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Rotor Resistance Estimation of Vector Controlled Induction Motor Drive using GA/PSO tuned Fuzzy Controller

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Abstract: Induction motor with indirect field oriented control is preferred for high performance applications due to its excellent dynamic behavior. However, it is sensitive to variations in rotor time constant, especially variation in rotor resistance which needs to be estimated online. Conventionally the model reference adaptive system with fuzzy logic controllers as adaptation is used, which works satisfactorily for one particular operating condition and fails under variable operating condition. Therefore the need arises for a fuzzy controller whose parameters are tuned using evolutionary algorithm. In this paper, the input/output gain and the membership function parameters of the fuzzy system are optimized using genetic algorithm and particle swarm optimization to obtain an optimal designed fuzzy controller for rotor resistance estimation. The system is investigated in MATLAB/Simulink environment. Results shows that the steady state error in estimation of rotor resistance by the proposed controller under stringent operating condition is better with the proposed controller as compared to the conventional trial and error based fuzzy controller.

Index Terms: Induction motor (IM), Indirect Rotor flux Field Oriented Vector Control (IRFOC), Rotor Flux Model Reference Adaptive system (RF-MRAS), Proportional Integral (PI) controller, Mamdani fuzzy controller, Genetic Algorithm (GA), Particle Swarm Optimization (PSO).

1. Introduction

Traditionally AC machines were used in applications which require only rough speed regulation and where the transient response is not critical [1].The advances in the field of power electronics has contributed to the development of control techniques for AC machine, thus matching its performance with that of a DC machine [2]. These techniques are known as vector control techniques and can be categorized as Direct/feedback field oriented control method and Indirect/ feed forward method [3].

One of the main issues of vector control is its dependence on motor model and is therefore sensitive to the motor parameter variations [4, 5].The variations are mainly due to the saturation of the magnetizing inductance and the stator/rotor resistance due to temperature and skin effect. These parameter variations lead to changes in the flux amplitude and its orientation along the d-axis. The system thus becomes unstable and also increases the losses in the system. It has been studied that the variation of rotor resistance is the most critical in indirect field oriented vector controlled drives [6]. It is therefore necessary to estimate this change, failing which the orthogonality between the synchronous frame $d_e - q_e$ variables is lost, leading to cross coupling and poor dynamic performance of the drive system. Therefore major efforts were put in for online estimation of rotor resistance. Several online parameter estimation techniques are reported in the literature, having some pros and cons as listed in Table-1 below [7].

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Table 1. Online Parameter Estimation Techniques

Name	Working Principle	Pros and Cons
Spectral Analysis	Involves external signal injection into the motor [8, 9].	Need of external hardware circuit. Occurrence of torque pulsation and mechanical resonance in motor drive system.
Observer based technique	The wide band harmonics spectrum present in the PWM voltage fed to the motor is considered as the noise input [10, 11].	Requires no external signal injection. Large memory requirement. Computational complexity. Instability due to linearization and erroneous parameters.
Model reference adaptive system based technique.	Calculation of parameter to be identified in two different ways [12-18]. First based on references inside the control system known as the estimated value. Second based on measured signal known as the reference value.	Simpler implementation and less computation. Accuracy of estimation heavily depends on the machine model.
Artificial Intelligence and Other methods.	Parameter estimation based on fuzzy logic and neural network [19-22]. Other methods include estimation based on voltage measurement across open circuit phase winding using special switching techniques, Using recursive least square method and criterion function based [23-24].	Requires application specific processor. Issues related to sampling time for real time interface.

It is important to note here that [25-27] reviewed Model reference adaptive system based estimation schemes where the adaptation mechanism makes of proportional integral (PI) or fuzzy controller for the generation of the change in rotor resistance ΔR .The PI controller does not give satisfactory performance for operating conditions where frequent variation in motor speed and load torque is required. Fuzzy logic controller when compared with PI controller do not require precise mathematical model , can handle nonlinearity and are more robust, but the drawback is that the success of the controller depends on the knowledge and skill in designing an efficient inference engine.

In this paper the performance of a rotor flux based model reference adaptive system (RF-MRAC) is investigated The RF-MRAC under investigation evaluates the performance of an optimal fuzzy controller based on bio-inspired algorithm and is compared with a conventional fuzzy controller for online rotor resistance identification of an indirect rotor flux oriented controlled (IRFOC) induction motor drive. The parameter values of the input/output gain constants and of the membership functions of the genetic algorithm (GA) and particle swarm optimization algorithm (PSO) tuned optimal fuzzy controller have been determined simultaneously using a performance index related to integral square error of the rotor flux. The main goal is to obtain an optimal fuzzy controller with the objective to: 1) reduce the d-axis flux settling time 2) reduce the steady state error between the actual and reference d-axis flux and 3) to improve the accuracy in estimating the actual change in rotor resistance under four quadrant motor drive operating conditions. Extensive simulation results are presented to show the performance of the optimally tuned fuzzy controller.

The paper is organized as follows: Section 2 provides an overview of the rotor flux model reference adaptive controller and also describes the functions of the various blocks involved in the modeling of the vector controlled I.M drive with the rotor resistance identification scheme. Section 3 describes the fuzzy control scheme as an adaptive mechanism of the rotor flux based model reference adaptive system. Section 4 describes the tuning of proposed optimal fuzzy controller parameters using GA and PSO. Section.5 gives the simulation results and discussion of the proposed optimal designed Mamdani fuzzy controller adaptive scheme under different drive operating conditions and concluding remarks are given in Section 6.

2. Proposed Scheme

A. Basic Structure of MRAC

In the RF MRAC scheme as shown in Figure.1 the reference model computes the flux (Ψr^{v}) using the three phase voltage and current fed to the motor drive and the adjustable model computes the flux (Ψr^{i}) using the current and the speed of motor. The reference model is independent of rotor resistance, whereas the adjustable model depends on rotor resistance. The error signal $\varepsilon = (\Psi r^{v} - \Psi r^{i})$is fed to the adaptation block which makes use of a conventional fuzzy controller to yield the estimated rotor resistance(R_r). In the modified scheme to reduce the detuning effect by accurate estimation of rotor resistance, the conventional fuzzy controller is replaced by an optimal tuned fuzzy controller whose parameters are tuned using GA/PSO as shown in Figure 2.

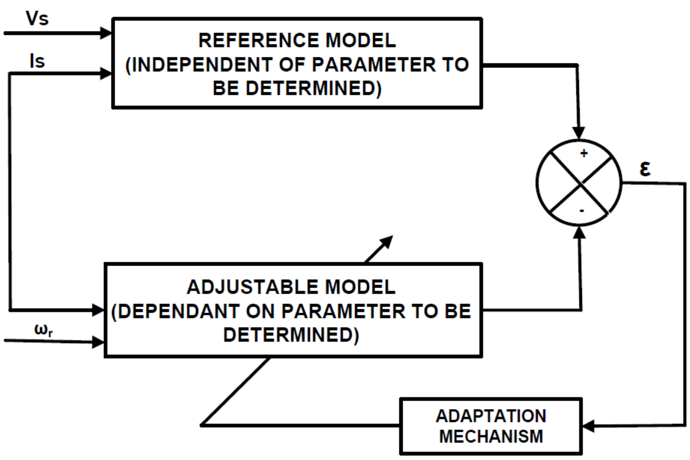

Figure 1. Block diagram of MRAC

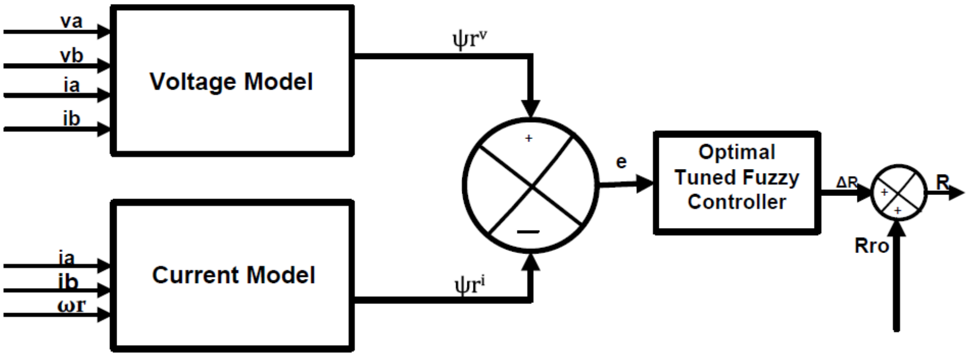

Figure 2. Proposed RF MRAC for rotor resistance estimation

B. Theoretical development of the Proposed Scheme

B.1. Modeling of IRFOC drive

The dynamic model of induction motor for rotor flux oriented vector control application can be written as follows

$$p\begin{bmatrix} id_{se} \\ iq_{se} \\ \lambda d_{re} \\ \lambda q_{re} \end{bmatrix} = \begin{bmatrix} \frac{-Rs}{\sigma Ls} & \omega e & \frac{-Lm}{Lr\sigma Ls}p & \frac{\omega eLm}{Lr\sigma Ls} \\ -\omega e & \frac{-Rs}{\sigma Ls} & \frac{-\omega eLm}{Lr\sigma Ls} & \frac{-Lm}{Lr\sigma Ls}p \\ \frac{Lm}{Tr} & 0 & \frac{-1}{Tr} & \omega sl \\ 0 & \frac{Lm}{Tr} & -\omega sl & \frac{-1}{Tr} \end{bmatrix} \begin{bmatrix} id_{se} \\ iq_{se} \\ \lambda d_{re} \\ \lambda q_{re} \end{bmatrix} + \begin{bmatrix} \frac{vd_{se}}{\sigma Ls} \\ \frac{vq_{se}}{\sigma Ls} \\ 0 \\ 0 \end{bmatrix} \quad (1)$$

where, operator p indicates derivative operator $\frac{d}{dt}$, id_{se}, iq_{se} are the stator currents and λd_{re}, λq_{re} the rotor fluxes in $d_e - q_e$ frame. Similarly Rs, Ls, Rr and Lr are the stator résistance, stator self inductance, rotor resistance and the rotor self inductance respectively. The rotor time constant is given as $Tr = \frac{Lr}{Rr}$ and leakage inductance is σLs where $\sigma = 1 - \frac{Lm^2}{LsLr}$. For rotor flux oriented control the rotor flux λr is directed along the d-axis and is equal to λd_{re} and therefore $\lambda q_{re} = 0$. Thus the equation (1) modifies to as shown below.

$$p\begin{bmatrix} id_{se} \\ iq_{se} \\ \lambda d_{re} \\ 0 \end{bmatrix} = \begin{bmatrix} \frac{-Rs}{\sigma Ls} & \omega e & \frac{-Lm}{Lr\sigma Ls}p & 0 \\ -\omega e & \frac{-Rs}{\sigma Ls} & \frac{-\omega eLm}{Lr\sigma Ls} & 0 \\ \frac{Lm}{Tr} & 0 & \frac{-1}{Tr} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} id_{se} \\ iq_{se} \\ \lambda d_{re} \\ 0 \end{bmatrix} + \begin{bmatrix} \frac{vd_{se}}{\sigma Ls} \\ \frac{vq_{se}}{\sigma Ls} \\ 0 \\ 0 \end{bmatrix} \quad (2)$$

From equation (2) it can be seen that the $d_e - q_e$ axis voltage are coupled by the following terms:

$$v_d\ decoupling = \omega e iq_{se} - \frac{Lm}{Lr\sigma Ls} p\lambda d_{re} \quad (3)$$

$$v_q\ decoupling = \omega e id_{se} + \frac{\omega eLm}{Lr\sigma Ls} \quad (4)$$

To achieve linear control of stator voltage it is necessary to remove these decoupling terms and is cancelled by using a decoupled method that utilizes nonlinear feedback of the coupling voltage.

B.2. Modeling of Rotor Resistance Estimator

The block diagram of an IRFOC induction motor drive with rotor resistance estimation scheme is shown in Figure.3. The scheme consists of the current control loop within the speed control loop. The scheme uses four PI controllers namely the speed controller, flux controller, the d and q axis current controller. The proportional and integral gains of the controllers are calculated using pole-zero cancellation method and are as given in Appendix-1. The bandwidth of the inner current loop is chosen higher than the flux and speed controller.

In order to avoid cross coupling between the *d-q* axis voltages, voltage decoupling equations (3) & (4) are adjusted with the output of the controllers to obtain good current control action. The d-axis and q-axis reference voltages vd_{ref} and vq_{ref} thus obtained are transformed to the stationary i.e. stator reference frame with the help of field angle θ_e.The two phase voltage vd_{ss} and vq_{ss} in the stator reference frame are then transformed to three phase stator reference voltages v_a, v_b, v_c which acts as modulating voltage for the modulator by using the sine-triangle pulse width modulation (SPWM) scheme . The modulator output which is in the form of pulses is used to drive the IGBT with anti-parallel diode acting as switches for the conventional two level voltage source inverter(VSI).

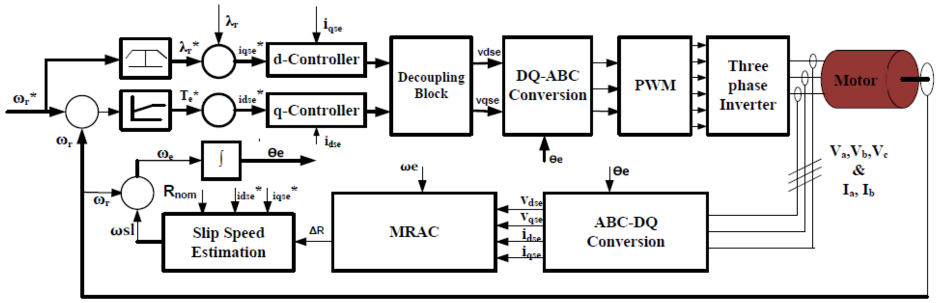

Figure 3. Block diagram of a voltage controlled IFOC drive

As shown in Figure 3 the stator currents are measured and transformed as *d-q* axis currents, which are then used as feedback signals for the current controller. The *d-* axis current id_{se} is passed through a low pass filter with time constant equal to rotor time constant T_r to obtain the rotor flux which acts as feedback input to the flux controller. The rotor speed ω_r, iq_{se}, λd_{re} and rotor time constant T_r are used to determine the rotor flux position θ_e for $e^{-j\theta_e}$ and $e^{j\theta_e}$ transformation.

B.3. Rotor Resistance Identification Using Rotor Flux

The block diagram of the rotor flux based MRAC for identification of rotor resistance is shown in Figure.1, where the inputs v_a , v_b , i_a , i_b and ω_r are the motor terminal voltages, current and speed feedbacks.

The rotor flux Ψr^v obtained from the voltage model which acts as the reference output of the model adaptive reference scheme is obtained by measuring the machine terminal voltage and currents, which are then transformed to the stationary reference frame as vd_{ss}, vq_{ss}, id_{ss} & iq_{ss}. The rotor flux is given by

$$\Psi r^v = \sqrt{\Psi dr^{sv^2} + \Psi qr^{sv^2}} \tag{5}$$

where, Ψdr^{sv} and Ψqr^{sv} are the d-axis and q-axis rotor flux in the stationary reference frame which are derived as:

$$\psi dr^{sv} = \frac{L_r}{L_m}(\psi ds^{sv} - \sigma L_s ids^s) \tag{6}$$

$$\Psi qr^{sv} = \frac{L_r}{L_m}(\Psi qs^{sv} - \sigma L_s iqs^s) \tag{7}$$

given that $\Psi ds^{sv}=\int(vd_{ss} - R_s id_{ss})dt$ and $\Psi qs^{sv}=\int(vq_{ss} - R_s iq_{ss})dt$ are the stator d-q flux in stationary reference frame, σ is the leakage inductance and R_s is the stator resistance. Similarly the flux output

$$\Psi r^i = \sqrt{\Psi dr^{si^2} + \Psi qr^{si^2}} \tag{8}$$

is obtained from the current model for the adjustable model is obtained by measuring the current and motor speed ω_r, where

$$\Psi dr^{si} = \int(\frac{L_m}{T_r} id_{ss} - \omega_r \Psi qr^s - \frac{1}{T_r}\Psi dr^s)dt \tag{9}$$

and

$$\Psi qr^{si} = \int(\frac{L_m}{T_r} iq_{ss} + \omega_r \Psi dr^s - \frac{1}{T_r}\Psi qr^s)dt \tag{10}$$

The difference between ψ_{r^v} and ψ_{ri} acts as the error signal for the adaptive mechanism whose output indicates the change in rotor resistance ΔR which is added up with the nominal resistance value i.e. R_{ro} to achieve the actual rotor resistance R_r.The obtained new value of R_r is then used to determine the slip speed ω_{sl} and is added up with the rotor speed ω_r to obtain the synchronous speed ω_e.

3. Implementation of Fuzzy logic controller

Fuzzy logic controllers based on fuzzy theory are used to represent the knowledge and experience of a human operator in terms of linguistic variables called fuzzy rules. The experienced human operator adjusts the system inputs to get a desired output. The ability of the controller to get the desired control action for complex nonlinear system without the requirement of mathematical model has made it an important and useful tool in controlling nonlinear systems [25, 27].

The generic structure of a Mamdani fuzzy is shown in Figure.4 It consists of two inputs $e_1(k)$ and $e_2(k)$and one output Δu . The input $e_1(k)$ have been selected as the rotor flux error i.e. $e_1(k) = \psi r^v - \psi r^i$ and its time derivative as $e_2(k)$. There are two normalizing factors k1 and k2 for inputs $e_1(k)$ and $e_2(k)$ and one de-normalizing factor $k3$ for output Δu.. The de-normalizing factor $k3$ directly affects the ripple on the controller output because of the structure of the fuzzy-PI controller. In normalization process the input values are scaled in the range [-1, 1] and the de-normalization process converts the crisp output value of the fuzzy controller to a value depending on the output control element.

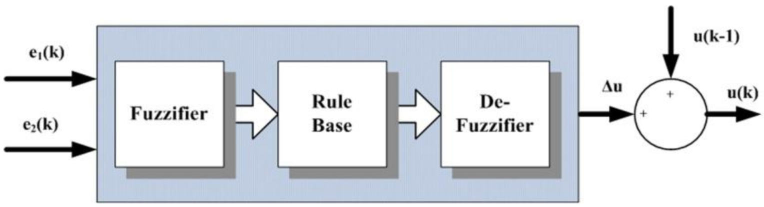

Figure 4. Block diagram of a fuzzy controller

In the fuzzifier the crisp values of input $e_1(k)$ and $e_2(k)$ are converted into fuzzy values. For this purpose seven triangular fuzzy sets are defined for each input and the output. Figure.5. illustrates the triangle membership functions of the first input i.e. $e_1(k)$ which are defined by seven linguistic variables as Negative Big (NB) Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM) and Positive Big (PB) .The overlap rates of the memberships are taken as 50%.

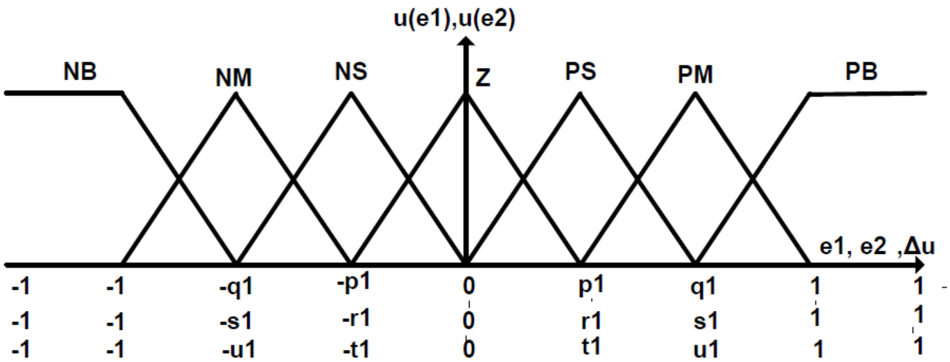

Figure 5. Input/output variable fuzzy membership function

The fuzzy rule base represent the knowledge of human operators who make necessary changes in the controller output to obtain system with minimum error and faster response. For this the behavior of the input signals $e_1(k)$ and $e_2(k)$ has to be observed and accordingly it is to be decided whether the controller output Δu is to be increased or decreased. The proposed controller make use of the sliding mode rule base shown in Table.2 as it is easy to implement for real time application and also simplify the design process if optimization of the rule base is required.

Table 2. Fuzzy rule table base for rotor resistance estimation

e_1 \ e_2	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	Z
NM	NB	NB	NB	NM	NZ	Z	PS
NS	NB	NB	NM	NS	Z	PS	PM
Z	NB	NM	NS	Z	PS	PM	PB
PS	NM	NS	Z	PS	PM	PB	PB
PM	NS	Z	PS	PM	PB	PB	PB
PB	Z	PS	PM	PB	PB	PB	PB

The developed fuzzy logic uses the min – max compositional rule of inference. The inference mechanism of the fuzzy controller is implemented with regard to the rule base given by $\mu(\Delta u) = \min(\mu(e1), \mu(e2))$.The defuzzification procedure makes use of the centre of gravity method and is given as ΔR =

$$\frac{\sum_{i=1}^{n} y_i \mu_{eo}(y_i)}{\sum_{i=1}^{n} \mu_{eo}(y_i)} \tag{11}$$

where, n is the number of fuzzy sets in the output .The final controller output can be obtain as

$$R(t) = R^*(t-1) + k3 * \Delta R(t) .$$

In this study the PI type fuzzy controller is preferred as it minimizes the steady state error The input / output gain parameters $k1, k2$ and $k3$ and the parameters of the input and output membership function for the conventional fuzzy controller are selected by trial and error based method based on determining the Integral Square Error (ISE) of the rotor flux as the performance index.

4. Fuzzy Controller tuning using GA and PSO

A. Design of fuzzy controller using genetic algorithm

The conventional Mamdani Fuzzy controller is modified as shown in Figure.7 where a real coded GA is used for determining the input/output gains and the parameters of the membership functions. The real coded GA are more accurate, occupies less space in memory, operates faster and can converge to global optimum faster than binary coded GA.

The parameters to be optimized consist of the three normalized gain parameters $k1, k2$ and $k3$ and the peak and boundary points of the membership function to be defined as parameters $p1, q1$ for input $e_1(k)$, $r1, s1$ for input $e_2(k)$ and $t1, u1$ for output Δu , as illustrated in Figure. 5. The seven sliding mode rule parameters are not considered for tuning. This results in the number of parameters to be optimized from sixteen to nine and has given acceptable results with simplified design process of the optimization algorithm.

In the developed fuzzy controller following conditions have been considered to minimize the optimization parameters.

- Triangular member ship functions are used for the inputs and output.
- The number of fuzzy sets for the input and output variables are seven with initial overlap of 50%.
- One input can execute maximum two member ship functions.
- The peak values of the first and last membership functions are +1 and -1.

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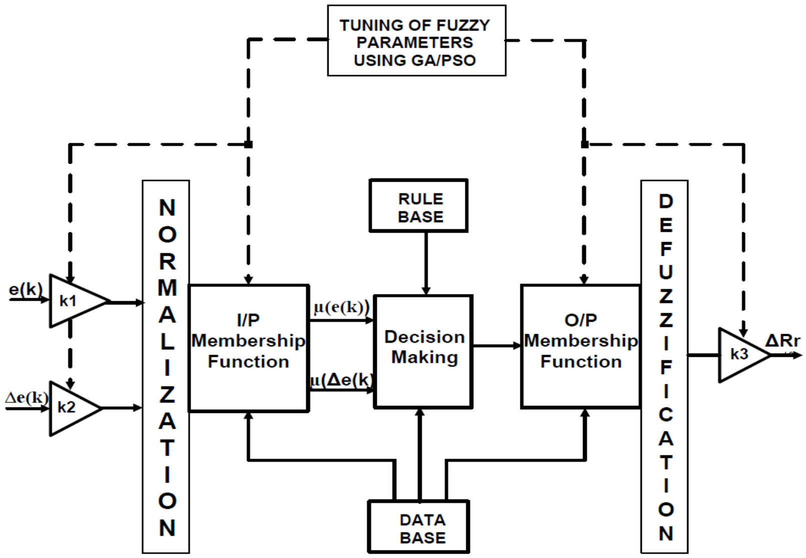

Figure 7. Block diagram of GA/PSO based fuzzy

The flowchart of the GA used in the study is shown in Figure. 8, where the controller tuning is based on the simultaneous optimization of parameters of the input/output gains and the membership function. This approach which is difficult to implement is based on the simple reason that the parameters are fully interdependent and will therefore provide an optimal solution.

B. Objective function

The fitness function F as integral square error (ISE) defined for the fuzzy controller is given as

$$F = \int_0^t E_r \, dt \tag{12}$$

where, $E_r = e^2$, given e is the error between the reference flux ψ_{r^v} and the actual rotor flux ψ_{ri} as determined in equation (5) and (8) and t is the total simulation time. . The GA parameters that are to be initialized are the lower and upper limits of the parameters to be optimized, the population size, the number of generations, the mutation and crossover probability and the elitism property [28, 29].

In the implemented algorithm, the population size is set by the user with the initial population created randomly with uniform distribution. The initial score of each chromosome in the initial population is determined by using the fitness function F . The stochastic uniform method is used for the selection process where the uniform lays out a line in which each parent corresponds to a section of the line of length proportional to its expectation. In real coded GA the cross over method uses the scattered function instead of single or two point crossovers applied for binary coded GA. The scattered function creates a random binary vector with its values as zero or one. It then selects the genes where the vector is a one from the first parent and if zero selects the gene from the second parent which is then combined to form the child or a new individual for the next generation. Genetic algorithms sometimes converge to a local minimum. In order to overcome this premature convergence the mutation function is used. The mutation function makes small changes in an individual, which provides greater diversity thus broadening the search area. In this study the Gaussian function centered on zero is used as mutation function. The optimization process goes on as shown in the flowchart till the performance index F is minimized or the tolerance criterion is met

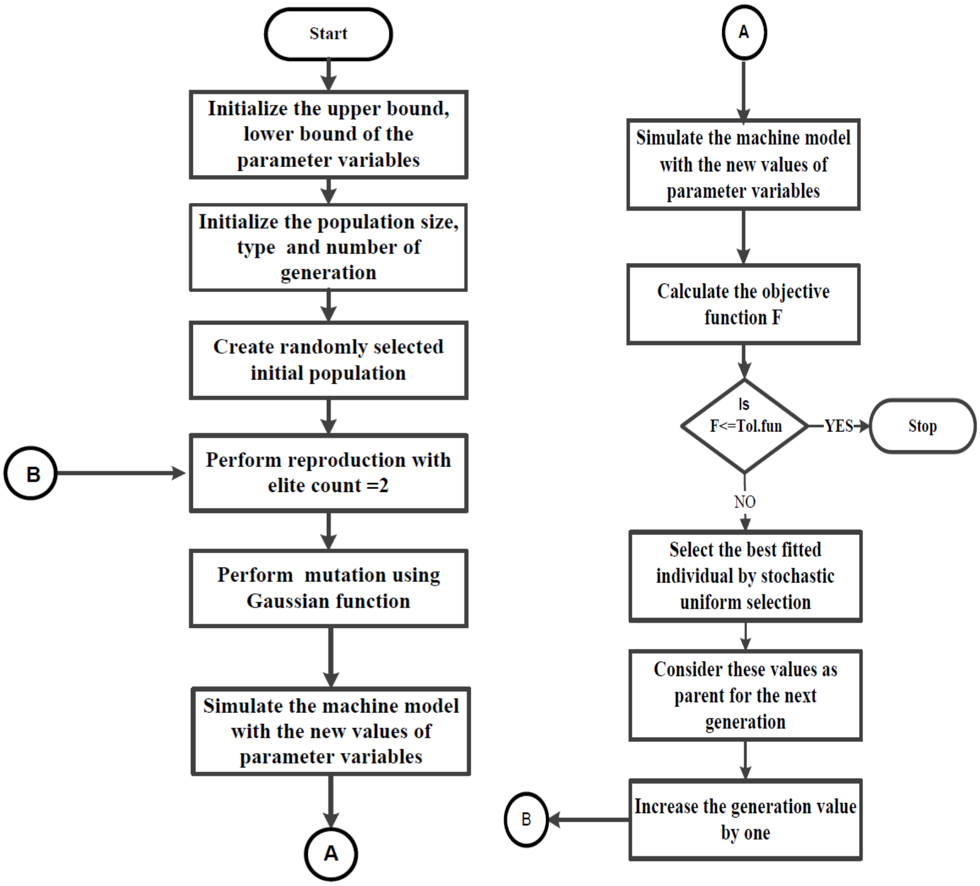

Figure 8. Flow chart of genetic algorithm

B. Design of Fuzzy Controller Using PSO

PSO is a stochastic optimization technique based on population inspired in the social behavior of big masses of birds [30]. In PSO the potential solution called particles fly through the search space and in doing this iteratively the less optimum particles fly to optimum particles, till all the particles converge at the same point. To achieve convergence PSO applies two types of learning component.

$$v_i^{k+1} = w_i\, v_i^k + C_1\, rand_1 * \left(pbest_i - x_i^k\right) + C_2\, rand_2 * \left(gbest - x_i^k\right) \tag{13}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{14}$$

The first is the cognitive component which is the experience that every particle gets along the optimization process. The second is the social component which is the experience that all swarms get during the optimization process. The advantage of PSO over GA is that it is easier to implement and there are fewer parameters to adjust. Second it has more effective memory due to its cognitive and social component and third the least successful particle can also occupy the search space and use the information related to the most successful particle to improve upon where as in GA they are discarded. The flow chart of the PSO algorithm is shown in Figure. 9 below.

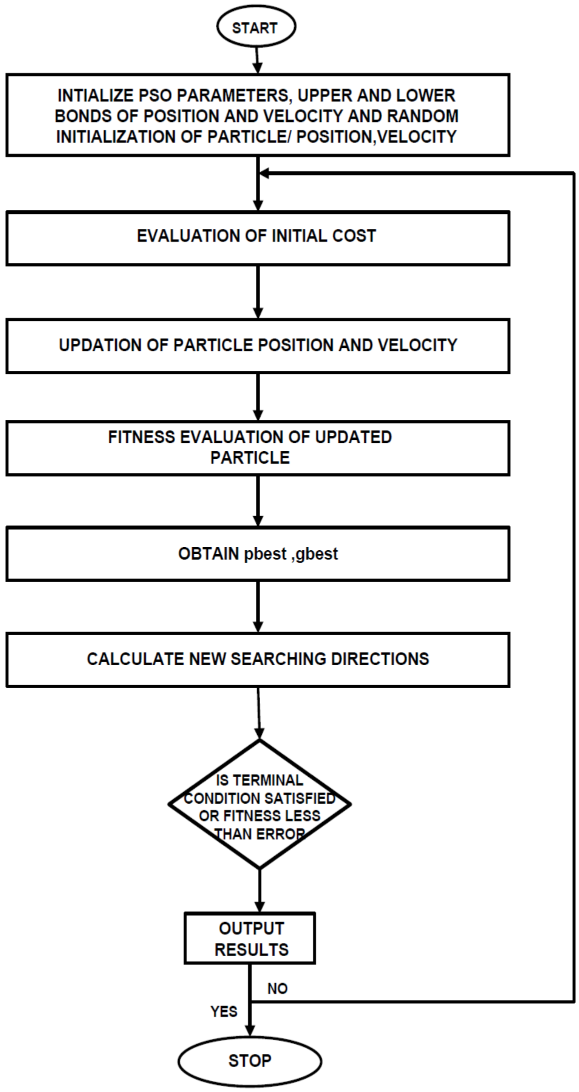

Figure 9. Flow chart of PSO algorithm

The number of parameters to be optimized and their upper and lower limits are kept same as that of GA with the initial overlap of the membership function is taken as 50%. The values of options of GA/PSO chosen for the optimization are given in Table 3.

Table 3. Optimization parameters/values of GA/PSO

Genetic algorithm parameters		Particle swarm optimization parameters	
Parameters	Values/methods	Parameters	Values/methods
Population size	30	Population size	30
Maximum generation	50	Maximum generation	50
Selection method	Stochastic uniform	Cognitive attraction(C_1)	0.5
Chromosome length	9	Social attraction (C_2)	1.25
Crossover fraction	0.8	Particle inertia	0.9
Migration rate	0.2	Initial velocity	0.2
Elitism rate	2		
Mutation function	Gaussian		

The tuned values of the input/output gain parameters $k1, k2, k3$ are given in Table.4 and the tuned values of the membership function parameter $p1, q1, r1, s1, t1$ and $u1$ are given in Table 5.

Table 4. Value of gain parameter variables

Tuning method	Fuzzy input/output normalized gain parameter variables		
	$k1$	$k2$	$k3$
Conventional Trial & Error	1	0.1	13
Using GA	0.9787	0.3003	29.973
Using PSO	0.7885	0.3198	27.823

Table 5. Value of member ship function gain parameter variables

Tuning method	Fuzzy input/output membership function gain parameter variables					
	$p1$	$q1$	$r1$	$s1$	$t1$	$u1$
Conventional Trial & Error	0.1254	0.2373	0.4429	0.1043	0.1202	0.32
Using GA	0.0955	0.5471	0.2590	0.8851	0.4699	0.9969
Using PSO	0.0015	0.7101	0.3903	0.7849	0.4969	0.9656

5. Results and Discussion

A simulation model of voltage controlled IRFOC as shown in Figure.3 is developed in MATLAB/Simulink environment to ascertain the effectiveness of the proposed adaptive algorithm. The parameters and ratings of the test motor are given in Appendix-2. The SPWM technique is used with a switching frequency of 10 kHz. The system is tested for step increase in rotor resistance. For this an external resistance is connected to the rotor circuit of the three phase slip ring induction motor externally. Generally rotor resistance changes due to increase in motor temperature; however, such sudden practical change in rotor resistance rarely occurs in practice due to the large thermal time constant and is considered here just to show the effectiveness of the controller. The effectiveness of the adaptive controller is first tested for step increase in rotor resistance for operating condition as stated in Case-I and II and for step decrease in rotor resistance for condition as stated in Case-III. Under these operating conditions the performance analysis of the proposed GA/PSO tuned fuzzy controller based RF-MRAC in terms of settling time and steady state error is made and is compared with the conventional fuzzy controller.

Case-I: Increase in rotor resistance for constant speed and load torque

The IFOC drive is operated at constant speed of 1000 rpm with load torque of 4 Nm. A step change in rotor resistance R_r equals to 1.5 times its nominal value R_{nom} is made at t= 7 sec. Variation in actual rotor flux and estimation of rotor resistance for this step change is shown in Figure.10. It is observed that the actual and the reference value of the d-axis flux remains same i.e. 0.936 ωb till the instrumented and actual value of rotor resistance are equal. At t=7 sec when the change in rotor resistance is initiated it is seen that that the fuzzy adaptive based MRAS whose gain and membership parameters that are tuned by trial and error method, there is a pronounced peak overshoot of the actual rotor flux from its reference value and takes about approximately 4 sec to settle down. This increase in rotor flux which is more than 20% may lead to over excitation of the motor resulting in increased core losses and saturation. For the same operating condition it is seen from Figure.11and Figure.12 that the peak overshoot of the actual rotor flux for step change in rotor resistance is minimal about 10% where the parameters of the fuzzy adaptive based MRAS is optimized using GA& PSO. Similarly the comparison of the conventional and the optimal tuned fuzzy controller for tracking the step change in rotor resistance are shown in Figure. 10(c) and Figure.11(b) and Figure.12(b) respectively .The performance index with reference to settling time and the steady state error for estimation of rotor resistance are shown in Table. 6.

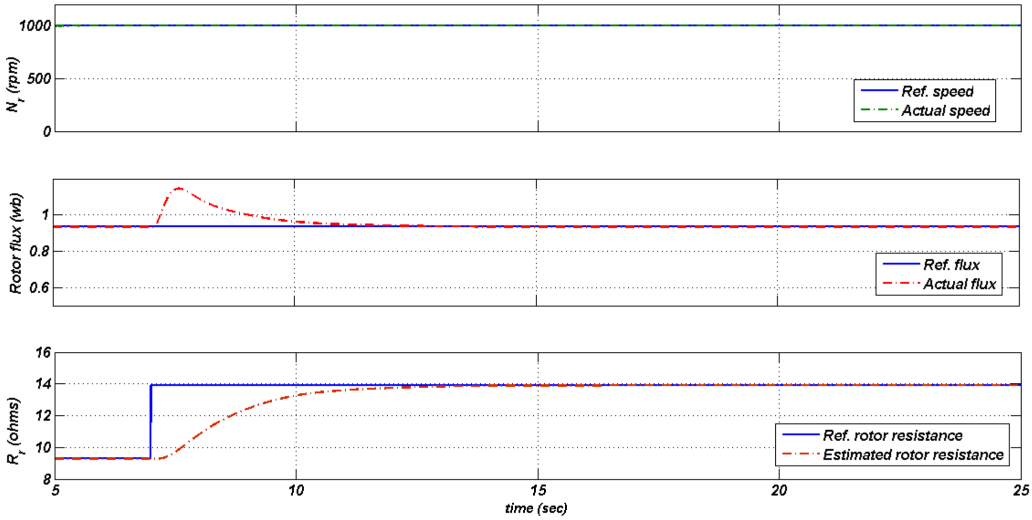

Figure 10. Variation of rotor flux and R_r for step increase in R_r for Case-I: Conventional fuzzy controller.

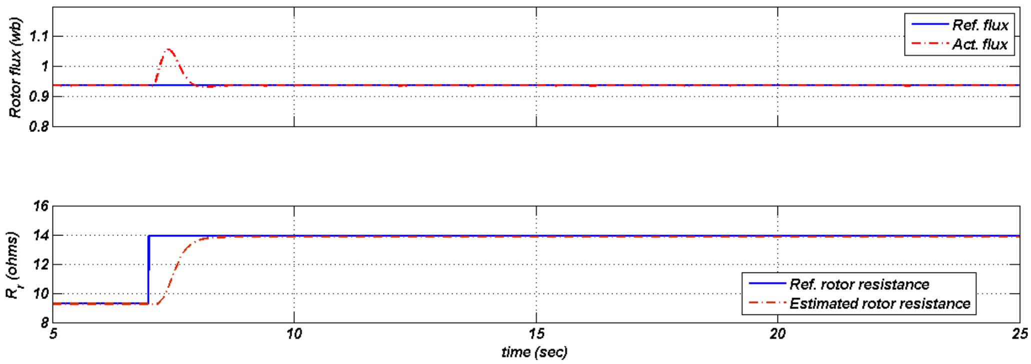

Figure 11. Variation of rotor flux and R_r for step increase in R_r for Case-I: GA tuned fuzzy controller

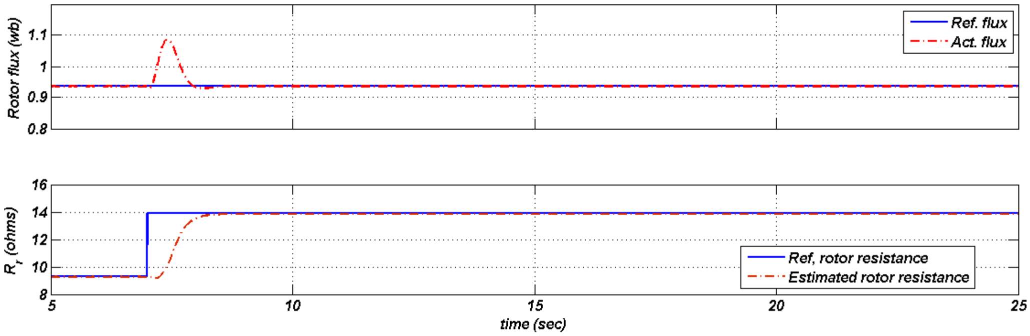

Figure.12. Variation of rotor flux and R_r for step increase in R_r for Case-I: PSO tuned fuzzy controller

Case II: Increase in rotor resistance for variable speed with constant load torque

The effect of step increase in rotor resistance is investigated when the drive is subjected to variable speed operation as shown in Figure. 13.The drive operates at 1000 rpm from 2-12 sec and then operates at zero speed at full load torque from 12-17 sec and thereafter operates in the reverse direction at 500 rpm from 17-25 sec. exhibiting the operating condition of industrial overhead crane drive system. The step increase in rotor resistance as described above is again initiated at t = 7 sec. It is seen from Figure.14 and 15 for an optimal fuzzy controller the actual flux deviates from its reference value marginally when the drive is operating in the reverse direction. It is also observed from Figure.13 that the steady state error in terms of rotor resistance estimation is more pronounced with the conventionally tuned fuzzy controller as shown in table where as it very low for the optimal tuned fuzzy controller as observed in Figure 14 and 15.

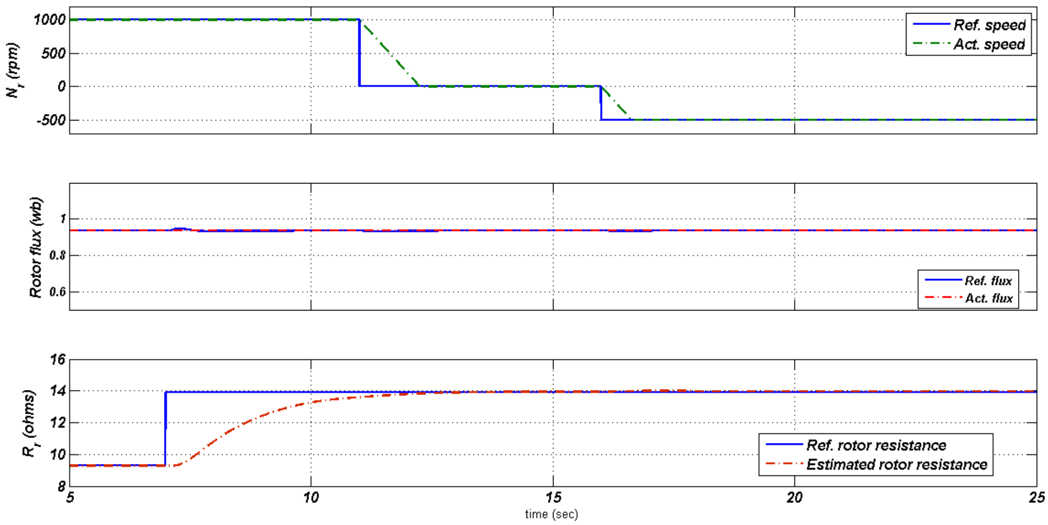

Figure 13. Variation of rotor flux and R_r for step increase in R_r for Case-II : Conventional fuzzy controller.

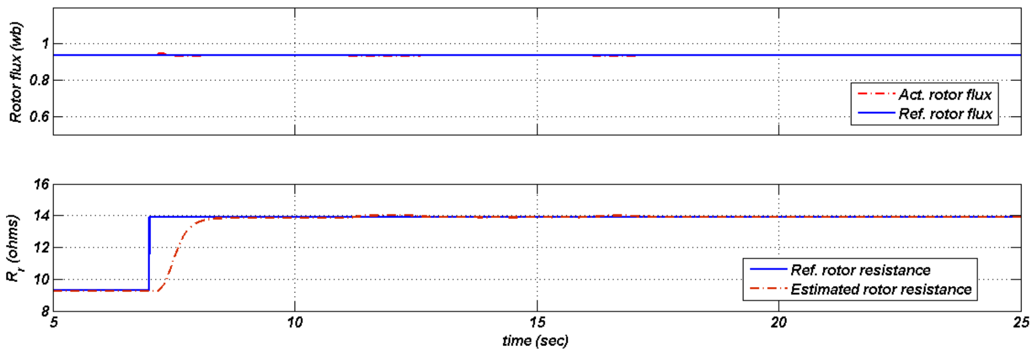

Figure 14. Variation of rotor flux and R_r for step increase in R_r for Case-II : GA tuned fuzzy controller.

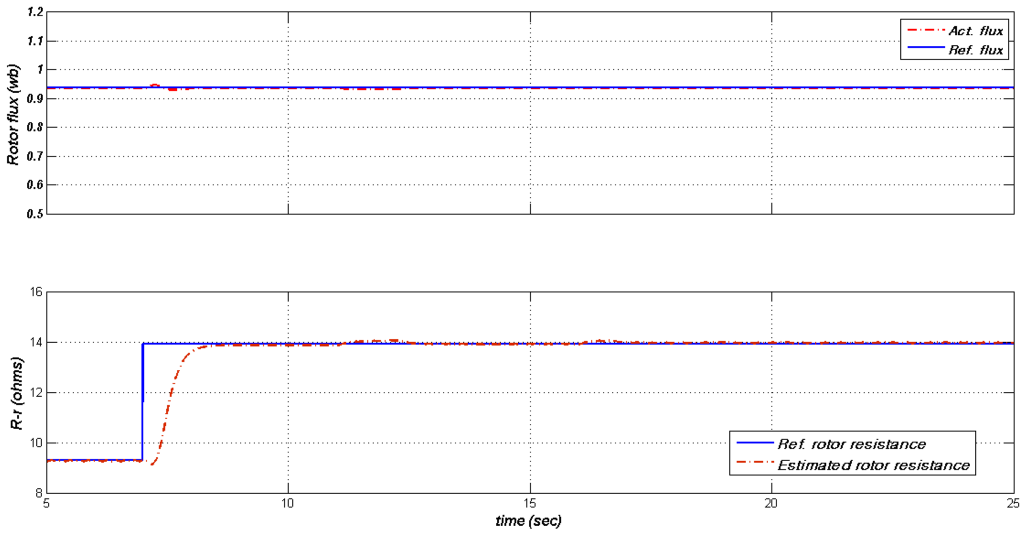

Figure 15. Variation of rotor flux and R_r for step increase in R_r for Case-II: PSO tuned fuzzy controller.

Case-III: Decrease in rotor resistance for constant speed with variable load torque

The drive is operated at constant speed of 1000 rpm but is subjected to variable load torque as shown in Figure.16 indicating an extruder drive application. Under this operating condition, a step decrease in rotor resistance R_r equal to 0.7 its nominal value R_{nom} is made at t = 7sec indicating a symmetrical inter turn short of the rotor winding . This condition is simulated by entering a wrong rotor resistance parameter value in the controller at t= 7sec. It is seen from Figure.16 (b) that there is a prominent under excitation in rotor flux during step decrease in rotor resistance. This will lead to increase in motor current as the torque developed is proportional to the flux and stator current. It is observed from Figure.16 that the estimation of change in rotor resistance during change in load torque from 4 to 2 Nm of a conventional controller deteriorate and becomes more prominent when the drive operates in the braking region from t =22 to 25 sec as compared to the GA/PSO tuned fuzzy controller shown in Figure.17 and 18 .

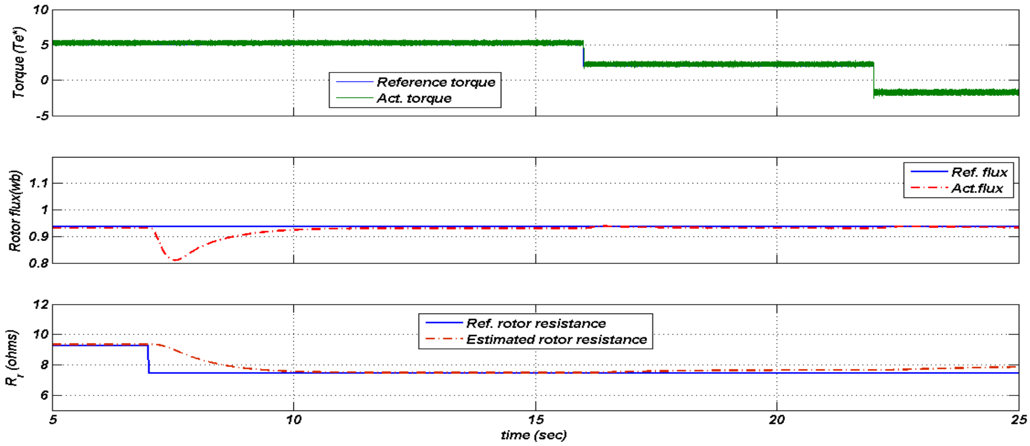

Figure. 16 Variation of rotor flux and R_r for step decrease in R_r for Case-III: Conventional fuzzy controller.

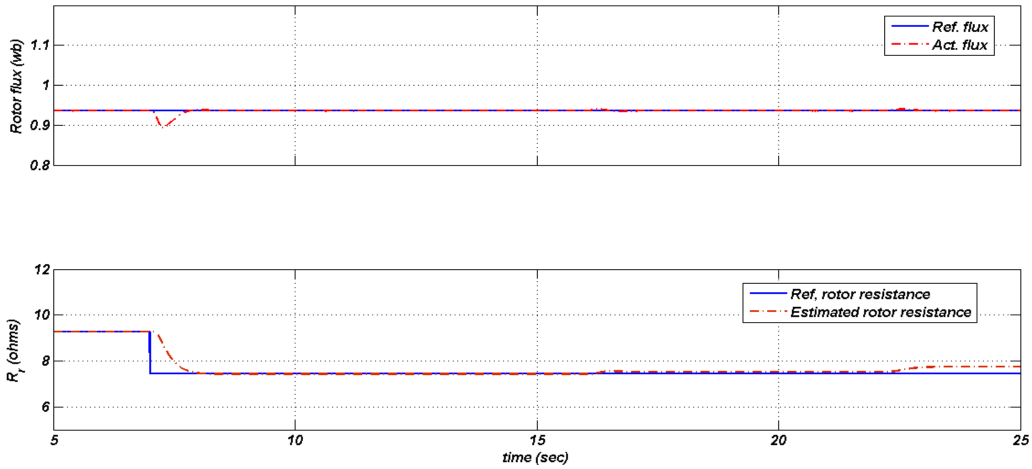

Figure 17. Variation of rotor flux and R_r for step decrease in R_r for Case-III: GA tuned fuzzy controller.

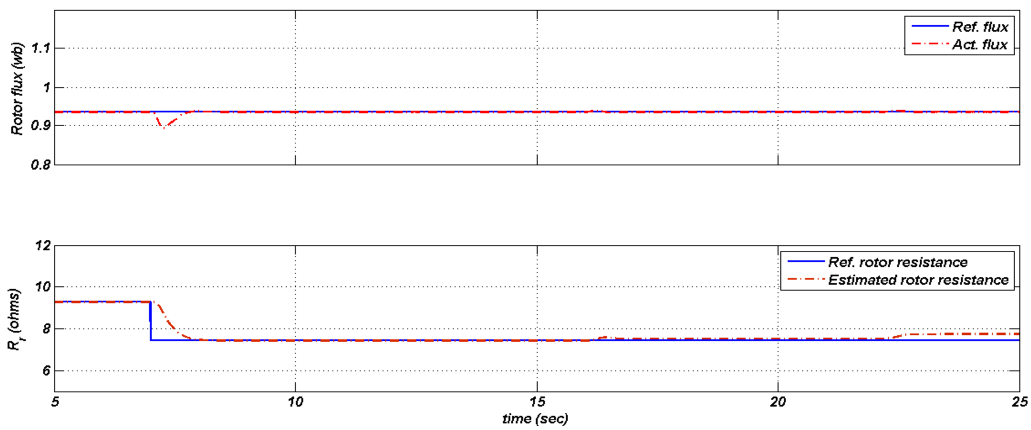

Figure 18. Variation of rotor flux and R_r for step decrease in R_r for Case-III: PSO tuned fuzzy controller.

6. Conclusion

A new approach for the rotor resistance identification of induction motor drive using GA/PSO tuned fuzzy controller has been presented. The identification is online and is based on the steady state model of indirect field oriented controller. Based on the investigations it can be concluded that the performance of the optimal tuned fuzzy controller is better than the conventional Mamdani type fuzzy controller. The d-axis flux settles approximately in about one second and the peak overshoot in the flux value during change in motor operating condition or change in rotor resistance is less than 10% .It is also observed from the results that the tracking of change in rotor resistance by optimal tuned fuzzy controller in terms of steady state error (ITSE) and settling time is far better than Mamdani fuzzy controller. As far as the ease of use of algorithm is concerned, optimization using PSO is better than GA due to the less number of options to be initialized. Moreover it is seen that the steady state error in estimation of rotor resistance by the two stochastic algorithms are comparable. In the study although the proposed optimal fuzzy controller is obtained using GA/PSO, so as to perform optimally under one working condition, however it is seen that a noticeable improvement has been achieved over the conventional controller both in transient and steady state even if the drive is subjected to varying working condition as in Case-II and III.

Table 6. Comparison of controller performance

Case	Tuning with Trial & Error method		Tuning with GA		Tuning with PSO	
	Settling Time (sec)	Steady State error (ITSE)	Settling Time (sec)	Steady State error (ITSE)	Settling Time (sec)	Steady State error (ITSE)
Case- I	5	0.5482	1	0.2451	1.5	0.2678
Case- II	5.2	8.559	1	3.26	1	3.83
Case-III	5	54.47	1.1	13.46	1.15	22.52

Appendix -1 . Proportional (k_p) and Integral (k_i) gains of PI Controllers

PI Controller	k_p	k_i
Speed control loop	1.295	0.2967
Flux control loop	110.6	1083.5
Inner $d_e - q_e$ current loops	98.61	9087.04

Appendix-2. The motor parameters chosen for simulation study

Parameters	Values(units)
Power	0.746KW
Voltage	415V
Stator current	1.8Amp
Speed (rpm)	1450 rpm,
Stator Resistance (R_s)	10.75 Ω
Rotor Resistance (R_r)	9.28 Ω
Self Inductance (L_s/L_r)	0.5318 H
Moment of Inertia (J)	0.011787 kgm2,
Friction coefficient (B)	0.0027 Nm/rad/sec

6. References

[1]. Finch J W and Giaouris D, "Controlled AC Electrical drives," *IEEE Transactions on Industrial Electronics*, Vol. 55, No.2, pp.481-491, Feb. 2008

[2]. B. K. Bose, "Power Electronics and motor drives, Recent Progress and Perspectives," *IEEE Transactions on Industrial Electronics,* Vol. 56, No.2, pp. 581-588, Feb.2009.

[3]. S.Ogasawara, H. Akagi and A. Nabae, "The Generalized theory of Indirect vector controlled AC machines," *IEEE Transactions on Industrial Applications*, Vol.24, No.3, , pp. 470-478, May/June, 1988.

[4]. T. Matsuo and T. Lipo, "Rotor parameter identification scheme for vector controlled Induction motor drive," *IEEE Transactions on Industrial Applications*, Vol. 1A-21, No.3, pp. 624-632, May/June 1985.

[5]. R. Krishnan and A.S. Bhardawaj, "A Review of Parameter sensitivity and adaptation in Industrial vector controlled Induction motor drive system," *IEEE Transactions on Power Electronics*, Vol.6, No.4, pp.695-703, Oct 1991.

[6]. A. Shiri, A.Vahedi and A. Shoulane, "The effect of parameter variation on the performance of Indirect vector controlled IM Drive*," IEEE ISTE 2006, Montreal*, Quebec, Canada.

[7]. Toliyat H.A, Emil Levi and Raina, M, "A Review of RFO Induction motor parameter Estimation Technique," *IEEE Transactions on Energy Conversions*, Vol.18, No.2, pp.271-283, June 2003.

[8]. T. Matsuo and Thomas. T. Lipo, "Identification for vector controlled Induction motor drives," *IEEE Transactions on Industry Applications*, Vol. IA-21, No.4, June 1985.

[9]. S.Wade, M.W.Dunnigan and B. W. Williams, "A new method of rotor resistance estimation for vector controlled induction machines," *IEEE Transactions on Industrial Electronics*, Vo.l 44, N o.2, pp. 247-257, April 1997.

[10]. T. Du , P. Vaz and F.Tronach, "Design and application of extended observers for joint state and parameter estimation in high performance AC drives," Proc. *Inst. Elect. Engg-Elect. Power Appl*. Vol. 142, No.2, Mar.1995.

[11]. Bilal Akin, Umur Orguner and Aydin Ersak, "A comparative study on kalman filtering techniques designed for state estimation of Industrial AC drive system," *IEEE International conference on Mechatronics*, ICM'04, pp. 439-445, June 2005.

[12]. Luis .J. Garces, "Parameter Adaption for the Speed-Controlled Static AC drive with a squirrel cage I.M.," *IEEE Transactions on Industrial Applications*. Vol. 1A-16, No. 2, pp. 173-178, 1980.

[13]. R.D. Lorenz and D.B. Lawson, "A simplified approach to continuous online tuning of field oriented induction machine drives," *IEEE Transactions on Industry Applications*, Vol.26, No.3, pp.420-424, May/June 1990.

[14]. T.M. Rowan, R.J. Kerman and D.Leggate, "A simple on-line adaption for indirect field orientation of an induction machine*," IEEE Transactions on Industrial Applications*, Vol.27, No.4, pp. 20-727, July/Aug 1991.

[15]. M. Bousak, G.A. Capolino and M. Poloujadoff, “Parameter identification in vector controlled induction machine with flux model reference adaptive system,” In *Proc. ICEM, Manchester,* U.K, Sep.1992, pp. 838-842.

[16]. Vukosavic, S.N.and Stojic. M.R, “On-Line Tuning of the Rotor Time Constant for Vector Controlled Induction motor in Position control Applications,” *IEEE Transactions on Industrial Electronics*.Vol.40, No.1, pp.130-138, , Feb 1993.

[17]. S.Maiti, Chakraborty, C.,Hori andY.,Ta,M.C, “Model reference adaptive controller based rotor resistance techniques for vector controlled I.M using reactive power,” *IEEE Transactions on Industrial Electronics*, Vol.55, No.2, pp.594-601, Feb. 2008.

[18]. Hossein M. Kojabadi, “Active power and MRAS based rotor resistance identification of an IM drive,” Elsevier, *Simulation Modelling Practice and Theory*, Vol.17, pp. 376-389, 2009.

[19]. H.A . Toliyat,S. Arfeen, Khwaja.M. Rahman and David Figureoli, “Rotor time constant updating scheme for a rotor flux oriented induction motor drive,” *IEEE Transactions on Power Electronics*, Vol. 14, No.5, pp. Sept.1999.

[20]. B. Karanyil, M.F. Rahman and C. Grantham , “Stator and rotor resistance observer for I.M. drive using Fuzzy logic and ANN,” *IEEE Transactions on Energy Conservations*, Vol.20, No.4, pp.770-778, Dec.2005.

[21]. B. Karanyil, M.F. Rahman and C.Grantham, “On-line stator and rotor resistance estimation scheme using artificial neural network for vector controlled speed sensorless induction motor drives,” *IEEE Transactions on Industrial Electronics*, Vol.54, No.1, pp. 167-176 , Feb. 2007.

[22]. Xing. Yu, Mathew. W. Dunnigan and Barry. W. Williams, “A novel rotor resistance identification method for an indirect rotor flux oriented controlled induction machine system,” *IEEE Transactions on Industrial Electronics*, Vol. 17, No. 3, May 2002.

[23]. K. Wang, J. Chiasson, M. Bodson and L.M. Tolbert, “An online rotor time constant estimation for the induction machine,” *IEEE Transactions on control system technology*, Vol.15, No. 2, pp. 339-348, March 2007.

[24]. Lino Rosell Valdenbro and Edson Bim, “A Genetic algorithm approach for adaptive field oriented control of induction motor drives,” *IEEE International conference on Electric Machine and Drives*, IEMD’99, pp. 643-645, May 1999.

[25]. B Karanyil, M F Rahman and C. Grantham, “PI and fuzzy Estimators for on line tracking of rotor resistance of Indirect vector controlled Induction motor drive,” Proc. of the *International Electrical machine and drives conference IEMDC*, June 17-20, pp. 820-825, June 2001.

[26]. Edson Bim, “Fuzzy Optimization for Rotor Constant Identification of an Indirect FOC Induction Motor Drive,” *IEEE Transactions on Industrial Electronics*, Vol. 48, No. 6, pp. 1293-1295, 2001.

[27]. F. Zidani, M.S. Nait Said , MEH Benbuzid, D. Diallo and R. Abdessemed, “A fuzzy rotor resistance updating scheme for an IFOC induction motor drive,” *IEEE Power Engineering Review*, 21(11), pp. 47-50, Nov. 2001.

[28]. N.Ozturk and E.Celik*, “*Speed control of permanent magnet synchronous motors using fuzzy controller based on genetic algorithm,” Elsevier, *Electrical Power and Energy Systems*, Vol. 43, pp. 889-898, 2012.

[29]. Ursem B.K and Vadstrup .P,“Parameter identification of Induction motors using stochastic optimization,” Journal of Applied Soft Computing, Vol.4 (1), pp.49-64, 2004.

[30]. Kennedy J and Eberhart R, “Particle swarm optimization,” Proc. *IEEE International conference on neural networks*, pp.1942-1948, 1995.

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