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Fuzzy Neural Networks for Identification and Control of DC Drive Systems

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Abstract—**This paper demonstrates the application of Fuzzy Neural Networks (FNN's) in identification and control of DC motor drive system. This technique compensates the drawbacks of the fuzzy-logic controllers (FLC) with fixed membership function and quantization levels. The membership function and quantization levels are adapted according to the system operating condition changes. Two FNN are proposed with different learning rates. The first is FNN identifier to provide the sensitivity inference about the drive system changes. The second is FNN controller with adaptiveiablty to regulate the drive system against the operating condition changes and disturbances. An online backpropagation algorithm is used to achieve both FNN identifier and controller objectives. Experimental setup of the suggested technique is developed of the DC drive system. Comparison between the developed technique and FLC is highlighted and the experimental test results are listed.**

Keywords—**Fuzzy Logic, Fuzzy Neural Network, Electrical Drive Control, Digital Control.**

I. Introduction

During the past years many control techniques have been developed for improving the performance of electrical drives. One is the steady state and dynamic tracking ability to set operating point changes, and the other is the ability to recover from the load disturbance.

Conventional controllers (such as PI) for such drives [1, 2] are designed on the basis of local linearization about an operating condition. These controllers are very effective if the speed command and load changes are small and the operating conditions do not force the system too far away from the linearizing point.

In application such as robot arm, and machine tools, the drive operates under a wide range of load characteristics and the parameters of the drive system vary extensively. Thus to ensure a specific dynamic response independent of variations of the parameters, size of speed command and load disturbances, a modern control technique is needed.

In this paper, details about the theory and practical implement of both FNNI and FNNC models of drive system are illustrated.

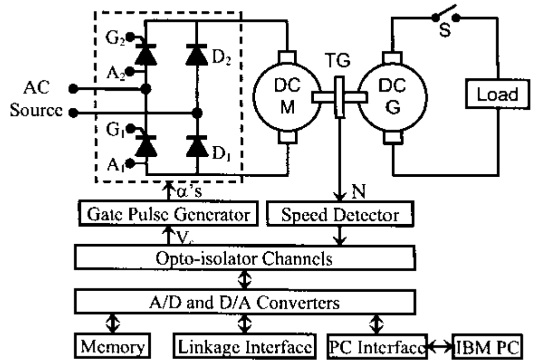

Fig. 1. Block Diagram of the Proposed DC Drive System.

The performance of the developed control technique is evaluated experimentally on a scaled down laboratory model consists of DC motor generator set of 5 KW each. Speed tracking and regulating performance are listed using the developed FNN control technique when the system is subjected to speed and load changes. Several experimental results show that the developed FNN control system provides an appreciable improvement of motor performance and very effective control objectives.

II. System Configuration

The proposed scheme consists of a separately excited DC motor supplied by variable DC voltage through a full wave half controlled thyristorized bridge. A DC generator is mechanically coupled with the motor to represent a suitable dynamic loading of the motor. A Pentium 200MHz computer is facilitated with the system to control the input voltage of the motor depending on the motor speed. The motor speed is detected using tachogenerator (1V/300rpm) coupled mechanically with the motor shaft. Suitable interfacing circuits are included with the computer to achieve proper conversion of the system variables. Analog variable of the system such as motor speed is converted to digital coding using analog to digital converter (A/D). Also the controlling signal from the computer is converted to analog signal using a digital to analog converter (D/A).

A full wave thyristorized bridge consisting of two thyristors and two diodes are used. A wide range of

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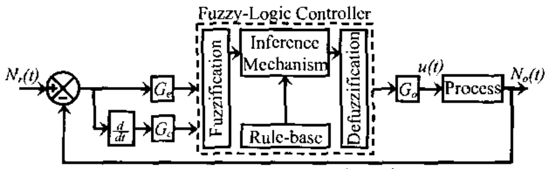

Fig. 2. Fuzzy-Logic Control Architecture

armature voltage control can be adjusted using a suitable firing technique of the bridge thyristors. The firing delay angles, α's, of the thyristor gates can be adjusted by a remote DC controlling voltage level, V_c. A linear firing angle change according to the controlling voltage can be obtained using reliable firing technique. An optoisolator module is used to ensure two important functions, the first is to amplify the firing pulse power, and the second is to provide the need isolation between the high voltage power circuit and the low voltage firing circuit and computer. Fig. 1 shows a functional block diagram of the suggested control scheme.

III. Fuzzy-Logic Control (FLC)

Fuzzy control is a practical alternative for a variety of challenging control applications. It provides a convenient method for constructing nonlinear controllers via the use of heuristic information that may come from an operator who has acted as a controller for process [6]. The fuzzy controller provides reasonable tracking of the motor speed to a prespecified reference command. Also it achieves visible regulating objectives of the motor speed when a load changes are subjected. The normalized error between the motor speed and reference command, in addition, the rate of change of this error are used to generate a controlling signal to update the motor input voltage. The normalized speed error and its rate of change of the motor are defined as follows:

$$e(K) = (\, N_r(K) - N_m(K)\,) \,/\, N_{max}$$

$$\Delta e(K) = e(K) - e(K\text{-}1)$$

where $N_r(K)$, $N_m(K)$, N_{max}, $e(K)$, and $\Delta e(K)$ are the reference speed, actual motor speed, maximum speed, normalized speed error, and its rate of change at the Kth interval.

The block diagram of a fuzzy logic control system is shown in Fig. 2. The fuzzy logic controller composes of four parts namely; fuzzification, inference mechanism, rule base, and defuzzification [4].

The fuzzification transfers the normalized speed error and the rate of error change degree of match with linguistic values by comparing it with the membership functions to obtain the membership values of each linguistic label. The Inference mechanism takes the fuzzy values of the FLC inputs to determine fuzzy outputs using stored rule base. The Rule base is arranged for all possible cases of the inputs and outputs. The rules are a set of **IF ...THEN ...** rules such as:

IF normalized speed error is negative small **AND** its rate of change is negative small **THEN** output is negative big.

The last part of the FLC is defuzzification, it converts the controller output from linguistic labels into controlling voltage to control the input voltage of the derive system. The most commonly used method is the center of gravity (COG). This method computes the center of gravity of the final fuzzy space and produces a result which is sensitive to all the rules executed;

$$U_o = \frac{\sum_{i=1}^{n} \mu_c(x_i)\ x_i}{\sum_{i=1}^{n} \mu_c(x_i)}$$

where U_o is the output of the defuzzification part, $\mu_c(x_i)$ is the degree of membership function of the input x_i, and n is the number of output linguistic variables. The FLC output at the Kth interval becomes:

$$u(K) = u(K\text{-}1) + U_o$$

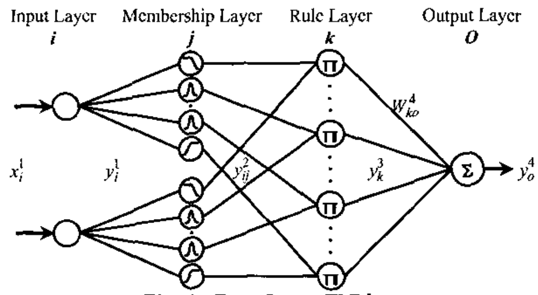

Fig. 3. Four-Layer FNN.

IV. Fuzzy Neural Networks

A. Description of the Fuzzy Neural Networks (FNN)

A four-layer FNN is shown in Fig. 3. It comprises of input layer, i, membership layer, j, rule layer, k, and output layer, o. The signal propagation and the basic function in each layer are introduced below [7, 12, 13].

First Layer—Input Layer: For every node i in this layer, the net input and the net output are represented as:

$$net_i^1 = x_i^1$$

$$y_i^1 = f_i^1\left(net_i^1\right) = net_i^1 \qquad i = 1, 2 \qquad (1)$$

where x_i^1 represents the ith input to the node of layer 1.

Second Layer—Membership Layer: Each node j performs a membership function which is adopted as Gaussian function [7]. For the jth node the net input and the net output are represented as:

$$net_{ij}^2 = -\frac{(x_i^2 - m_{ij})^2}{(\sigma_{ij})^2}$$

$$y_{ij}^2 = f_{ij}^2\left(net_{ij}^2\right) = \exp\left(net_{ij}^2\right) \qquad j = 1, \ldots, n \tag{2}$$

where m_{ij} and σ_{ij} are respectively, the mean and the standard deviation of the Gaussian function in the jth term of the ith input linguistic variable, x_i^2. n is the total number of the linguistic variables with respect to the input nodes.

Third Layer—Rule Layer: The input signals for each node are multiplied to produce outputs, y_k^3. For the kth rule node the net input and the net output are represented as:

$$net_k^3 = \prod^{k} x_{ij}^3$$

$$y_k^3 = f_k^3\left(net_k^3\right) = net_k^3 \qquad k = 1, \ldots, l \tag{3}$$

where x_{ij}^3 represents the input to each node of layer 3, l is the number of rules with complete rule connection if each input node has the same linguistic variables.

Fourth Layer—Output Layer: The overall output is computed by summation of all input signals. The net input and the net output are represented as:

$$net_o^4 = \sum w_{ko}^4 x_k^4$$

$$y_o^4 = f_o^4\left(net_o^4\right) = net_o^4 \qquad o = 1 \tag{4}$$

where the connecting weight w_{ko}^4 is the output action strength of the oth output associated with the kth rule and x_k^4 represents the kth input to the node of fourth layer.

B. On-Line Learning Algorithm

To describe the on-line learning algorithm of the FNN using the supervised gradient decent method [7, 9], first the energy function E is defined as:

$$E = \frac{1}{2}(y_d - y)^2 = \frac{1}{2}e^2 \tag{5}$$

where y_d is the desired response, y is the actual output, and e is the difference between the desired response and the actual output.

The learning algorithm based on backpropagation method is described below.

Fourth Layer: The error term to be propagated is given by:

$$\delta_o^4 = -\frac{\partial E}{\partial net_o^4} = -\frac{\partial E}{\partial e}\frac{\partial e}{\partial y}\frac{\partial y}{\partial y_o^4}\frac{\partial y_o^4}{\partial net_o^4} \tag{6}$$

The weights are updated by the amount:

$$\Delta w_{ko}^4 = -\eta_w \frac{\partial E}{\partial w_{ko}^4} = \eta_w \delta_o^4 x_k^4 \tag{7}$$

where η_w is the learning-rate parameter of the connecting weights of the FNN.

The weights of the output layer are updated according to the following equation:

$$w_{ko}^4(K+1) = w_{ko}^4(K) + \Delta w_{ko}^4 = w_{ko}^4(K) + \eta_w \delta_o^4 x_k^4 \tag{8}$$

where K is the number of iterations.

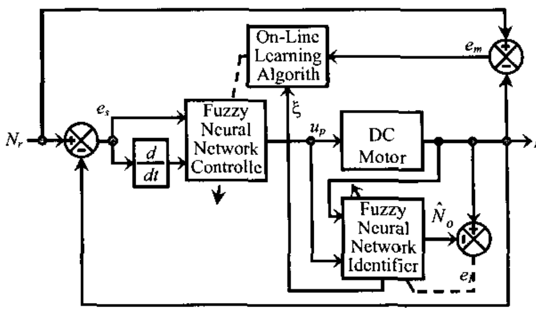

Fig. 4. FNN Control System.

Third Layer: Only the error term needs to be calculated and propagated:

$$\delta_k^3 = -\frac{\partial E}{\partial net_k^3} = \delta_o^4 w_{ko}^4 \tag{9}$$

Second Layer: The error term is computed as follows:

$$\delta_j^2 = -\frac{\partial E}{\partial net_j^2} = \sum_k \delta_k^3 y_k^3 \tag{10}$$

The updated law of m_{ij} becomes:

$$\Delta m_{ij} = -\eta_m \frac{\partial E}{\partial m_{ij}} = \eta_m \delta_j^2 \frac{2(x_i^2 - m_{ij})}{(\sigma_{ij})^2} \tag{11}$$

where η_m is the learning-rate parameter of the mean of the Gaussian functions.

The updated law of σ_{ij} becomes:

$$\Delta \sigma_{ij} = -\eta_\sigma \frac{\partial E}{\partial \sigma_{ij}} = \eta_\sigma \delta_j^2 \frac{2(x_i^2 - m_{ij})^2}{(\sigma_{ij})^3} \tag{12}$$

where η_σ is the learning-rate parameter of the standard deviation of the Gaussian functions. The mean and standard deviation of the hidden layer are updated as follows:

$$m_{ij}(K+1) = m_{ij}(K) + \Delta m_{ij} \tag{13}$$

$$\sigma_{ij}(K+1) = \sigma_{ij}(K) + \Delta \sigma_{ij} \tag{14}$$

V. FNN Control System Implementation

The overall structure of the FNN control system is shown in Fig. 4. It consists of two major parts: FNNI, and FNNC, in addition, on-line learning algorithm.

The main purpose of the FNNI is to mimic the dynamic characteristics of the controlled DC drive system [7, 9]. Two inputs of the FNNI are considered, which are the control input, u_p, and output speed of the DC motor, N_o. The FNNI is trained by backpropagation algorithm to obtain an estimated motor speed of the DC motor, $\hat{N}_o$. The learning process minimizes an energy function contains the error between the actual and estimated motor speed to provide the sensitivity derivative of the DC motor drive system to train the FNNC.

The energy function of FNNI is redefined as follows:

$$E_I = \frac{1}{2}(N_o - \hat{N}_o)^2 = \frac{1}{2}{e_I}^2 \qquad (15)$$

Appling Eq. (6), the error term δ_o^4 can be defined as:

$$\delta_o^4 = -\frac{\partial E_I}{\partial net_o^4} = e_I \qquad (16)$$

The sensitivity derivative of the DC motor drive system, $\partial N_o / \partial u_p$, is calculated using Eqs. (7-14) and (16) when the identification error becomes small enough, i.e., $\hat{N}_o \cong N_o$;

$$\frac{\partial N_o}{\partial u_p} \cong \frac{\partial \hat{N}_o}{\partial u_p} = \frac{\partial y_o^4}{\partial x_1^1} = \sum_{k=1}^{R_I} w_{ko}^4 \left[y_k^3 (-2) \frac{x_1^1 - m_{1k}}{\sigma_{1k}^2} \right] = \xi \qquad (17)$$

where R_I is the number of rules in the FNNI.

The purpose of the FNNC is to synthesis the control signal of the DC motor drive[7, 12]. The inputs of the FNNC are the speed error and its rate of change. The FNNC is trained by the backpropagation algorithm to generate the control signal. The learning process minimizes an energy function contains the error between desired and actual motor speed.

The energy function for the FNNC is redefined as follows:

$$E_c = \frac{1}{2}(N_r - N_o)^2 = \frac{1}{2}{e_m}^2 \qquad (18)$$

The error term δ_o^4 in Eq. (6) becomes:

$$\delta_o^4 = -\frac{\partial E_c}{\partial net_o^4} = e_m \xi \qquad (19)$$

The remainder of the on-line learning algorithm of both FNNI and FNNC is the same as described by Eqs. (7-14).

VI. Experimental Results

The performance of the drive system using the developed FNN controller is evaluated by applying several tests over a wide range of operating conditions. Comparison of the drive system behavior using FLC and the FNNC is shown. The initial operating conditions, disturbance size and other constrains are the same at each test for both controllers. Series of different tests were performed on the drive system in order to determine the most suitable values of the scaling factors, and learning rate parameters. The values of scaling factors of FLC, G_c, G_c, and G_u are found to be, 0.01, 1, 5, respectively. The values of learning-rate parameters of FNN control system, η_w, η_m, and η_σ are found to be, 0.15, 0.00001, and 0.00005, respectively.

At each test the laboratory drive system is started up to the required operating condition using a developed starting technique. According to the motor armature current, motor speed, current limits, and reference speed, the real-time controller calculates the firing instants of the thyristorized bridge. The experimental tests of the laboratory drive

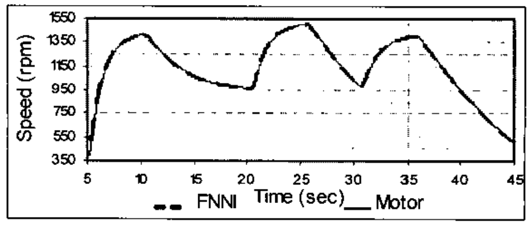

Fig.5. Response of FNNI

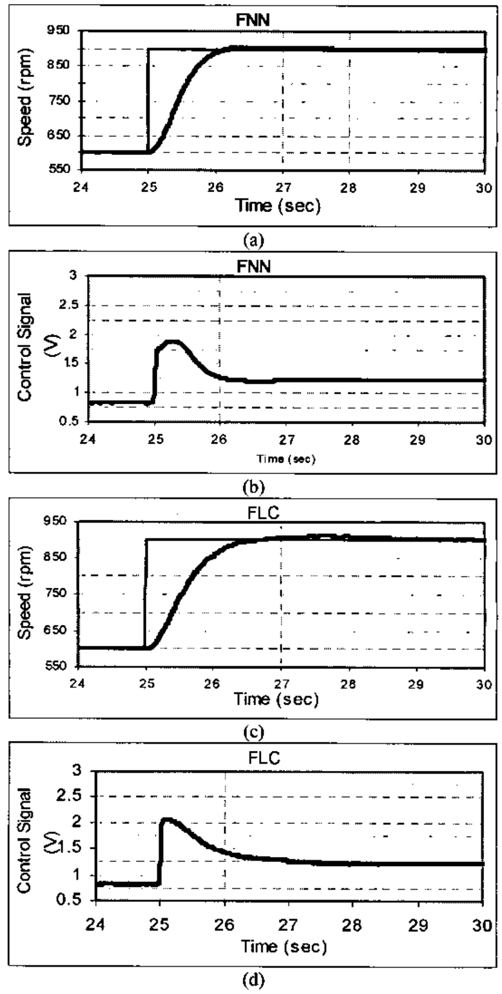

Fig. 6. Response of Speed Step from 600 to 900rpm (a) Speed of FNN, (b) Control Signal of FNN, (c) Speed of FLC, and (d) Control Signal of FLC.

system can be classified into three major types as following.

A. Fuzzy Neural Network Identifier Assessment

The FNNI is used to obtain linear model of the whole drive system with perfect following of the experimental model changes. An assessment of the FNNI model accuracy with the real drive system is shown in Fig. 5. The

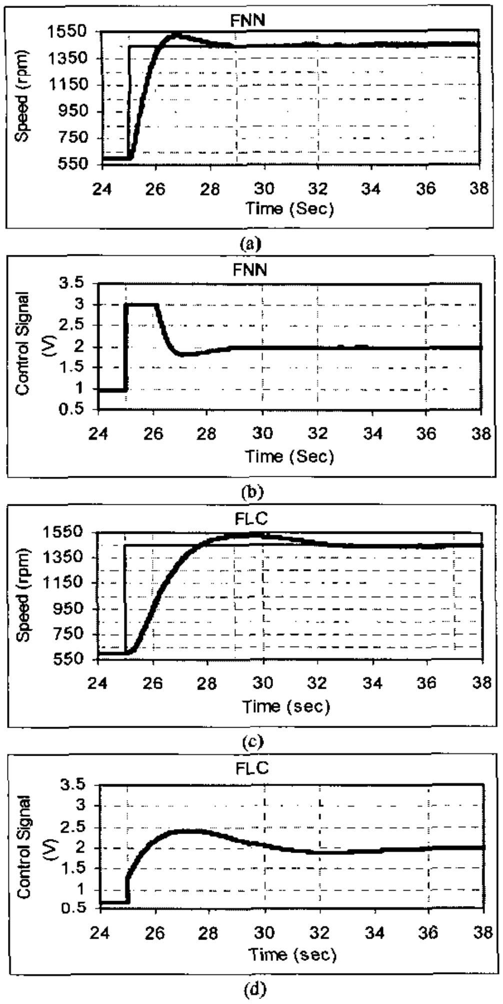

Fig. 7. Response of Speed Step from 600 to 1450rpm (a) Speed of FNN, (b) Control Signal of FNN, (c) Speed of FLC, and (d) Control Signal of FLC.

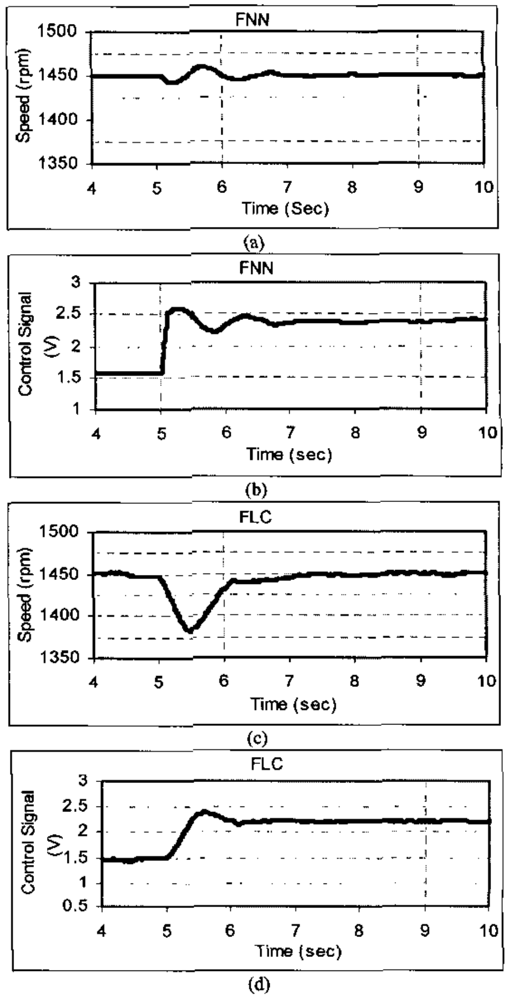

Fig. 8. Response to Load Step 800W (a) Speed of FNN, (b) Control Signal of FNN, (c) Speed of FLC, and (d) Control Signal of FLC.

speed trajectory of both the identified and experimental models is displayed. It is obviously clear that the identified model achieved a very close agreement of the drive speed trajectory even at fast changes.

B. Reference Speed Command Tracking Test

The effectiveness of the FNNC is obvious by comparing the motor speed performance using FNNC and FLC. Two important tests are listed to illustrate the dynamic tracking ability to reference speed command changes. The first test is performed when the system is subjected to speed step from 600 to 900 rpm. While a larger speed step about 600 to 1450 rpm, is applied in the second test. The motor speed and control voltage of the thyristor circuits are shown for each test. Fig. 6, and 7 show the motor performance of the small and large steps respectively. Significant improvement of the drive system performance is insured by using the intended controller comparing with the use of FLC even at the small disturbances.

C. Load disturbance test

The drive system performance is compared using FNNC and FLC when a load disturbance is applied on the motor. Different disturbance sizes were performed by switch on a variable resistance across the armature circuit of a DC generator mechanically coupled with motor. Two tests are shown for 800 and 1400 watts load step. Fig. 8 and 9 show these test results respectively. In both tests, the load disturbances are removed after a short time without any considerable overshoot.

The motor speed and control voltage of the thyristor are listed in each test. From the above tests, it is shown that the

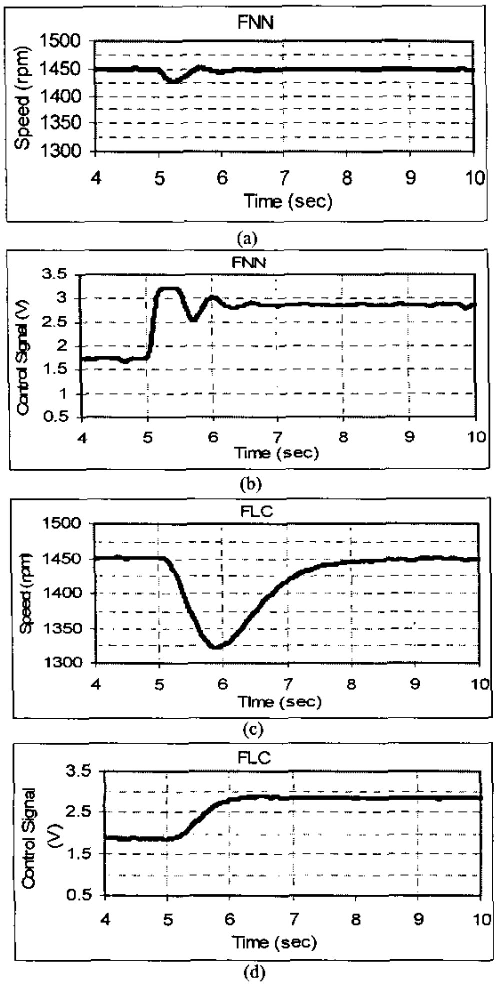

Fig. 9. Response to Load Step 1400W (a) Speed of FNN, (b) Control Signal of FNN, (c) Speed of FLC, and (d) Control Signal of FLC.

use of FNNC achieves many features such as visible reduction of speed drop, less overshoot of the speed and very short settling time to reach of its steady state speed.

VII. Conclusion

Practical implementation of realistic speed control of DC motor drive is performed. Fuzzy neural network controller is applied to achieve an adaptive membership function shape. According to the system operation changes the controller updates the control voltage which is used to adopt the input voltage of the motor and consequently the motor speed. A FNNI is implemented to feed the FNNC with suitable sensitivity derivative to achieve perfect tracking and regulating control objectives. Detailed comparison between the developed FNN control technique and traditional FLC has confirmed that the effectiveness and superiority of the proposed controller are obvious. Significant speed tracking and regulating performance are achieved using the developed FNN control technique when the system is subjected to speed and load changes. It observed that the FNN control technique improves the system performance visibly when the drive system is subjected to a large disturbance.

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