

ADAPTIVE NEURAL CONTROL OF NPR

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Abstract

Controller adaptation is always a major concern. A controller that meets certain performance design objectives can not be satisfactory unless it can preserve such quality in the presence of system parameters fluctuation. For the nuclear power reactors (NPR) a controller that preserves stability and performance for wide range of operation conditions and fluctuations is especially desirable. This paper presents a design of an adaptive controller using artificial neural networks (ANN) to infinite impulse response IIR model of NPR. The objective is to maintain the stability and robustness of the overall control system against the fluctuation of system parameters during different operation conditions. The adaptive neural controller is systematic, methodical, easy to design, and can give improved system performance over wide range of NPR operation conditions.

Keywords

Adaptive control, artificial neural networks ANN, nuclear power reactors NPR.

I. Introduction

Using ANN in control system, which is developed in the last few years, introduces an advanced tool for control techniques. The main theory of neural controllers (neurocontrollers) is learning the network to work as a controller to improve the performance of the NPR under control [1, 2]. To drive the NPR according to reference signal (reference patterns), a neurocontroller will be designed to generate a control signal $U(n)$ which will lead the reactor model to follow its reference pattern. The important point of using neurocontroller is the strategy used to design and learn the neurocontroller how it can generate the control signal. The learning method depends on feeding the neurocontroller by the input and output patterns required for control signal generation and learning the neurocontroller how to generate the control signal. The method of neurocontroller learning is a like of the human learning so it is sometimes called cerebellar learning or cerebellar model articulation controller (CMAC) [3]. The basic idea of the neurocontroller approach is to learn an approximation of the system characteristics and then to use it to generate the appropriate control signal. The approximation of the system characteristics is understood as gradual learning based on the observation of the plant input-output data in the real time during the different operating conditions. In this paper, the adaptive linear element (ADALINE) supervised neurocontroller will be applied to the linearized IIR model of the NPR [4, 5]. In section (II) supervised neurocontroller will be presented to explain the general aspect of the neurocontroller design. In section (III), the general learning algorithm will be clarified. In section (IV), Least Mean Square (LMS) learning rule will be discussed to illustrate the methodology of the ADALINE learning. In section (V), applying of ADALINE neurocontroller to the NPR IIR model will be illustrated. Finally, in section (VI) the conclusion will be introduced.

II. Supervised neurocontroller

Figure (1) shows the block diagram of the supervised neurocontroller system. The plant control signal is initially produced by a conventional PID pole assignment controller. The controller is used in a negative feedback configuration. The plant operates normally under the conventional PID controller. The switch Sw1 is closed while the switch Sw2 is open. The negative feedback signal will be summed to the reference signal at summing node S1. The output of the node S1 will be the input of the conventional controller. The output of the conventional controller will be considered as the control signal of the plant through the node S2. While the plant is running under the conventional PID controller, the learning of the neurocontroller is running. The learning of the neurocontroller is carried out by using patterns from the input and output samples. After the learning process has been accomplished under different operation conditions, the neurocontroller will be used instead of the conventional PID controller. In this case the switch Sw1 is open and the switch Sw2 is closed. The output of the neurocontroller will be the control signal of the plant [6-8].

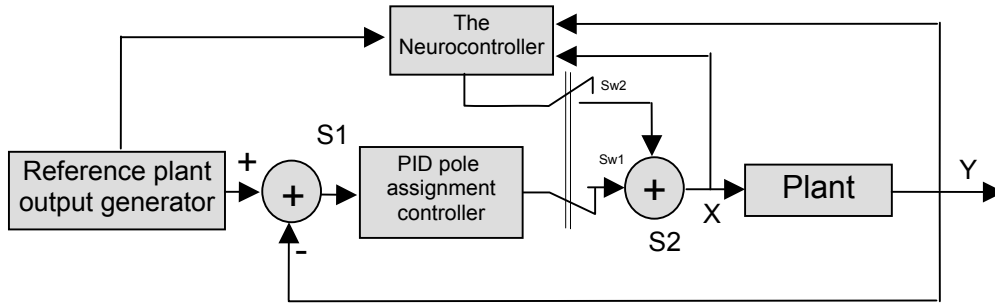


Figure (1). Supervised neurocontroller system design

The methodology of neurocontroller system design can be described briefly as learning of a neural network to act as a controller. The control signal generation by using the neurocontroller has the following steps:

1. Determining inverse model parameters which are used in control signal generation U_n which will be the output of this model under the effect of PID controller.
2. Learning of the neurocontroller to generate the control signal according to reference pattern which is obtained from the previous inverse model.
3. Learning the network until the RMS value come to the lowest value as far as possible (to minimize the resultant error).
4. Applying the control signal, generated from the neurocontroller, to the system.
5. Using the output of the system as a feedback input of the neurocontroller to generate the following control signal.
6. Repeating the above steps until the end of patterns.

III. The General Learning Aspect

Neural networks have different types and every type has its own learning rule. Almost all learning methods have the same general aspect. This algorithm mainly modifies network parameters (weights) according to its learning rule to accommodate the network's characteristics to its desired pattern [3]. In general, for the neuron I and its input j the weight vector $w_i = [w_{i1} w_{i2} \dots \dots \dots w_{im}]^T$ increases in proportion to the product of input x and learning signal r . The neuron's activation function is $f(net_i) = f(w_i^T x)$. The learning signal r is in general a function of the W_i , X and sometimes of the teacher's signal d_i . We thus have for the network shown in figure (2):

$$r = f(w_i, x, d_i) \quad (1)$$

The increment of the weight vector W_i produced by the learning step at time t according to the general learning rule is

$$\Delta w_i(t) = cr[w_i(t), x(t), d_i(t)]x(t) \quad (2)$$

Where c is a positive number called the learning constant that determines the rate of learning. The weight vector adapted at time t becomes at the next instant, or learning step,

$$w_i(t+1) = w_i(t) + cr[w_i(t), x(t), d_i(t)]x(t) \quad (3)$$

The superscript convention will be used in this text to index the discrete-time training steps as in equation (3). For the k 'th step we thus have from (4) using this convention.

$$w_i^{k+1} = w_i^k + cr(w_i^k, x^k, d_i^k)x^k \quad (4)$$

The learning in (3,4) assumes the form of a sequence of discrete-time weight modifications. Continuous-time learning can be expressed as :

$$\frac{dw_i(t)}{dt} = crx(t) \quad (5)$$

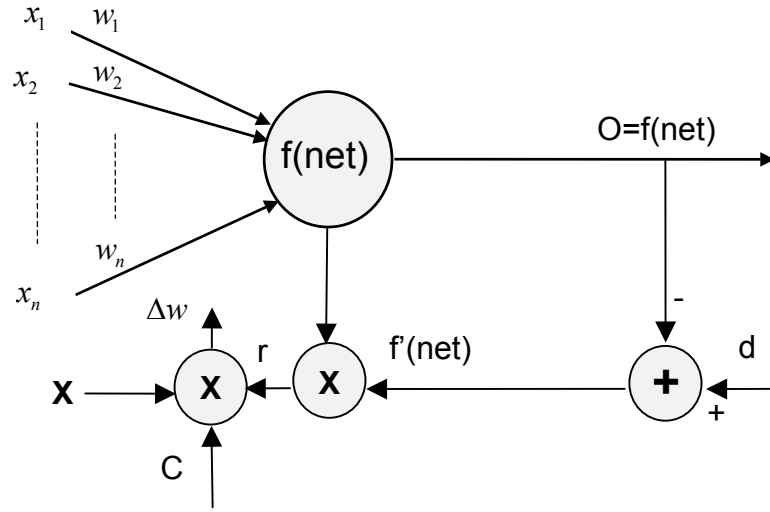


Figure (2). Neural networks learning algorithm

IV. The LMS Learning Rule

The LMS learning rule, based on Wiener filters, is applicable for the supervised training of neural networks [3]. It is independent of the activation function of neurons used since it minimizes the squared error between the desired output value d_i and the neuron's activation value $net_i = w_i^t x$. The learning signal for this rule is defined as follows:

$$r = d_i - w_i^t x \quad (6)$$

The weight vector increment under this learning rule is

$$\Delta w_i = c(d - w_i^t x)x \quad (7)$$

or, for the single weight the adjustment is

$$\Delta w_{ij} = c(d_i - w_i^t x)x_j, \text{ for } j = 1, 2, \dots, n \quad (8)$$

Assuming that $f(net) = net$, we obtain that $f'(net) = 1$.

V. ADALINE Neurocontroller

Using ADALINE network as a neurocontroller for the model of the NPR is considered as interpolation of the linear discrete control system. The design of the network, used for the ADALINE neurocontroller, is shown in figure (3). The input vector of the neurocontroller is feedback signals of the system and the output of the neurocontroller is the control signal U_n . The IIR model of the NPR [9-10] has the following form :

$$Y_n + a_1 Y_{n-1} + a_2 Y_{n-2} = b_0 U_{n-1} + b_1 U_{n-2} + b_2 U_{n-3} \quad \text{then} \quad (9)$$

$$U_n = w_1 Y_{n-1} + w_2 Y_{n-2} + w_3 Y_{n-3} - w_3 U_{n-1} - w_4 U_{n-2} + Bias$$

Values of system model parameters a_1 , a_2 , b_0 , b_1 and b_2 can be calculated as a function of system constants. The values of these parameters are listed in table (1). The output of the NPR is the thermal power Y_n and the control signal is the control rod speed U_n .

$b_0 = 0.99882$	$b_1 = -0.868$	$b_2 = -0.06618$
$a_1 = -2$	$a_1 = -2$	$a_2 = 1$

Table (1). The model parameters of the NPR.

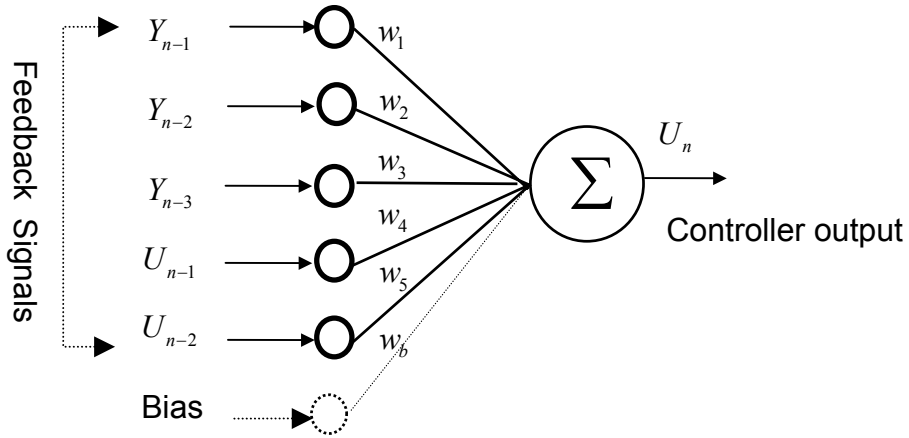


Figure (3). ADALINE neurocontroller of the NPR model.

Training parameters used in ADALINE neurocontroller learning of the NPR model are listed in table (2).

Parameters of Network Learning	Parameter value
Learning speed constant (c)	0.002
Activation function constant	1
Number of inputs I	5
Number of outputs K	1
Total weights	6
Learning iterations	3150
Good patterns percent %	100%
Target error RMS	0.001
Number of patterns	20

Table (2). ADALINE neurocontroller training parameters for the NPR model.

The LMS learning rule has been employed for training of the ADALINE neurocontroller to generate the control signal. The output of the neurocontroller U_n is used to drive the controlled system. Figure (4) shows the control signal, generated from the traditional system PID controller U_t , w.r.t. the output of the ADALINE neurocontroller U_n . Both of them seem extremely so closed. In figure (5) patterns errors are presented w.r.t the pattern index. Pattern errors show the change of pattern errors due to input pattern changes and indicate the high precision of the neurocontroller, the maximum value of the pattern errors is 0.001. The decrement of the RMS error due to training is shown in figure (6). When the RMS value reaches the desired value, the learning process stops and the final weights considered as ADALINE neurocontroller parameters. To validate the capabilities of the ADALINE neurocontroller, the control signal generated by the neurocontroller has been used to drive the system instead of the traditional controller signal and a comparison between the responses of the system under both of them is presented. Figure (7) shows identical system responses in these two cases w.r.t reference r , this indicates the adaptability of ADALINE neurocontrollers.

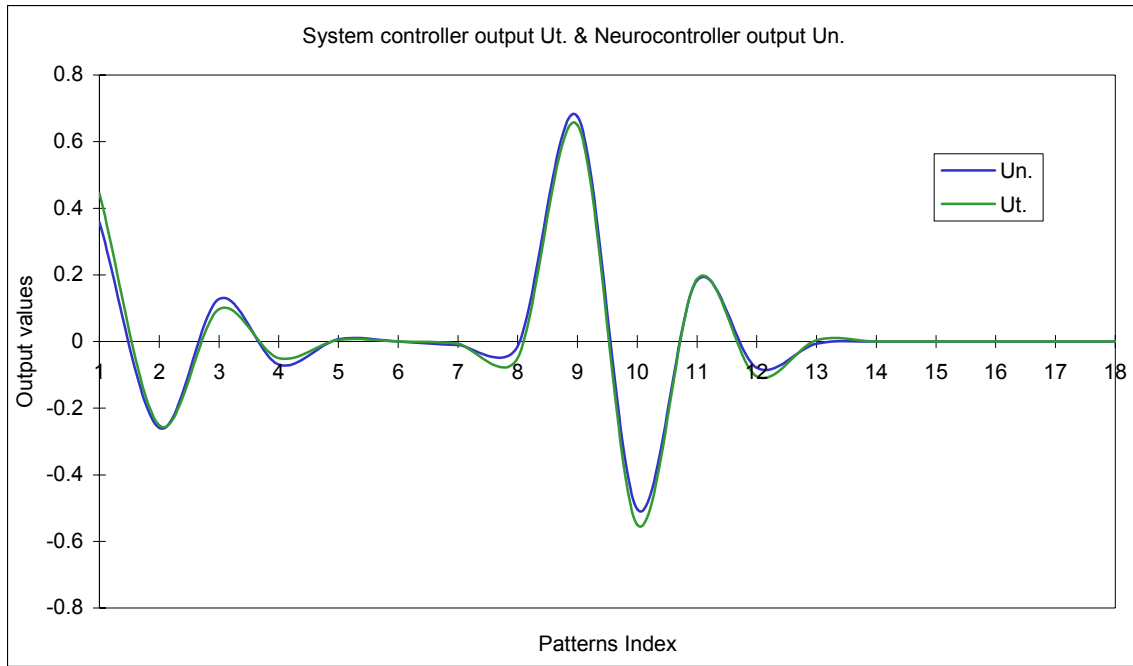


Figure (4). ADALINE neurocontroller output U_n w.r.t the traditional PID controller U_t .

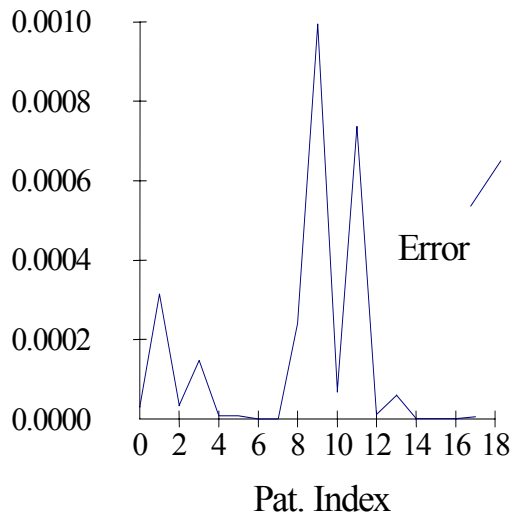


Figure (5) Pattern errors

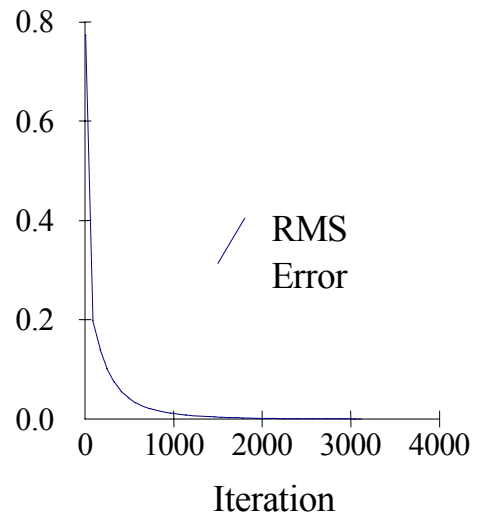


Figure (6) RMS changes during learning

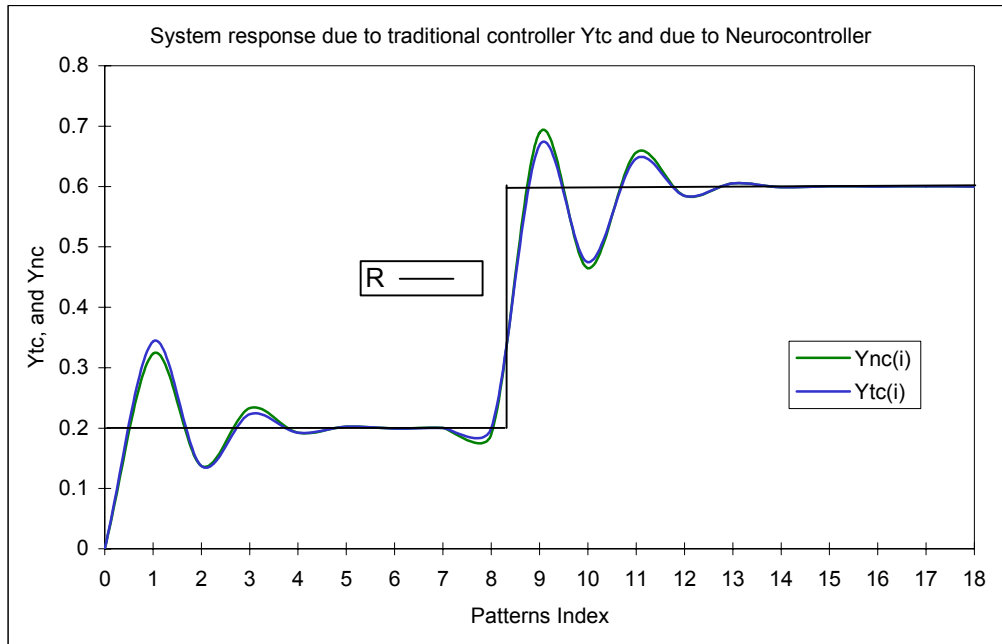


Figure (7) The system response (neurocontroller) Y_{nc} and (traditional controller) Y_{tc} .

As a result of learning, weights got their final values. Final values of weights are considered as the ADALINE neurocontroller parameters. Weights of the ADALINE neurocontroller are listed in table (3).

W_1	W_2	W_3	W_4	W_5	Bias
0.124063	0.853829	-1.015952	-1.019320	-0.133104	0.497335

Table (3) Weights of the ADALINE neurocontroller .

VI. Conclusion

From the obtained results we can conclude that the neurocontrollers have high precision, the maximum value of pattern errors was 0.001, so it can replace the traditional control systems, see figure (5). The neurocontrollers are reliable to follow up the changes of the system set point as in figure (7). The neurocontrollers have a simple learning rule compared with the complicated rules of the traditional controllers. The ADALINE neurocontrollers are suitable for dealing with linear or quasi linear discrete systems and they can be considered as an interpolation of adaptive discrete control systems.

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