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HANDWRITTEN CHARACTER RECOGNITION USING FUZZY NEURAL NETWORK

Dr.J.Venkatesh
Professor, Systems and Production,
Anna University,
Coimbatore, Tamilnadu, India.
venkijv@rediffmail.com

C. Sureshkumar*
Professor- IT,
J.K.K.N College of Technology,
Tamilnadu, India.
ck_sureshkumar@yahoo.co.in

Abstract: In this paper, a novel approach for robust trajectory tracking of induction motor drive is presented. By combining variable structure systems theory with fuzzy logic concept and neural network techniques, a new algorithm is developed. Fuzzy logic was used for the adaptation of the learning algorithm to improve the robustness of learning and operating of the neural network. The developed control algorithm is robust to parameter variations and external influences. It also assures precise trajectory tracking with the prescribed dynamics. The algorithm was verified by simulation and the results obtained demonstrate the effectiveness of the designed controller of induction motor drives which considered as highly non linear dynamic complex systems and variable characteristics over the operating conditions.

Keywords: Induction motor, fuzzy-logic control, neural network control, and indirect field oriented control.

I. INTRODUCTION

In lieu of the advances in power electronics and microprocessors, digitally controlled induction motor drives have become increasingly popular. In many industrial drives advanced digital control strategies for the control of field-oriented induction motor drives with a conventional speed PID controller, have gained the widest acceptance in high performance AC servo systems, if the load changes are small and the operating conditions do not force the system too far away from the linear equilibrium point. However, in certain applications, such as steel wills, paper wills, robotics, machine tools, the drive operates under a wide range of lead change characteristics and the system parameters vary substantially. To overcome this drawback, the control algorithm should include a complicated computation process to eliminate the variations in the load disturbance and systems parameters and also obtain high performance AC system. However, the control algorithms applicable to these systems have become increasingly more complicated, requiring extensive computations for real-time implementation. In recent years, Artificial Neural Network intelligent (ANN) and Fuzzy Logic Controllers (FLC) have gained great important and proved their dexterity of many respects [2,3]. In this field several works have been presented [7,8,9,12,13]. It has great potential using to neural topology does not need the mathematical model of the system to be controlled. In modelling and control of dynamical systems, many different versions of neural network structures are used. Since the late 1990s, several applications using neural networks for the compensation of the non linearity caused by the influence of disturbances, i.e. load or parameter variations were described [1,2,3]. Combination of different artificial intelligent technologies in the control field found interesting and efficient applications [4,6]. In fact, neural network have several attributes that make them an interesting new alternative to control an induction motor: one attribute is their highly parallel structure if networks with a higher number of hidden layers are used. All the neurons in a layer can compute simultaneously to enhance the speed. Another attribute is the simplicity of the required computations performed by each neuron of the network. In this study, Multi-Layer Perceptron (MLP) neural networks using the back-propagation learning rule were used to identify the process model. The control signal is then calculated iteratively according to the responses of a reference model and the identified neural model of the process. A fuzzy logic block is added to improve the overall loop properties. The paper is structured as follows. Section 2 describes a mathematical of induction motor drive; Section 3 gives the structure of the proposed control scheme. The recurrent NN identifier and fuzzy PD control design are discussed in sections 4,5 and 6. Section 7 and 8 provide the simulation results and conclusions. It is an important key issue in many scientific and engineering fields to classify the acquired data or estimate an unknown function from a set of input-output data pairs. As is widely known, fuzzy neural networks (FNNs) have been proposed and successfully applied to solving these problems such as classification, identification, control, pattern recognition, and image processing, etc [1]-[4]. A fuzzy system consists of a bunch of fuzzy if-then rules. Conventionally, the fuzzy if-then rules were usually derived from human experts as linguistic knowledge. Knowledge of both land-use and land cover is important for socio-economic planning of a region. While the land use relates to human activities like residential, institutional, commercial and recreational etc., the land cover relates to the various types of features present on the surface of the earth. For proper planning exercise information on both the above aspects should be available separately, however, the remote sensing digital data available from satellite images are found mixed up at many points.

II. INDUCTION MOTOR MODEL

Using the Park transformation the three phase stator windings can be transformed into equivalent quadratic-phase windings.

The AC motor dynamic models are described by a set electrical and mechanical non-linear differential equations

A. The Proposed Control Scheme

$$\frac{dw_r}{dt} = \frac{n_p M}{J L_r}(\psi_{rd} i_{sq} + \psi_{rq} i_{sd}) - \frac{T_L}{J} \qquad (1)$$

$$\frac{di_{sd}}{dt} = \frac{M R_r}{\sigma L_s L_r^2}\psi_{rd} + \frac{n_p M}{\sigma L_s L_r} w_r \psi_{rd} - \frac{M^2 R_r + L_r^2}{\sigma L_s L_r^2} i_{sd}$$

$$\frac{di_{sq}}{dt} = \frac{M R_r}{\sigma L_s L_r^2}\psi_{rq} - \frac{n_p M}{\sigma L_s L_r} w_r \psi_{rd} - \frac{M^2 R_r + L_r^2}{\sigma L_s L_r^2} i_{sq} + \frac{1}{\sigma L_s} u_{sq} \qquad (2)$$

The reference input signal is ωr. A Recurrent Neural Network Indentifier (RNNI) was used to determine online an approximate current non linear model of the unknown motor dynamics. The Recurrent Neural Network controller (RNNC) was used to produce an adaptive control so that the motor speed can accurately track the reference commends wr. The control signal unet is combinated with the output signal fuzzy of the Fuzzy-Logic (FLC) to produce the actual plant input signal u.

$$\frac{d\psi_{rd}}{dt} = -\frac{R_r}{L_r}\psi_{rd} - n_p w_r \psi_{rq} + \frac{R_r}{L_r} M i_{sd}$$

$$\frac{d\psi_{rq}}{dt} = -\frac{R_r}{L_r}\psi_{rq} + n_p w_r \psi_{rd} + \frac{R_r}{L_r} M i_{sq} \qquad (3)$$

$$\sigma = 1 - \frac{M^2}{L_s L_r}$$

The widely used back-propagation learning algorithm, in order to automaytically the parameters of the RNNI and RNNC. The control goal is that the plant output w, follows as closely as possible the out signal ym of the reference model. The reference model of the plant is an ideal model that has the desired characteristics related to the rise time, overshoot, steady-state error, etc. where f is an unknown non linear function we want to identify, ω and iqs are the output and input of the plant respectively , n and m are the order of the ω and iqs. We now consider the identification of the unknown function f based on neural network. The network structure of the proposed RNNI. Such a neural network contains three layers: input layer; hidden layers and output layer. Each layer is composed of several neurons. The number of the neurons in the input and output layers depends on the number of the selected input and output variables. The numbers of hidden layers and the number of neurons in each depend on the system dynamics and the desired degree of accuracy.

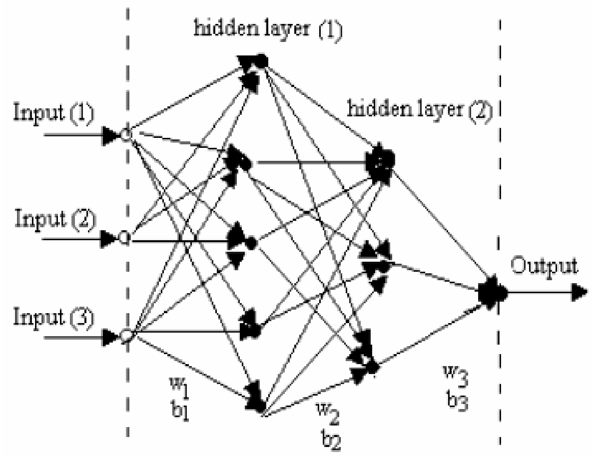

Figure 1. Architecture of Three Layer Neural Network

In Artificial neural network applications, selection of the number of neurons in the input layer is an important aspect. A trial- Fig.1 Block diagram representation of the adaptation learning control scheme and-error basis [5], can be used to select a proper of the hidden neurons. All the neurons in adjacent layers are interconnected. The strength of the interconnected is determined by the weighting vector of the Neural Network (NN). The most common method of NN training is back error propagation algorithm [6]. The algorithm is based on the gradient search technique that minimizes a cost function of the Mean Squares Errors (MSE). The weights wij of the interconnections between two adjacent layers can be updated on the following formula [5,6]. Where η is a prescribed learning rate and k is the iteration number, subscripts i, j indicate the i-th node in the input layer and the j-th node in the hidden layer respectively. The cost function E for training the neural network is defined as: where O neuron output, d is desired or set-value, K is number of the neurons in the output layer and P is the number of the training patterns.

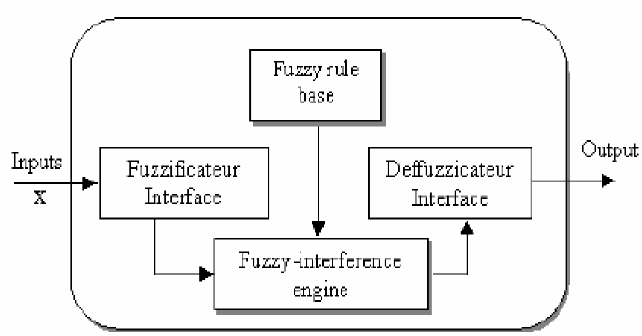

Figure 2. Basic Configuration of the fuzzy logic system

In all learning process bipolar sigmoidal activation function has been used. This activation function is non linear and very useful for continuous training scheme. It is defined as: λ is a positive number called as steepness coefficient. This parameter is very important in learning procedure and lies down between one and infinity theoretically.

B. Learning Algorithm

The proposed learning algorithm of SVFNN consists of three phases. In the first phase, the initial fuzzy rule (cluster) and membership of network structure are automatically established based on the fuzzy clustering method. The input space partitioning determines the initial fuzzy rules, which is used to determine the fuzzy kernels. In the second phase, the means of membership functions and the connecting weights between layer 3 and layer 4 of SVFNN (see Fig. 1) are optimized by using the result of the support vector learning method with the fuzzy kernels for pattern classification and function approximation, respectively. In the third phase, unnecessary fuzzy rules are recognized and eliminated and the relevant fuzzy rules are determined.

C. Learning Phase

Establishing initial fuzzy rules the first phase establishes the initial fuzzy rules. The input space partitioning determines the number of fuzzy rules extracted from the training set and also the number of fuzzy sets. We use the centers and widths of the clusters to represent the rules. To determine the cluster to which a point belongs, we consider the value of the firing strength for the given cluster. The highest value of the firing strength determines the cluster to which the point belongs. The whole algorithm of SVFNN for the generation of new fuzzy rules as well as fuzzy sets in each input variable is as follows. Suppose no rules are existent initially.

D. Recurrent Neural Network Controller

The structure of the Neural Network Controller (RNNC) is similar to one of the Neural Network Identifier (RNNI). The objective of RNNC is to develop a back-propagation algorithm such that the output ω(k) of the plant can track the reference command ωr(k). An Integral Proportional (IP) controller is adapted in the speed control loop to calculate the next value of u using the current iterative value of u, as well as the current and previous iterative values of the error e(k+1). The iterative calculation of the control signal is given by:

$$\omega(k)=f\left(\omega(k-1),\ldots,\omega(k-n+1),iqs(k-1),\ldots iqs(k-m)\right) \quad (4)$$

Where kP and kI are the integral–proportional parameters. We need to train ten neural network identifiers to model the Input- Output behavior of the plant and to iteratively calculate the control value, so as to get a small expected error e, during each sampling period tk. Hence, the tracking problem now, becomes that of adjusting the weights of the RNNC.

$$w_{ij}(k+1) = w_{ij}(k) + \eta \frac{\partial E}{\partial w_{ij}(k)} \quad (5)$$

The constant coefficient in the equation (14) were chosen to guarantee bounded-input bounded-output stability and the steady-state reference track is dictated by the amplitude and functional form of the input r(k) to the reference model. For the proposed fuzzy controller, the universe of discourse is first partitioned into the five linguistic variables NB, NS, ZE, PS, PB, triangular membership functions are chosen to represent the linguistic variables. Fig. 5 and Fig. 6 show the membership functions and the output of the fuzzy controller.

$$E=\frac{1}{2}\sum_{l=1}^{P}\sum_{r=1}^{K}\left(O_r^l-d_r^l\right)^2 \quad (6)$$

The labels NB, NS, PB, PS, and ZE denote ‘Negative Big’, ‘Negative Small’, ‘Positive Big’, ‘Positive small’ and Zero, respectively. The max-min inference method was used and the defuzzification was based on the centre of area method.

E. Simulation Results

The parameters of the induction motor considered in this study are summarized in appendix. The performances of the proposed controllers are evaluated under a variety of operating conditions. The use of both neural network functions with fuzzy compensation yielded satisfying results. The controller algorithm is housed inside the personal computer with Pentium-IV microprocessor and all numerical values of the simulation model are obtained either by measurements or identification from laboratory experiments. The software environment used for these simulation experiments with Simulink package and numerical integration is done by the Runge-Kunta 4 algorithm. The reference discrete model with good performance and realisation for a motor speed control system can be chosen as:

$$\omega_r(k+1) = 0.48\ \omega_r(k) + 0.25\ \omega_r(k-1) + r(k) \quad (7)$$

For all simulations performed in this study, the initial values for the adjustable parameters (weights and biases) of both networks are randomized using the Nguyen Widrow algorithm [10]. The proportional and derivative parameters of the proposed control scheme are kp=0.52 and kd=0.01. The plots of these figures show the performances as the combining NNFLB controller for a variety of step changes in the desired set point. In the simulations, the learning rate of the recurrent neural network identifier and recurrent neural network controller scheme were set to η=0.2 using trial and error to obtain a good speed response. The number of feed ward neural network scheme node uses one hidden layer, and the respective number of neurons at the input, hidden, and output layer are NN2x8x1. Basically, it represents an input-output non linear pattern matching network where the non linearity is introduced by hyperbolic-tan-type transfer function φ (.) at the hidden and output layer neurons. An external force of 4 [Nm] is applied to the the induction motor and the speed

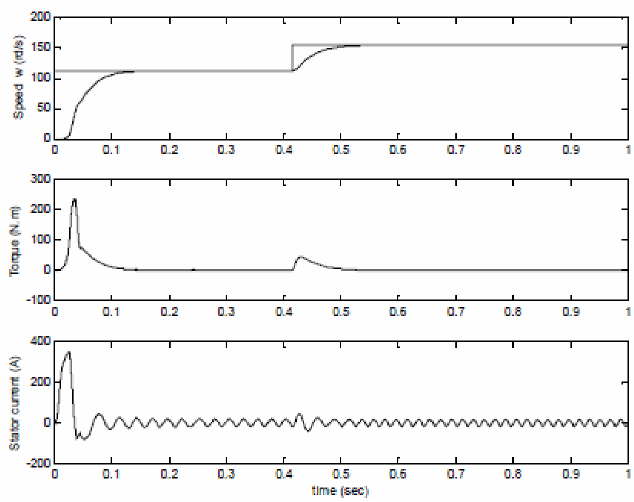

Figure 3. Speed Response Under no load torque

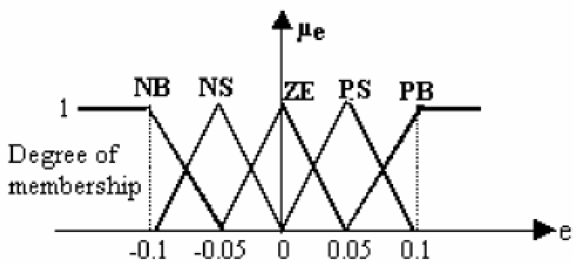

Figure 4. Membership Functions of Error

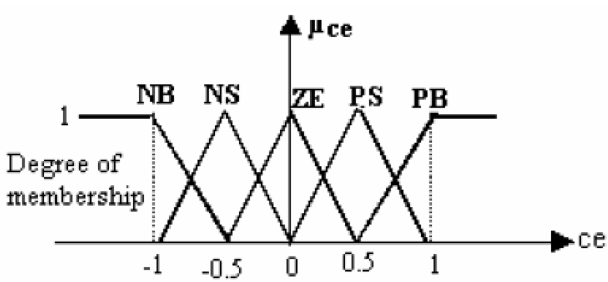

Figure 5. Membership functions of change in Error

response is shown in fig. 9. As shown in fig.10, at t=0.8s, the reference speed is changed from 48 rad/s to 150 rad/s. At t=2 s, the reference speed is changed from 150 rad/s to 100 rad/s. In the next simulation, the NN-FLB is evaluated under combining trajectory of a square – triangular reference track. One can see from the fig.11 that the results were very successful and the obtained results confirm the validity of the proposed control scheme. One can observe the superior properties of the loop controlled by the NN-FLB control mechanism and the conventional controller such as the proportional, integral and derivative PID.

III. Conclusion

This paper has presented a fuzzy-neural network scheme for controlling the speed of induction motor. The system was analysed and designed, and performances were studied extensively by simulation to validate the theoretical concepts. A dynamical neural network is used to identify the plant online and the control signal is then calculated iteratively according to the responses of a reference model and the identified neural model of the process. Theoretical analysis and simulation results demonstrated that the proposed control scheme could accurately and rapidly predict the induction machine dynamics. The proposed control scheme had a good speed response, regardless of parameter variations or external force. The resulting are promising and further studies on similar schemes will be carried out.

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