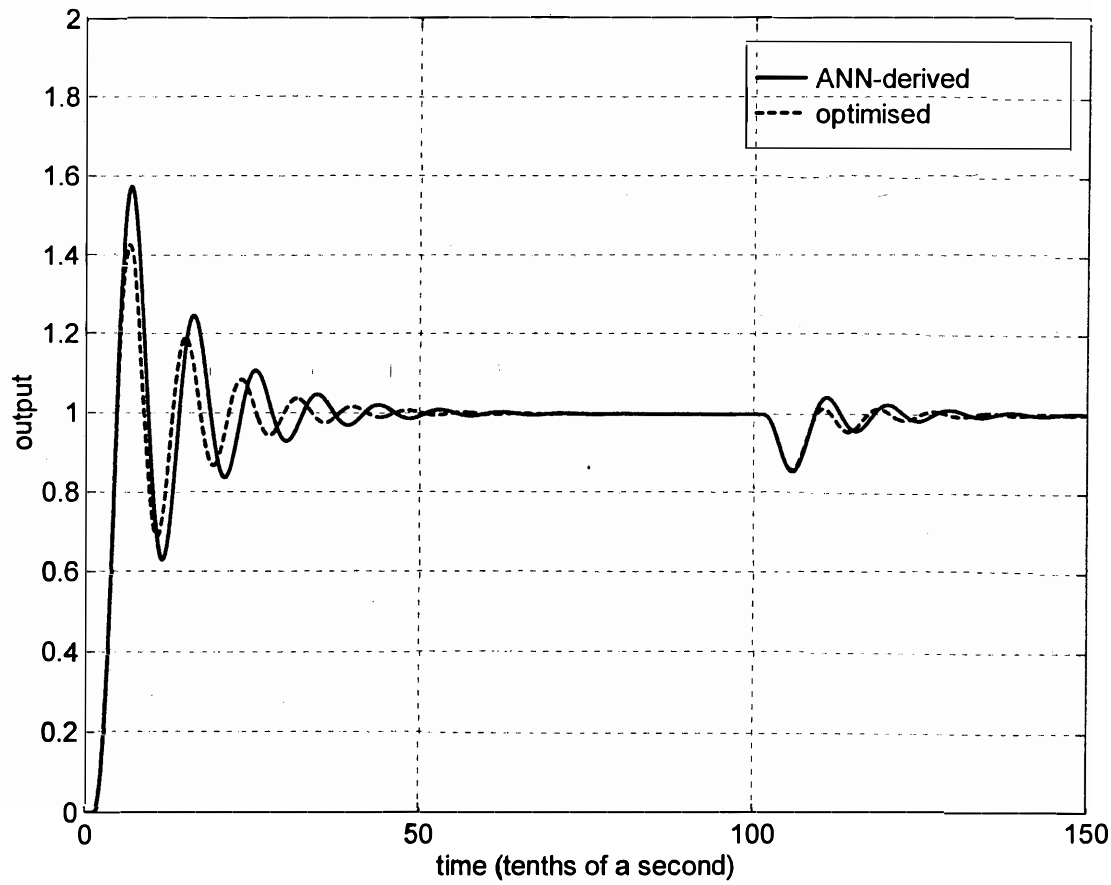

Fig. 7 Closed-loop step and disturbance response

The tuning of the controller that provides good rejection of step-type disturbances is then determined via ANN as given in the next table

K_p	T_i	T_d	N
1.6578	4.0026	0.6576	10

A simulation was then set up using these PID parameters and the exact fourth order transfer function (3) of the plant, as well as using the PID parameters determined by Cohen-Coon method. The results are shown in Fig.7. The disturbance had the step size of -0.5 units. As can be expected the set-point tracking is not good in either case, but we point out that the controller was not tuned for good set-point tracking. However, the disturbance rejection of the actual fourth-order plant (4) in the closed loop with the PID controllers tuned via ANN and by Cohen-Coon method is very good. The dashed line shows the response when controller settings is based on the Cohen-Coon method for the equivalent model (1) of the actual fourth order model (4) of the process. The solid line shows the response when the ANN-derived controller setting is used. It can be seen that the ANN-derived settings of the controller produce disturbance rejection very close to that obtained with the Cohen-Coon method. This confirms the validity of our approach for process parameter identification and assisted controller tuning.

Conclusions

The paper proposed a new ANN based method for identification of a process model and assisted controller tuning. The method gives directly the values of the process model parameters. These parameters are then utilized for optimal controller tuning. The method possesses simplicity and applicability for a wide range of process parameter values. It is suitable as a complete 'in-chip' solution that can be loaded to EPROM and utilized as a separate unit attached to the implemented controllers. At this stage the solution can be improved by utilizing only one ANN instead of three currently used for process parameter determination, but this seems to be only a technicality. A potential domain of application of the method is in process control field applications, as the ANNs involved can be trained in advance.

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