OPTIMIZED FUZZY VARIABLE-STRUCTURE CONTROL FOR A FIELD-ORIENTED CONTROL OF AN INDUCTION MOTOR

Ahmed Bensenouci* ahmed_bensenouci@hotmail.com
A. M. Abdel Ghany* ghanyghany @hotmail.com
M. N. Syed-Ahmad* na_zih@hotmail.com

*IEEE Member

Department of Electrical Technology
College of Technology at Al-Baha, P.O. Box 6, Al-Baha

Abstract: In this paper, the design of optimized fuzzy variable-structure controllers for a Field-Oriented Induction Motor (FOIM) is presented. An optimized Proportional-Integral (PI) is first found using an optimization procedure known as Neuro-Genetic Algorithm (NGA). Further, two types of fuzzy controllers, namely, the Split Fuzzy (SF) and the Full Fuzzy (FF) are presented and whose structures are obtained using Adaptive Neuro-Fuzzy Inference System (ANFIS). The later uses the data generated from the optimized PI-controlled FOIM. Comparison between PI, SF and FF is made for parameter variation, load disturbance, and motor speed regulation and tracking. Finally, an improved Concept-based Fuzzy variable-structure controller (CF) for speed control is proposed and its robustness is demonstrated through load disturbance and command speed tracking.

Keywords: Fuzzy Logic, ANFIS, Neuro-Genetic Algorithm, Variable Structure Control, and Induction Motor.

1. Introduction

Induction motors (IM) represent the workhorse of the industrial drive systems. They are less costly, more rugged, and more reliable than DC motors.

The problems related to the induction motor are:

1. Stator and rotor parameters variation during motor operation
2. Difficulty in measuring the rotor time constant because of the temperature effect
3. Saturation effect on the rotor inductance and on the decoupling process between the rotor flux and torque
4. Nonlinear behavior and time-varying dynamics

Because of these problems, classical control design could not be done properly especially when parameter variation and load disturbance occur [1]. To reduce the nonlinear coupling, field-oriented technique is usually used. The later is based on the decoupling between the torque and rotor flux. FOIM is known to fasten the transient response. Two well-known methods used are: *Direct* and *Indirect* [2]. The former requires the knowledge of the module and the position of rotor flux. For this purpose, sensors with Hall effect or a dynamic model can be used. In the later (used here), only the position of rotor flux should be known.

In general, a high performance motor drive system is characterized by [3]:

- Fast step tracking response without overshoot
- Minimum speed dip and restore time, due to a step load change
- Achievement of zero steady-state error in the command tracking and load regulation

However, if regulation characteristics with small speed dip and short restore time following a step load change is required, relatively large overshoot, and short settling time in the speed tracking may result. So, to improve the system performance, the controller must be robust against speed variation and external perturbation.

Conventional PI controller has been widely used in industrial applications due to its simple control algorithm and easy implementation. However, It is difficult and complex to design a high performance PI-controller IM drive system [3] because of system parameter variation and load disturbance change.

In this respect, fuzzy logic control [4,5] represents an attractive approach since it is a:

1. *Linguistic* controller, i.e., no need for a precise and accurate
2. *Flexible nonlinear* controller, i.e., can overcome nonlinearities
3. *Robust* controller, i.e., insensitive to parameter variation

This paper presents the design steps of an optimized fuzzy variable-structure controller [6,7] for a field-oriented control of an induction motor as follows:

1. An optimization procedure for the PI-controller gains, known as NGA, is used. NGA is based on the combination of Artificial Neural Network (ANN) with the Genetic Algorithm (GA).
2. A data history of the motor speed and rotor flux is used to train 2 types of fuzzy controllers: *split* (SF) and *full* (FF) fuzzy controllers. In SF, a

fuzzy block replaces each part of the PI whereas in FF, a fuzzy block replaces the whole PI.

3. An improved variable-structure concept-based fuzzy controller (CF) for motor speed is proposed. The idea is to change the controller structure depending on the error between the desired and actual speed. To improve robustness, a filter (one-time constant) is added.

Simulation tests were carried out using MATLAB-SIMULINK. The effectiveness is demonstrated through comparison with the optimal PI under diverse tests, namely, parameter variation, load disturbance, and regulation and tracking of the motor speed.

2. System Model

Figure 1 shows the circuit diagram of a Field-Oriented control of an Induction Motor (FOIM). The state space model of an induction machine using current model is given [2] by

$$\frac{d\mathbf{x}}{dt} = \mathbf{f(x)} + \mathbf{Bu}$$

Where

$\mathbf{x}=[x_1, x_2, x_3]^t$ with $x_1=\phi_{dr}$ $x_2=\phi_{qr}$ $x_3=ù_m$ $T_r=L_r/R_r$

$\mathbf{u}=[I_{ds}, I_{qs}]^t$

And

$$\frac{dx_1}{dt} = -\frac{1}{T_r}x_1 + n_p(\omega_{syn} - n_p x_3)x_2 + \frac{L_{sr}}{T_r}I_{ds}$$

$$\frac{dx_2}{dt} = -\frac{1}{T_r}x_2 + n_p(-\omega_{syn} + n_p x_3)x_1 + \frac{L_{sr}}{T_r}I_{qs}$$

$$\frac{dx_3}{dt} = \frac{n_p L_{sr}}{JL_r}(x_1 i_{qs} - x_2 i_{ds}) - \frac{B}{J}x_3 - \frac{T_L}{J}$$

For field-oriented, the speed of the synchronously reference frame ω_{syn} and the rotor flux ϕ_r are:

$$ù_{syn} = ù_m + \frac{I_{qs}}{T_r\phi_r} \quad \& \quad \phi_r = \sqrt{[x_1^2 + x_2^2]}$$

The system parameter values are given in Table A.

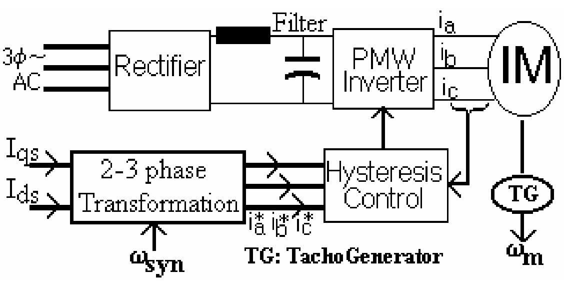


Figure 1 Induction motor circuit

3. Neuro-Genetic Algorithm (NGA)

The PI gains are optimized using the Neuro-Genetic Algorithm (NGA) where a combination between Artificial Neural Network (ANN) and Genetic Algorithm (GA) is used. The goal is to minimize a cost function represented by the error between the desired and actual variables to be controlled. NGA was found to save a lot of computational time since it avoids the simulation of the system for each value of the gains as needed by GA.. The steps, illustrated in Figure 2, are as follows:

1. Determine the search interval (trial-&-error, stability criterion, etc.) for the controller gain K.
2. Compute the cost function J for several values of K in the search interval.
3. Use ANN to interpolate between these cost function values
4. Operate GA only on ANN output.

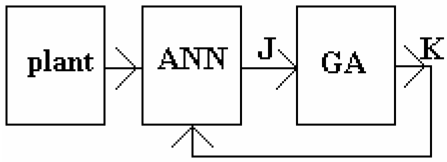


Figure 2 Neuro-Genetic Algorithm

4. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Fuzzy logic system (FLS) is based on the theory of fuzzy sets and uses linguistic variables that are words rather than numbers. This allows for human tolerance and data imprecision. In FLS, input variables are transformed into fuzzy sets *(fuzzification)* using membership functions, and processed by a collection of *(if-then)* fuzzy rules to get the output. These rules form *fuzzy inference engine* (FIS).

There are two well-known types of FIS: Mamdani [8] and Sugeno [4]. The main difference is at the output level where Sugeno uses a constant or linear output membership functions rather than a distributed fuzzy set used by Mamdani. Because it is a more compact and computationally efficient than Mamdani, Sugeno system lends itself to the use of adaptive techniques for constructing fuzzy models. These adaptive techniques can be used to customize the membership functions so that the fuzzy system can model best the data.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) constructs a fuzzy inference system based on given input/output data sets. The membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least-squares type of method.

5. Test Results

5.1 Proportional-Integral Control

To achieve the steady-state values of the motor speed ω_m and the rotor flux ϕ_r, a Proportional plus Integral (PI) controller is used for a Field-Oriented Induction Motor (FOIM).

Optimum values for the PI gains are obtained using superimposed technique discussed in [9] as follows:

1. Vary K_{i1} while $K_{p1}=K_{p2}=K_{i2}=0$ (use $I_{ds}=0.6.580$ [A] in the ϕ_r -loop to achieve nominal flux of 1.7 [Wb]) to get K_{i1opt}
2. Vary K_{i2} while $K_{p1}=K_{p2}=K_{i1}=0$ (use $I_{qs}=0.3925$ [A] in the ω_m – loop to achieve nominal speed of 157.1 [rad/sec]) to get K_{i2opt}
3. Vary K_{p1} while $K_{i1}= K_{i1opt}$, $K_{p2}=0$, $K_{i2}= K_{i2opt}$ to get K_{p1opt}
4. Vary K_{p2} while $K_{i1}= K_{i1opt}$, $K_{p1}=K_{p1opt}$, $K_{i2}= K_{i2opt}$ to get K_{p2opt}

NGA is used to determine the optimum gain values that are: $K_{p1}=0.2$, $K_{i1}=0.08$, $K_{p2}=0.1$, and $K_{i2}=15$.

5.2 Fuzzy Logic Control

Using the optimum PI controller gains found previously, training data for ANFIS are generated using the input-output pairs as shown in Table 1. For each fuzzy controller, a history block is used. For the Split Fuzzy (SF), 2 blocks are generated for each PI controller. For the Full Fuzzy (FF), one block is generated for each PI controller. The design steps are:

1. Run the simulation of the FOIM using PI controllers
2. Using the input-output sets given in Table 1, create fuzzy blocks for the speed and the flux using ANFIS
3. For SF, replace each part of each PI by its corresponding fuzzy block. For FF, replace each PI by its corresponding fuzzy block.
4. Test the robustness of the fuzzy controller using different operating conditions

Table 1 Training set for Fuzzy Controllers

Type	**Both SF & FF**	**Split Fuzzy(SF)**	**Full Fuzzy(FF)**
	Input	*Output*	*Output*
Speed control (ω_m)	$ew=\omega_{ref}-\omega_m$ ew(t-dt) ew(t-2dt) ew(t-3dt) ew(t)dt	uwp & uwi	$uw=I_{qs}$
Rotor Flux Control (ϕ_r)	$ef=\phi_{ref}- \phi_r$ ef(t-dt) ef(t-2dt) ef(t-3dt) ef(t)dt	ufp & ufi	$uf = I_{ds}$

Note: The sampling time, $dt=T_s$, is taken as 0.01 sec.

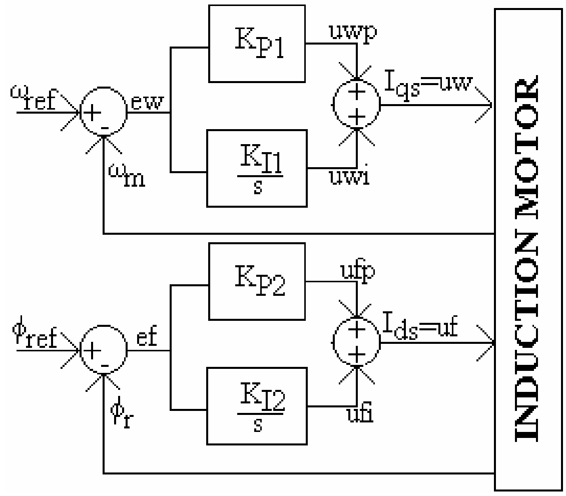
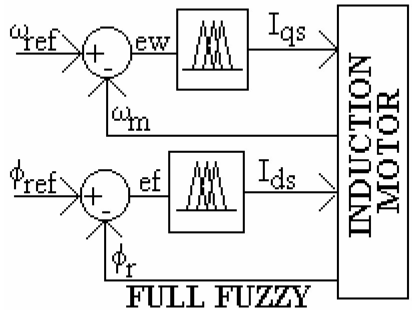
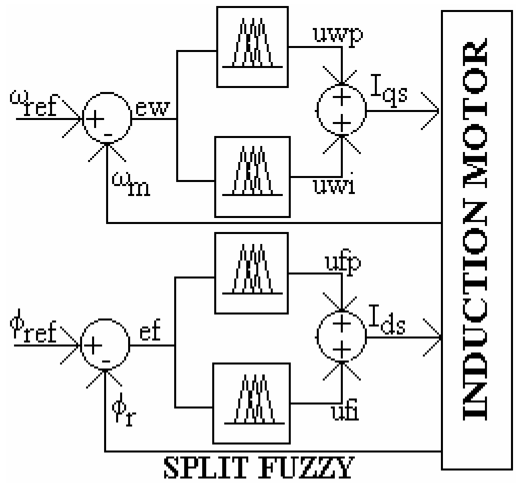


Figure 3 PI Control of Speed and Flux



(b) Full Fuzzy (FF)



(b) Split Fuzzy (SF)

Figure 4 Fuzzy Control of FOIM

The structure of FIS consists of 2 bell-type MMFs for each input. The training error is around 10^{-6}. To test the robustness of the fuzzy controllers, some tests are used and the results are compared to the PI ones, namely,

1. Change in load torque
2. Change in speed reference
3. Change in system parameters

Test 1: ***Load torque variation***
In order to compare the PI with the fuzzy controllers, a new load torque pattern (not used during training process) is used. The time response of ω_m and ϕ_r are shown in Figure 5. It is worth noting that both fuzzy (SF & FF) responds identically with lower overshoot and faster settling time (not clearly shown in ω_m because of the scale) than the PI.

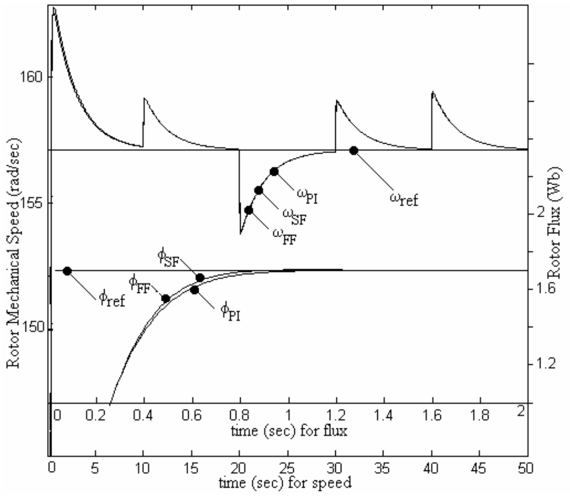


Figure 5 Time Response to load torque variation

Test 2: ***Speed Reference Tracking***
A random pattern for the desired speed (ω_{ref}) tracking is applied and the time responses of ω_m and ϕ_r are shown in Figure 6. It is clear that both fuzzy (SF & FF) show identical performance with lower overshoot and faster response in motor speed.

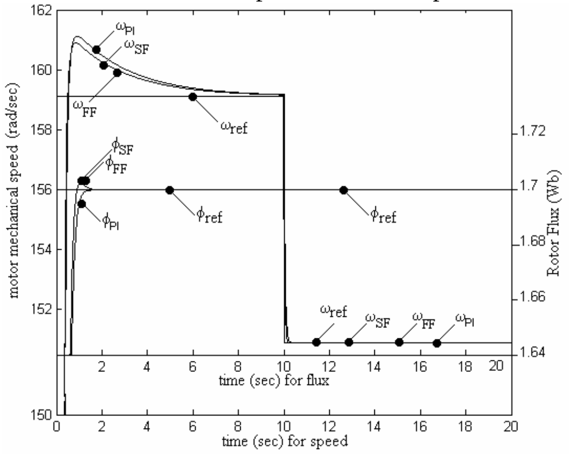


Figure 6 Speed and Flux variation during ω_{ref} change

Test 3: ***System Parameter Changes***
A 50% increase in the stator inductance L_s and resistance R_s, and rotor resistance R_r. The time response of ω_m and ϕ_r are shown in Figure 7. It is clear that fuzzy controllers exhibit better performance.

5.3 Variable Structure for Speed Control

To fully analyze the structure of the fuzzy controllers, an improved Concept-based Fuzzy variable-structure controller (CF) is presented. It is based on [9] added to it a filter with one-time constant, as shown in Figure 8, where G=T=8.

The control input $u=I_{qs}$ takes only one value, uwp or uwi, depending on the error magnitude (tolerance, tol), that is,

$$uw = I_{qs} = \begin{cases} uwp & \text{for} \quad |ew| > tol \\ uwi & \text{for} \quad |ew| \le tol \end{cases}$$

The value of the tolerance, tol, could be found using [9]. Here, 5 [rad/sec] is selected.

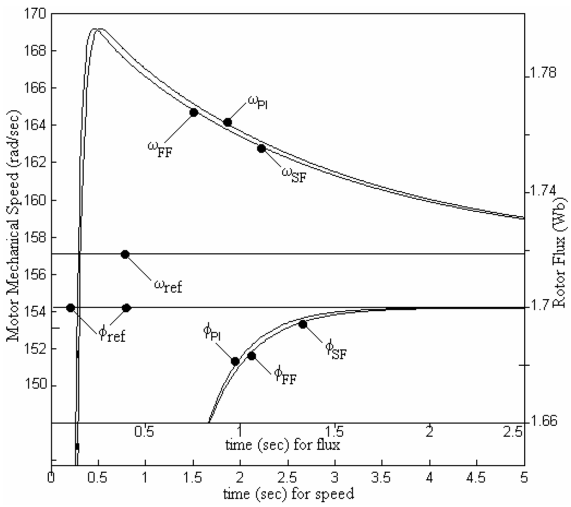


Figure 7 Speed and Flux Regulation for a 50% Increase in L_s, R_s and R_r

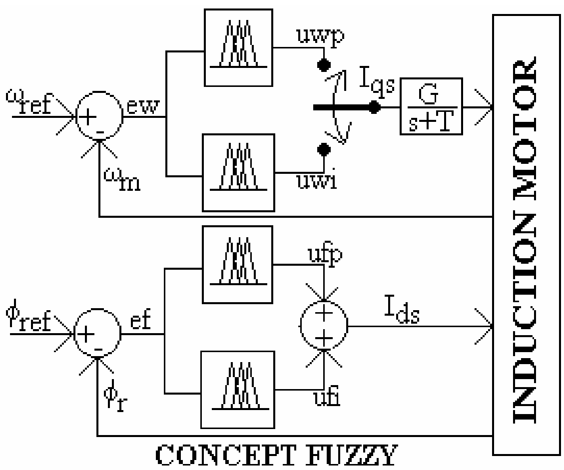


Figure 8 Improved Variable-Structure Fuzzy Concept-Based Controller (CF)

Figure 9 shows the time response of ω_m and I_{qs} during load torque T_L disturbance whereas Figure 10 shows the time response of ω_m and I_{qs} for speed tracking with T_L disturbance. This controller shows robustness to load torque variation but with the presence of chattering that should be eliminated or at least reduced.

6. Conclusion

This paper has presented the basic steps to design fuzzy controllers for field-oriented control of an induction motor. The first step was to find optimum values for the PI controllers used for speed and rotor flux controls. The PI controllers were used to generate fuzzy blocks through ANFIS. Three configurations were presented, namely, the Split Fuzzy (SF), the Full Fuzzy (FF) and the Concept VSC Fuzzy (CF).

From the tests performed, it can be noticed that both SF and FF exhibit identical behavior and present better performance (lower overshoot and faster settling time) than the PI one, with chattering free. However, for the CF, robustness is demonstrated but the chattering is still present that should be eliminated or at least reduced.

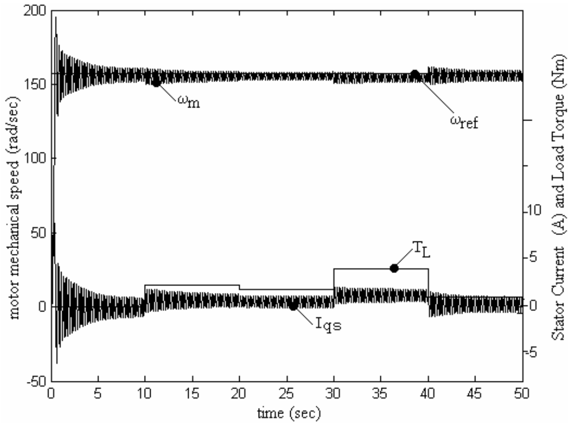


Figure 9 Speed control during T_L variation

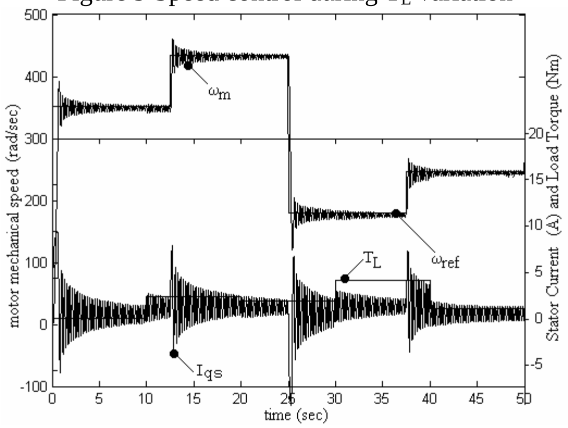


Figure 10 Speed Tracking with T_L variation

7. References

1. M. Gopal, *Modern Control System Theory*, Wiley Eastern Ltd. 2nd edition, 1993.
2. P.C. Krause, C.H. Thomas, "Simulation of Symmetrical Induction Machinery", *IEEE Trans. Pow. App. Syst.,* Vol. 84, No. 11, pp. 1038-53, 1965.
3. C.M. Liaw, Y.S. Kung, C.M. Wu, "Design and Implementation of a Performance Field-Oriented Induction Motor Drive", *IEEE Transactions on Industrial Electronics*, Vol. 38, No. 4, Aug. 91, pp. 275-282.
4. Sugeno, M., *Industrial applications of fuzzy control*, Elsevier Science Pub. Co., 1985.
5. L. Hakju, L. Jaedo, S. Sejin, "Approach to Fuzzy Control of an Indirect Field-Oriented Induction Motor Drives", *ISIE 2001*, Pusan, Korea, 2001 IEEE, pp. 1119-23.
6. M.E. Aggoune, F. Boudjemaa, A. Bensenouci, et al., "Design of Variable Structure Voltage Regulator Using Pole Assignment Technique", *IEEE Transactions on Automatic Control,* Vol. 39, No. 10, Oct. 94, pp. 2106-10.
7. A. Bensenouci, et al., "Variable Structure Control Schemes For A Dc Motor", *MEPCON'2001*, Cairo, Egypt, Dec. 29-31, 2001.
8. E.H. Mamdani, "Applications of Fuzzy Logic to Approximate Reasoning Using Linguistic Synthesis", *IEEE Trans. Computers., Vol. 26, No. 12, pp. 1182-91, 1977.*
9. A. Bensenouci, A.M. Abdel Ghany, " Power System Voltage Regulator Based on Variable Structure Control with Free Chattering", *2nd IASTED Int. Conference On Power And Energy Systems, Europes 2002*, June 25-28, 2002, Crete, Greece

8. Appendix

Table A: Model Parameter Values

Parameters	Values
Number of Poles, N_p	2 poles
Rotor Resistance, R_r	3.805 Ω
Rotor Inductance, L_r	0.274 H
Stator Resistance, R_s	4.85 Ω
Stator Inductance, L_s	0.274 H
Mutual Inductance, L_{sr}	0.258 H
Inertia, J	0.031 Kg.m^2
Viscous Coefficient, B	0.008 N/sec
Nominal Speed, ω_n	1490 rpm

9. Biography

Dr. Ahmed BENSENOUCI obtained his Ph.D. in Electrical Engineering from Purdue University, Indiana, USA, his Master of Engineering in Electric Power Engineering from Rensselaer Polytechnique Institute, NY, USA, and his B.S. in Electrical Engineering from Ecole Nationale Polytechnique, Algiers, ALGERIA.

He got promoted to Associate Professor in Ecole Nationale Polytechnique, ALGERIA in 1992 where he was working since 1989. From 1994 to 1996, he worked at the University of 7th of April, Zawia, Libya and during 1996 to 1998, at the University of Malaya, KL, Malaysia, as a Staff member. From 1998 til now, he is with the College of Technology at Al-Baha, Saudi Arabia. His research areas include Power System Modeling and Analysis and Application of Advanced Techniques (Neural Networks, Fuzzy, Genetic Algorithm, Variable Structure, …etc) to the Analysis and Control of Power System.