Genetic Algorithms Based Fuzzy Speed Controllers for Indirect Field Oriented Control of Induction Motor Drive

Moulay Rachid Douiri, Mohamed Cherkaoui, and Ahmed Essadki

Abstract**—** In this paper the genetic algorithms is applied to automate and optimize the fuzzy controller design process. To do this, the normalization parameters, membership functions and decision table are converted into binary bit string. This optimization requires a predefined objective function. The task of such a design algorithm is the modification of the existing knowledge and at the same time, the investigation of new feasible structures. The proposed approach in this paper is employed for the speed control of an induction motor drive with indirect field oriented control.

Keywords**—** Fuzzy logic controller, Genetic algorithms, Indirect field oriented, Induction motor.

I. Introduction

Vector control theory, commonly known as control by flux orientation, was first established by Siemens'company : Blaschke (1972)[1]. It is to impose the offset angle between the vector of stator magnetomotive force and the rotor flux'one. The result of this is the separation between coupled flux (main) and electromagnetic torque. This leads to distinguish between the component of stator current that controls the coupled flux and the component that governs the electromagnetic torque [1], [2]. Thus, we recognize one of intrinsic characteristics of the DC motor, namely the torque linearity due to orthogonality of vectors and excitation flux armature current.

Today, the new trends in this field now involve the application of modern non-linear control techniques to further enhance the performance of such controllers as well as optimizing drive operation based on a specific requirement [3], [4], [5].

The research underlying this paper involves the development of a novel synthesis methodology to automate and at the same time, to optimize the performance of fuzzy controllers based on a predefined objective function for any particular application. It also aims, in particular, to design an optimal fuzzy controller for induction motor drives with indirect field oriented control. Two intelligent techniques were used in this paper namely fuzzy logic and genetic algorithms.

It was in the mid 1960's that a new theory called fuzzy logic was proposed which gradually helped to supplement the expert systems as another branch of artificial intelligence. L.A. Zadeh [6], the originator of this theory, argued that most human thinking is fuzzy or imprecise in nature, and therefore, Boolean logic which involves distinct "0" and "1" cases cannot properly emulate the human thinking process [7]. In recent years, Fuzzy logic has emerged as an important artificial intelligence tool to characterize and control a system dose model is not known, or ill-defined. It has been widely applied in process control, estimation, identification, diagnostics, stock market prediction, agriculture, military science, etc.

The fuzzy logic controller (FLC) to be investigated is the Mamdani's type [8], although there exist other types, for example, the Sugeno's [9] and the Yamakawa's [10].

The genetic algorithm (Holland [11], 1975; Goldberg [12], 1989) is inspired by nature. In nature, different individuals in a population are competing for various resources, including mates. The competition is based on the principle of natural selection and survival of the fittest, i.e., those individuals which are successful in the competition live longer and will have more offspring's, and hence their genetic lines will last longer. Genetic Algorithms are basically computational method in which the competition and reproduction (evolution) which exist in nature are emulated. In these algorithms, potential solutions of the problem (phenotypes) are encoded into a chromosome like data structure (genotype). The set of these genotypes termed population is evolved using different genetic operators (e.g., selection, crossover, mutation ...). The evolutions of genotypes are such that individuals with higher fitness will substitute genotypes of lower fitness [11], [12].

This paper is organized as follows: The principle of indirect field oriented control is presented in the second part, the fuzzy logic speed controller in section three, the genetic algorithm optimization based auto-design of fuzzy speed controllers in the fourth section, the five part is devoted to illustrate the simulation performance of this control approach, a conclusion and reference list at the end.

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II. Mathematical Model of an Induction Motor with Indirect Field Oriented Control

The dynamic behavior of an induction motor in the synchronously rotating frame can be described by the following state equations:

$$\begin{bmatrix} \dot{i}_{ds} \\ \dot{i}_{qs} \\ \dot{\Psi}_{dr} \\ \dot{\Psi}_{qr} \end{bmatrix} = \begin{bmatrix} -\frac{R_s}{\sigma L_s} - \frac{R_r(1-\sigma)}{\sigma L_r} & \omega_e & \frac{L_m R_s}{\sigma L_s L_r^2} & \frac{p\omega_r L_m}{2\sigma L_s L_r} \\ -\omega_e & -\frac{R_s}{\sigma L_s} - \frac{R_r(1-\sigma)}{\sigma L_r} & \frac{p\omega_r L_m}{2\sigma L_s L_r} & \frac{L_m R_s}{\sigma L_s L_r^2} \\ \frac{L_m R_r}{\sigma L_r} & 0 & -\frac{R_r}{L_r} & \omega_e - \frac{p}{2}\omega_r \\ 0 & \frac{L_m R_r}{\sigma L_s L_r^2} & -(\omega_e - \frac{p}{2}\omega_r) & -\frac{R_r}{L_r} \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ \Psi_{dr} \\ \Psi_{qr} \end{bmatrix} + \frac{1}{\sigma L_s} \begin{bmatrix} v_{ds} \\ v_{qs} \\ 0 \\ 0 \end{bmatrix} \quad (1)$$

$$\Gamma_{em} = \frac{3p}{4} \cdot \frac{L_m}{L_r} (i_{qs}\Psi_{dr} - i_{ds}\Psi_{qr}) \quad (2)$$

The Fig. 1 illustrates the principle of indirect method using phase diagram. At any instant, d electrical axis is in angular position θ_e relative to α axis. The angle θ_e is the result of the sum of both rotor angular and slip angular positions, as follows:

$$\begin{cases} \theta_e = \theta + \theta_{sl} \\ \omega_e t = \omega t + \omega_{sl} t = (\omega + \omega_{sl}) t \end{cases} \quad (3)$$

where:
ω and θ are the position and rotor angular velocity;
θ_{sl} and ω_{sl} are the position and sliding angular velocity.

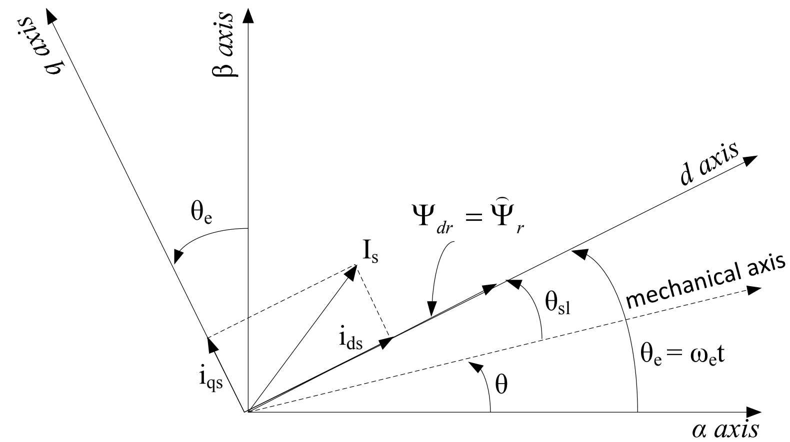


Fig. 1 vector diagram for indirect field oriented control

The rotor flux $\widehat{\Psi}_r$, which includes a magnetizing flux and a rotor leakage flux, coincides with d-axis as shown in Fig. 1. So, to control with decoupling, the current i_{ds}'s stator flux component coincides with d-axis and the current i_{qs}'s torque coincides with q-axis. For control with ideal decoupling, it's need:

$$\Psi_{qr} = \frac{d\Psi_{qr}}{dt} = 0, \qquad \Psi_{dr} = \widehat{\Psi}_r, \qquad \frac{d\Psi_{dr}}{dt} = 0 \quad (4)$$

Using these two first conditions and induction motor equations, we have the main equations of indirect vector control [2], [21]:

$$\omega_{sl} = \frac{L_m}{\widehat{\Psi}_r} \cdot \frac{R_r}{L_r} . i_{qs} \quad (5)$$

$$\frac{L_r}{R_r} \cdot \frac{d\widehat{\Psi}_r}{dt} + \widehat{\Psi}_r = L_m i_{ds} \quad (6)$$

$$\Gamma_{em} = \frac{3}{2} . p . \frac{L_m}{L_r} . i_{qs} . \widehat{\Psi}_r \quad (7)$$

III. Fuzzy Speed Controller

A conventional PI controller can be described by:

$$\Gamma_{em}^{*} = k_p e + k_i \int_0^t e(t) dt \quad (8)$$

where k_p and k_i are the proportional and the integral gain coefficients and $e=\omega_r^{*} - \omega_r$ is the speed error between the command speed ω_r^{*} and the actual motor speed ω_r. If the above integral equation is converted into a differential equation by taking the derivative with respect to time, the equivalent equation will be:

$$\dot{\Gamma}^{*}_{em} = k_p.\dot{e} + k_i.e \tag{9}$$

The PI controller (9) can be written in a fuzzy rule form as follows:

If $e(k)$ is LV_e, and $\Delta e(k)$ is $LV_{\dot{e}}$, then $\Delta\Gamma^{*}_{em}(k)$ is $LV_{\dot{\Gamma}}$ (10)

with LV: linguistic variable

The most significant variables entering the fuzzy logic speed controller have been selected as the speed error (e) and its change ($\dot{e}$), the output this controller is $\dot{\Gamma}^{*}_{em}$ [13], [14]. The equation input/output controller FLC written at time *(k)*:

$$e(k) = \omega_r^{*}(k) - \omega_r(k) \tag{11}$$

$$\dot{e}(k) = e(k) - e(k-1) \tag{12}$$

$$\Gamma^{*}_{em}(k) = \Gamma^{*}_{em}(k-1) + \dot{\Gamma}^{*}_{em}(k) \tag{13}$$

The principle of this strategy is shown in Fig. 2.

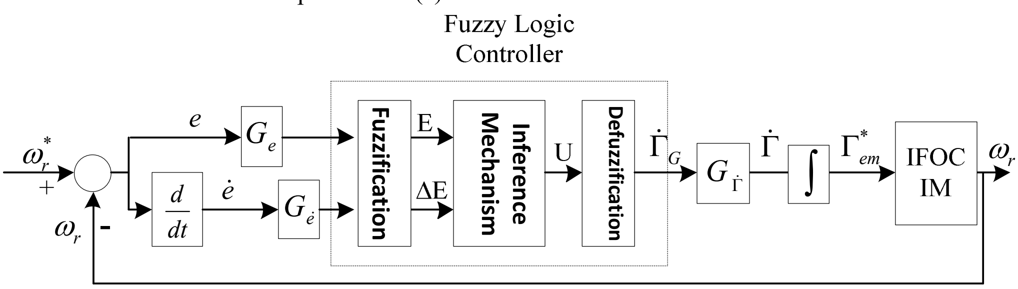


Fig. 2 basic structure of the fuzzy logic controller for indirect field oriented control.

The fuzzy sets are characterized by standard designations: *NB* (negative big), *NM* (negative medium), *NS* (negative small), *AZ* (approximate zero), *PS* (positive small), *PM* (positive medium) and *PB* (positive big).

Fuzzy distribution is symmetric, and non-equidistant in our choice. We have chosen also in our application the triangular-shaped membership function. Fig. 3 shows the diagram of fuzzy.

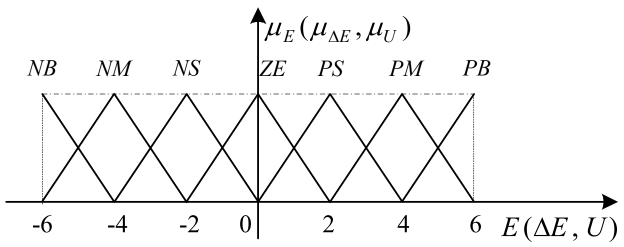


Fig. 3 the shape of membership functions for fuzzy logic controller.

In order to design a universal FLC, we can transform the values range in standard ranges. Therefore, the input and output gains are introduced:

$$G_e = \frac{e_G(k)}{e(k)},\; G_{\dot{e}} = \frac{\dot{e}_G(k)}{\dot{e}(k)},\; G_{\dot{\Gamma}} = \frac{\dot{\Gamma}(k)}{\dot{\Gamma}_G(k)} \tag{14}$$

From behavior study of the system closed-loop speed based on experience, we can establish the command rules which connect output with inputs [15], [7]. As we have seen, there are seven fuzzy sets, which imply forty-nine possible combinations of these inputs, in which forty-nine rules. The rules are like:

Rule 1: if $e = NB$ and $\dot{e} = NB$ then $\dot{\Gamma}$ is NB (15)

Or

Rule 2: if $e = NB$ and $\dot{e} = NM$ then $\dot{\Gamma}$ is NB (16)

Or …

Rule 49: if $e = PB$ and $\dot{e} = PB$ then $\dot{\Gamma}$ is PB (17)

They can be presented in a matrix called matrix inference shown in the Table I.

Fuzzy controller with two inputs is represented by its characteristic surface (Fig. 4). This latter expresses the real value variations of controller output based on input when the latter traverse the discourse universe.

Table I: The fuzzy linguistic rule table.

$\dot{\Gamma}$		e						
		NB	NM	NS	ZE	PS	PM	PB
$\dot{e}$	NB	NB	NB	NB	NB	NM	NS	AZ
	NM	NB	NB	NB	NM	NS	AZ	PS
	NS	NB	NB	NM	NS	AZ	PS	PM
	AZ	NB	NM	NS	AZ	PS	PM	PB
	PS	NM	NS	AZ	PS	PM	PB	PB
	PM	NS	AZ	PS	PM	PB	PB	PB
	PB	AZ	PS	PM	PB	PB	PB	PB

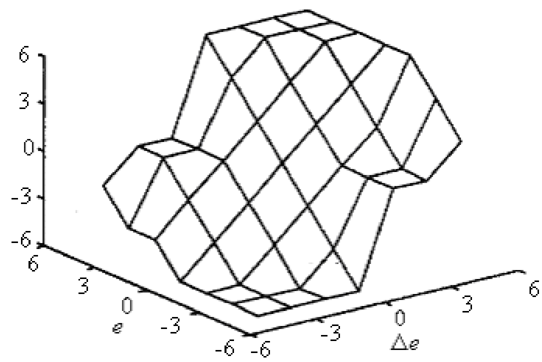


Fig. 4 control surface for the conventional fuzzy controller.

We choose min-max inference method, for each rule, we obtain the partial membership function by relation (18) [16], [17]:

$$\mu_{R_i}(\dot{\Gamma}_G) = \min\left(\mu_{C_i}, \mu_{O_i}(\dot{\Gamma}_G)\right) \quad i=1,2,...,m \qquad (18)$$

where μ_{Ci} is a membership factor assigned to each rule R_i; $\mu_{Oi}(\dot{\Gamma}_G)$ is the membership function related in operation imposed by rule R_i.

The resulting membership function is then given by [16], [17]:

$$\mu(\dot{\Gamma}_G) = \max\left(\mu_{R_1}(\dot{\Gamma}_G), \mu_{R_2}(\dot{\Gamma}_G), ..., \mu_{R_m}(\dot{\Gamma}_G)\right) \qquad (19)$$

The defuzzification process employs the center of gravity method. As a result, the control increment is obtained by the following formula [16], [7]:

$$\dot{\Gamma}_G = \frac{\int \dot{\Gamma}_G . \mu(\dot{\Gamma}_G) d(\dot{\Gamma}_G)}{\int \mu(\dot{\Gamma}_G) d(\dot{\Gamma}_G)} \qquad (20)$$

IV. Genetic Algorithms Based Fuzzy Logic Controller

The genetic algorithm is applied to automate and optimize the fuzzy controller design process. This optimization requires a predefined objective function. Moreover, the normalization parameters, membership functions and decision table are converted into binary bit string constructed by cascading.

An individual bit length is 597 bit and composed of three gene block:

Gene block 1 (Normalization factors): Determine the proper domain of the control surface, which represents 10 bit normalization factors for speed error, 10 bit normalization for speed error derivative, 10 bit denormalization factor for control output.

Gene block 2 (Membership functions): To have complete freedom in partitioning the state space, asymmetrical membership functions should be chosen that consequently suggest three different design parameters, i.e. M_1, .M_2, and, M_3 for each membership functions (Fig. 5). Let us consider seven membership functions for each variable for a controller with two inputs, 42 parameters are required to define the entire set of membership functions, where every parameter is encoded with 10-bit resolution.

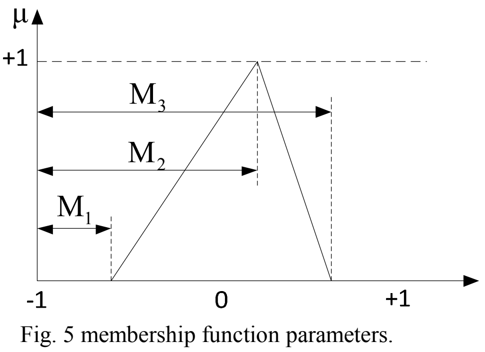


Fig. 5 membership function parameters.

Gene block 3 (Decision table): Every consequent part of a fuzzy rule should be encoded in a binary form. Since every consequent can take on only one of seven different values based on Table 1, every consequent can be represented by only three bits i.e. 3×49 parameters = 147 bits will represent the entire decision table (Fig. 6).

Normalization factors			Membership functions parameters					Decision table				
G_e	$G_{\dot{e}}$	$G_{\dot{\Gamma}}$	M_1	M_2	M_3	....	M_{42}	R_1	R_2	R_3	....	R_{49}

Fig. 6 bit-string representation of entire controller.

Each individual represents a possible solution to the problem; a particular fitness function is required for the evaluation of the individuals [12], [18]. In this way, for every particular chromosome (i.e. each solution), the fitness function returns a single numerical value, which indicates the quality of that solution. In the context of optimization it is the performance index of the closed loop system that becomes the fitness function. Our goal is to have a response speed with a short rise time, small overshoot, and near-zero steady state error. In this respect, a multiple objective function is required:

$$J = \underbrace{\int_0^t |e|dt}_{(1)} + \underbrace{4\int_0^t \delta(\frac{dz}{dt}).\left|z^* - z(t)\right|dt}_{(2)} + \underbrace{0.5\int_0^t |e|tdt}_{(3)} \qquad (21)$$

with:

(1) Measure of a fast dynamic response;

(2) The penalty on the multiple overshoot of the response, where *δ(dz/dt)* detects the instances that overshoots (or undershoots) occur:

$$\int_{0^-}^{0^+} \delta(\frac{dz}{dt}) = \begin{cases} 1 & if \quad \frac{dz}{dt} = 0 \\ 0 & if \quad \frac{dz}{dt} \neq 0 \end{cases} \qquad (22)$$

and $|z^*-z(t)|$ determines the response deviation from the desired value;

(3) Measure the steady state error.

The genetic algorithm with the free parameters shown in Table II was able to find the near-optimum solution (Table III) with a population of 44 individuals, in almost 358 generations Fig. 8. This is due to the large number of design parameters involved in concurrent optimization.

The principle of genetic algorithms based fuzzy logic controller is shown in Fig. 7.

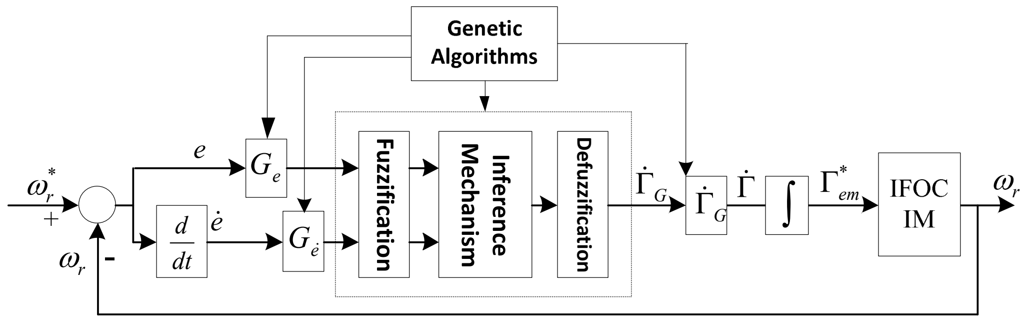


Fig. 7 basic structure of the genetic algorithms based fuzzy logic controller for indirect field oriented control.

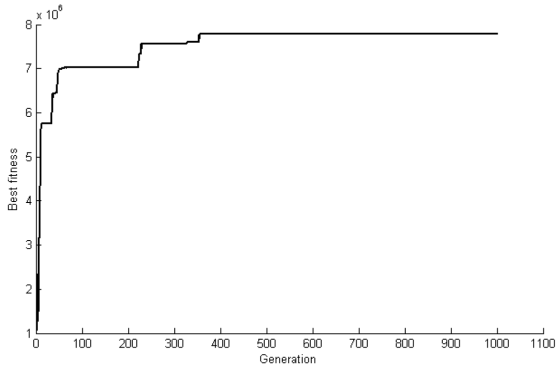


Fig. 8 speed of convergence.

The optimization algorithm and the motor drive response are then verified under loading and unloading conditions. A speed command of 50 *rd/s* at 0.02 *s* is given to the drive system, the full load is applied at 0.2 *s*; then load is completely removed at 0.4 *s*. and then accelerated further to 100 *rd/s*, full load is applied at 0.8 *s*; then load is completely removed at 1 *s*. Later, after speed reversal of -50 *rd/s* at 1.2 *s*, full load is applied at 1.4 *s* and the load is fully removed at 1.6 *s*. Fig. 9 shows the speed optimization result and response of the drive system.

The FLC-GA speed response (Fig. 9) shows that the drive can follow the low command speed very quickly and smoothly without overshoot, no steady-state error and -Rapid rejection of disturbances, with a low dropout speed (Fig. 10 and Table IV). The current responses are sinusoidal and balanced, well as the decoupling between the flux and torque is verified (Fig. 11 and 12).

Table III Normalization factors found by genetic algorithms.

	G_e	$G_{\dot{e}}$	$G_{\dot{\Gamma}}$
FLC	7.58	4.01	5.34
FLC-GA	3.22	0.11	8.61

Table II Genetic algorithm parameters.

GA property	Value	GA property	Value/Method
Number of generations	358	Selection method	Roulette wheel
No of chromosomes in each generation	44	Crossover method	Double-point
No of genes in each chromosome	3	Crossover probability	0.8
Chromosome length	597	Mutation rate	0.05

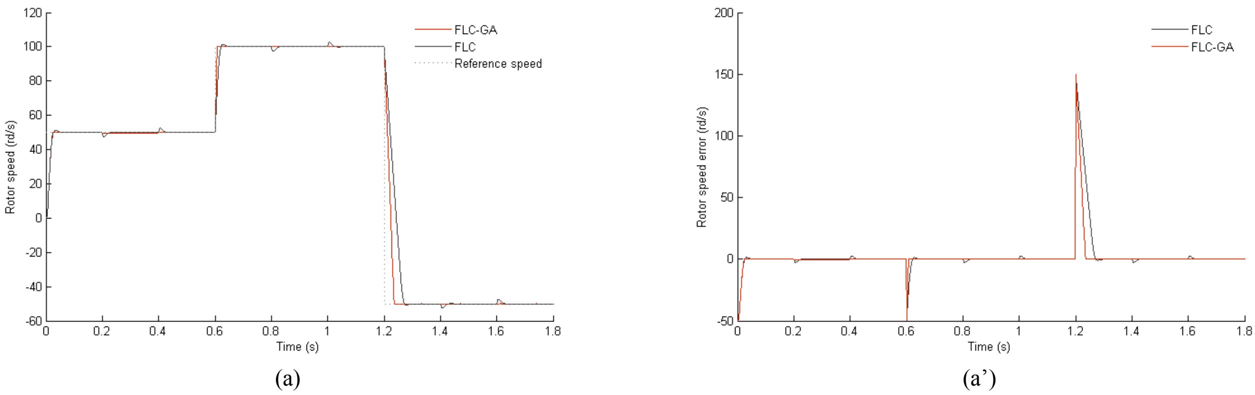
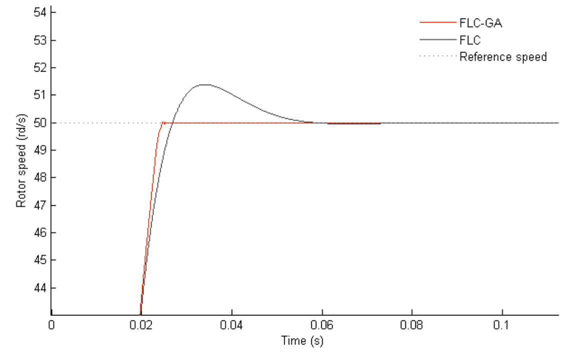
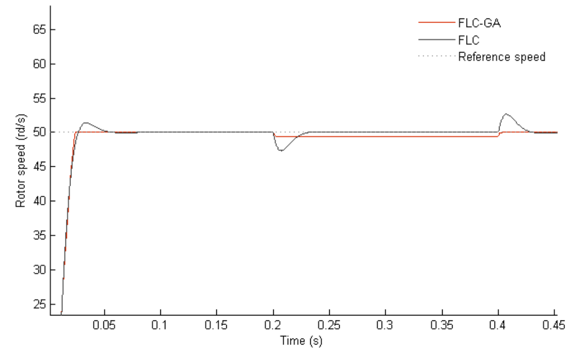


Fig. 9 rotor speed acceleration and reversal: (a) FLC and FLC-GA (a') speed error.

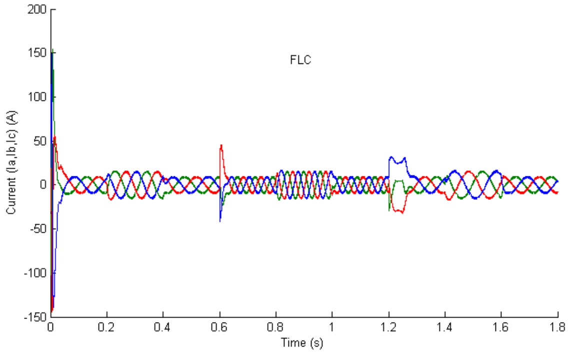


(b)



(b')

Fig. 10 zoom speed: (b) starting transient performance and overshoot (b') response due to load and unload change.



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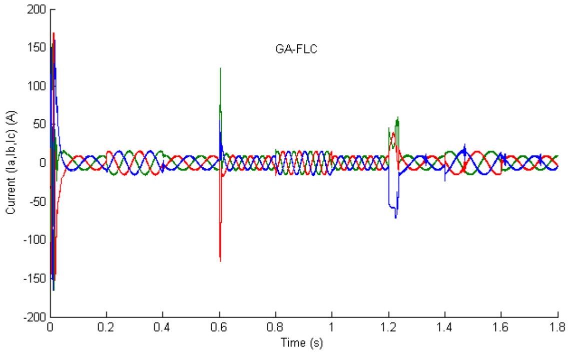
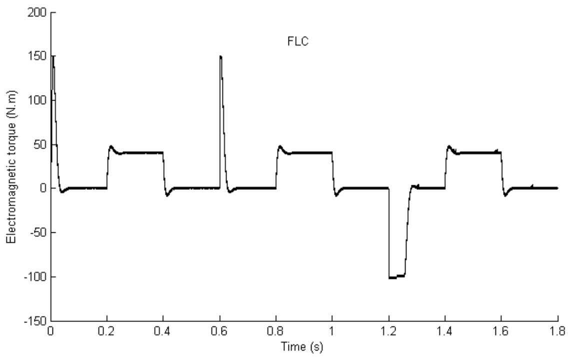
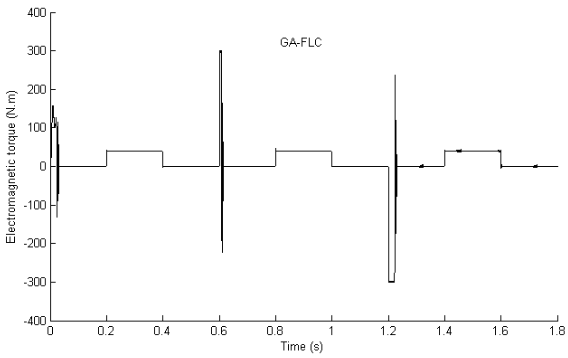


(c')

Fig. 11 three phase stator current: (c) FLC (c') FLC-GA.



(d)



(d')

Fig. 12 electromagnetic torque response: (d) FLC (d') FLC-GA.

Table IV Summary of results.

	Rise time (s)	Overshoot (%)	Settling time (%)	Steady state error (%)
FLC	0.03	2.9	0.08	0.7
FLC-GA	0.02	0.05	0.001	0.4

V. CONCLUSION

This work uses the Genetic algorithm based auto-design of fuzzy logic controller as the speed controller of the indirect field oriented controlled induction motor drives. By comparison with FLC controller, it testifies that this method is not only robust, but also can improve dynamic performance of the system. The GA-FLC proposed approach achieves:

-Good pursuit of reference speed;

-Starting without overshoot;

-Rapid rejection of disturbances, with a low dropout speed;

-Good support for changes in engine parameters.

APPENDIX

Rated power = 7.5*Kw*, Rated voltage = 220*V*, Rated frequency = 60*Hz*, R_r = 0.17*Ω*, R_s = 0.15*Ω*, L_r = 0.035*H*, L_s = 0.035*H*, L_m = 0.0338*H*, J = 0.14*Kg.m*^{2}.

LIST OF SYMBOLS AND ABBREVIATIONS

FLC	Fuzzy Logic Controller
GA	Genetic Algorithms
IM	Induction Motor
$\sigma = 1 - \frac{L_m^2}{L_s L_r}$	Leakage coefficient
$\Psi_{dr} = L_m i_{ds} + L_r i_{dr}$	*d*-axis rotor flux [*Wb*]
$\Psi_{qr} = L_m i_{qs} + L_r i_{qr}$	*q*-axis rotor flux [*Wb*]
R_s , R_r	Stator and rotor resistance [*Ω*]
L_m , L_r , L_s	Magnetizing, rotor and stator inductance [*H*]
p	Number of poles
ω_e	Electrical angular speed [*rd/s*]
ω_r	Rotor speed [*rd/s*]
v_{ds} , v_{qs}	*dq*-axis stator voltage [*V*]
i_{ds} , i_{qs}	*dq*-axis stator current [*A*]
i_{dr} , i_{qr}	*dq*-axis rotor current [*A*]
J	Inertia moment [*Kg.m*^{2}]
Γ_{em}	Electromagnetic torque [*N.m*]
G_e , $G_{\dot{e}}$, $G_{\dot{\Gamma}}$	Normalized and denermalized factors
e_G , $\dot{e}_G$, $\dot{\Gamma}_G$	Normalized and denermalized error vectors
μ_A	Membership functions for labels *A*
*	Reference symbol

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