Induction Motor Drives Control Based on Hybrid Genetic Algorithm Fuzzy Controller

Qussay Salim Tawfeeq
Electrical and Electronic Engineering Department
University of technology-Baghdad

Abstract
The nonlinearity and time varying characteristics of an Induction Motor (IM) make it very difficult to be controlled. although PID controller are widely used in this field but the complex mathematical model of (IM) makes the design procedure of any PID controller very tedious ,in which the time varying behavior of (IM) reduces the accuracy of any PID controller used. The use of Fuzzy Logic Controllers (FLC) in such control problem is widely used too, since Fuzzy Logic does not need any mathematical model and only uses linguistic rules that are based on human expert . However, still checking the parameters of (FLC) is a hard task for such a system specially the center and width of the used member ship functions.
In this paper a Hybrid Genetic Based (FLC) is introduce to control the (IM). The Parameters measurements of (IM) has been carried out using Genetic Algorithm (GA) based technique in which only transient speed measurement is required for an easy, fast and effective identification of all the require machine parameters under the required operative condition as shown in the given results.

Keywords—Genetic Algorithm, Fuzzy Logic Control, Internal Model Control, Induction Motor

الخلاصة
الصفات اللاخطية والمتغيرات بالزمن الموجودة في المحركات الحثية تجعل عملية السيطرة عليها صعبة جدا بالرغم من ان المسيطرات التفاضلية التكاملية التناسبية (PID) تستخدم بكثرة في هذه المجالات لكنها تحتاج الى نموذج رياضي محكم مما يجعلها خيار غير جيد في حالة السيطرة على المحركات الحثية وفي هذه الحالة تخرج النتائج غير دقيقة.

تم استخدام مسيطرات المنطق المضبضب بكثرة في هذه الحالات لانها لا تعتمد على نموذج رياضي للمنظومة ، ولكنها تعتمد على قوانين لغوية ماخوذة من الخبرة البشرية ، ولكن اختيار معاملات المسيطرات تبقى عملية صعبة وتعتمد على صدفة الاختيار وبالاخص دالة العضوية لهذه المسيطرات.

في هذا البحث ،مسيطر مضبب معتمد على خوارزمية الجينات تم استخدامه للسيطرة على المحرك الحثي ،حيث تم قياس معاملات المحرك الحثي باستخدام الخوارزمية الجينية لكي تنقل قياسات السرعة بطريقة سهلة وسريعة وفعالة الى الميسطر، وهذا ما يمكن رؤيته في النتائج الموجودة في هذا البحث.

1. Introduction
For many years PID controllers have been used for the control of (IM) process. Tuning of PID controllers is needed to obtain the satisfactory performance. There are many methods for tuning PID gains namely Ziegler-Nichols (ZN), Cohen and Coon (CC), Internal Model Control (IMC) and Performance criteria optimization. Ziegler-Nichols tuning is one of the most widely used method to tune the PID controllers. In all these methods the precise mathematical model for (IM) is needed and the design procedure is complicated [Leonard 1997, Shaw 1999, Cincirone 2005] .

The adaptive learning algorithm of Universal Learning Network (ULN) represents the modeling and control of nonlinear black box systems with large time delay [Zurada 1996]. The main difficulty in control is due to the disturbances and parameter uncertainties. The fuzzy set theory is particularly useful for application in control with uncertainties [Cincirone 2003]. In recent years, there have been several applications of Genetic Algorithm to control of dynamical systems. Genetic Algorithm (GA) [Reznik 1997] is a parallel, global search technique based on the concept of natural selection. This technique has the capability to solve nonlinear and complex optimization problems.

The main issue in the evolutionary design of fuzzy systems using GA is their genotype representation. The rules are encoded into the chromosome while fixing the membership function [Trentin 2006]. Each membership function is represented by several critical points and GA is used to evolve the membership function using all the possible rules [Crockett 2006, Abu-Rub 2006]. Since in a fuzzy system the membership function and rule set are co-dependent, they should be designed or evolved at the same time. Homaifar [Devaraj 2005] proposed that GA is used to tune the membership function and evolve the rule set at the same time.

There are some drawbacks in doing so: first, the computational efficiency associated with fuzzy logic is lost using a high number of rules [Astrom 2001, Gen 2000] and second, the robustness decreases with the increasing number of rules. In most applications, not all the possible rules need to be used; only a portion of the rules are needed. In this paper, a method for optimal design of a fuzzy logic controller using genetic algorithm is proposed that can evolve the rule set and the membership function simultaneously.

To obtain good performance from a vector controlled induction motor (IM) drive [Leonard 1997] it is very important to have an accurate knowledge of the electrical and mechanical parameters of the machine under all operating conditions. However, in reality the motor parameters are only approximately known from manufacturer's data and standard tests. The use of optimization techniques for machines parameters estimation has been investigated in the literature; for example the Levenburg-Marquardt method [Shaw 1999], Least-Square strategy [Shaw 1999]-[Zurada 1996], and Genetic Algorithms (GA) [Cincirone 2003]-[Reznik 1997] [Trentin 2006].

2. System Description and Model Development.

The genetic algorithm [Abu-Rub 2006]-[Astrom 2001] uses the principles of natural selection and genetics from natural biological systems, in a computer algorithm, to simulate evolution. Essentially the GA is an optimization technique that performs a parallel, stochastic, but direct search that evaluates more than one area of the search space and can discover more than one solution to a problem. A "fitness function" measures the fitness of an individual (possible solution) to survive in a population of individuals.

The genetic algorithm will seek the solution that minimizes the fitness function, generating at each step a new generation of solutions using the operations of mutation and crossover and selecting the best individuals for the population at the following step. At initialization a specified number of individuals and generations are chosen with the first population of individuals being generated randomly. The individuals are then tested and a fitness value is associated to each of them. Through the genetic operation of selection the individuals with the higher fitness value will have a higher probability to be selected in the population at the following step. Once the selection procedure has terminated, the genetic operations of mutation and crossover are used to create the new generation of individuals starting from the selected individuals.

Once the new generation is created, each individual is again tested and the whole procedure is iterated. The algorithm will update the best individual at each generation.

The search procedure will terminate when a fixed termination criteria (maximum number of generations or a target error) is fulfilled. Using a GA procedure off-line, the electrical and mechanical parameters of the IM are estimated [Trentin 2006] and recorded against the d-axis motor current, id, which is used to define the different drive operative conditions. The improved vector control therefore implements the accurate machine parameters with values varying as a function of the drive operating conditions. A similar GA routine has been used for the system control optimization. The parameters of torque current, flux current and speed controllers are coded into a string. Each of these strings represents an individual; a possible solution for the optimization problem.

During the optimization the program will recursively run a Simulink simulation of the experimental drive under test and evaluate each of the individuals in the current population. Using the simulation results, a fitness value will be associated to all the individuals. The search procedure will then continue and will terminate when the fixed maximum number of generations is reached. The final output of the procedure will be an optimum set of parameters with minimized fitness function. The evaluation of the fitness function (FF) in this work is made by weighting the transient overshoot value (OS), the rise time (tr) and the steady state error (e_{ss}) relative to the output voltage DC component in the dq reference frame:

$$FF=Ko*OS + Kr*tr + Ks*e_{ss} \quad (1)$$

The gains, K_o K_r and Ks, can be chosen according to the importance given to the optimization of each of the three performance factors for the final system response based on the target application. The algorithm will try to minimize (1). The control parameters were found for a range of operating conditions (id values) of the IM. The result was therefore a set of parameters for the controllers, each one chosen for the level of saturation of the IM. Through a curve fitting technique the parameters of each controller can be described and implemented with a function which selects the optimized control action for the current operating condition.

3 Identification of IM parameters.

The unknown electrical parameters of the IM are the rotor resistor (RR), the magnetizing inductance (Lm) the leakage inductance of the stator (L1) and rotor (L2). The stator resistor (RS) is assumed to be known because it is easy to measure. The unknown mechanical parameters are the rotating system inertia (J), the friction (B) and the viscosity of the oil (υ) which cools the IM. To reduce the number of unknown mechanical parameter a particular experimental test was carry out on the motor. This test consists in accelerating the IM up to a certain speed, disconnecting the supply and leaving the IM to naturally decelerate. From this test it was possible to estimate the relation between the mechanical parameters, so effectively only one parameter is unknown.

Fig.1 shows the block diagram of the vector control scheme used to control the IM. A standard αβ model in the stator reference frame was used in the motor simulation. A measurement of the speed transient was taken running the motor using the vector control with the parameters supplied by the IM manufacturer and the first guess control parameters given in Table1. Using a GA routine [Trentin 2006] it was possible to estimate the IM parameters as a function of the flux producing current, i_d.

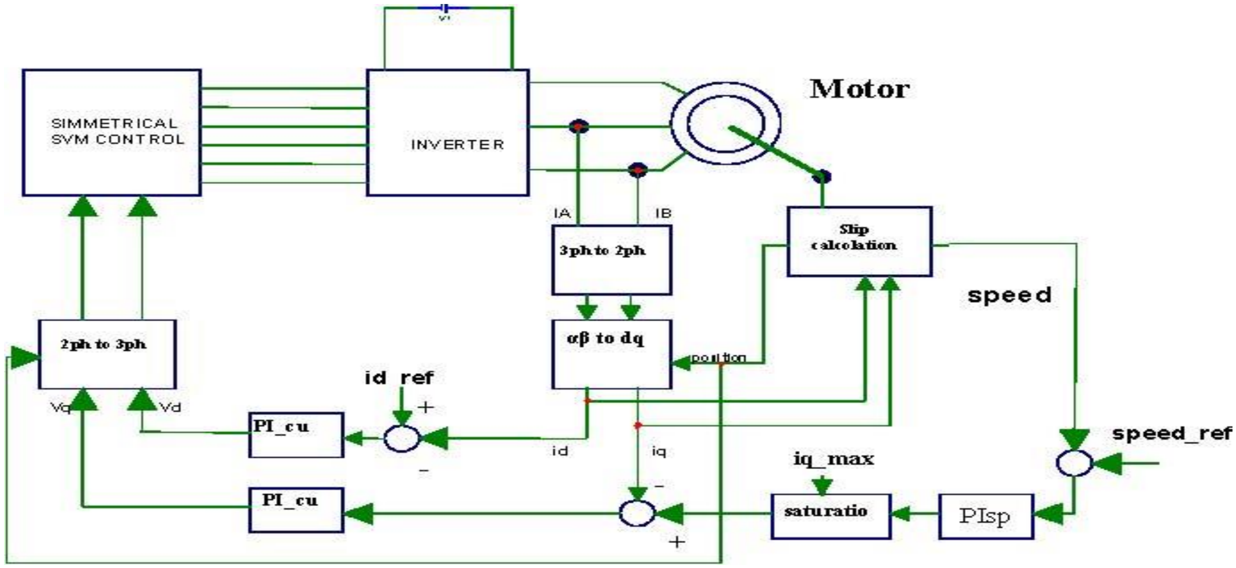
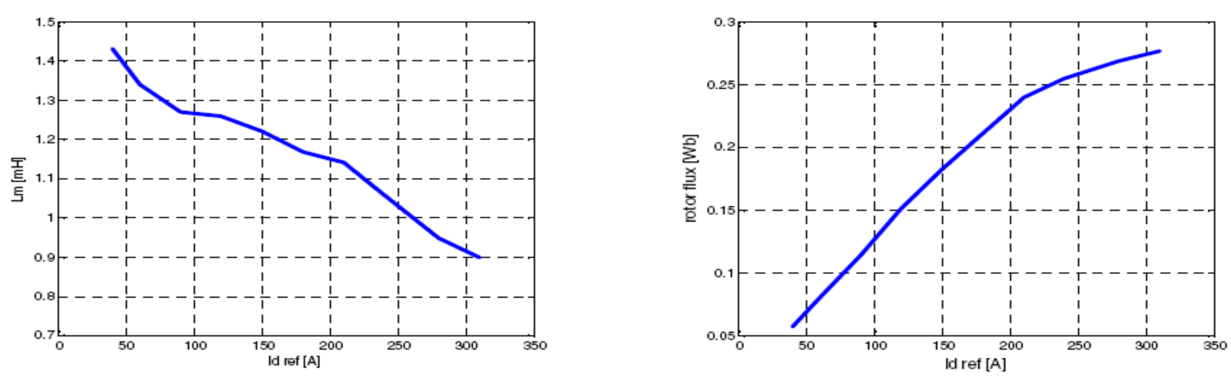


Fig. 1: Block diagram of the vector control used to estimated the parameter of the induction machine

Table I: Motor characteristics and Control Parameters

Type	AC induction		Sample time	250[μsec]
Cooling	Oil		"speed of current loop"	250[μsec]
Rated speed	0-15000 [rpm]		"speed of speed loop"	0.01[sec]
Continues torque	1350 [Nm]		Integral part of current. PI	53
Continues Power	410 [kW]		Proportional part of current PI	0.083
Stator resistor R_S	0.003475 [Ω]		Integral part of speed PI	6
Rotor resistor R_R	0.0034 [Ω]		Proportional part of speed PI	5
Magnetizing Inductor L_m	0.96 [mH]		Id_ref (range)	40-310[A]
Stator leakage inductor L_1	35 [μ]		Iq_ref (range)	20-50[A]
Rotor leakage inductor L_2	26 [μ]		Speed reference (range)	80-200[rpm]

Figure 2 shown the behaviour of the magnetizing inductance, Lm, and the rotor flux as a function of the demanded flux producing current, id-ref. The parameters of the motor selected by the GA are shown in table II for an i_{d_ref} of 270A.



(a) (b)

Fig. 2: Value of Lm (a) and rotor flux (b) in function of I_{d_ref} found by the GA

Table II: Motor parameters optimized by the GA at the beginning of the saturation region

Inertia J	1.1 [kgm^2]
Friction B	1.07e-3 [Nms]
Viscosity υ	6.42e-6 [kgs^2]
Rotor resistor	0.00366 [Ω]
Magnetizing inductance L_m	0.96 [mH]
Stator leakage L_1	30 [µ]
Rotor leakage L_2	50 [µ]

4 Identification of the control parameter for all saturated conditions

During the optimization test the IM was controlled with a traditional rotor flux-based vector control algorithm using approximate parameters values. Once the accurate parameters of the IM have been derived using the GA in different operating conditions (as a function of the d-axis motor current, id), it is possible to increase the complexity of the vector control algorithm [Crockett 2006] based on the rotor flux control to further improve the control performance. Furthermore, using another offline GA routine, it was possible to further optimize the controller design. Because the values found from the GA routine are still estimations of the real parameters, the control presented in this paper does not take into account any feed forward compensation. The removal of the feed forward terms is meant to reduce the number of parameter to be used in the control to assist the GA in reaching an optimized solution.

Figure 3 shows the block diagram for the system simulation used by GA to find the optimum parameters for the current control loop. The model of the IM is the same as for the previous simulations. The electrical and mechanical parameters presented do not have a large variability as Id_ref changes and therefore are assumed to be constant. A GA search has been run for different values of Id_ref giving a set of optimized parameters for the PI controllers (proportional and integral gains) which can then be used under different operating conditions

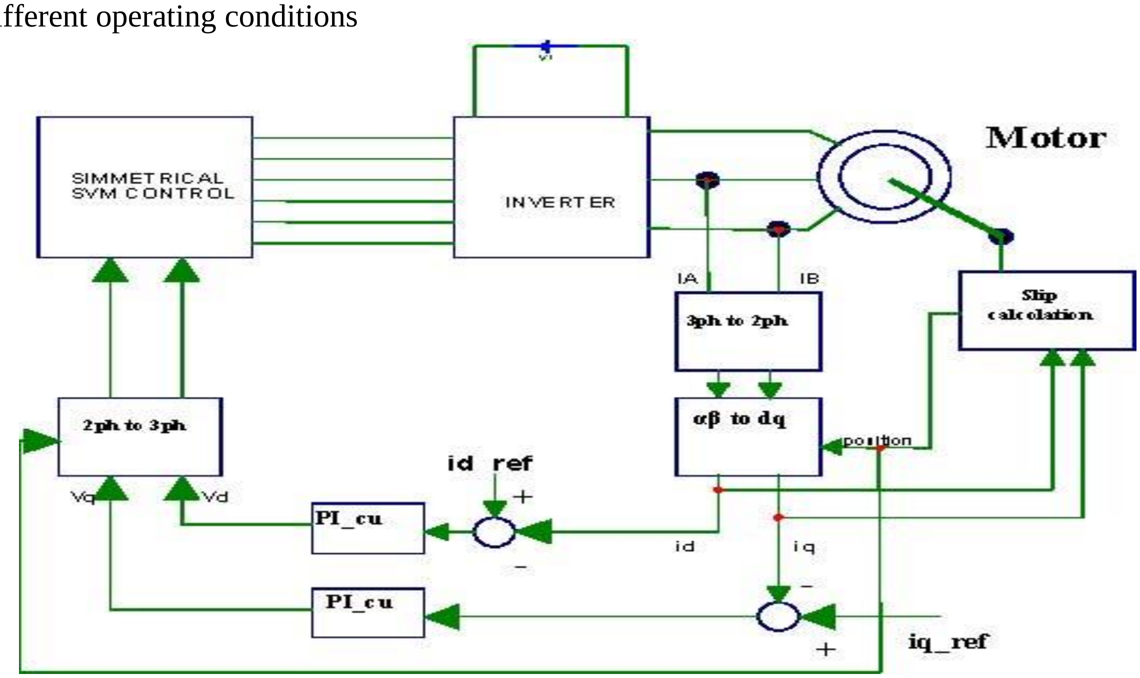
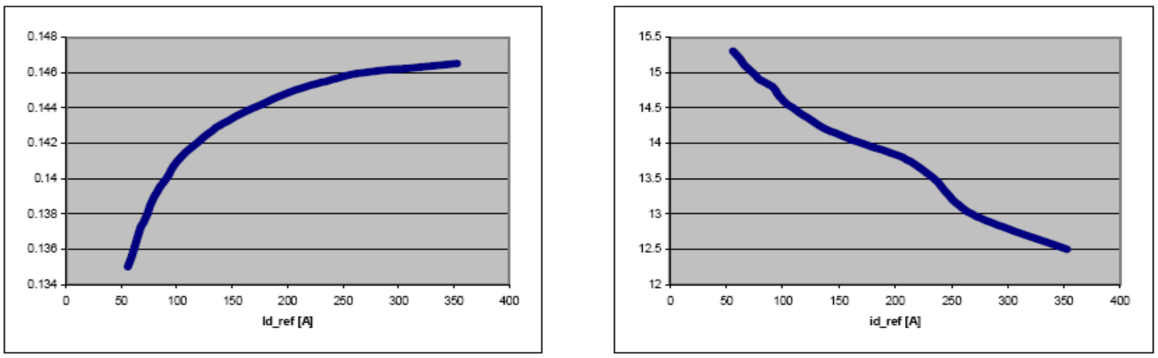


Fig. 3: Block diagram of the control used for the optimization of the current PI

With similar simulation models and using the same principles, the GA routine has been used to optimize the parameters of the PI controller of the speed and flux control loops. Figure 4 shows the result of the GA search for the control parameters which have a relevant variation as the magnetizing inductance varies: (a) the value of the proportional part of the PI of the current loop and (b) the value of the integral part of the PI of the speed loop in function of the id_ref.



5 (a) flux producing current control loop (b) speed control loop

Fig. 4: Proportional part and Integral part of the PI found by the GA

Figure 5 show the complete block diagram of the vector control scheme for the control of the IM which has been implemented on the laboratory based test rig. In this control scheme there are four PI controllers for the speed, flux and the two currents on the dq reference frame. The rotor time constant necessary to implement the rotor flux control is not constant, so this variable has been tabulated from previous experimental and simulation tests in the same way as the PI controller parameters. The saturation level for the current controllers is a function of the maximum current limit of the inverter and therefore the maximum value of iq is a function of id. The saturation of the control output voltage on the d axisis a function of the DC link voltage while on the q axis is function of the DC link voltage and the control output voltage on the d axis Ed_ref [Crockett 2006].

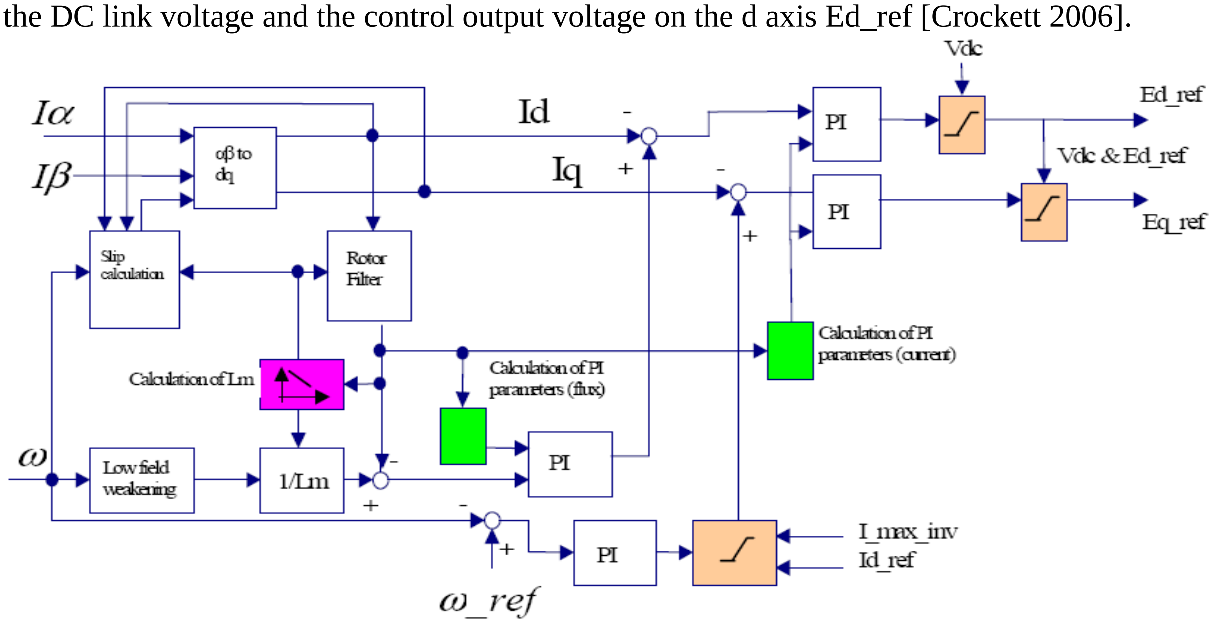


Fig. 5: Block diagram of the vector control scheme

6. Genetic Algorithm Implementation.

When designing a Fuzzy Logic Controller using Genetic Algorithms [14], the following issues are to be addressed

6.1 Representation

The representation strategy is how to encode the variables into the chromosome. The representation of rules used in this paper has three sections: rule selection, representation for the input variables and the representation for the output variables. The rule selection bit may be zero or one. one represent the selection of the rule. Depending on the ranges of the input variables and output variable, number of bits has been chosen for representing each rule of the rule set. The input variables of the pH process are error and the rate of change of error and output variable is base flow rate are consider for fuzzy variables. Five membership functions are allotted for each input and output variables. The input variables are represented by IP1 and IP2 and the output variable is represented by OP.

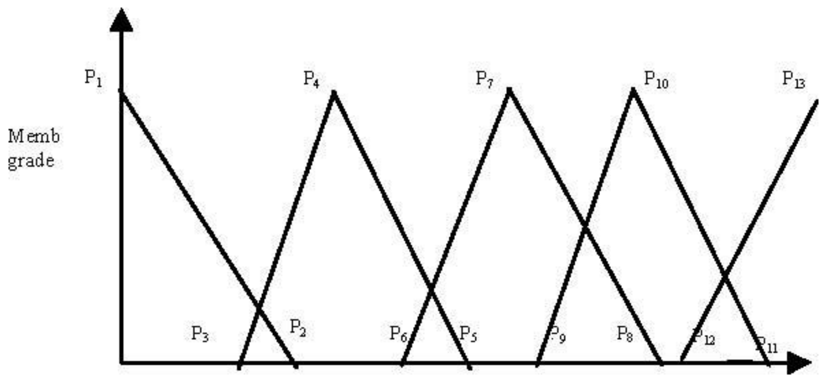


Fig. 6. Fuzzy Space.

Triangular membership function is used in this paper. Each membership function is represented by five membership points with overlap between each membership function as shown in figure 2. A total of 13 membership points (P1 to P13) are required for representing each input variable as a fuzzy set. In those thirteen points, first and last points (P1 and P13) are fixed. The remaining eleven membership points are evolved between the dynamic ranges such that P2 has [P3, P13], P3 has [P1, P13], P4 has [P2, P3], P5 has [P6, P10], P6 has [P4, P7], P7 has [P5, P13], P8 has [P9, P13], P9 has [P5, P10], P10 has [P7 P13] ,P11 has [P12 P13] and P12 has [P8 P13]. With the above representation a typical chromosome will look like the following:

$$\underbrace{\underline{100}}_{IP_1} \quad \underbrace{\underline{001}}_{IP_2} \quad \underbrace{\underline{011}}_{OP}$$

$$\underbrace{\underline{110}\ \underline{010}}_{P_1\ P_2} \quad \underbrace{\underline{011}\ \underline{111}\ \underline{100}}_{P_3\ P_4\ P_5} \quad \underbrace{\underline{011}\ \underline{111}}_{P_6\ P_7} \quad \underbrace{\underline{100}\ \underline{011}\ \underline{111}}_{P_8\ P_9\ P_{10}} \quad \underbrace{\underline{100}\ \underline{100}\ \underline{001}}_{P_{11}\ P_{12}\ P_{13}}$$

MF_1 MF_2 MF_3 MF_4 MF_5

6.2 Fitness Function

The next important consideration is the choice of fitness function. Evaluation of the individual is accomplished by calculating the objective function value for the problem using the parameter set. The result of the objective function calculation is used to calculate the fitness function of the individuals. The Integral Square Error, settling time and over shoot are taken as performance indices and the objective function is given by minimize

$$f = f_{ISE} + fos + fst \tag{7}$$

The minimization objective function given by (12) is transformed to fitness function as

$$\text{Fitness}=\frac{k}{1+f} \tag{8}$$

Where k is a constant. In the denominator a value of 1 is added with f in order to avoid division by zero.

7. Simulation Results

The GA-based algorithm is applied to find the optimal parameters of the Fuzzy controller. The objective function in this pH process is minimization of error. The optimization variables are represented as binary numbers in GA population. The initial population is randomly generated between the variables lower and upper limits. Tournament selection is applied to select the members of the new population. The performance of GA for various values of cross-over and mutation probabilities in the ranges 0.6-1.0 and 0.001-0.1, was evaluated. The Descriptions of the IM variables with corresponding symbols and its values are given in Table.1.The best results of the proposed GA are obtained with the following control parameters. Number of generations = 30, Population size = 20, Crossover probability = 0.8, Mutation probability = 0.08. The GA took 20s to complete the 30 generations. After 30 generations, it is found that all the individuals have reached almost the same fitness value. This shows that GA has reached the optimal solution. Fig.3 shows the convergence of proposed GA algorithm. It is observed that the variation of the fitness during the GA run for the best case and shows the generation of optimal variables. It can be seen that the fitness value increases rapidly in the first 5 generations of the GA. Then the value increases slowly, and settles down near the optimum value with most of the individuals in the population reaching that point. The optimal membership functions of error, rate of change of error and the feed flow rate are shown in Fig.7 and Fig.8 respectively. First, the GA is used to optimize the square-wave tracking performance of the inner loop of the i_{sd} current, measured by means of the IAE (Integral Absolute Error) of i_{sd} with respect to its reference i_{sd}*. This operation requires less than one minute, due to the very short transients of the current. Fig. 9 (a) shows the 'sd current response of the randomly generated controllers in the first iterations (first row) and after GA convergence (second row). The second optimization task regards the flux controller. In this case the objective is to minimize the weighted sum of two terms. The first one is the tracking IAE of the flux with respect to its reference for a square wave of period T= 0.5s. The second term integrates the absolute difference between the control action filtered by a first-order linear filter with time constant T=0.02 s, and the unfiltered actual action i_{sd} (t) itself. This term, hereafter called smoothness index (SI), is intended to penalize controllers with an excessively oscillatory control action which may cause stresses for the IM producing vibrations, and extra losses. As shown in table II, the SI is multiplied by a factor β introduced for normalization purposed. The effects of the GA optimizations are visible in fig.9(b), which provide the details of the steady-state flux behavior. Even through ripples are very small since the beginning of tl$\tau_{\Sigma\omega} = \tau_{is} + \tau_{fw} + \tau_{sh}$ e nervousness of the flux influences the i_{sd} response (as shown in fig. 9(c), first row). The results of the automated optimization are illustrated in Fig.10, which reports the i_{sq} current (a) at the beginning and (b) at the end of the GA evolution. The last optimization step regards the speed response. In this case, the setpoint is a square wave with period T=1.4 s and amplitude equal to the rated speed. After 0.5s from every change of the reference signal, a step change of load torque (from 0 to 70% of motor rated torque) is applied. In order to evaluate also the overall disturbance rejection. Fig. 10 (b) first row shows the final speed response of the optimized control system and Fig. 10 (c) first row reports the i_{sq} response during the same experiment. To give a detailed idea of the progress of GA search, Fig. 11 (a) shows the evolution of the fitness function and the proportional gain of the speed controller (the trends of the other parameters are similar, and thus omitted for brevity) in a typical GA run. The effects of non persistent elitism are clearly visible in these figures (notice the discontinuities in the thick line representing the elitist individual). It is worth noting that the optimization algorithm converges in a very short time in spite of the noisy experimental fitness measurements. To provide a quantitative comparison with other available design strategies, Fig. 11(b) and (c) compare the result of a cascaded control system obtained with the GA with a one designed with the IM model and adopting standard controller synthesis techniques. In particular, the gains of the current controllers have been selected so as to achieve a first order closed loop response with time constant equal to τ_{is}= 11.2ms, and the speed loop has been approximated with a first order system having time constant (i.e equal to the sum of all the delays found in the speed control loop, namely the current control τ_{is}, the speed low pass filter τ_{fw}, and the delays due to the digital implementation τ_{sh}).

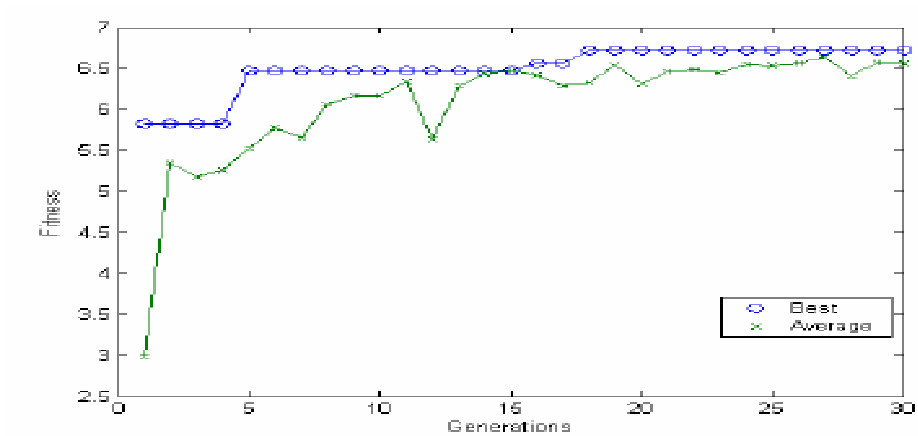


Fig. 7.Convergence of proposed GA

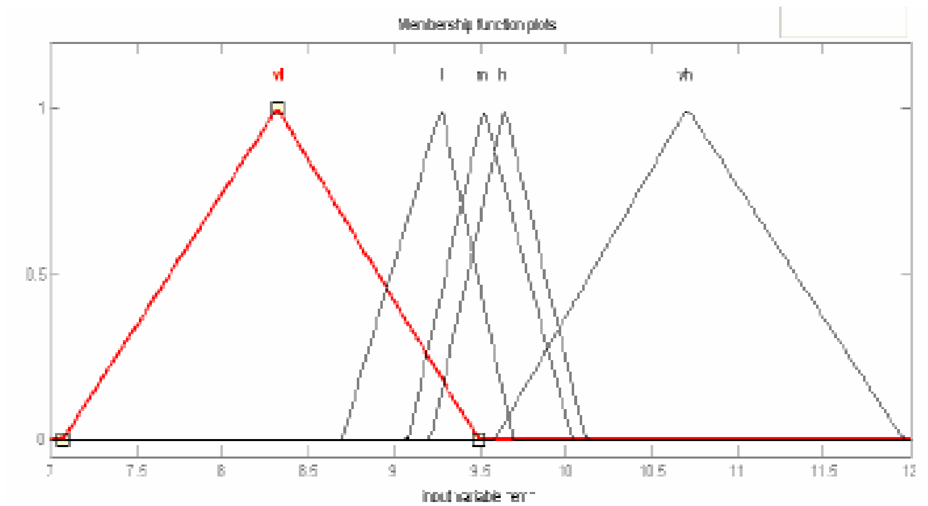


Fig. 8. Optimal design of error

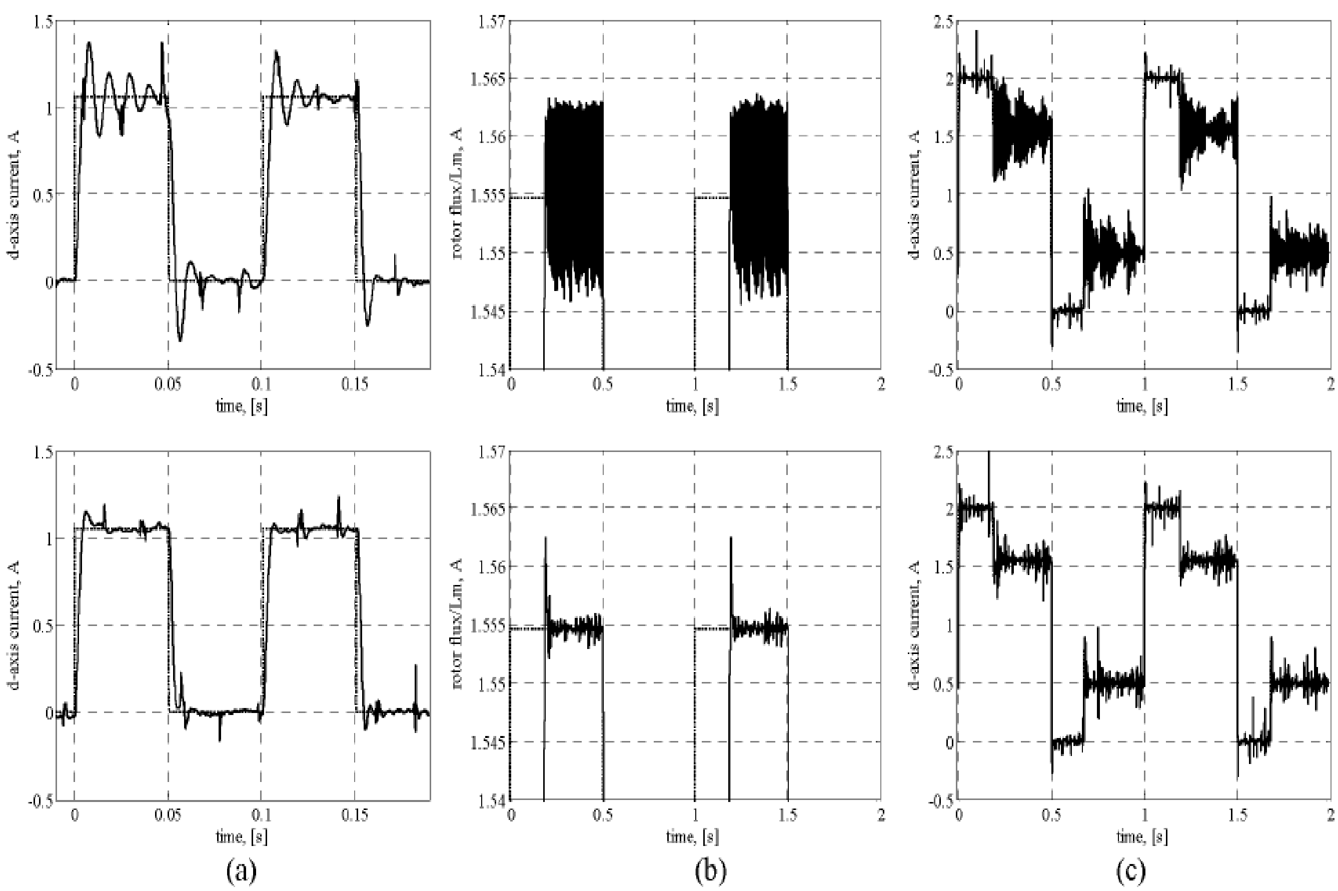


Fig. 9. Comparison of signals at the beginning (first row of figures) and at the end (second row) of the GA evolution. Namely, figures show (a) i_{sd} current during the first inner-loop optimization, (b) rotor flux during the second loop optimization and (c) i_{sd} current during the flux control loop optimization.

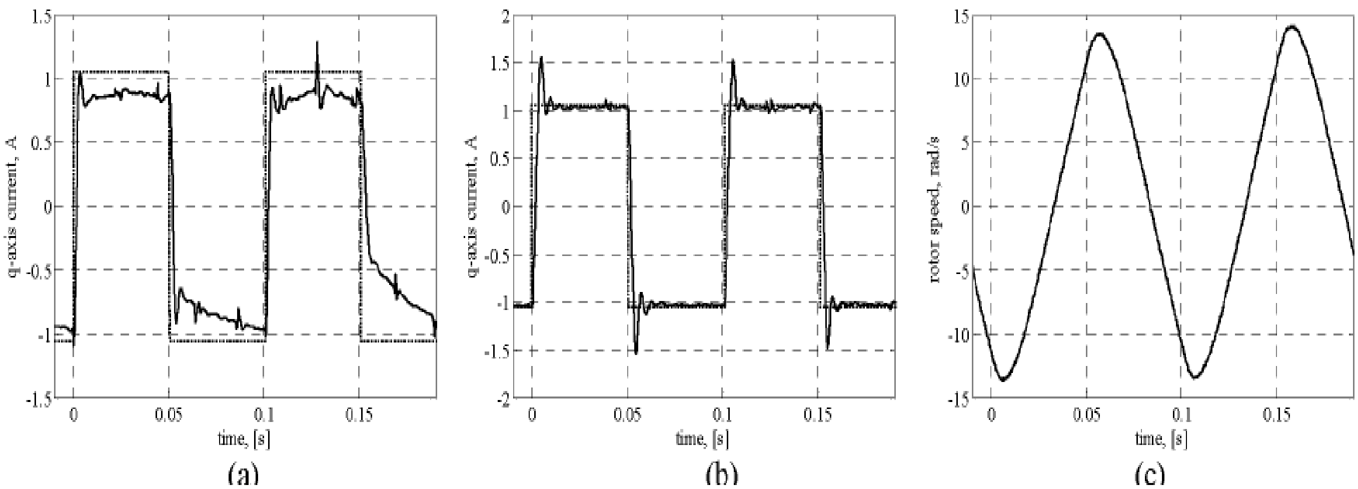


Fig. 10. Comparison of the i_{sq} current (a) at the beginning and (b) at the end of the GA evolution. The figure (c) shows the speed oscillations occurring during i_{sq} tuning, which remain below the 400 of the rated speed.

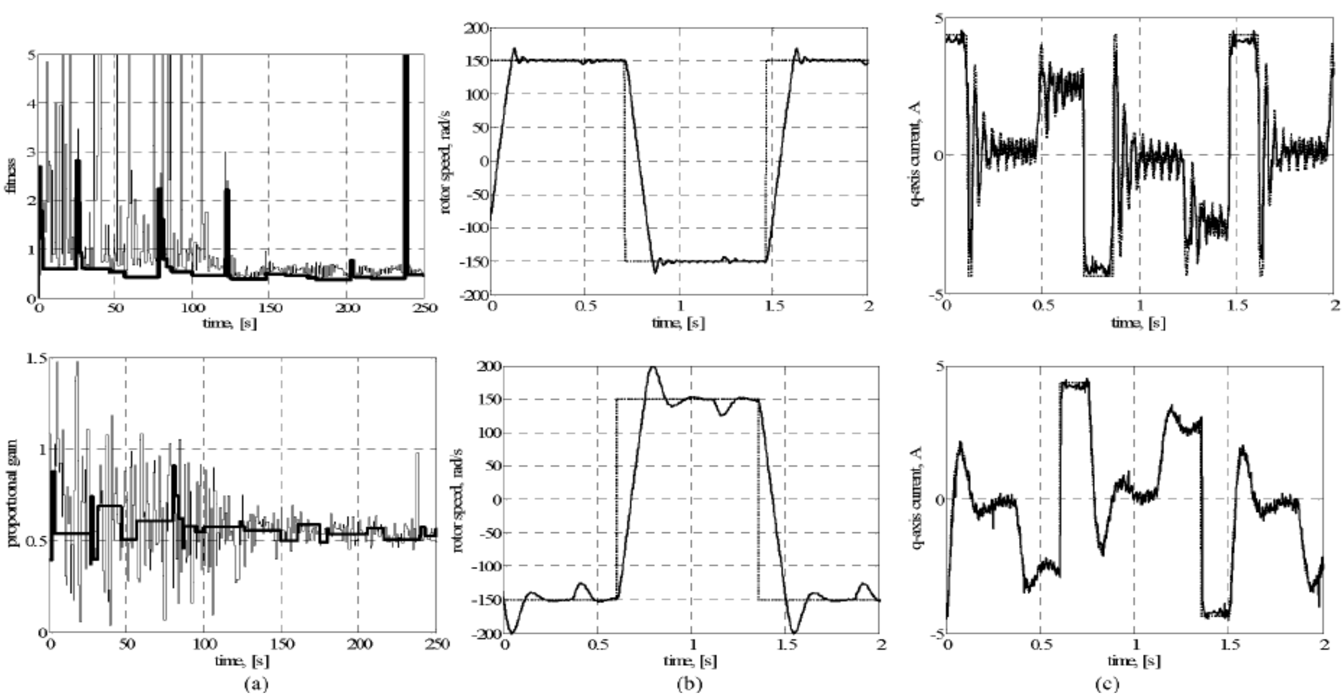


Fig. 11. The figures in the column (a) trace the trends of the fitness values (first row) and proportional gain (second row) associated to the generic (thin line) and elitist (thick line) individuals over evolution time. Moreover, subfigures in column (a) and (b) compare the speed and current responses obtained with GA (first row) and linear design (second row).

8- Conclusion

This paper proposed an effective automatic design procedure for IM based on GAs. The proposed evolutionary algorithm exhibited a satisfactory behavior, with reduced computational requirements and repeatable and generally accurate results. As in the case of population-based GAs, a real-coded implementation of a GA in an interesting tradeoff between simplicity of the code, interpretability of the probability vectors and chromosomes, and accuracy of the final solutions. The optimized flux-based vector control for a high power induction motor drive thanks to the accurate knowledge of the machine parameters using a new effective and reliable parameter estimation method based only on speed transient measurements.

The proposed method uses a Genetic Algorithms heuristic optimization. The same Genetic Algorithms routine is also used to optimize the control loops required for the vector control of the IM. Having proved the reliability of this technique and showing excellent agreement between the simulation and experimental results, it was possible to improve the vector control scheme by using a rotor flux estimator, which gives significant benefits especially during the field weakening. The proposed a Genetic Algorithm for obtaining the optimal design of the Fuzzy controller. In the proposed approach, the development of rule base and the formation of the membership function are evolved simultaneously. The performance of the algorithm in obtaining the optimal values of Fuzzy controller parameters has been analyzed in IM through computer simulation. The simulation result shows the proposed GA is able to optimize the Fuzzy controller satisfactorily and show the better performance compared to fuzzy logic control and Internal Model Control.

References

Abu-Rub H., Schmirgel, H. Holtz: J. (2006). "Sensorless control of induction motor for maximum steady-state torque and fast dynamic at field weakening" IEEE IAS Tampa

Astrom K.J. and Hagglund, T. (2001). "The future of PID control", Control Engineering Practice, pp.1163– 1175.

Cincirone M., Pucci, M. Cincirone, G. Capolino: G. A. (2005)"Constrained Minimization for Parameter Estimation of Induction Motor in Saturated and Unsaturated Conditions", IEEE Trans. on Ind. Electronics, vol. 52, No. 5, October 2005, pp. 1391-1401

Cincirone M., Pucci, M. Cincirone, G. Capolino: G.A. (2003). "A New Experimental Application of Lest-Squares Techniques for the Estimation of the Parameter of the Induction Motor", IEEE Trans. on Ind. Applications, vol. 39, No. 5, September 2003, pp. 1247-1255.

Crockett, K , Bandar, Z. Fowdar, J, O'Shea, (2006). On Producing Balanced Fuzzy Decision Tree Classifiers", IEEE World Congress in Computational Intelligence 2006, Vancouver, Canada. IEEE, pp 8415- 8421

Devaraj D. and Yegnanarayana, B. (2005). “Genetic Algorithm-Based Optimal Power Flow for Security Enhancement”, IEE Proceedings on Generation, Transmission and Distribution, 152(6) pp. 899 – 905

Gen M. and Cheng, R. (2000). “Genetic Algorithms and Engineering Optimization”, New York: Wiley.

Leonard W. (1997). “Control of Electrical Drives”, Springer.

Reznik L., (1997). "Fuzzy Controllers", Victoria University of Technology, Melbourne, Australia Newnes.

Shaw S.R., Leeb: S.B. (1999). "Identification of Induction Motor Parameters from Transient Stator Current Measurement", IEEE Trans. on Ind. Electronics, vol. 46, No. 1, February, pp. 139-149

Trentin A., Zanchetta, P. Wheeler, P. Clare, J. Wood, R. Katsis: D. (2006). “A New Method for Induction Motors Parameter Estimation Using Genetic Algorithms and Transient Speed measurements” IEEE IAS. Tampa

Zurada J.M., (1996). "Introduction to Artificial Neural Systems", Jaico Publishing House, 2^{nd} edition. India.