HIGH-PERFORMANCE OF POWER SYSTEM BASED UPON ANFIS CONTROLLER

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ABSTRACT

The proposed controller incorporates fuzzy logic (FL) algorithm with artificial neural network (ANN). ANFIS replaces the conventional PI controller, tuning the fuzzy inference system with a hybrid learning algorithm. A tuning method is proposed for training of the neuro-fuzzy controller. The best rule base and the best training algorithm chosen produced high performance in the ANFIS controller. Simulation was done on Matlab Ver. 2010a. A case study was Chopper-Fed DC Motor Drive, in continuous and discrete modes. Satisfactory results show the ANFIS controller able to control dynamic highly-nonlinear systems. Tuning it further improved the results.

1. INTRODUCTION

Fuzzy Logic Controller (FLC) provides superb and fast control [1]. It does not need accurate mathematical modeling of the system it controls. It also functions well in complex, non-linear, multi-dimensional systems that have varying parameters or imprecise signals. Its main design problem is in determining a consistent and complete rule set, and the shape of the membership functions (MFs). Obtaining the desired response through it means a long trial-and-error - still insufficient if the training data are not enough for all the operating modes [2].

Fuzzy logic (FL) and artificial neural networks (ANNs), despite their successful use in many challenging control situations, still have drawbacks that limit them to only some applications. Their combined advantages have thus become the subject of much research into ways of overcoming their disadvantages. Neuro-fuzziness is one resulting rapidly emerging field. ANFIS network, proposed by Jang, is one popular neuro-fuzzy system [1-3].

For specific-problem training of an ANFIS network, [1] proposes use of hybrid learning rule, which combines gradient descent technique and least-square estimator (LSE). Being a method of supervised learning, it needs a teaching signal, which can be difficult to provide when the ANFIS network is to be a feedback controller, as the desired control actions that the teaching signal represents are unknown. Literatures have proposed several ANFIS learning methods in which ANFIS is applied as a MIMO controller. Djukanović *et al.*, for example, uses a special ANFIS learning technique called temporal back propagation (TBP); control of a nonlinear MIMO system is by considering both the controller and the plant as a single unit each time step. The method, however, is complex and distinctly computation-heavy [4, 5].

2. THE FLC BASED ON ANFIS

ANFIS is an intelligent tool in FLC design. It can generate and optimize MFs and rule bases from even simple data. It combines neural network (NN) learning with FL knowledge representation. This paper presents a novel neuro-fuzzy controller (NFC) controlling the speed of a vector-controlled IM drive. The proposed NFC adapts a hybrid learning algorithm that minimizes the square of the error between the desired and the actual output. The FLC parameters are trained by a 5-layer ANN structure, eliminating the trials and errors of conventional FLC. Response of the proposed FLC is compared with that of conventional PI speed controller. Figure 1 is a block diagram of a fuzzy control system. An FLC has these elements [6, 7]:

To be capable of choosing the FLC inputs and outputs, the controller design must automate successful human-expert system control. The expert (designers of the FLC) tells us the user's choice of inputs in decision making [8].

$$e(t) = r(t) - y(t) \quad (1)$$

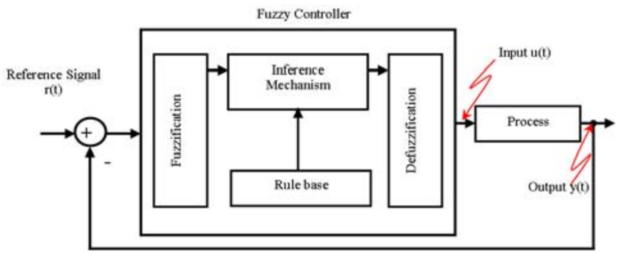


Figure 1. *The Fuzzy Controller in general [6]*

Among available choices, (e.g., integral of error e), this is a good intuitive one. The controlled variable of the FLC is $u(t)$ but in this paper the FLC output is the incremental change Δu in the FLC output. As a common rule base, this will be helpful in any FLC (fuzzy PI type, PD type, or PID type). Upon determination of the fuzzy controller inputs and outputs, the MFs for the input and output variables must be considered. Literature survey shows the MFs for each input in a two-input FLC to be mostly 3, 5, 7, 9, or 11. Generally, the more the MFs between the defined ranges, the more the possible rules and the better the response. This paper defines all the controller input MFs (i.e., e and Δe) and the controller output incremental change (i.e., Δu) within a normalized, common domain. Similarly, all other MFs when the number is 3, 5, 9, or 11 can be divided into normalized domain [9-11].

The next step is to design the rule base. The incremental change in controller output Δu for a fuzzy controller is determined by rules like this:

$$If\ e\ is\ E\ and\ \Delta e\ is\ \Delta E,\ then\ \Delta u\ is\ \Delta U \quad (2)$$

The set of rule bases for computing the output is rather standard. If the MF has 7 inputs the corresponding rules are 7^2 = 49. Likewise, in all other cases, the possible rules are 3^2=9, 5^2=25, 9^2=81, and 11^2=121. These usually use a rule base that considers a 2D phase plane, where the FLC drives the system into "sliding mode". Rule-base 1 is for 9 rules, rule-base 2 is for 25 rules, rule-base 3 is for 49 rules, and rule-base 4 is for 81 rules.

The NFC incorporates FL algorithm with a 5-layer ANN structure (see Fig. 2) [4, 11, 12]. A tuning block adjusts the parameters of the fourth layer, correcting any control deviations. The NFC inputs are the speed error and the rate of change of the actual speed error;

$$\left.\begin{aligned} Input\ 1 &= \varepsilon_w = w^* - w \\ input\ 2 &= \Delta\varepsilon_w = \frac{\varepsilon_w(n) - \varepsilon_w(n-1)}{T} \times 100\% \end{aligned}\right\} \quad (3)$$

With w* being the command speed and T the sampling time. The proposed controller is a Sugeno fuzzy model with a five- layer ANN structure. The first layer is for the inputs, the second layer is for fuzzification, the third and the fourth layers are for evaluation of the fuzzy rules, and the fifth layer is for defuzzification. Figure. 2 shows a two-input first-order Sugeno fuzzy model with two rules. The details mathematical of training ANFIS and the methods for reduced trial and error can see at [13, 14].

Sugeno is more compact and computationally efficient representation. It is the better adaptive technique for construction of fuzzy models. Both methods can be used to customize MFs for the best modeling of the data. Some final considerations for each [15]:

1. Advantages of Sugeno Method are efficient computation, works well with linear techniques (e.g., PID control), works well with optimization and adaptive techniques, guaranteed continuous output surface, and suits mathematical analysis.

2. A*dvantages of Mamdani* Method are intuitive, widely accepted, and suits human input.

3. CASE STUDY

The case study was a chopper-fed DC-motor drive simulated in continuous and discrete (see Figure 3 (a and b)) forms [16, 17] on MATLAB Ver. 2012a. The chopper, through which a DC motor is fed by a DC source, comprises a GTO thyristor and a free-wheeling diode D1.

As for the response to a change in reference speed and load torque, initial condition state vector 'xInitial' for starting with wm=120rad/s and TL=5Nm are saved in the 'power_dc drive_init.mat' file, which loads onto the workspace when simulation begins (see Model Properties). The Simulation/Configuration Parameters menu is checked, next the "Data Import/Export" is selected, and then the "Initial state" is checked, enabling the initial conditions.

To switch from constant "Ref. Speed (rad/s)" and "Torque (N.m)" blocks to Step blocks, the two Manual Switch blocks are clicked on, twice. At t=0.4s, the reference speed (wref) changed from 120rad/s to 160rad/s. At t=1.2s, the load torque changed from 5Nm to 25Nm. The simulation is repeated, and the drive response to variations in the reference speed and load torque observed.

4. SIMULATION RESULTS

Matlab Ver. 2012a toolbox was used to simulate the ANFIS (Fuzzy Logic Controller (FIS) with rule reviewer) controller:

- The controller configuration is first set up, and then the input data set, output data set which collected from simulation of system, and the FIS function type rearranged.
- Next, the identification parameters of the FLC are set through the ANFIS editor, and the input/output data loaded. Figure 4 shows many trial cases for the training of the FLC of the Chopper-Fed DC Motor Drive in continuous and discrete modes, and check the error signal, training algorithm, No. of epoch, type of MF, No. of nodes in layers. Finally compare between the outputs and select the best ANFIS to use in the next step.

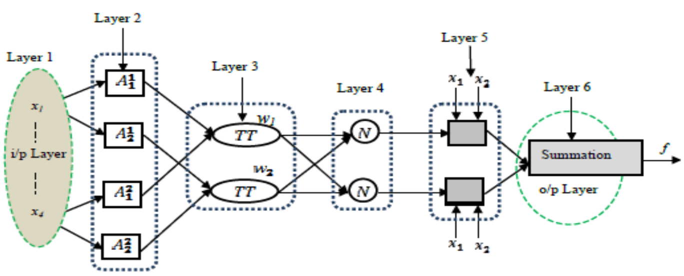


Figure 2. *The NFIS architecture of the 2-input Sugeno fuzzy model with 2 rules [11]*

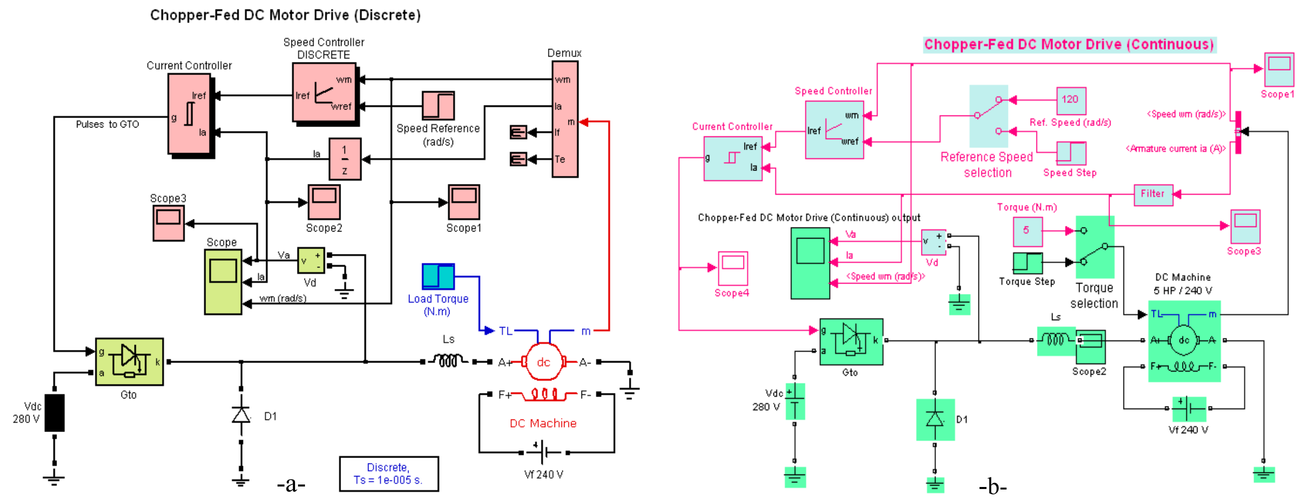
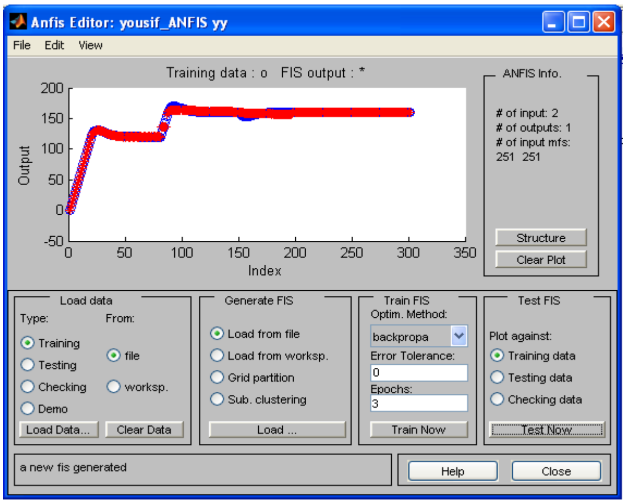


Figure 3. The Chopper-Fed DC Motor Drive in.(a) Discrete. (b) Continuous

- The design FLS that used 12 rules shown in Figure 5a. Figure 5b shows the FLS structure, Figure 5c the MFs for the FLS, and Figure 5d shows the surface error. This structure is select from the comparison after training processes.
- The design output post connection to the Chopper-Fed DC-Motor Drive is shown in Figure 6 for the discrete form and in Figure 7 for the continuous form, showing the motor speed (w *rad/s*), the armature current (I_a), and the voltage (V_a). Figures 6c and 6d respectively are simulations of the discrete and continuous circuits.



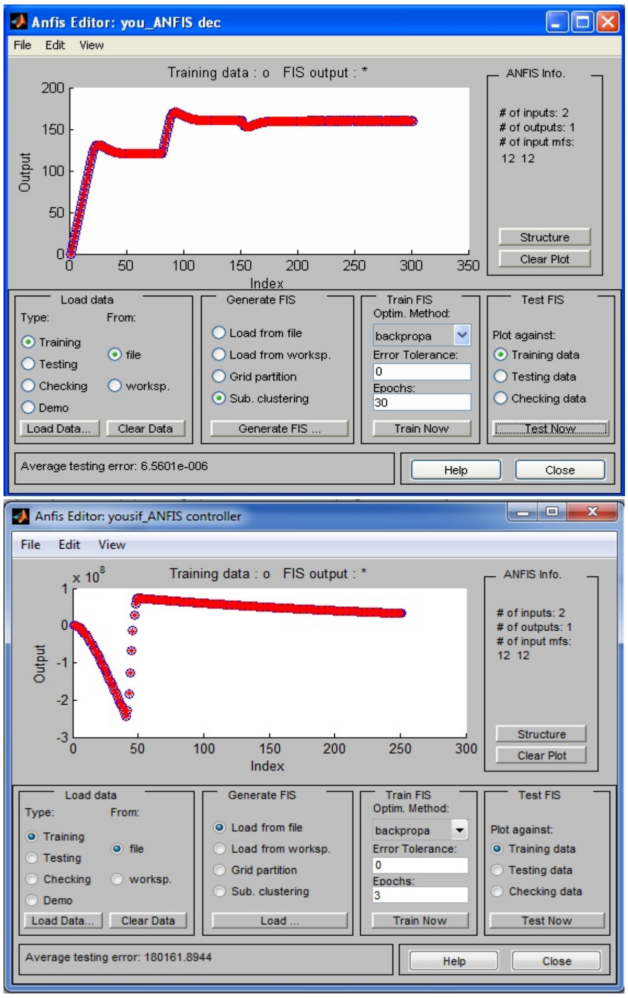


Figure 4. *Different cases of training the ANFIS controller for the Motor Drive (continuous and discrete forms).*

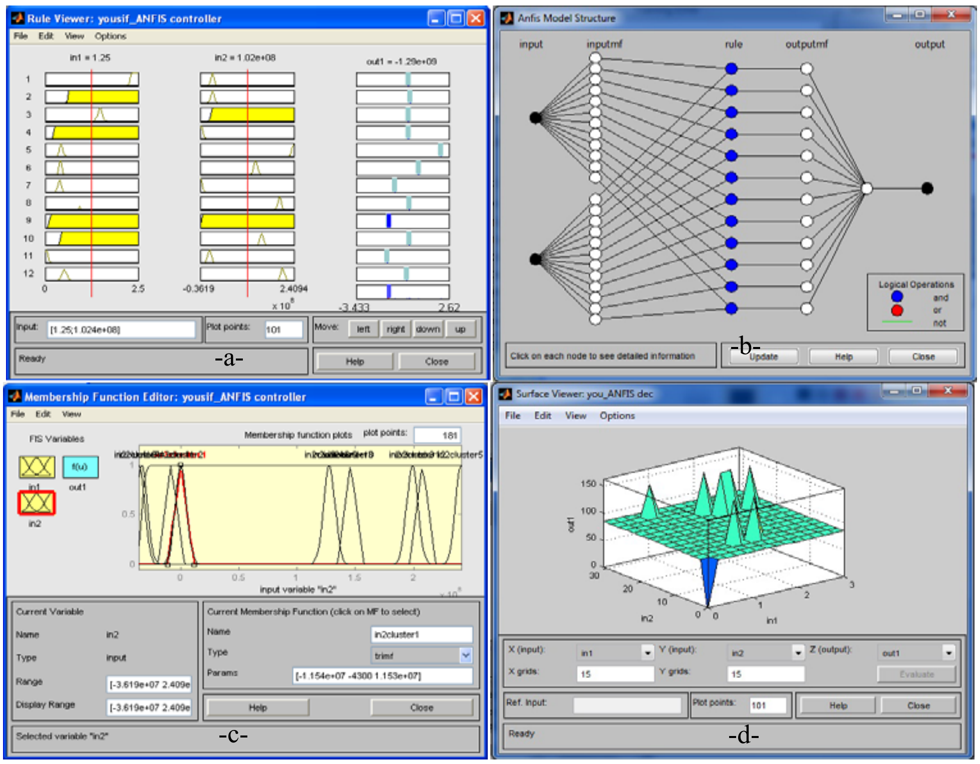


Figure 5. *(a) Rules viewer, (b) FLS structure, (c) MFs for the FLS, (d) The surface error.*

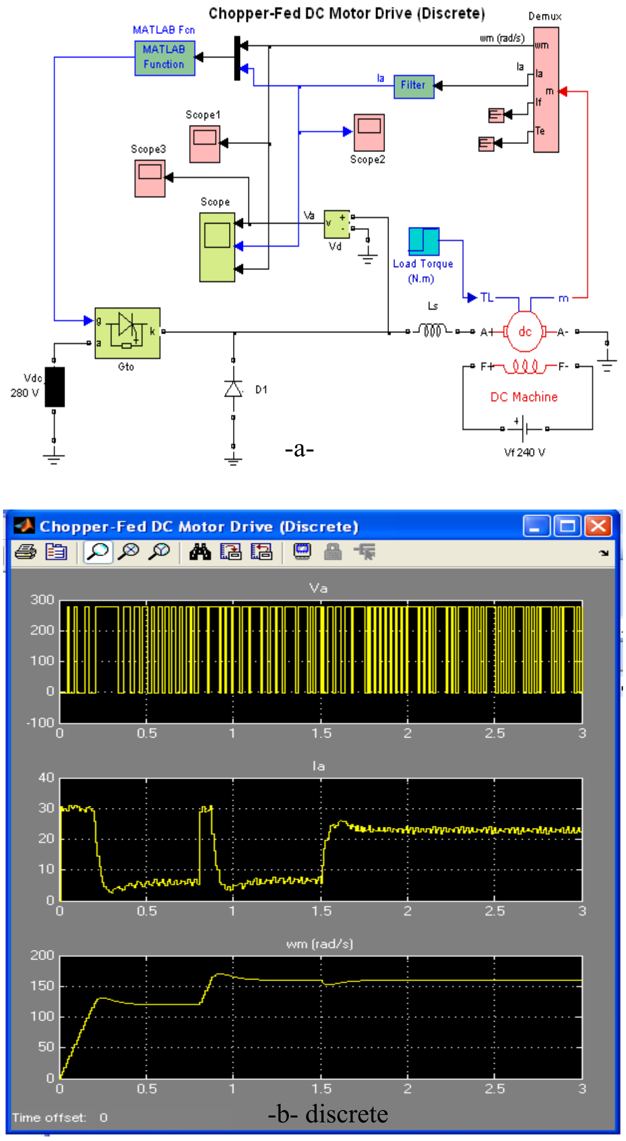


Figure 6. *The implement and simulation of ANFIS controller with Chopper-Fed DC Motor* (Discrete Form)

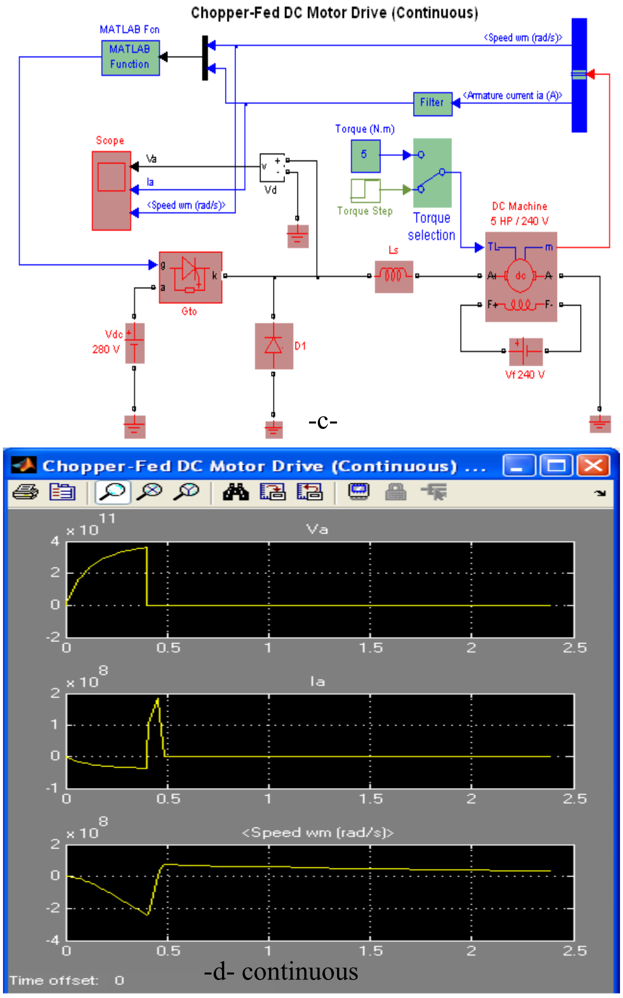


Figure 7. *The implement and simulation of ANFIS controller with Chopper-Fed DC Motor* (Continuous Form)

5. CONCLUSIONS

The simulation results show the ANFIS capable of compressing a nonlinear dynamic system into following the desired output. This ability depends on the accuracy of the setting for the ANFIS controller rules. The results and simulations of this paper show three determining factors for the setting: one, that more rules do not equate higher accuracy (the number of rules must be set with a specific trial-and-error value), two, the rules can be reduced by FSC and a similar performance as that produced by a larger rule set is possible (with FSC, the value of the influence radius is chosen by trial hits), and three, the error signal in the identification process can depend on the cost function of an optimal-parameter value, modeling accuracy, and knowledge of system performance.

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