A NEURO FUZZY CONTROLLER FOR INDUCTION MACHINES DRIVES

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ABSTRACT

With the advent of recent power semiconductor technologies and various intelligent control algorithms, an effective control method based on vector control technology can be fully implemented in real-time application. DC motor drives being the most widely used technique is slowly being replaced by vector-control based high-performance IM drives. Over the last two decades researchers have been working to apply AIC for induction motor drives in order to contribute to this novel development we present a neuro fuzzy controller (NFC) for the IM motor drive, which has the advantages of both FLC and ANN, is presented in this paper.

Keywords: *Nfc, Im Drives, Induction Motor (Im), Low/Zero-Speed Operation, Sensorless Control.*

1. INTRODUCTION

Induction motors (IM's) have been used as the workhorse in industry for a long time due to their easy build, high robustness, and generally satisfactory efficiency [1]. The vector control technique, which is developed upon the field orientation principle proposed by Haase in 1968 and Blaschke in 1970, decouples the flux and torque control in an IM [2]. Thus, it makes the control task of IM drives similar to a separately excited dc motor while maintaining the general advantages of ac over dc motors and, hence, suitable for high-performance variable-speed drive applications. With the advent of recent power semiconductor technologies and various intelligent control algorithms, an effective control method based on vector control technology can be fully implemented in real-time application. Because of these facilities, nowadays, vector-controlbased high-performance IM drives have occupied most of the positions that were previously stationed by dc motor drives [2]. Among various ac motors, induction motor (IM) occupies almost 90% of the industrial drives due to its simple and robust construction; however, the control of IM is complex due to its nonlinear nature and the parameters change with operating conditions. Artificial intelligent controller (AIC) could be the best candidate for IM control. Over the last two decades researchers have been working to apply AIC for induction motor drives [3-8]. This is because that AIC possesses advantages as compared to the conventional PI, PID and their adaptive versions. The main advantages are that the designs of these controllers do not depend on accurate system mathematical model and their performances are robust. In this paper a neuro-fuzzy controller (NFC), as an AIC, is considered because of limitations of either fuzzy logic or neural network [8]. A simple fuzzy controller implemented in the motor drive speed control has a narrow speed operation and needs much more manual adjusting by trial and error if high performance is wanted [3]. On the other hand, it is extremely tough to create a serial of training data for ANN that can handle all the operating modes [6].

Neuro-fuzzy controllers (NFCs), which overcome disadvantages of fuzzy logic controllers and neural network controllers, have been utilized by authors and other researchers for motor drive applications [5-9]. Despite many advantages of NFCs, the industry has been still reluctant to apply these controllers for commercial drives due to high computational burden caused by large number of membership functions, weights and rules, especially on self-tuning condition. High computation burden leads to low sampling frequency, which is not sufficient for implementation. In [7] the authors found relatively high torque ripple caused by low sample rate in a discrete direct torque control based on a neuro-fuzzy structure. In [5] only weights were tuned to lower the computational burden, but the cost is performance decreasing.

In recent years, scientists and researchers have acquired significant development on various sorts of control theories and methods. Among these control technologies, intelligent control methods, which are generally regarded as the aggregation of fuzzy logic control, neural network control, genetic algorithm, and expert system, have exhibited particular superiorities. The fuzzy logic controller (FLC) method can be utilized in systems that have vagueness or uncertainty. Membership functions with values between 0 and 1 are used in FLC to deal with the control puzzle, such as nonlinearity, load disturbance, and parameter disturbance.

The artificial neural network (ANN) is a computation and information processing method that mimics the process found in biological neurons. The basic element of a neural network is the perceptron, which is also called the neuron. The relationship between two perceptrons is defined as the weight, which can be tuned or trained offline, online, or combination of both. However, either fuzzy logic control or ANN has its own drawbacks, which cannot be avoided and neglected.

A simple fuzzy controller implemented in the motor drive speed control has a narrow speed operation and needs much manual adjusting by trial and error if high performance is wanted. On the other hand, it is extremely tough to create a serial of training data for ANN that can handle all the operating modes .A neuro-fuzzy controller (NFC) for the IM motor drive, which has the advantages of both FLC and ANN, is presented in this paper. Over the last decade, the authors and other researchers reported works on the application of NFC for variable speed drives. However, the conventional NFCs utilized in earlier works have a large number of membership functions and rules. These cause high computational burden for the conventional NFC, which is the major limitation for practical industrial applications. In order to overcome the high computational burden, a novel NFC scheme for the IM drive is proposed in this paper. In this controller, only three membership functions are used for each input, and the output does not have any membership function for low computational burden, which will be suitable for real-time implementation. Furthermore, for the proposed NFC, an improved self-tuning method is developed based on the knowledge of intelligent algorithms and motor control requirements. The main task of the tuning method is to adjust the parameters of the FLC in order to minimize the square of the error between actual and reference speeds. In order to reduce the computational burden and minimize the square of the error between desired and actual outputs, only the output layer's parameters are tuned online based on the back propagation algorithm. Minimum trial and error is needed in designing the proposed NFC as one has to select only few membership functions for the inputs.

This paper presents a novel speed control scheme of the IM drive based on a newly developed FC. A complete simulation model for the indirect field-oriented control of IM incorporating the proposed self-tuned NFC is developed in Matlab/Simulink. The performance of the proposed self-tuned NFC-based IM drive is investigated at different operating conditions both in simulation and in experiment. In order to prove the superiority of the proposed NFC, the performances of the proposed controller are also compared to those obtained by a conventional proportional–integral (PI) and FLC controller. The proposed NFC-based IM drive is found to be more robust as compared to the conventional PI and FLC controllers.

2. FUZZY LOGIC

In this context, FL is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information.

FL's approach to control problems mimics how a person would make decisions, only much faster. FL requires some numerical parameters in order to operate such as what is considered significant error and significant rate-of-change-of-error, but exact values of these numbers are usually not critical unless very responsive performance is required in which case empirical tuning would determine them. For example, a simple temperature control system could use a single temperature feedback sensor whose data is subtracted from the command signal to compute "error" and then time-differentiated to yield the error slope or rate-of-change-of-error, hereafter called "error-dot". Error might have units of degs F and a small error considered to be 2F while a large error is 5F. The "error-dot" might then have units of degs/min with a small error-dot being 5F/min and a large one being 15F/min. These values don't have to be symmetrical and can be "tweaked" once the system is operating in order to optimize performance. Generally, FL is so forgiving that the system will probably work the first time without any tweaking.

3. ARTIFICIAL NEURAL NETOWRK

Artificial neural networks emerged after the introduction of simplified neurons by McCulloch and Pitts in 1943 (McCulloch & Pitts, 1943). These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational tasks. The basic model of the neuron is founded upon the functionality of a biological neuron. "Neurons are the basic signaling units of the nervous system" and "each neuron is a discrete cell whose several processes arise from its cell body".

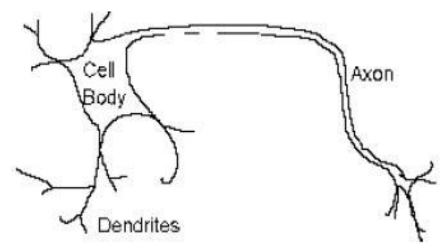

Fig 1. Structure of Neuron

The neuron has four main regions to its structure. The cell body, or soma, has two offshoots from it, the dendrites, and the axon, which end in presynaptic terminals. The cell body is the heart of the cell, containing the nucleus and maintaining protein synthesis. A neuron may have many dendrites, which branch out in a treelike structure, and receive signals from other neurons. A neuron usually only has one axon which grows out from a part of the cell body called the axon hillock. The axon conducts electric signals generated at the axon hillock down its length. These electric signals are called action potentials. The other end of the axon may split into several branches, which end in a presynaptic terminal. Action potentials are the electric signals that neurons use to convey information to the brain. All these signals are identical. Therefore, the brain determines what type of information is being received based on the path that the signal took. The brain analyzes the patterns of signals being sent and from that information it can interpret the type of information being received. Myelin is the fatty tissue that surrounds and insulates the axon. Often short axons do not need this insulation. There are uninsulated parts of the axon. These areas are called Nodes of Ranvier. At these nodes, the signal traveling down the axon is regenerated. This ensures that the signal traveling down the axon travels fast and remains constant (i.e. very short propagation delay and no weakening of the signal). The synapse is the area of contact between two neurons. The neurons do not actually physically touch. They are separated by the synaptic cleft, and electric signals are sent through chemical 13 interaction. The neuron sending the signal is called the presynaptic cell and the neuron receiving the signal is called the postsynaptic cell. The signals are generated by the membrane potential, which is based on the differences in concentration of sodium and potassium ions inside and outside the cell membrane. Neurons can be classified by their number of processes (or appendages), or by their function. If they are classified by the number of processes, they fall into three categories. Unipolar neurons have a single process (dendrites and axon are located on the same stem), and are most common in invertebrates. In bipolar neurons, the dendrite and axon are the neuron's two separate processes. Bipolar neurons have a subclass called pseudo-bipolar neurons, which are used to send sensory information to the spinal cord. Finally, multipolar neurons are most common in mammals. Examples of these neurons are spinal motor neurons, pyramidal cells and Purkinje cells (in the cerebellum). If classified by function, neurons again fall into three separate categories. The first group is sensory, or afferent, neurons, which provide information for perception and motor coordination. The second group provides information (or instructions) to muscles and glands and is therefore called motor neurons. The last group, interneuronal, contains all other neurons and has two subclasses. One group called relay or projection interneurons have long axons and connect different parts of the brain. The other group called local interneurons are only used in local circuits.

4. MATHEMATICAL MODELING

When creating a functional model of the biological neuron, there are three basic components of importance. First, the synapses of the neuron are modeled as weights. The strength of the connection between an input and a neuron is noted by the value of the weight. Negative weight values reflect inhibitory connections, while positive values designate excitatory connections [Haykin]. The next two components model the actual activity within the neuron cell. An adder sums up all the inputs modified by their respective weights. This activity is referred to as linear combination. Finally, an activation function controls the amplitude of the output of the neuron. An acceptable range of output is usually between 0 and 1, or -1 and 1. Mathematically, this process is described in figure below,

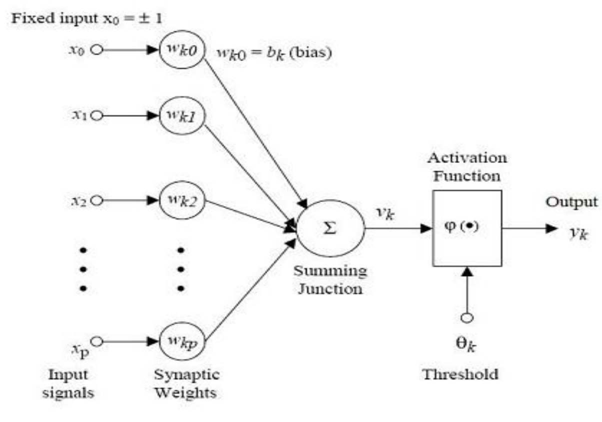

Fig 2. Block diagram of Mathematical modeling

5. DYNAMICS AND CONTROL STRUCTURE

Equations (1)–(4), which are shown at the bottom of the page, denote the mathematical model in a synchronously rotating reference frame for a three-phase squirrel-cage IM, where *Ve ds* and *ve qs* are the *d−q*-axis stator voltages, respectively; *ie ds*, *ie qs*, *ie dr*, and *ie qr* are the *d−q*-axis stator currents and *d−q*axis rotor currents, respectively; *Rs* and *Rr* are the stator and rotor resistances per phase, respectively; *Ls*, *Lr*, and *Lm* are the self inductances of the stator and rotor, and the mutual inductance, respectively; *P* is the number of poles; *p* is the differentiation operator (*d/dt*); *ωe* and *ωr* are the speed of the rotating magnetic field and the rotor speed, respectively; *Te* and *TL* are the electromagnetic developed torque and the load torque, respectively; *Jm* is the rotor inertia; *Bm* is the rotor damping coefficient; and *θr* is the rotor position. The parameters of the two different motor models that have been utilized in simulations are given in the Appendix.

$$\begin{bmatrix} v_{qs}^{e} \\ v_{ds}^{e} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} R_s + pL_s & \omega_e L_s & pL_m & \omega_e L_m \\ -\omega_e L_s & R_s + pL_3 & -\omega_e L_m & pL_m \\ pL_m & (\omega_e - \omega_r)L_m & R_r + pL_r & (\omega_e - \omega_r)L_r \\ -(\omega_e - \omega_r)L_m & pL_m & (\omega_e - \omega_r)L_r & R_r + pL_r \end{bmatrix} \begin{bmatrix} i_{qs}^{e} \\ i_{ds}^{e} \\ i_{qr}^{e} \\ i_{dr}^{e} \end{bmatrix} \quad \ldots\ldots(1)$$

$$T_e = J_m \frac{d\omega_r}{dt} + B_m \omega_r + T_L \quad \ldots\ldots(2)$$

$$T_e = \frac{3}{2}\frac{P}{2} L_m \left(i_{qs}^{e} i_{dr}^{e} - i_{ds}^{e} i_{qr}^{e} \right) \quad \ldots\ldots(3)$$

$$\frac{d\theta_r}{dt} = \omega_r \quad \ldots\ldots(4)$$

The two axis stator voltages and currents are related to the three-phase representations by

$$\begin{bmatrix} X_{qs}^{e} \\ X_{ds}^{e} \end{bmatrix} = \begin{bmatrix} -\sin\omega_e t & \cos\omega_e t \\ \cos\omega_e t & \sin\omega_e t \end{bmatrix} \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} \quad \ldots\ldots(5)$$

where x may represent the current or voltage.

6. CONTROL STRUCTURE

The key feature of the field-oriented control is to keep the magnetizing current at a constant rated value by setting *ie dr* = 0. So, the torque-producing current component can be adjusted according to the torque demand. With this assumption, the mathematical formulations can be rewritten as

$$\omega_{sl} = \frac{R_r i_{qs}^{e}}{L_r i_{ds}^{e}} \quad \ldots\ldots(6)$$

$$i_{qs}^{e} = -\frac{L_m}{L_r} i_{qr}^{e} \quad \ldots\ldots(7)$$

$$T_e = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r} \lambda_{dr}^{e} i_{qe}^{e} \quad \ldots.(8)$$

where *sl* is the slip speed and *e dr* is the *d*-axis rotor flux linkage. Equations (1)-(8) are used to simulate the whole dr stem. The schematic diagram of the proposed NFC-based indirect field oriented control of induction motor is shown in Fig.1. The basic configuration of the drive system consists of an induction motor fed by a current controlled voltage source inverter. The normalized speed error percentage is processed by the neuro-fuzzy controller to generate the reference torque $T^*_e(n)$. The command current $i_q(n)$ is calculated from equation (8) as following:

$$i_q^*(n) = T_e^*(n) \frac{2}{3}\frac{2}{P}\frac{L_r}{L_m}\frac{1}{\lambda_{dr}^*} \quad \ldots\ldots(9)$$

7. DESIGN OF NEURO-FUZZY CONTROLLER

The proposed NFC incorporates fuzzy logic and a learning algorithm with a four-layer artificial neural network (ANN) structure as depicted in Figure below. The learning algorithm modifies the NFC to closely match the desired system performance.

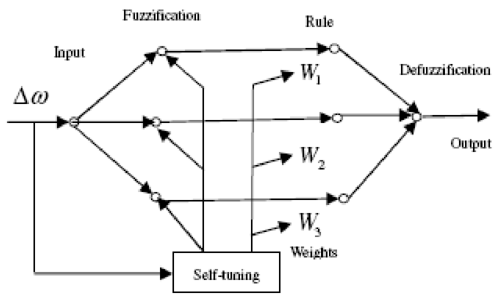

Fig 3. Structure of Nero Fuzzy Controller

8. RESULT OBSERVATION

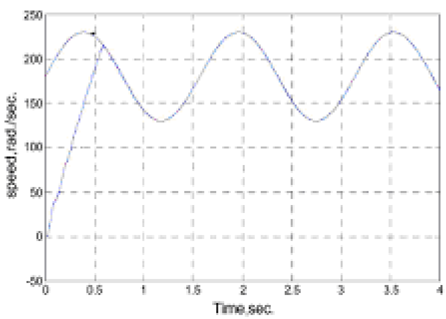

Fig 4. Simulated speed responses of the drive with NFC for a sinusoid speed reference.

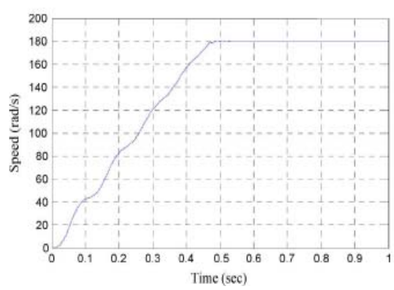

Fig 5. Simulated speed responses with doubled magnetizing inductance showing speed with respect to time and stability of the speed.

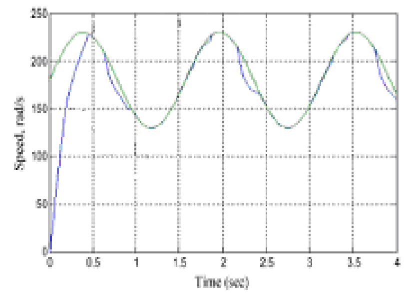

Fig 6. A simulated speed response of the drive with FLC for a sinusoid speed reference the actual speed is indicated by green line and control speed is depicted by blue line.

9. CONCLUSION

The performance of the proposed NFC-based IM drive has been extensively investigated both in simulations and experimentally at different dynamic operating conditions It is found that the NFC based IM drive has a small settling time without any overshoot/undershoot and steady-state error. The tuning method has been developed based on the backpropagation algorithm. The performance of the proposed NFC-based IM drive has been investigated both in simulation and experimentally at various operating conditions.

A performance comparison of the proposed NFC with conventional PI and FLC controllers has also been provided. The results show that the proposed NFC-based IM drive is superior to conventional PI and FLC controllers.

REFERENCES:

[1] P. L. Cochran, Polyphase Induction Motors: Analysis, Design, and Applications. New York: Marcel Dekker, 1989.

[2] A. M. Trzynadlowski, The Field Orientation Principle in Control of Induction Motors. Norwell, MA: Kluwer, 1994.

[3] M. N. Uddin, T. S. Radwan and M. A. Rahman, "Performances of Fuzzy-Logic-Based Indirect Vector Control for Induction Motor Drive", IEEE Trans. Ind.

Applications, Sep/Oct, 2002, pp. 1219-1225

[4] T. Chen, T. T. Sheu, "Model reference neural network controller for induction motor speed control", IEEE Transactions on Energy Conversion, June, 2002, pp. 157-163.

[5] M. N. Uddin, H. Wen, "Development of a self-tuned neuro-fuzzy controller for induction motor drives", Conference Record of the 2004 IEEE IAS Ann. Meeting, pp. 2630-2636.

[6] P. Grabowski, F. Blaabjerg, "Direct torque neuro-fuzzy control of induction motor drive, DSP implementation", IEEE IECON Proceedings, 1998, pp. 657-662.

[7] M. N. Uddin, M. A. Abido and M. A. Rahman, "Development and Implementation of a Hybrid Intelligent Controller for Interior Permanent Magnet Synchronous Motor Drive" IEEE Transactions on Industry Applications for publication, Jan./Feb. 2004, pp. 68-76.

[8] G. Buja, M. P. Kazmierkowski, "Direct torque control of PWM inverter-fed AC motors - A survey", IEEE Transactions on Industrial Electronics, August, 2004, pp. 744-757.

[9] F. Rashidi, "Sensorless speed control of induction motor derives using a robust and adaptive neuro-fuzzy based intelligent controller", Proceedings of the 2004 IEEE International Conference on Industrial Technology, ICIT, 2004, pp. 617-627

[10] A. Rubaai , D. Rickattes and M. D. Kankam, " Development and Implementation of an Adaptive Fuzzy-Neural Network Controller for Brushless Drives", IEEE Transactions on Industry Applications, vol. 38, no.2, March/April 2002, pp. 441-447.

[11] C. T. Lin, C. S. G. Lee, "Neural fuzzy systems: a neuro-fuzzy synergism to intelligent systems", Prentice Hall, 1996.

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