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RBF Identifier Based Adaptive Sugeno Type FLC for Vector Controlled Asynchronous Motor

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Abstract: - In this paper a simulation study of Adaptive Sugeno type Fuzzy Logic Control (FLC) for indirect field oriented controlled (IFOC) asynchronous motor drive system have been suggested. The structure of control scheme consists of neural network identifier and FLC. The Radial Basis Function (RBF) neural network parameters are online updated by using back-propagation method. The consequent parameters of FLC are tuned online by using the RBF identified model. Speed control of asynchronous motor performance parameters such as steady state error, rise time, overshoot, undershoot and settling time are obtained for the suggested controller and compared with the conventional PI controller. Simulation results are included to show the suitability, effectiveness and robustness of the adaptive Sugeno type FLC. Adaptive Sugeno type FLC using the Matlab / Simulink simulation software was compared with the results obtained from conventional PI type controller.

Keywords: - *Adaptive Sugeno type FLC, Asynchronous Motor, Indirect Field Oriented Control, PI Control, Radial Basis Function.*

I. INTRODUCTION

In today's industry particularly, asynchronous motors are widely used in the electric drive and control field due to high efficiency, low-maintenance, robust and simple structures. Speed control of asynchronous motors, because it has non-linear structure, the effects of variable ambient conditions and external corrupted inputs, it is quite difficult to obtain a good performance [1-3]. In recent years, electronic devices technologies and control technology with advances can be obtained from DC motor high dynamic performance in, it was possible to obtain the asynchronous motors [4]. In asynchronous motor through the use of IFOC, as in the DC motor, the flux and torque components are provided by controlling separately from each other an excellent dynamic performance [5]. In order to increase the performance of asynchronous motor drives, the benefits of using methods based on artificial intelligence have been demonstrated clearly by the researches in recent years. In nonlinear controller design, Artificial Neural Networks (ANN) provide the ability for modelling nonlinear systems. ANN is an ideal feature for learning and adaptability control systems. ANN can be applied successfully even under the control of motor with an unknown load parameters. RBF neural network is widely used in the powerful calculation tool in pattern recognition, system modelling and identification fields [6-9]. Sugeno and Mamdani fuzzy control methods in the field are the most popular. Because of that Sugeno method is faster in performance, easier to apply, does not require experience, and can be used with optimization and adaptable method according to Mamdani method, it is especially used in the solution of nonlinear dynamic systems and control problems [10-11]. Adaptive control is one of the widely used control strategy that designed in a modern control system to ensure better performance and accuracy. The purpose of the adaptive control is adjustable unknown and variable control parameters. Identification process of nonlinear and complex systems using artificial neural networks provide successful results. Modelling and control applications realized by the use of adaptive fuzzy systems are commonly used in the literature. Therefore, various methods have been developed to ensure the contribution of adaptation techniques and increase the effectiveness of fuzzy systems [12-14]. In this study, adaptive Sugeno-type FLC has been developed to control the speed of a three-phase asynchronous motor. Here FLC parameters adapted using system error and the Jacobian matrix obtained from the identifier. Simulation study of asynchronous motor vector-based speed control using adaptive Sugeno controller and conventional PI controller is presented in MATLAB/Simulink environment. In this work, asynchronous motor driving method uses IFOC method Space Vector Pulse Width Modulation (SVPWM) is used in the inverter switching. According to simulation results, Adaptive Sugeno type FLC is more successful than the conventional PI type controller [15-18].

II. MATHEMATICAL MODEL OF ASYNCHRONOUS MOTOR

Three phase asynchronous motor mathematical model can be expressed by the five order nonlinear state equation in rotating d-q reference frame model as follows [19-21].

Equivalent resistance;

$$R_E = R_s + \frac{R'_r L_m^2}{L_r'^2} \tag{1}$$

Leakage coefficient;

$$\sigma = 1 - \frac{L_m^2}{L_s L_r'^2} \tag{2}$$

$$\frac{di_{sd}}{dt} = \frac{1}{\sigma L_s}\left[-R_E i_{sd} + \sigma L_s \omega_s i_{sq} + \frac{L_m R_r}{L_r^2}\psi_{rd} + \omega_r \frac{L_m}{L_r}\psi_{rq} + V_{sd} \right] \tag{3}$$

$$\frac{di_{sq}}{dt} = \frac{1}{\sigma L_s}\left[-R_E i_{sq} - \sigma L_s \omega_s i_{sd} + \frac{L_m R_r}{L_r^2}\psi_{rq} - \omega_r \frac{L_m}{L_r}\psi_{rd} + V_{sq} \right] \tag{4}$$

$$\frac{d\psi_{rd}}{dt} = \frac{R_r L_m}{L_r} i_{sd} - \frac{R_r}{L_r}\psi_{rd} + (\omega_s - \omega_r)\psi_{rq} \tag{5}$$

$$\frac{d\psi_{rq}}{dt} = \frac{R_r L_m}{L_r} i_{sq} - \frac{R_r}{L_r}\psi_{rq} - (\omega_s - \omega_r)\psi_{rd} \tag{6}$$

$$\frac{d\omega_r}{dt} = \frac{3}{2}\frac{pL_m}{JL_r}(i_{sq}\psi_{rd} - \psi_{rq} i_{sd}) - \frac{B}{J}\omega_r - \frac{T_L}{J} \tag{7}$$

Slip speed;

$$\omega_{sl} = \omega_s - \omega_r = \frac{R'_r i_{qs}}{L'_r i_{ds}} \tag{8}$$

Synchronous position;

$$\theta_s = \int \omega_s dt \tag{9}$$

where, ω_s and ω_r are the electrical synchronous stator and rotor speed, respectively; V_{sd} , V_{sq}, i_{sd} , i_{sq} , ψ_{rd} and ψ_{rq} are d-q axis stator voltages, d-q axis stator currents and d-q axis rotor fluxes, respectively; R_s and R_r are the stator and rotor resistances per phase, respectively; L_s, L_r and L_m are stator and rotor main inductances and the mutual inductance, respectively; p is the number of motor poles, J is the rotor inertia, B is the viscous friction coefficient, T_L is the load torque, R_E is the equivalent resistance, σ is the leakage coefficient.

III. DESIGN OF ADAPTIVE SUGENO CONTROLLER BASED ON RBF NEURAL NETWORK

Sugeno Fuzzy Model (SFM) known as the TSK fuzzy model, is proposed by Takagi, Sugeno and Kang. SFM is a systematic approach to obtain fuzzy rules from a given set of input-output. When we compare Sugeno method with Mamdani method, Sugeno method is faster and easier to implement. Because Sugeno method is used with optimization and adaptive methods, it can be successful in solution problems of nonlinear dynamic systems [22-23, 24].

A typical fuzzy rule of SFM has following form:

If x = *A* and *y* = *B* and *then z* = *f (x, y)*

where A and B are input fuzzy sets, z = f(x, y) is a function which provides crisp outputs.

Generally, f(x, y) is depend on x, y and it is a polynomial but f(x, y) can be any function as long as it properly defines the output of a system including specified region by the input rule.

When *f (x, y)* is the first-order polynomial, fuzzy interference system results proposed in 1970 are defined first-order fuzzy model. *f* constant coefficient model is called zero-order Sugeno fuzzy model. This model is a special case of Mamdani model that has one ton of fuzzy set came from the result of each rule. Also this model is considered as a special case of Tsukamoto model which is a fuzzy set defined as step function came from result of central constant factor. Fig.1. shows the fuzzy inference mechanism of the first order Sugeno model. Because each rule is a sharp output, the result is obtained from weighted average of sharp output value. This approach is a method which compensate waste of time and computational load in the rinsing process of Mamdani model.

Moreover, it is an online system model and it is an inference mechanism which is suitable for controller design. In practice, the weighted aggregation operator $(z=w_1z_1+ w_2z_2)$ is used instead of the weighted average operator. Unless sum of activation degree of rules is close to ‘‘1’’ (Σwi=1), this simplification process can cause to loss linguistic meaning of membership functions (MF) [25, 26, 27].

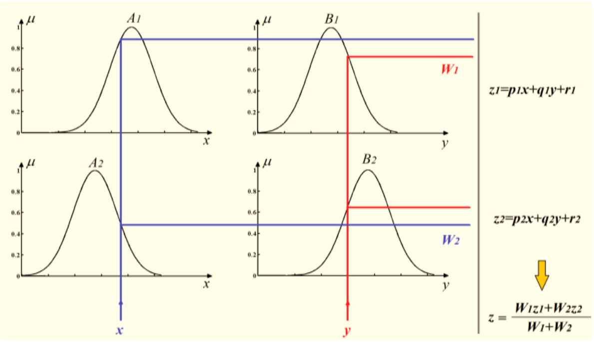

Fig. 1: Sugeno Fuzzy Model

If conditions of neighbour MF is enough, Zero-order Sugeno model will be a suitable function depending on their input variables. However in Mamdani model, overlaps in MFs don’t have good effect on regularity of interpolation [25, 29]. Output of each rule is referred as a linear combination of input. Numerical output value is calculated by taking weight average of sharp output value for each output functions. Results in Sugeno model are discrete digital values determined by (w_i) require operator. Merge result for Sugeno method is obtained by summing weighted results given as the Fig. 1.

$$w_i = \min(\mu_{Ai}, \mu_{Bi}) \tag{10}$$

$$z_i = p_i x + q_i y + r_i \tag{11}$$

The output of adaptive Sugeno controller is given as:

$$z = \frac{\sum_i w_i z_i}{\sum_i w_i} \tag{12}$$

IV. RBF NEURAL NETWORK

RBF neural network is a kind of neural network that uses radial basis functions as activation function. Due to the good generalization capabilities and a simple network structure, RBF neural network has recently attracted much attention [30]. The RBF neural network is used to identify the system online. RBF neural network has three layers: the input layer, the hidden layer, and the output layer. We supposed that RBF neural network was provided with 3 inputs, 6 hidden layer nodes and one output node. The structure of network is shown in Fig.2.

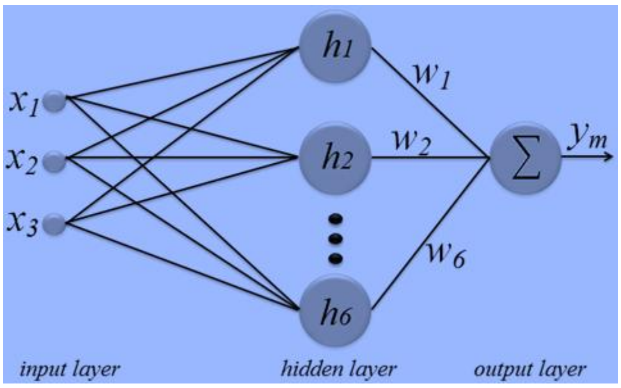

Fig. 2: RBF neural network structure

The output of hidden layer can be defined as follows:

$$h_j(x) = \exp\left[\frac{-\left\|X - C_j\right\|^2}{2b_j^2}\right] \tag{13}$$

where h_j denotes the output of the *jth* node in hidden layer, X is the input vector, $C_{ij}=[c_{1j}, c_{2j}, \ldots c_{ij}, \ldots c_{nj}]T$ is center vector, b_j is the basis width parameter of the j_{th} node. c_j and b_j must be chosen according to the scope of the input value. The output of network is given as:

$$y_m(k) = \sum_{j=1}^{J} w_j h_j(x) \tag{14}$$

where w_j is weights of the RBF neural network. The performance index function can be presented as:

$$E(t) = \frac{1}{2}[y(k) - y_m(k)]^2 \tag{15}$$

where *y(k)* is ideal output. Based on the gradient descent method, the RBF neural network parameters can be updated as follow:

$$w_j(k+1) = w_j(k) + \eta[y(k) - y_m(k)]h_j + \alpha[w_j(k) + w_j(k-1)] \tag{16}$$

$$c_{ij}(k+1) = c_{ij}(k) + \eta[y(k) - y_m(k)]h_j w_j \frac{(x_i - c_{ij})}{b_j^2} + \alpha[c_{ij}(k) + c_{ij}(k-1)] \tag{17}$$

$$b_j(k+1) = b_j(k) + \eta[y(k) - y_m(k)]h_j w_j \frac{\left\|x - c_j\right\|^2}{b_j^3} + \alpha[b_j(k) + b_j(k-1)] \tag{17}$$

where, $\eta \in (0,1)$ is a learning rate and $\alpha \in (0,1)$ is momentum factor. The Jacobian matrix algorithm is as follows [16-18]:

$$\frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial y_m(k)}{\partial u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_{1j} - x_1}{b_j^2} \tag{19}$$

where x_1=u(k). The PI controller parameters are adjusted by Jacobian matrix of control plant that is obtained by RBF neural network identification.

V. DESIGN OF ADAPTIVE SUGENO CONTROLLER BASED ON RBF NEURAL NETWORK

The adaptive Sugeno type controller based on RBF neural network identification is proposed in this paper for speed control of asynchronous motor. The proposed control system structure is as shown in Fig.3.

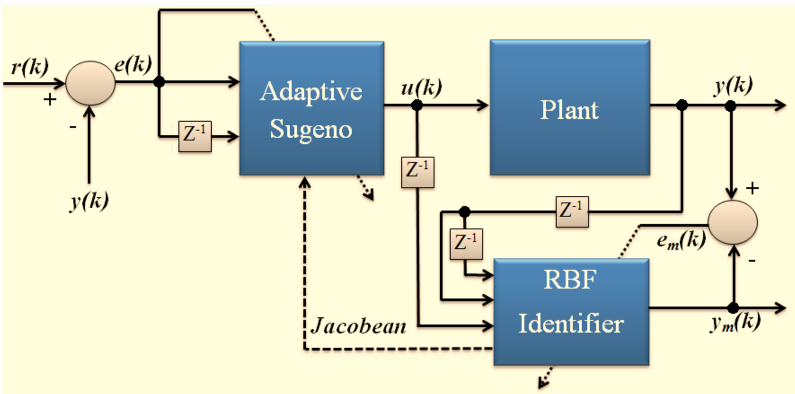

Fig. 3: Adaptive Sugeno Controller based on RBF neural network

In Fig. 3, *r(k)* is the reference input, *y(k)* is the output of plant, $y_m(k)$ is the output of RBF identifier, *u(k)* is the control signal, *e(k)* is the plant error, and $e_m(k)$ is identification error.

$$e(k) = r(k) - y(k) \tag{20}$$

$$e_m(k) = y_m(k) - y(k) \tag{21}$$

The input variables of Sugeno controller are chosen as error and change of error. The back-propagation method is used for adjustment of consequent parameter of Sugeno controller.

$$p(k+1) = p(k) + \eta e(k) \frac{\partial y(k)}{\partial u(k)} \frac{w_i}{\sum_i w_i} e(k) \tag{22}$$

$$q(k+1) = q(k) + \eta e(k) \frac{\partial y(k)}{\partial u(k)} \frac{w_i}{\sum_i w_i} \Delta e(k) \tag{23}$$

$$r(k+1) = r(k) + \eta e(k) \frac{\partial y(k)}{\partial u(k)} \frac{w_i}{\sum_i w_i} \tag{24}$$

where, the $\frac{\partial y(k)}{\partial u(k)}$ can be obtained by identification of RBF neural network.

VI. SIMULATION RESULTS

The computer simulation of vector controlled asynchronous motor drive is simulated by using MATLAB/Simulink environment. IFOC and SVPWM have been used in the drive system of asynchronous motor. The performance comparisons between the proposed adaptive Sugeno type FLC based on RBF neural network and the conventional PI controller scheme are shown in Fig.4-7. For both types of controller, the performance of asynchronous motor drive is presented during starting, step change in speed and step change in load. The block diagram of simulation system is shown in Fig.4. The parameters of the asynchronous motor used in simulation research are as in appendix. The PI controller parameters which are tuning by trial-and-error method have been considered with proper coefficients. These parameters are K_p=3, K_i=200 for speed controller, K_p=50, K_i=100 for torque controller and K_p=20, K_i=800 for flux controller. The inverter switching frequency is selected to be 5 kHz, a nominal DC link voltage of 550 V is chosen. The sample interval time T_s =0.02 ms was used in the simulation. The first order model is used for the reference model of proposed method.

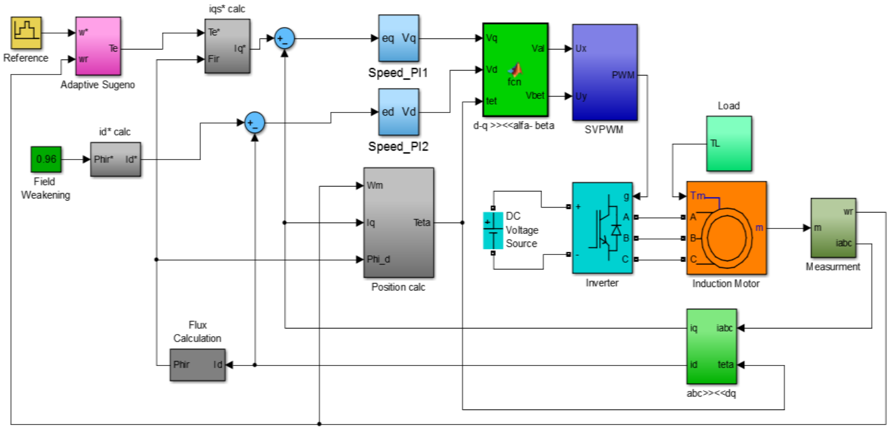

Fig. 4: Simulink model for IFOC asynchronous motor drive system

The asynchronous motor is initially started unloaded. The Fig. 5 shows comparison of asynchronous motor speed response between adaptive Sugeno type FLC based on RBF neural network and PI controllers for step increase and step decrease in reference. The reference speed is increased from 200 rpm to 600 rpm at t=0.5 sec and from 600 rpm to 1000 rpm at and t=1.0 sec. The reference speed is decreased from 1000 rpm to 600 rpm at t=1.5 sec. It can be seen that from Fig.5, the response of the asynchronous motor drive system based on proposed adaptive Sugeno type FLC method has rise time and settling time than that based on conventional PI control method at step change in reference speed. Fig. 6 shows electromagnetic torque response for step change in reference speed. It is seen from the Fig.6 that the adaptive Sugeno type FLC scheme has the fast torque response and low torque ripple compared with the conventional PI controller.

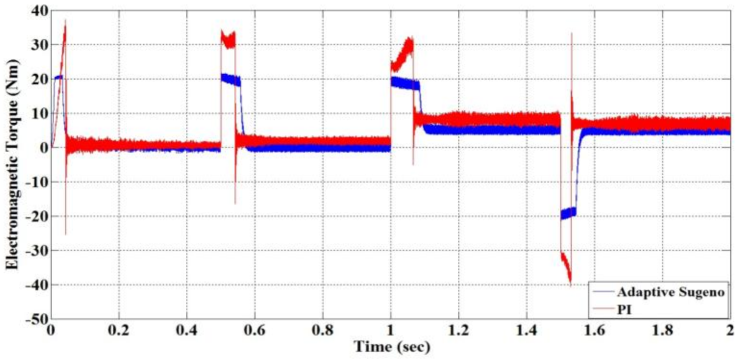

Fig. 6: Electromagnetic torque response for step change reference speed

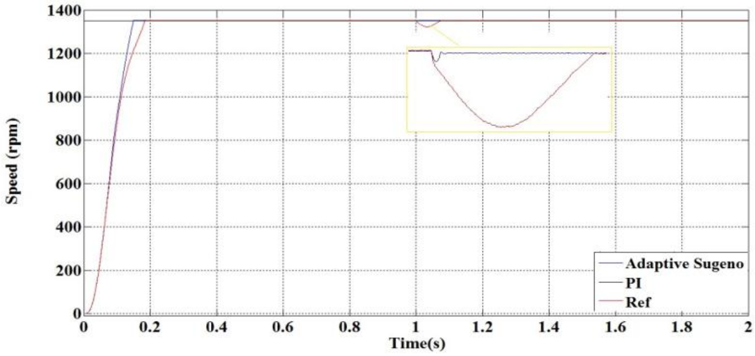

Fig. 7: Speed response for step constant in load torque

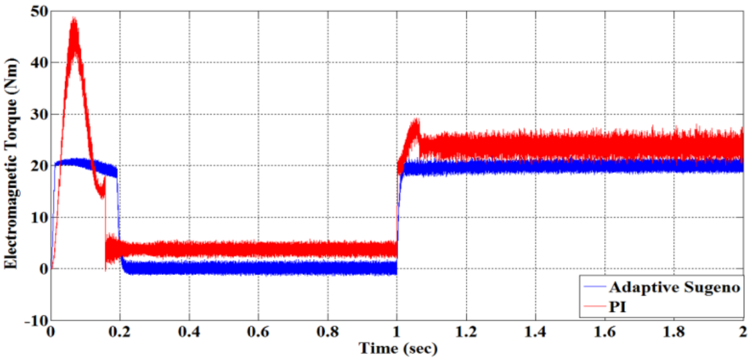

Fig. 8: Electromagnetic torque response for step constant in load torque

Fig.7 shows speed response of motor at step constant in load torque at steady state speed of 1350 rpm. When the load torque step change 0 Nm to 19 Nm at t=1.0 sec, in the conventional PI control, the speed drops to 1328 rpm and takes 0.075 sec to recover the speed to rated value and in the proposed control, the speed drops to 1348 rpm and takes 0.015 sec to recover the speed to rated value.

Fig. 8 shows electromagnetic torque response for step constant in load torque. It is seen from the Fig.8 that the adaptive Sugeno type FLC based on RBF neural network has the fast torque response and low torque ripple compared with the conventional PI controller.

VII. CONCLUSION

A RBF neural network based adaptive Sugeno type FLC strategy for speed control of asynchronous motor is proposed in this paper. The parameter of proposed controller is modified online. This study has been developed and tested in MATLAB/Simulink. In order to prove the superiority of the proposed controller, a performance comparison with conventional PI controller has been provided. Simulation result shows that the adaptive Sugeno type FLC has the adaptability, strong robustness and good performance in the variable speed and load when compared with the conventional PI controller. The obtained results have shown clearly the adaptive Sugeno type FLC algorithm based on RBF neural network is improved the performance of asynchronous motor drive system. It can be used in the motor applications when the high dynamic performance, wide speed range and low torque ripple is required.

APPENDIX

Table 1. Parameters of asynchronous motor

Parameter	Value
Rated Power [P]	3 kW
Rated Speed [n]	1430 d/d
Rated Stator Voltage [U]	380 V
Rated Stator Current [I]	6.7 A
Rated Shaft Load Torque [M]	19 Nm
Number of Poles [p]	2
Rated Frequency [f]	50 Hz
Rotor Resistance [Rr]	1.93Ω
Stator Resistance [Rs]	1.45Ω
Mutual Inductance [Lm]	188 mH
Stator Inductance [Ls]	200 mH
Rotor Inductance [Lr]	200 mH
Moment of Inertia of Rotor [J]	0.03 kg.m2
Coefficient of Friction [B]	0.01

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