OPTIMAL FUZZY GAINS SCHEDULING OF PI CONTROLLER FOR INDUCTION MOTOR SPEED CONTROL

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SUMMARY

In this paper, an optimal fuzzy gain scheduling of PI controller is adopted to speed control of an induction motor. First, a designed fuzzy gain scheduling of PI controller is investigated, in which fuzzy rules are utilized on-line to adapt the PI controller parameters based on the error and its first time derivative. However, the major disadvantage of the fuzzy logic control is the lack of design techniques, for this purpose we propose an optimization technique of the fuzzy logic adapter parameters using genetic algorithm. The effectiveness of the complete proposed control scheme is verified by numerical simulation. The numerical validation results of the proposed scheme have presented good performances compared to the fuzzy controller which have parameters chosen by the human operator.

Keywords: *fuzzy logic, genetic algorithm, PI controller, adaptation, optimization, and vector control.*

1. INDRODUCTION

Nowadays, like a consequence of the important progress in the power electronics and of micro-computing, the control of the AC electric machines known a considerable development and a possibility of the real time implantation applications. It is widely recognized that the induction motor is going to be the main actuator for industrial purposes [1]. Indeed, as compared to the DC machine, it provides a better power/mass ratio, a simpler maintenance and relatively lower cost. However, it is traditionally for a long time, used in industrial applications that do not require high performances, this because its control is a more complex problem, its high non-linearity and its high coupled structure. Furthermore, the motor parameters are time-varying during the normal operation and most of the state variables are not measurable. On the other hand, the direct current (D.C) machine was largely used in the field of the variable speed applications, where torque and flux are naturally decoupled and can be controlled independently by the torque producing current and the flux producing current. Since Blashke and Hasse have developed the new technique known as vector control [1, 2, 3], the use of the induction machine becomes more and more frequent. This control strategy can provide the same performance as achieved from a separately excited DC machine, and is proven to be well adapted to all type of electrical drives associated with induction machines[4].

The most widely used controller in the industrial applications is the PID-type controllers because of their simple structures and good performances in a wide range of operating conditions [5]. In the literature, the PID controllers can be divided into two main parts: In the first part, the controller parameters are fixed during control operation. These parameters are selected in an optimal way by known methods such as the Zeigler and Nichols, poles assignment... etc. The PID controllers of this part are simple but cannot always effectively control systems with changing parameters or have a strong nonlinearity; and may need frequent on-line retuning [6]. In the second part, the controllers have an identical structure to PID controllers but their parameters are tuned on-line based on parameters estimation of the process. Such controllers are known as adaptive PID controllers.

In control by fuzzy logic [8, 9], the linguistic description of human expertise in controlling a process is represented as fuzzy rules or relations. This knowledge base is used by an inference mechanism, in conjunction with some knowledge of the states of the process (say, of measured response variables) in order to determine control-actions. The controllers based on fuzzy logic (FLC) can be considered as non-linear PID controller where their parameters are determined on-line based on the error and its derivative [5, 6]. However, this standard FL controller can not reacts to change in operating conditions. The FL controller needs more information to compensate nonlinearities when the operation conditions change. When the number of the fuzzy logic inputs is increased, the dimension of the rule base increases too. Thus, the maintenance of the rule base is more time-consuming. An other disadvantage of the FL controllers is the lack of systematic, effective and useful design methods, which can use a priori knowledge of the plant dynamics.

To overcome the disadvantages of PID controllers and FLC, we propose in this paper a combination between them together. PID parameters controller can be tuned on-line by an adaptive mechanism based on a fuzzy logic for induction machine speed control.

However, the major drawback of fuzzy control is the lack of design technique [10, 11]. Most of the fuzzy rules are human knowledge oriented and hence rules will deviate from person to person in spite of the same performance of the system. The selection of suitable fuzzy rules, membership functions and their definitions along the universe of discourse always involve a painstaking trial-and-error process [7]. GA most known and is most largely employed in the technique of global research with a capacity to explore and exploit a given operation space using the measurement of the available performance [12]. Recently of many applications combining the fuzzy concepts and GA appeared, particularly, the use of GA for the fuzzy logic systems control design. Thus approaches are called genetic-fuzzy system [13, 14]. In this way, we propose a technique to optimize the parameters of fuzzy adapter of PI controller; the controller resulting from this combination is known on the name: adaptive FLC-PI-GA in order to apply it to the speed control of the induction machine.

In this paper, the design of an optimal fuzzy gain scheduling of PI controller combines the merits of the sliding mode control and the fuzzy inference mechanism is proposed. A fuzzy gain scheduling of conventional PI controller is investigated, in which the fuzzy logic system is used on-line to generate the PI controller parameters. The indirect field-oriented control of induction motor is presented in section 2. Section 3 shows the development of the fuzzy tuning of PI controller based on the error and its first time derivative. Then, an optimal fuzzy gain scheduling of PI controller is being designed in which an optimization technique using genetic algorithm is developed to optimize the fuzzy logic controller. Finally, the combined proposed controller was applied for induction motor speed control through a numerical simulation. Section 7 concludes this paper.

2. INDIRECT FIELD-ORIENTED CONTROL OF INDUCTION MOTOR

The dynamic model of three-phase, Y-connected induction motor can be expressed in the *d-q* synchronously rotating frame as [1, 3, 4]:

$$\begin{cases} \dfrac{di_{ds}}{dt} = \dfrac{1}{\sigma.L_s}.\left(-\left(R_s + \left(\dfrac{L_m}{L_r}\right)^2.R_r\right).i_{ds} + \sigma.L_s.\omega_e.i_{qs} + \dfrac{L_m.R_r}{L_r^2}.\phi_{dr} + \dfrac{L_m}{L_r}.\phi_{qr}.\omega_r + V_{ds}\right) \\ \dfrac{di_{qs}}{dt} = \dfrac{1}{\sigma.L_s}.\left(-\sigma.L_s.\omega_e.i_{ds} - \left(R_s + \left(\dfrac{L_m}{L_r}\right)^2.R_r\right).i_{qs} - \dfrac{L_m}{L_r}.\phi_{dr}.\omega_r + \dfrac{L_m.R_r}{L_r^2}.\phi_{qr} + V_{qs}\right) \\ \dfrac{d\phi_{dr}}{dt} = \dfrac{L_m.R_r}{L_r}.i_{ds} - \dfrac{R_r}{L_r}.\phi_{dr} + (\omega_e - \omega_r)\phi_{dr} \\ \dfrac{d\phi_{qr}}{dt} = \dfrac{L_m.R_r}{L_r}.i_{qs} - (\omega_e - \omega_r)\phi_{dr} - \dfrac{R_r}{L_r}.\phi_{qr} \\ \dfrac{d\omega_r}{dt} = \dfrac{p^2.L_m}{L_r.J}.(i_{qs}.\phi_{dr} - i_{ds}.\phi_{qr}) - \dfrac{f_c}{J}.\omega_r - \dfrac{p}{J}.T \end{cases} \tag{1}$$

Where σ is the coefficient of dispersion and is given by (2):

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

L_s, L_r, L_m stator, rotor and mutual inductances;
R_s, R_r stator and rotor resistances;
ω_e, ω_r electrical and rotor angular frequency;
ω_{sl} slip frequency $(\omega_e - \omega_r)$;
τ_r rotor time constant (L_r / R_r);
p pole pairs

The main objective of the vector control of induction motors is, as in DC machines, to independently control the torque and the flux; this is done by using a *d-q* rotating reference frame synchronously with the rotor flux space vector [2, 3]. In ideally field-oriented control, the rotor flux linkage axis is forced to align with the *d*-axes, and it follows that [3, 4, 15]:

$$\phi_{rq} = \frac{d\phi_{rq}}{dt} = 0 \tag{3}$$

$$\phi_{rd} = \phi_r = cons\tan t \tag{4}$$

Applying the result of (3) and (4), namely field-oriented control, the torque equation become analogous to the DC machine and can be described as follows:

$$T_e = \frac{3}{2}\frac{p \cdot L_m}{L_r} \cdot \phi_r \cdot i_{qs} \tag{5}$$

And the slip frequency can be given as follow:

$$\omega_{sl} = \frac{1}{\tau_r}\frac{i_{qs}^*}{i_{ds}^*} \tag{6}$$

Consequently, the dynamic equations (1) yield:

$$\begin{cases} \dfrac{di_{ds}}{dt} = -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma\tau_r}\right)i_{ds} + \omega_e i_{qs} + \dfrac{L_m}{\sigma L_s L_r \tau_r}\phi_{rd} + \dfrac{1}{\sigma L_s}V_{ds} \\ \dfrac{di_{qs}}{dt} = -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma\tau_r}\right)i_{qs} - \omega_e i_{ds} + \dfrac{L_m}{\sigma L_s L_r \tau_r}\phi_{rd} + \dfrac{1}{\sigma L_s}V_{ds} \\ \dfrac{d\phi_r}{dt} = \dfrac{L_m}{\tau_r}i_{ds} - \dfrac{1}{\tau_r}\phi_{rd} \\ \dfrac{d\omega_r}{dt} = \dfrac{3}{2}\dfrac{p^2 L_m}{JL_r}i_{qs}\phi_{rd} - \dfrac{f_c}{J}\omega_r - \dfrac{p}{J}T_l \end{cases} \tag{7}$$

The decoupling control method with compensation is to choose inverter output voltages such that [10]:

$$V_{ds}^* = \left(K_p + K_i\frac{1}{s}\right)\left(i_{ds}^* - i_{ds}\right) - \omega_e \sigma L_s i_{qs}^* \tag{8}$$

$$V_{qs}^* = \left(K_p + K_i\frac{1}{s}\right)\left(i_{qs}^* - i_{qs}\right) + \omega_e \sigma L_s i_{ds}^* + \omega_r\frac{L_m}{L_r}\phi_{rd} \tag{9}$$

According to the above analysis, the indirect field-oriented control (IFOC) [3, 16] of induction motor with current-regulated PWM drive system can reasonably presented by the block diagram shown in the Fig. 1.

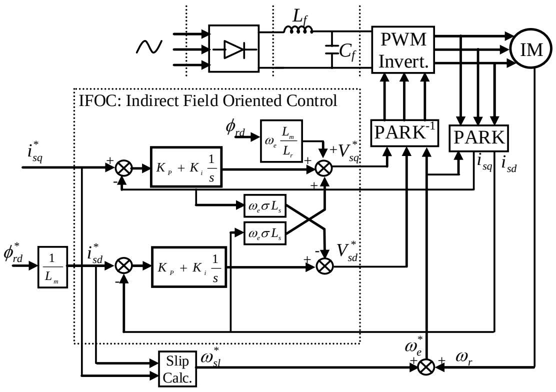

Fig. 1 Block diagram of IFOC for an induction motor.

3. THE SPEED CONTROL OF THE IM BY AN ADAPTIVE CONTROLLER FLC-PI

To overcome the disadvantages of PID controllers and FLC, we propose in this paper a combination between the two types of controllers. PID parameters controller can be adjusted by an adaptive mechanism based on a fuzzy inference (adaptive FLC-PI). In what follows we show the method of combination between these two types of controllers.

3.1. Fuzzy gain scheduling of PI controller

Gain scheduling means a technique where PI controller parameters (k_p and k_i gains) are tuned during control of the system in a predefined way [5, 6, 7]. It enlarges the operation area of linear controller (PI) to perform well also with a nonlinear system [5]. The diagram of this technique is illustrated in fig. 2. The fuzzy inference mechanism adjusts the PI parameters and generates new parameters during process control, so that the FLC adapts the PI parameters to operating conditions based on the error and its first time difference.

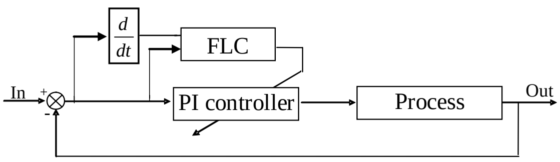

Fig. 2 PI control system with fuzzy gain adapter.

3.2. Description of the fuzzy scheduler

The parameters of the PI controller used in the direct chain k_p and k_i are normalized into the range between zero and one by using the following linear transformations [5]:

$$k_p^{'} = \left(k_p - k_{p\min}\right) \Big/ \left(k_{p\max} - k_{p\min}\right) \tag{10}$$

$$k_i^{'} = \left(k_i - k_{i\min}\right) \Big/ \left(k_{i\max} - k_{i\min}\right) \tag{11}$$

The inputs of the fuzzy adapter are: The error e and the derivative of error Δe, the outputs are : the normalized value of the proportional action ($k_p^{'}$) and the normalized value of the integral action ($k_i^{'}$).

The problem of selecting the suitable fuzzy controller rules remain relying on expert knowledge and try and error tuning methods. The parameters $k_p^{'}$ and $k_i^{'}$ are determined by a set of fuzzy rules of the form:

If e is A_i, and Δe is B_i, then $k_p^{'}$ is C_i, and $k_i^{'}$ is D_i. (12)

Where A_i, B_i, C_i and D_i are fuzzy sets on corresponding supporting sets. Because the data manipulated in the fuzzy inference mechanism is based on the fuzzy set theory, the associated fuzzy sets involved in the fuzzy control rules are defined as follows:

NB : negative big
NM : negative medium
NS : Negative small
ZE : Zero
PS : Positive small
PM : Positive medium
PB : Positive big
B : Big
S : Small

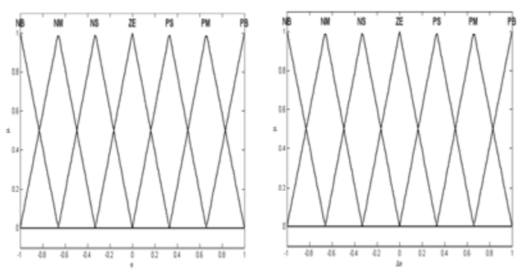

Fig. 3 Membership functions e and Δe.

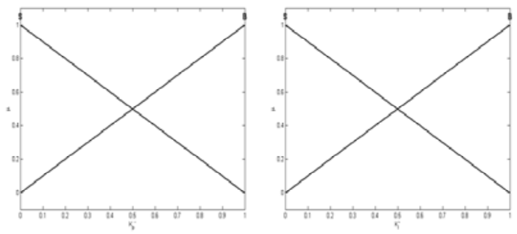

Fig. 4 Membership functions $k_p^{'}$ and $k_i^{'}$.

The fuzzy rules in (12) may be extracted from operator's expertise or based on the step response of the process [5]. The tuning rule for $k_p^{'}$ and $k_i^{'}$ are given in tables I and II respectively.

By using the membership functions shown in Fig. 4, we have the following conditions

$$\sum_{i=1}^{m} \mu_i = 1 \tag{13}$$

The fuzzy outputs $k_p^{'}$ and $k_i^{'}$ can be calculated by the centre of area defuzzification as:

$$\left[k_I^{'}, k_P^{'}\right] = \frac{\sum_{i=1}^{3} w_i c_i}{\sum_{i=1}^{3} w_i} = \frac{\left[c_1 \ \cdots \ c_2\right]\begin{bmatrix} w_1 \\ \vdots \\ w_2 \end{bmatrix}}{\sum_{i=1}^{2} w_i} = \upsilon^T W \quad (14)$$

Where $\upsilon = \left[c_1 \ldots c_2\right]$ is the vector containing the output fuzzy centers of the membership functions of $\varphi_I^{'}$ and $\varphi_P^{'}$, $W = \left[w_1 \ \cdots \ w_2\right] \Big/ \sum_{i=1}^{2} w_i$ is the firing strength vector and μ_i represents the membership value of the output $k_I^{'}$ or $k_P^{'}$ to output fuzzy set *i*.

Once the values of $k_p^{'}$ and $k_i^{'}$ are obtained, the new parameters of PI controller is calculated by the following equations:

$$k_p = \left(k_{p\max} - k_{p\min}\right) k_p^{'} + k_{p\min} \quad (15)$$

$$k_i = \left(k_{i\max} - k_{i\min}\right) k_i^{'} + k_{i\min} \quad (16)$$

Table I: fuzzy rules base for computing $k_p^{'}$.

Δe \ e	NB	NM	NS	ZE	PS	PM	PB
NB	B	B	B	B	B	B	B
NM	S	B	B	B	B	B	S
NS	S	S	B	B	B	S	S
ZE	S	S	S	B	S	S	S
PS	S	S	B	B	B	S	S
PM	S	B	B	B	B	B	S
PB	B	B	B	B	B	B	B

Table II: fuzzy rules base for computing $k_i^{'}$.

Δe \ e	NB	NM	NS	ZE	PS	PM	PB
NB	B	B	B	B	B	B	B
NM	B	B	S	S	S	B	B
NS	B	B	B	S	B	B	B
ZE	B	B	B	S	B	B	B
PS	B	B	B	S	B	B	B
PM	B	B	S	S	S	B	B
PB	B	B	B	B	B	B	B

Fig 5 shows the block diagram of the indirect field oriented control by an adaptive controller FLC-PI.

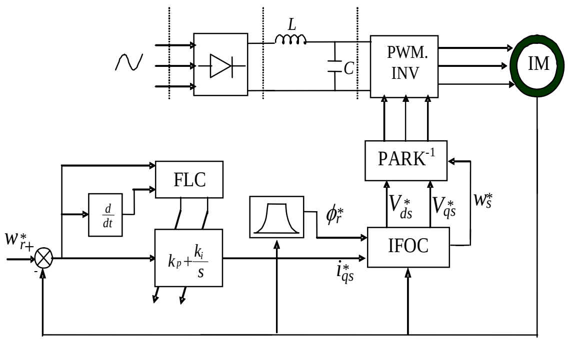

Fig. 5 Block diagram of IM control using fuzzy gain scheduling of PI controller

4. SPEED CONTROL OF IM WITH AN OPTIMAL FUZZY GAIN SCHEDULER OF PI CONTROLLER

4.1. Genetic Algorithms

GA's are parallel and global search techniques which take the concepts from evolution theory and natural genetics to evolve solutions to problems [12, 14, 1]. The basic idea is to maintain a population of chromosomes (representing candidate solutions to the concrete problem being solved) that evolves over time through a process of competition and controlled variation. GA's is theoretically and empirically proven to provide robust search in complex spaces, giving a valid approach to problem requiring efficient and effective searching [12, 14].

A GA starts with a population of randomly generated chromosomes, and advances towards better chromosomes by applying genetic operators modelled on the genetic processes occurring in nature. The population undergoes evolution in a form of natural selection. During successive iterations, called generations, chromosomes in the population are rated for their adaptation as solutions, and on the basis of these evaluations, a new population of chromosomes is formed using a selection mechanism and specific genetic operators such as crossover and mutation. An evaluation or fitness function must be devised for each problem to be solved. Given a particular chromosome, a possible solution, the fitness function returns a single numerical value, which is supposed to be proportional to the utility or adaptation of the solution represented by that chromosome. In these algorithms we maintain a population of solutions for a given problem; this population undergoes evolution in a form of natural selection. In each generation, relatively good solutions reproduce to give offspring that replace the relatively bad solutions which die. An evaluation or fitness function plays the role of the environment to distinguish between good and bad solutions. The process of going from the current population to the next population constitutes in the execution of GA. Although there are many possible variants of the basic GA, the fundamental underlying mechanism operates on a population 0000of chromosomes and consists of three operations [12]:

- Evaluation of individual fitness;
- Formation of gene pool (intermediate population);
- Recombination and mutation.

Fig. 6 illustrates the principal structure of the genetic algorithms based on this operation mode [3, 17, 19].

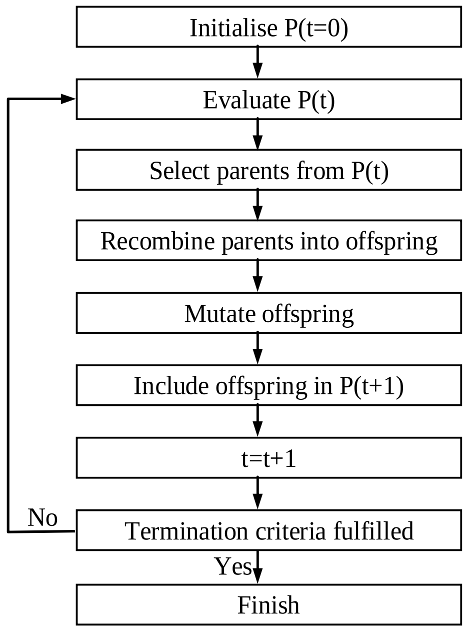

Fig. 6 Principal structure of genetic algorithm.

There are a number of ways of making the selection. We might view the population as mapping onto a roulette wheel, where each chromosome is represented by a space that proportionally corresponds to its fitness. By repeatedly spinning the roulette wheel, chromosomes are chosen using *stochastic sampling with replacement* to fill the intermediate population. The selection procedure proposed in [12], and called *stochastic universal sampling* is one of the most efficient, where the number of offspring of any structure is bound by the floor and ceiling of the expected number of offspring.

After selection has been carried out the construction of the intermediate population is complete, then the genetic operators, crossover and mutation, can occur. A crossover operator combines the features of two parent structures to form two similar offspring. It is applied with a probability of performance, the crossover probability (P_c). A mutation operator arbitrary alters one or more components of a selected structure so as to increase the structural variability of the population. Each position of each solution vector in the population undergoes a random change according to a probability defined by a mutation rate, the mutation probability (P_m).

4.2. Design of fuzzy-genetic system

Different approaches have been proposed to automate the design of fuzzy systems [13, 14, 19, 20]. Many of these approaches take the genetic algorithm as a base of the learning process. A GA was used to optimize the fuzzy logic input membership functions, the fuzzy rules, the output membership functions scaling factors and universe of discourse [13, 19, 20, 21].

4.2.1. Membership parameters optimization

GA is applied to modify the membership functions. When modifying the membership functions, these functions are parameterized with one to four coefficients (Fig. 7), and each of these coefficients will constitute a gene of the chromosome for the GA.

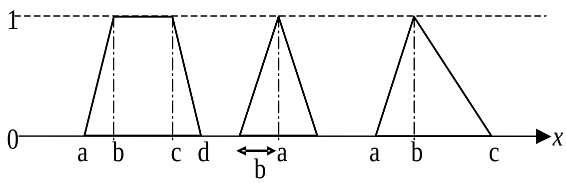

Fig. 7 Some parameterized membership functions

4.2.2. Fuzzy rule base optimization

Different methods are defined to apply GA to the rule base optimization, depending on its representation [13, 17]. For example, GA are used to modify the decision table of an FLC, which is applied to control a system with two input (trial-and-error) and one input (command action) variables. A chromosome is formed from the decision table by going row-wise and coding each output fuzzy set as an integer in 0, 1,…, n, where n is the number of membership functions defined for the output variable of the FLC. Value 0 indicates that there is no output, and value k indicates that the output fuzzy set has the k-th membership.

4.2.3. Optimization algorithm using GA of the fuzzy adapter

GA can be applied to the automatic generation of knowledge base of an optimal fuzzy logic controller (FLC). The key is to employ an evolutionary learning process to automate design of the knowledge base, which can be considered as an optimization or search problem [17, 19, 20, 21]. The application of the GA in the optimization process of the FL controllers can be formulated as follows:

1. *Start with an initial population of solutions that constitutes the first generation (P(0)).*
2. *evaluate P(0):*
   a) *Take each chromosome (KB) from the population and introduce it into the FLC,*

b) Apply the FLC to the controlled system for an adequate evaluation period,

c) Evaluate the behavior of the controlled system by producing a performance index to the KB.

3. While the termination condition is not met, do

a) create a new generation (P(t+1)) by applying the evolution operators (selection, crossover and mutation) to the individuals in P(t),

b) Evaluate P(t+1)

c) t = t+1.

4. End.

The mechanism of this optimization procedure can be represented in fig. 8 [13, 17, 19, 22].

We propose a genetic learning method for the Data Base (DB) of Mamdani fuzzy rule base system that allows us to define:

- The numbers of labels for each linguistic variable.
- The universe of discourse.
- The form of each fuzzy membership function.

The fuzzy adapter consists of two inputs (error and its derivative) and two outputs ($k_p^{'}$) and ($k_i^{'}$), where each input has seven membership functions. These subsets are labelled by linguistic terms such as: Zero (Z), Negative (N)... etc. We use GA to search the appropriate parameters values and to modify the decisions table of the FLC [20, 21, 22], where the chromosome is formed from the decision table and to code each membership function by a integer number from 0 to 2, number 2 indicates the number of membership function defined for the two outputs [12]. So, we can present the equivalent code by: Small (S): 1, Big (B): 2 and No output: 0.

In GA, we only need to select some suitable parameters, such as generations, population size, crossover rate, mutation rate, and coding length of chromosome [12, 14], then the searching algorithm will search out a parameter set to satisfy the designer's specification or the system requirement. In this paper, GA will be included in the design of fuzzy gains tuner of the PI controller.

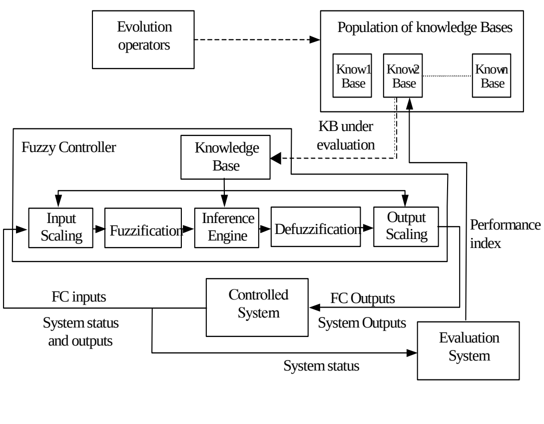

Fig. 8 Evolutionary learning of an FLC

The parameters for the GA simulation are set as follows:
(1) Initial population size: 30;
(2) Maximum number of generation: 100;
(3) Crossover: Uniform crossover with probability 0.8;
(4) Mutation probability: 0.01.

In this paper, the performance is measured using the following criteria.
(5) Minimum integral of squared which is given as follows:

$$J = \int_0^t e^2 dt = \int_0^t \left(\omega_r^* - \omega_r\right)^2 dt \tag{17}$$

Fig. 10 shows the tuning scheme of PI controller adapted by a fuzzy system where their parameters are optimized by the genetic algorithm.

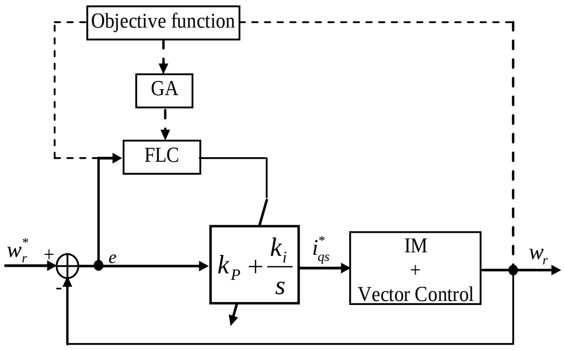

Fig. 9 The optimization technique of the fuzzy gain scheduling of PI controller.

4.2.4. Results of optimization procedure

The results obtained for the parameters optimization of the membership functions are represented in fig. 10 to fig. 13.

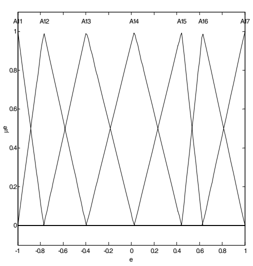

Fig. 10 Membership functions of e

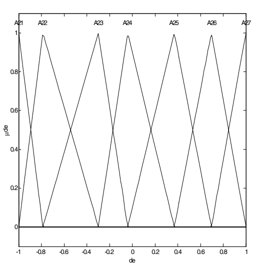

Fig. 11 Membership functions of Δe

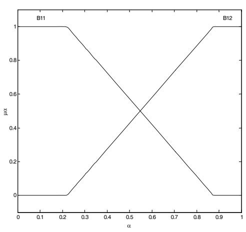

Fig. 12 Membership functions of $k_P^{'}$

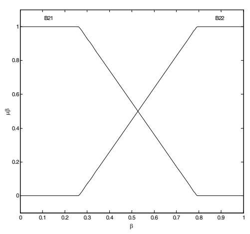

Fig. 13 Membership functions of $k_I^{'}$

The resulting rule bases from the optimization procedure are shown in table III and IV. In the tables for example, the first rule for the output k'_P and k'_I is:

If e is A_{11} **And** Δe is A_{21} **So** k'_P is B_{12} and k'_I is B_{21}

Where B_{12} is the second fuzzy set of the first consequent (k'_p) and B_{21} is the first fuzzy set of the second consequent (k'_i). We can re-write this rule as:

If e is NB **And** Δe is NB **So** k'_P is B and k'_I is S.

Table III: rule bases of the output k'_p.

e \ Δe	A_{21}	A_{22}	A_{23}	A_{24}	A_{25}	A_{26}	A_{27}
A_{11}	2	1	2	2	2	2	2
A_{12}	2	1	1	2	2	2	2
A_{13}	1	2	1	2	2	1	2
A_{14}	2	2	2	2	1	2	1
A_{15}	1	1	1	2	1	2	2
A_{16}	2	2	1	2	1	2	2
A_{17}	2	2	1	2	1	2	2

Table IV: rule bases of the output k'_i.

e \ Δe	A_{21}	A_{22}	A_{23}	A_{24}	A_{25}	A_{26}	A_{27}
A_{11}	1	1	2	1	1	1	1
A_{12}	2	2	2	1	1	2	2
A_{13}	2	1	2	2	1	1	2
A_{14}	2	2	1	2	1	2	2
A_{15}	2	2	1	1	2	2	1
A_{16}	2	2	1	2	2	2	1
A_{17}	2	2	1	1	1	2	2

5. SIMULATION RESULTS

To prove the rightness and effectiveness of proposed control scheme, we apply the designed controller to the control of the induction motor. The configuration of the overall control system is shown in Fig. 9. It mainly consists of an induction motor, a ramp comparison current-controlled pulse width modulated (PWM) inverter, a slip angular speed estimator, an inverse park, an outer speed feedback control loop and a fuzzy gain scheduling of PI controller or fuzzy gain scheduling of PI controller optimized by GA for the speed control.

Fig. 14 shows the parameters variations of PI controller with fuzzy gains tuning during the control operation. Fig. 15 shows the disturbance rejection of adaptive FLC-PI controller when the machine is operated at 200 [rad/sec] under no load and a nominal load disturbance torque (10 N.m) is suddenly applied at 0,5sec, followed by a consign inversion (-200rad/sec) at 1sec. The adaptive FLC-PI controller rejects the load disturbance rapidly with a negligible steady state error.

In the next simulation results, the fuzzy gains scheduling of PI controller optimized by GA is applied to speed tracking of induction motor. The simulated results of combined proposed controllers system due to step change in the reference commands are depicted in Fig. 16. The proposed controller is now compared under the same operating conditions of the drive system. From the simulated results, perfect tracking responses and robust characteristics also can be obtained for the optimal fuzzy gains scheduling of PI controller. Figure 16 confirm that the controller rejects the load disturbance very rapidly with no overshoot, with a minimum rise time and with negligible steady state error more than the first proposed controller. Fig. 17 shows the parameters variations of PI controller with fuzzy gains tuning optimized by GA during the control operation.

A comparison between the proposed controllers (fuzzy gains scheduling of PI controller and the fuzzy gains scheduling of PI controller optimized by genetic algorithms) is shown in fig. 21. In Fig. 21, it can be observed that the speed response of the optimal fuzzy scheduler of PI controller present best tracking responses and very robust characteristics and better that other conventional controller.

Fig. 18 shows the simulation results of the system with the adaptive FLC-PI optimized by GA when the machine is operated in delicate conditions such as disturbance application (T_l=5xT_{lN}) in the instant *t=0,5sec* and application of very low speed reference (*w_r=20rad/sec*) at *t=1sec.*

A test of robustness was also carried out by an increase in 300% of the rotor resistance of the machine (R_r) (Fig. 19) and of 70% of its moment of inertia (J) (fig. 20). The figures show that the proposed controller gave satisfactory performances thus judges that the controller is robust.

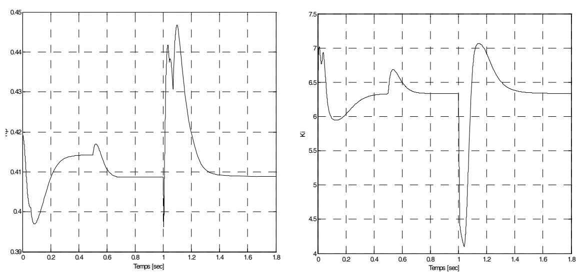

Fig. 14 Parameters variation of the adaptive PI controller using fuzzy inference mechanism.

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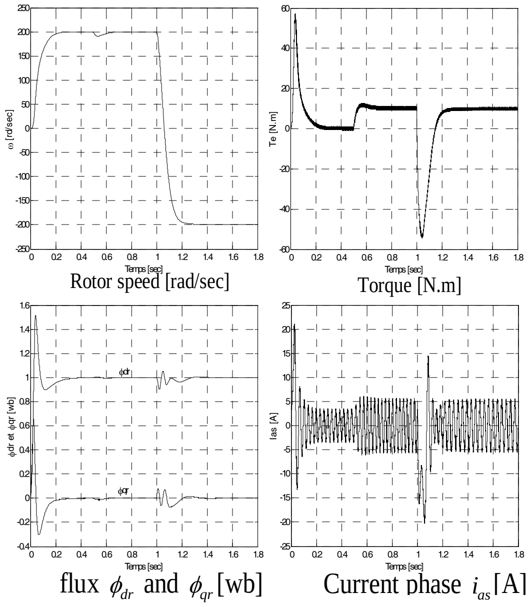

Fig. 15 Simulated results of adaptive PI controller using fuzzy system of IM control.

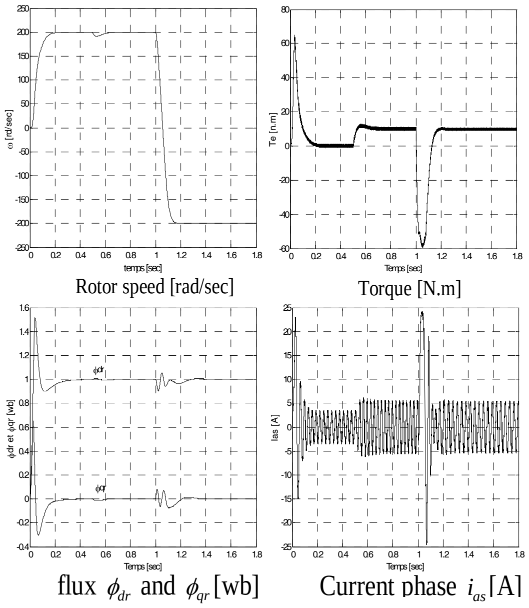

Fig. 16 Simulated results of adaptive PI controller using fuzzy system optimized by GA of IM control.

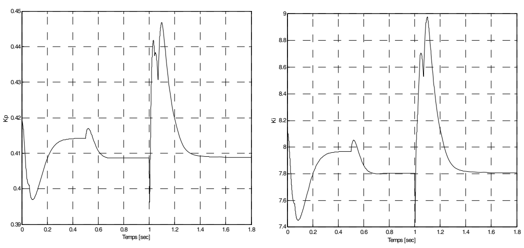

Fig. 17 Parameters variation during simulation test of the adaptive PI controller by optimal fuzzy inference mechanism.

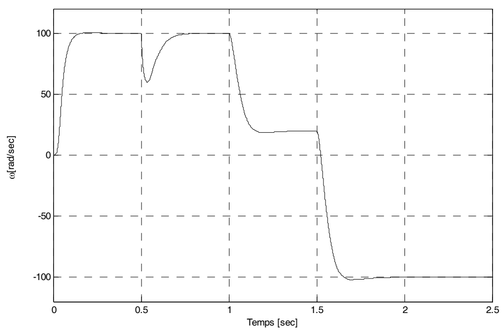

Fig. 18 IM speed control with FLC-PI optimized by GA in delicate conditions.

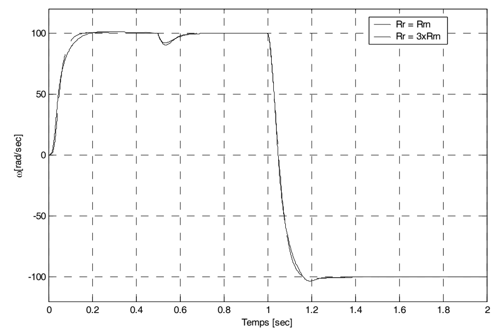

Fig. 19 The IM rotor speed control with adaptive FLC-PI optimized by GA for two different R_r.

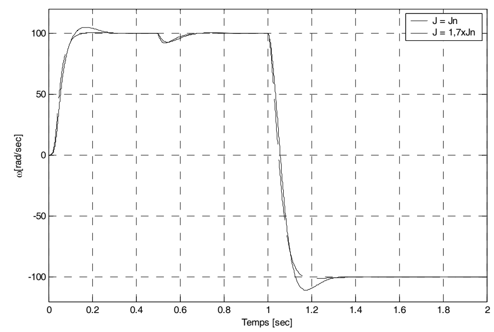

Fig. 20 The IM rotor speed control with adaptive FLC-PI optimized by GA for two different J.

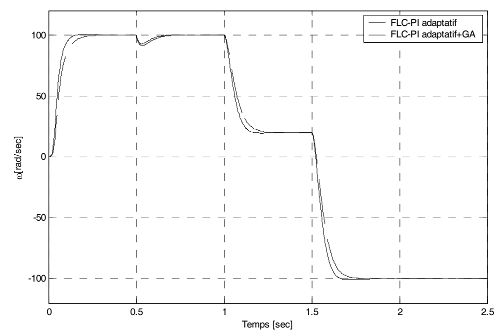

Fig. 21 Simulated results comparison of adaptive PI using fuzzy inference and adaptive PI using fuzzy inference optimized by GA of IM.

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6. CONCLUSION

In this work, we proposed a method of combination between the fuzzy controller and conventional PI controller in order to overcome the disadvantages of PI controllers and FLC, this combination gave us an adaptive PI controller which presented satisfactory performances (no overshoot, minimal rise time, best disturbance rejection). The major drawback of the fuzzy controller is the insufficient analytical design technique (choice of the rules, the membership functions and the scaling factors). That we chose with the use of the genetic algorithm for the optimization of this controller in order to control IM speed. In the system, GA is used to design an adaptive PI controller using fuzzy controller with optimal parameters. The optimal fuzzy gains scheduling of PI controller is used to achieve robust performance against parameter variations and external disturbances. The control dynamics of the proposed hierarchical structure has been investigated by numerical simulation. Simulation results have shown that the proposed optimal controller is robust with regard to parameter variations and external load disturbance (no overshoot, minimal rise time, best disturbance rejection). Finally, the proposed controller provides drive robustness improvement and assures global stability.

APPENDIX

Table V: Induction motor parameters

P_n [Kw]	1.5	I_{an} [A]	6.31	L_s [H]	0.274
V_n [V]	220	R_s [Ω]	4.85	f_n [Hz]	50
η	0.78	R_r [Ω]	3.805	J_n [kg/m^2]	0.031
Cosφ_n	0.8	L_r [H]	0.274	f_c [Nm.s/rd]	0.0014
ω_n[min^{-1}]	1428	L_m [H]	0.258	p	2

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