

## Optimal Gains Tuning of Speed Controller in Induction Motor Drives Using Particle SWARM Optimization

Hussein M. Wally

Assistant Researcher,  
Mechanical & Electrical Research Center,  
National Water Research Center, Egypt  
Email: Eng.hussein\_wally@yahoo.com

Haitham Z. Azazi

Department of electrical Engineering,  
Faculty of Engineering,  
Menoufiya University, Egypt,  
Email: Haitham\_azazi@yahoo.com

Fahmy M. El-Khouly

Department of electrical Engineering,  
Faculty of Engineering,  
Menoufiya University, Egypt,  
Email: Fahmyel@yahoo.com

### Abstract

The last decade has witnessed a great interest in using evolutionary algorithms (EAs), such as genetic algorithms (GA), evolutionary strategies and particle swarm optimization (PSO), for multivariate optimization. This paper presents a modern approach of speed control for three-phase induction motor (IM) using PSO algorithm to optimize the parameters of the proportional integral (PI) and Fuzzy-PI controllers. Comparison between different controllers is achieved, using PI and fuzzy-PI controllers which are tuned by two methods, firstly manually and secondly using PSO technique. Hybrid of FL and PI controller PSO-based for the speed control of given motor is also performed to eliminate the drawbacks of PI controller (overshoot, undershoot) and FL controller (steady-state error), which has a minimum number of fuzzy rules and membership functions (MFs). The overall system is simulated under various operating conditions and experimental results are prepared.

### ملخص البحث

لقد شهد العقد الماضي اهتماماً كبيراً في استخدام الخوارزميات التطورية (EAS)، مثل الخوارزميات الجينية (GA)، والطيريات (PSO)، وطريقة أفراد سرب الطيور المتكامل (PSO)، وذلك لتحسين الاستفادة من المتغيرات المتعددة. يقدم هذا البحث نهجاً حديثاً للتحكم في سرعة المحرك الحثي (IM) ثلاثي الأوجه باستخدام طريقة أفراد سرب الطيور المتكامل لتحسين معاملات كل من متغيرات المتكامل التناسبي (PI) والمتكامل التناسبي (F-PI) وبالمقارنة بين وحدات تحكم مختلفة، وذلك باستخدام المتكامل التناسبي - التكامل و المتكامل التناسبي - الضبابي والتي يتم ضبطها بطريقتين، إحداهما يدويًا والآخر باستخدام تقنية أفراد سرب الطيور المتكامل. يتم استخدام هجين بين المتكامل التناسبي - التكامل و المتكامل الضبابي مستنداً على تقنية أفراد سرب الطيور المتكامل القائم للتحكم في سرعة المحرك للقضاء على عيوب كل من المتكامل التناسبي - التكامل (التجاوزية فوق الحد المسموح للإشارة وتحت الحد) والمتكامل الضبابي (وجود خطأ في الحالة المستقرة)، ويتميز هذا النوع باستخدام الحد الأدنى من القواعد الضبابية والمهام العضوية (MFS). يتم إعداد محاكاة النظام تحت ظروف التشغيل المختلفة وإجراء النتائج التجريبية.

**Keywords:** Evolutionary Algorithms (EAs), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Fuzzy Logic (FL), Membership Functions (MFs).

### I. INTRODUCTION

Optimization is one of the most discussed topics in engineering and applied research. Many engineering problems can be formulated as optimization problems, e.g. economic dispatch problem, pressure vessel design, communication system, applications in power systems, etc. These problems when subjected to a suitable optimization algorithm help in improving the quality of solution [1-2]. Due to this reason the engineering community has shown a significant interest in soft computing techniques. In particular, there has been a focus on EAs for obtaining the global optimum solution to the problem, because in many cases it is not only desirable but also necessary to obtain the global optimal solution. EA have also become popular because of their advantages over the traditional optimization techniques such as decent method, quadratic programming approach, etc. Some important differences of EAs over classical optimization techniques are as follows [3]:

- EAs start with a population of points, whereas the classical optimization techniques start with a single point.
- No initial guess is needed for EAs; however, a suitable initial guess is needed in most of the classical optimization techniques.
- EAs do not require an auxiliary knowledge like differentiability or continuity of the problem, on the other hand classical optimization techniques depend on the auxiliary knowledge of the problem.
- The generic nature of EAs makes them applicable to wider variety of problems, whereas classical optimization techniques are problem specific.

Some common EAs are GA, evolutionary programming, PSO, differential evolution, bacterial foraging, etc. These algorithms have been successfully applied for solving numerical benchmark problems and real-life problems. Several attempts have been made to compare the performance of these algorithms with each other [4-9]. How the artificial intelligence, particularly neural network,

provides interesting solutions in the computer security problems are discussed in [10].

Induction motor can be considered as one of the largest consumers of electrical energy due to its well-known advantages including robustness, reliability, low price and maintenance free operation. The IMs are used in both industrial and commercial sectors in a wide range of applications, such as fans, compressors, pumps, conveyors, winders, mills, transports, elevators and home appliances [11]. Hence, the research potential of the drive is especially towards development of speed controller, so that performance of the motor is optimized. The optimized gain values are fed to the controller to simulate the drive.

In this paper, PI and fuzzy-PI gains (optimal values) for various operating regions of load are obtained by PSO based on the speed error and its derivative for 3 $\Phi$  IM. This paper considers three types of speed control methods for simulation and experimental study: PI controller with PSO and hand tuning (trial and error method), fuzzy speed controller and hybrid controller (hybridization of FL and PI) with PSO and hand tuning.

The remaining of the paper is organized as follows: in Section II, various methods of tuning control techniques are discussed, The Section III, a brief overview of PSO is presented, The Section IV, V describe a model and speed controller of IM, respectively. Simulation and experimental results are described in section VI and VII, respectively to demonstrate the advantage of proposed scheme. Conclusion and reference are given in the last section.

## II. METHODS OF TUNING THE PI-CONTROLLER

PI-Controllers have been applied to control almost any process in current use, from aerospace to motion control, from slow to fast systems. Alongside this success, however the problem of tuning PI-controllers has remained an active research area. Furthermore, with changes in system dynamics and variations in operating points PI-Controllers should be returned on a regular basis. This has triggered extensive research on the possibilities and potential of the so-called adaptive PI-controllers. Loosely defined, adaptive PI-controllers avoid time-consuming manual tuning by providing optimal PI-controller settings automatically as the system dynamics or operating points change [12]; there are various conventional methods used for tuning of PI-controller such as [13-14]:

1. Trial and error method.
2. Continuous cycling method (Ziegler Nichols method (Z-N)).
3. Process Reaction Curve methods (Ziegler-Nichols and Cohen-Coon methods).
4. Ziegler-Nichols method.
5. Cohen-Coon method.
6. The Intelligence methods such as the GA and PSO methods.

One of the disadvantages of Z-N method is prior knowledge regarding plant model. Once tuned the controller by Z-N method, a good but not optimum system response will be reached. The transient response can be even worse if the plant dynamics change. To assure an environmentally independent good performance, the controller must be able to adapt the changes of the plant dynamic characteristics. For these reasons, it is highly desirable to increase the capabilities of PI controllers by adding new features. Many random search methods, such as GA and PSO have received much interest for achieving high efficiency and searching global optimal solution in the problem space [15-16]. The numerical values of these controller gains depend on the ratings of the motor. It is observed that, from an evolutionary point of view, the performance of the PSO is better than that of GA. PSO seems to arrive its final parameter values in fewer generations than the GA, equally effective, but the efficiency is superior to the PSO over the GA. It appears that PSO outperforms the GA with a larger differential in computational efficiency when used to solve unconstrained nonlinear problems with continuous design variables and less efficiency differential when applied to constrained nonlinear problems with continuous or discrete design variables (uses less number of function evaluations) [17-22].

## III. PARTICLE SWARM OPTIMIZATION (PSO)

PSO is suggested by Eberhart and Kennedy in 1995 based on the analogy of swarm of bird and school of fish [23]. The PSO mimics the behavior of individuals in a swarm to maximize the survival of the species. The main advantages of the PSO algorithm over other heuristic optimization techniques are summarized as; simple concept, easy implementation, robustness to control parameters, computational efficiency, lower sensitivity to the nature of the objective function and derivative free property unlike many conventional techniques [11, 24]. Algorithm starts with  $N$  particles. Each particle represents a candidate solution to the problem. Each particle in search space has a current position  $x_i$  and a current velocity  $v_i$ . Value of each particle, is determined by fitness function  $F(x_i)$ . Each particle moves about the cost surface with a velocity and tries to modify its position as shown in Fig.1. The personal best position in search space  $localbest_i$  corresponds to the position, where particle  $i$ , represents the best fitness function. The general working of standard PSO algorithm is explained with the help of a flow chart as shown in Fig. 2. The global best position in search space  $globalbest$  represents the position yielding the best fitness function amongst all the  $localbest_i$ .

This algorithm is defined as follow:

1. Formation of initial population and initial velocities randomly.
2. Calculating the value of each particle by fitness function.
3. Finding local best of each particle.
4. Finding global best of all population.

5. The PSO algorithm updates the velocity for each particle then adds that velocity to the particle position or values. Velocities updates are influenced by both the best global solution associated with the lowest cost ever found by a particle and the best local solution associated with the lowest cost in the present population according to (1) and (2) as follow:

$$v_i^{n+1} = \omega v_i^n + \rho_1 \cdot r_1 \cdot (x_i^{localbest} - x_i^n) + \rho_2 \cdot r_2 \cdot (x_i^{globalbest} - x_i^n) \quad (1)$$

$$x_i^{n+1} = x_i^n + v_i^{n+1} \quad (2)$$

In these equations, super script  $n + 1$  denotes  $(n + 1)^{th}$  generation and super script  $n$  denotes  $n^{th}$  generation,  $x_i$  denotes to  $i^{th}$  particle and  $v_i$  is the velocity corresponding to this particle. The first part of equation (1) represents the inertia of the previous velocity, the second part tells us about the personal thinking of the particle and the third part represents the cooperation among particles and is, therefore, named as the social component. Also  $\rho_1$ ,  $\rho_2$  are learning factors (Acceleration constants) and  $r_1, r_2$  are independent uniform random numbers in the range  $[0, 1]$ .  $\omega$  (Inertia weight) is a control parameter, which is used to control the impact of the previous velocity on the current velocity.  $\omega$  is predefined by the user as shown in equation (3). Hence, it influences the trade-off between the global and local exploration abilities of the particles. For the initial stages of the search process, large inertia weight to enhance the global exploration is recommended while it should be reduced at the last stages for better local exploration. As originally developed,  $\omega$  often decreases linearly from about 0.9 to 0.4 during a run.

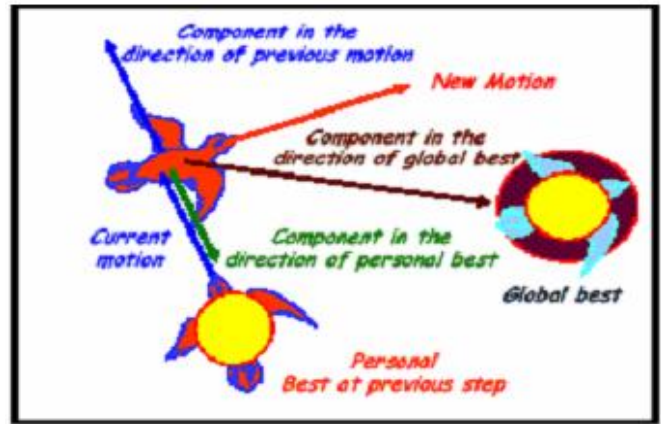
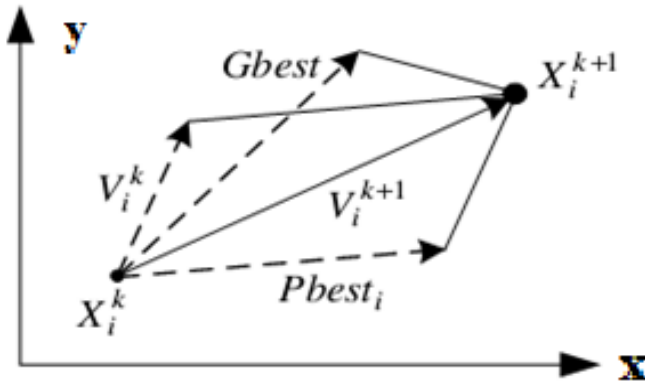


Fig. 1 Concept of modification of a searching point by PSO

In general, the inertia weight is set according to the following equation:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} \times iter \quad (3)$$

where,  $iter_{max}$  is the maximum number of iterations and  $iter$  is the current number of iterations.  $x_i^{localbest}$  is the best local solution for  $i^{th}$  particle and  $x_i^{globalbest}$  is the best global solution

6. Repetition of steps 2 - 5 until termination criteria satisfies [24-26].

The implementation of PSO program is very easy and takes a few lines in the program, so PSO reduces the time of the whole program. The steps of the PSO program is described in [14, 27].

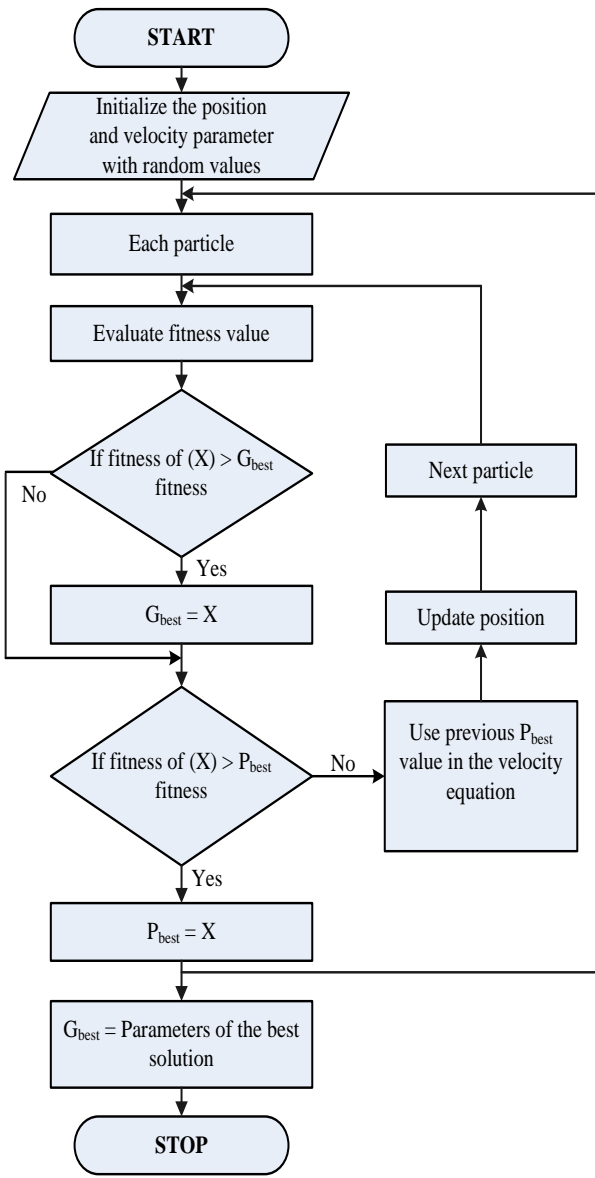


Fig.2 General PSO Algorithm

The proposed method uses PSO to optimize PI & Fuzzy-PI controller parameters; the PSO algorithm is used to update the PI & Fuzzy-PI parameters as shown in Fig.3.

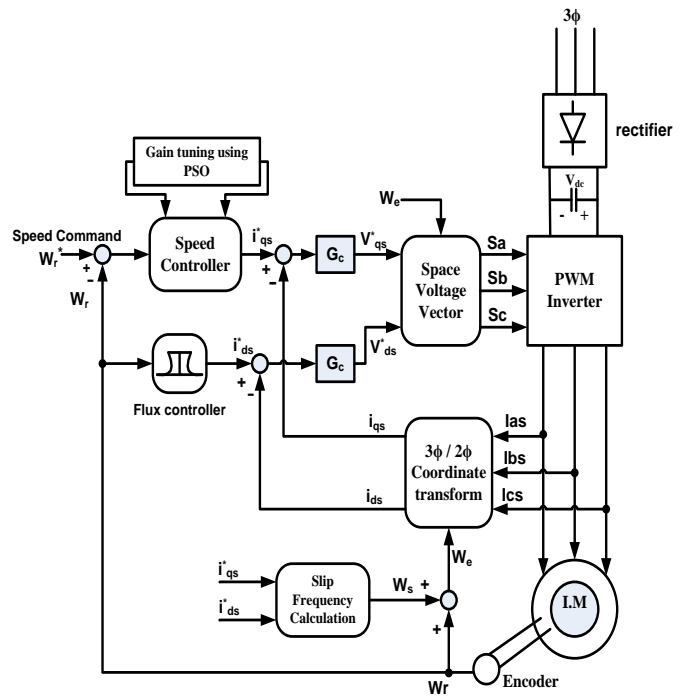


Fig.3 IM vector control block diagram with speed control loop

#### IV. INDUCTION MOTOR MODEL

Squirrel-cage induction motor is represented in its de-qe dynamic model [32]. This model represented in synchronous reference frame is expressed as follows;

$$\begin{bmatrix} V_{qse}^e \\ V_{dse}^e \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} R_s + pL_\sigma & \omega_e L_\sigma & p \frac{L_m}{L_r} & \omega_e \frac{L_m}{L_r} \\ -\omega_e L_\sigma & R_s + pL_\sigma & -\omega_e \frac{L_m}{L_r} & p \frac{L_m}{L_r} \\ -R_r L_m & 0 & R_r + pL_\sigma & (\omega_e - \omega_r) L_m \\ 0 & -R_r L_m & -(\omega_e - \omega_r) L_m & R_r + pL_\sigma \end{bmatrix} \begin{bmatrix} I_{qs}^e \\ I_{ds}^e \\ \lambda_{qr}^e \\ \lambda_{dr}^e \end{bmatrix} \quad (4)$$

The electromechanical equation is also given by;

$$T_e - T_L = J \frac{d\omega_r}{dt} + B\omega_r \quad (5)$$

Where, the electromagnetic torque is expressed as;

$$T_e = \frac{3p}{2} \frac{L_m}{L_r} (I_{qs}^e \lambda_{dr}^e - I_{ds}^e \lambda_{qr}^e) \quad (6)$$

$V_{qse}^e, V_{dse}^e$  are q,d-axis stator voltages respectively;  $I_{qs}^e, I_{ds}^e$  are q,d-axis stator current respectively;  $I_{qr}^e, I_{dr}^e$  are d,q-axis rotor current respectively;  $\lambda_{qr}^e, \lambda_{dr}^e$  are d,q-axis rotor flux respectively;  $R_s, R_r$  are the stator and rotor resistances per phase, respectively;  $L_s, L_r$  are the self inductances of the stator and rotor respectively;  $L_m$  is the mutual inductance,  $L_\sigma$  is the leakage inductance,  $\omega_r$  is the rotor speed,  $P$  is the number of poles,  $p$  is the differential operator,  $T_e$  is the

electromagnetic developed torque,  $T_L$  is the load torque,  $J$  is the rotor inertia and  $B$  is the rotor damping coefficient. The motor parameters are given in appendix (A).

**V. SPEEDCONTROLLEROFIM**

**A. PI Speed Controller**

PI-Controller is a good controller in the field of machine control, because the PI-controller is simple in structure and is easy to use, but the problem is the mathematical model of the plant must be known in order to solve the overall system. Generally, the speed error, which is the difference between reference speed ( $\omega_r^*$ ) and actual speed ( $\omega_r$ ), is given as input to the controllers. These speed controllers process the speed error and give torque value as an input. Then the torque value is fed to the limiter, which gives the final value of reference torque.

The general block diagram of the PI speed controller is shown in Fig.4. [3].

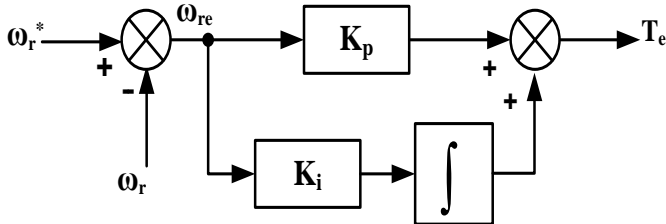


Fig.4 Block diagram of PI speed controller

**B. FL speed controller**

The PI speed controller, which has been discussed in the previous section, is simple in operation and has zero steady-state error when operating on load. But the disadvantages of this PI controller is the occurrence of overshoot while starting, undershoot while load application and overshoot again while load removal. Furthermore, it requires motor model to determine its gains and is more sensitive to motor parameter variations, load disturbances and suffer from poor performance when applied directly to systems with significant non-linearity [3]. These disadvantages of PI controller can be eliminated with the help of a FL controller, which doesnot need model of the drive and can handle non-linearity of arbitrary complexity.

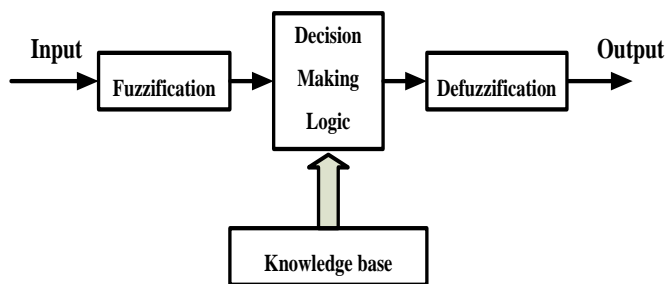


Fig. 5 Fuzzy Control System

FLC is a technique to embody human-like thinking into a control system. Fuzzy control has been primarily applied to

the control of processes through fuzzy linguistic descriptions. Fuzzy control system consists of four blocks as shown in Fig.5. [28].

By means computer simulations and experimentation a minimum number of fuzzy rules and MFswere found and proposed. A large number of rules and MFsincrease the computational burden drastically. Thus experimentally confirmed minimal of MFs for the two input vectors of  $\Delta\omega_r(n)$  and  $\Delta e(n)$  of the fuzzy logic blockcan be reduced to three and two, correspondingly. Minimal number of MFs for the output is two. Fuzzy rules of this controller are shown in Table.1.

TABLE 1

Proposed fuzzy controller rule base (Linguistic Rule Table)

$\Delta e(n) \backslash \Delta\omega_r(n)$	N	P
N	ZE	ZE
ZE	P	ZE
P	P	P

Speed error is calculated with comparison between reference speed and speed signal feedback as shown in Fig.6. Speed error  $\Delta\omega_r(n)$  and speed error changing  $\Delta e(n)$  are fuzzy controller inputs. Input variables are normalized with a range of specified membership functions and the normalization factors are named as  $\Delta\omega_r(n)$  and  $\Delta e(n)$ . Suitable normalization has direct influence on algorithm optimality and faster response.

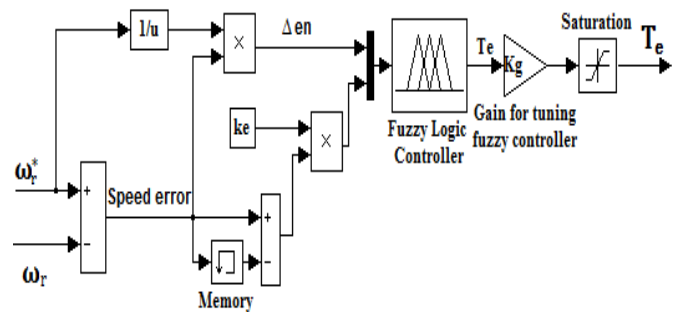


Fig.6 Fuzzy speed controller of three phase IM

Fig. 7 shows normalized membership functions for input and output variables. A fuzzy logic controller operation is based on the rules formed.

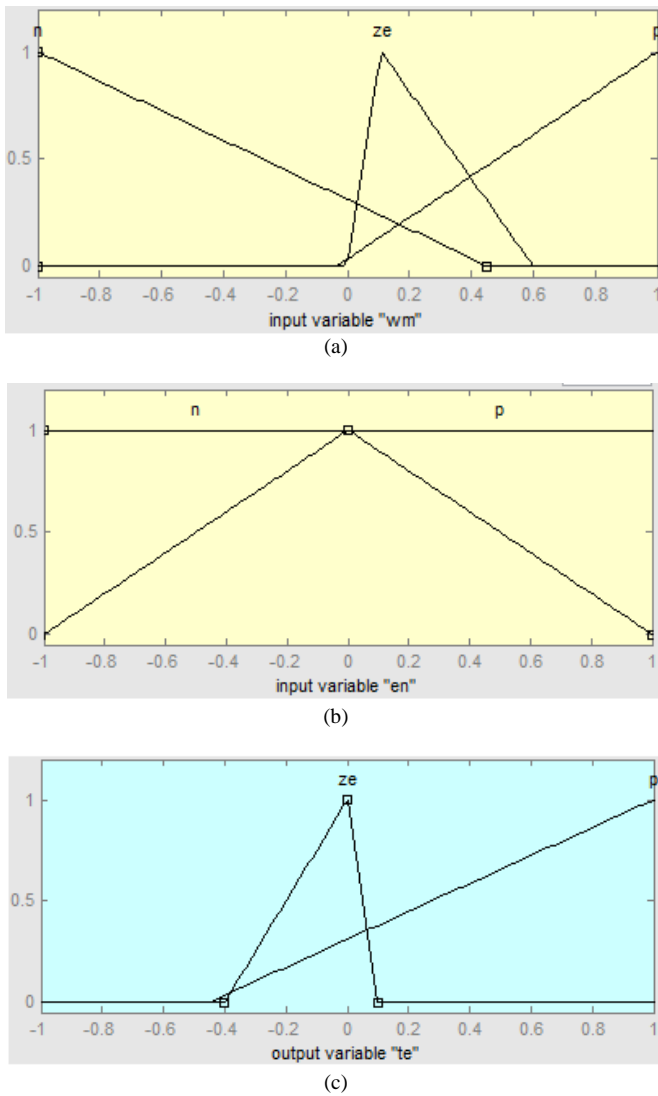


Fig.7. Membership functions for:

- (a) Input variable speed error  $\Delta\omega_m$
- (b) Input variable change of speed error  $\Delta e_n$
- (c) Output variable command torque  $T_e$

**C. Hybrid speed controller**

To take over the advantages present in both PI (zero steady-state error) and FL (negligible overshoot and undershoot) controllers, a hybridization of PI and FL controllers, called fuzzy pre-compensated PI (FPPI) controller, is done and is used as a single controller. In this controller, FL is used for pre-compensation of reference speed, which means that the reference speed signal  $\omega_r^*$  is altered in advance in accordance with the rotor speed  $\omega_r$ , so that a new reference speed signal  $\omega_{r1}^*$  is obtained and the main control action is performed by PI controller. Some specific features such as overshoot and undershoot occurring in the speed response, which are obtained with PI controller can be eliminated and this controller is much useful to the

load where torque and speed of the motor when vary time to time.

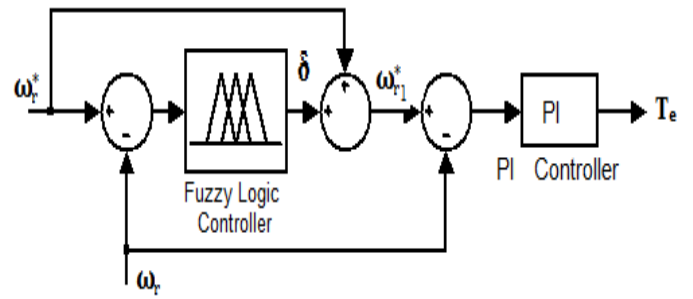


Fig.8 Block diagram of hybrid (Fuzzy-PI) speed controller.

As usual, the inputs to the FL are speed error ( $\omega_r^*$ ) and the change in speed error ( $\Delta\omega_r$ ), the output of the FL controller is added to the reference speed to generate a pre-compensated reference speed ( $\delta$ ), which is to be used as a reference speed signal by the PI controller shown in Fig.8. The fuzzy pre-compensator can be mathematically modelled as follows [29-31].

**VI. SIMULATION RESULTS**

The control algorithm of the proposed control methods have been developed and simulated using the MATLAB/SIMULINK software. The simulation allows investigation of both transient and steady state operations for the proposed methods which can also show the reduction in steady state error. The system parameters are reported in appendix (A).

The motor load is initiated at 1.5 sec and removed at 5 sec in the simulation study. Figs from 9 to 11 show the simulation results for the motor operated with optimal PI gain obtained from PSO, hand tuning (Trial and error method), FL speed controller and hybrid controller. The figures show motor speed, developed torque and motor speed error, respectively.

**A. PI controller with hand tuning gains and PSO optimal gains**

The PI speed controller gain parameters are selected by trial and error basis by observing their effects on the response of the drive. The values of  $K_p$  and  $K_i$  obtained from the hand tuning are 0.5 and 4, respectively, and the values of gains with PSO algorithm are 1.0143 and 7.1623, respectively. The dynamic performances of the motor with hand tuning gains and optimal gains with PSO of PI controller are shown in Fig.9.

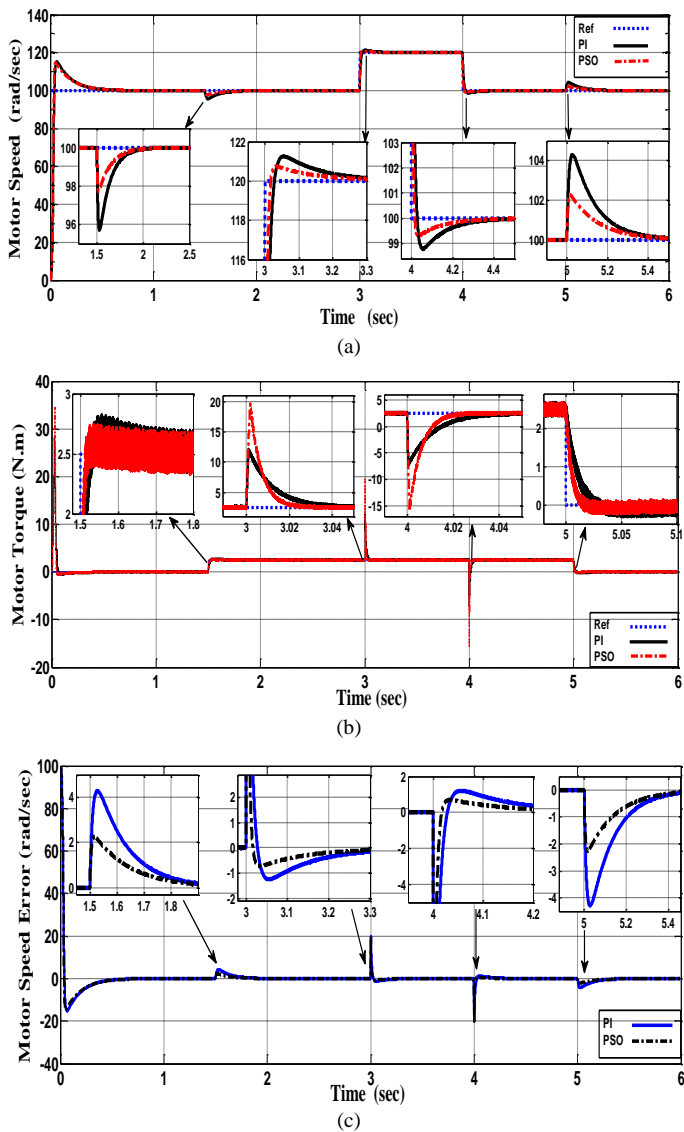


Fig.9 Simulation results of PI controller with hand tuning gains and PSO optimal gains: (a) Motor Speed, (b) Motor Torque, (c) Motor Speed Error.

It is noted that, overall dynamic performances of the motor when operated at PI controller with optimal gains with PSO is better than the hand tuning and the steady-state error of speed response is zero.

**B. FL and hybrid speed controller**

The simulation results of motor speed, torque and motor speed error responses of the motor, which operate with FL and hybrid speed controller (HC), are shown in Fig.10. For FL controller, for all the regions, there is no speed overshoot and ripples are negligible (main advantage of FL controller), but it offers more settling time and steady-state speed error (disadvantageous of this controller) as shown in Fig.10.c. Overshoot and undershoot occurred in the torque response, but are still better than PI controller with and without optimal tuning of gains.

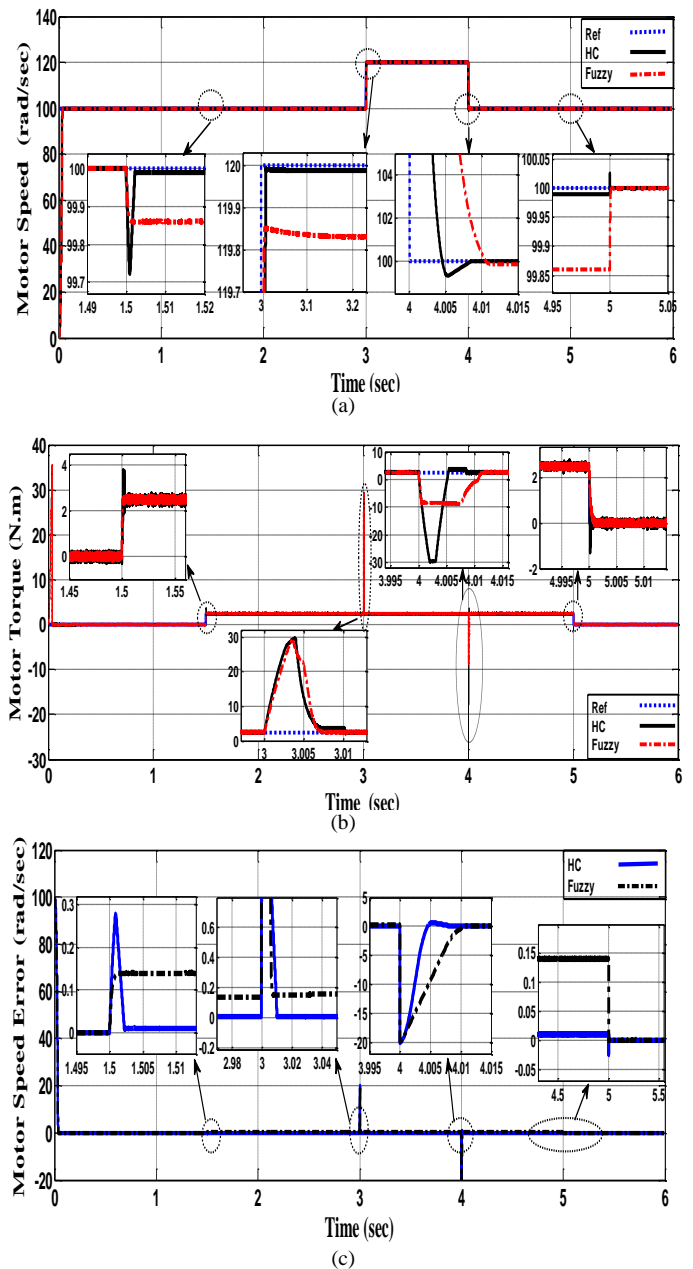


Fig.10 Simulation results of FL and hybrid speed controller: (a) Motor Speed, (b) Motor Torque, (c) Motor Speed Error.

On the other hand, speed response of HC has a minimum overshoot, which could be neglected and settles faster in comparison with FL controller. It is also noted that there is no steady-state error in the speed response throughout the operation when hybrid controller is activated. Furthermore, no oscillation in the torque response before it finally settles as shown in Fig.10.b, whereas oscillation occurred at PI controller with hand tuning. Good torque response is obtained with HC controller at this instant, speed response is better than PI and FL controllers.

**C. Hybrid speed controller with hand tuning gains and PSO optimal gains**

The simulation results of motor speed, motortorque and motor speed error responses, which operate with hybrid speed controller (HC) using hand tuning and optimal gains by PSO algorithms are shown in Fig.11. From this figures, it can show that speed response of PSO has smaller overshoot and settles faster than a hand tuning of HC controller. It is also noted that there is no steady-state error in the speed response throughout the operation when hybrid controller is activated in two cases as shown in Fig.11.c. Also there is a negligible ripple in speed response at HC in comparison with PI and FL controllers.

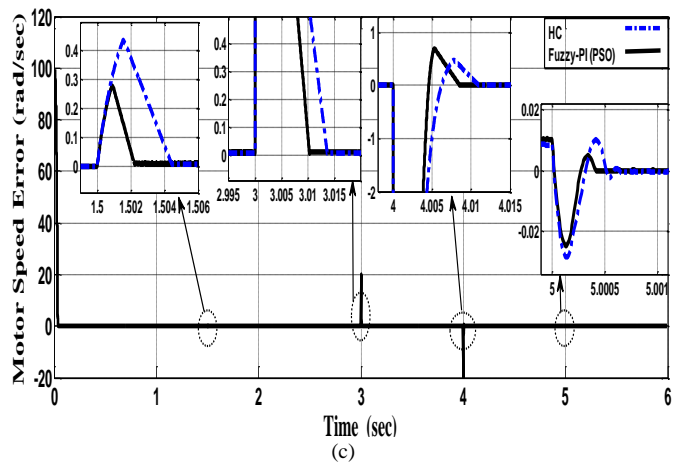
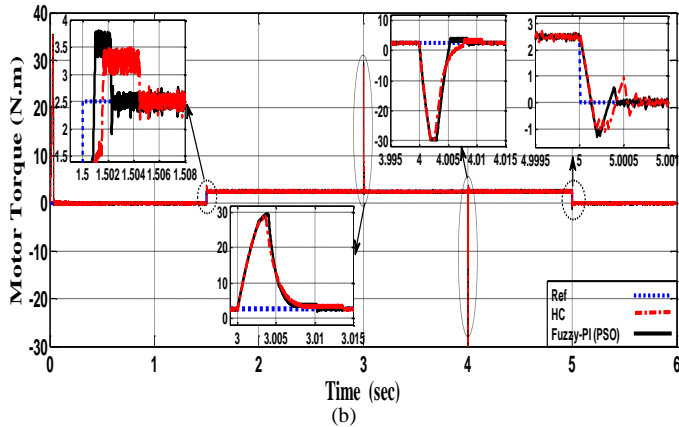
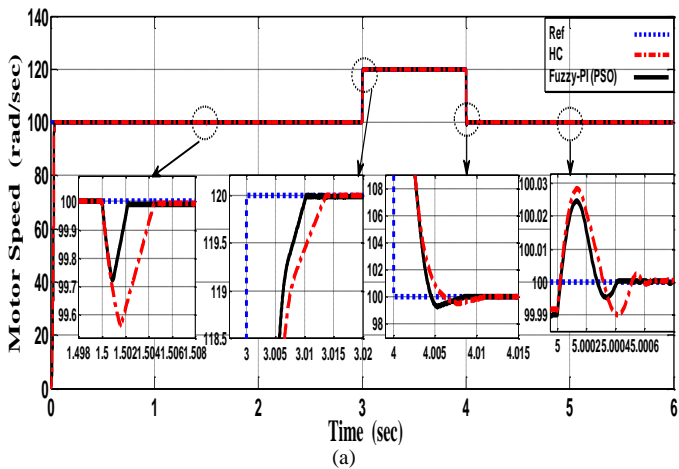


Fig.11 Simulation results of hybrid speed controller with hand tuning gains and PSO optimal gains: (a) Motor Speed, (b) Motor Torque, (c) Motor Speed Error.

**VII. EXPERIMENTAL RESULTS**

With the objective of evaluating the employed topology, laboratory prototype is setup. The block diagram of the experimental setup and a real view of the complete control system are shown in Figs.12 and 13, respectively. The main components of the system which labeled as in Fig.13 are listed in Table 2. The proposed tuning of speed controller in IM drives using PSO control is done on a digital signal processor board (DS 1104) plugged into a computer. The control algorithm is executed by ‘Matlab/Simulink’, and downloaded to the board through host computer. The output of the board is logic signals, which is fed to IGBT through driver and isolation circuits.

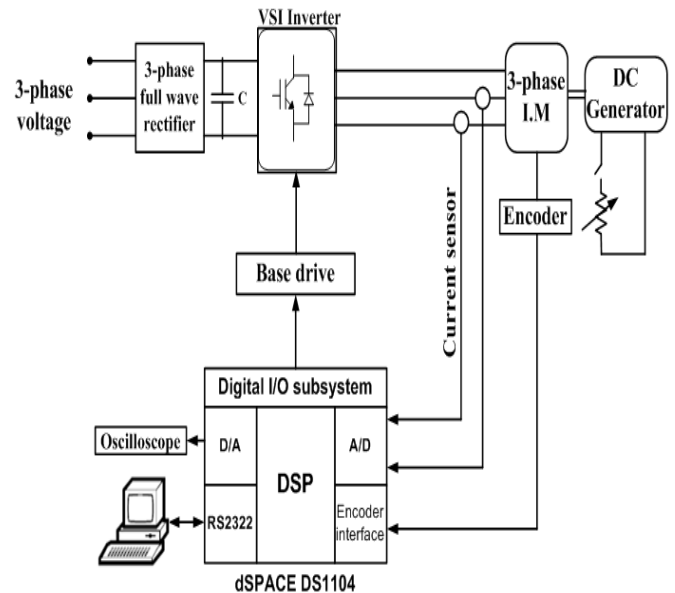


Fig. 12 Hardware schematic diagram for the experimental implementation of a.c drive system





Fig.13 Experimental setup of the a.c drives system

Table 2

Label	Component	Label	Component
M	Induction motor	D	DC machine
T	IGBT inverter module	L	Variable resistance
B	Base Drive Circuit	E	Incremental encoder
H	Measurement Circuit	C	DC link capacitors
I	Interface circuit	PC	personal computer
S	All other power suppliers	P	Variable AC power supply
R	Rectifier	Sb	Snubber circuit

**A. PI controller with hand tuning gains**

The experimental results of motor speed and motor speed error in case of using PI controller with hand tuning gains are shown in Fig. 14. It is illustrated from these figures, zero steady-state error when operating. But the disadvantages of this PI controller is the occurrence of overshoot while speed change from 100 to 120 rad/sec, undershoot while speed change to 100 rad/sec again.

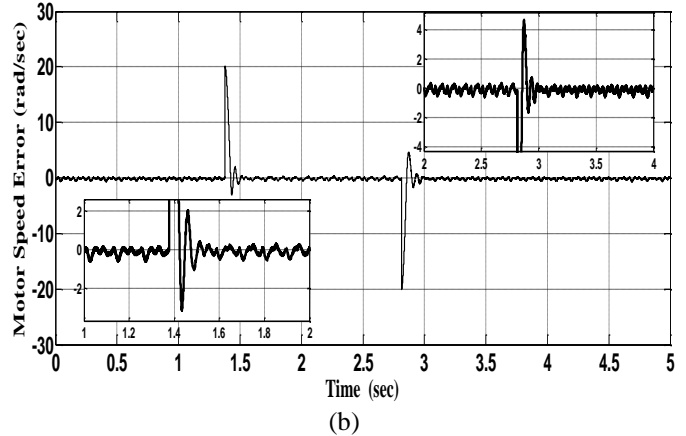
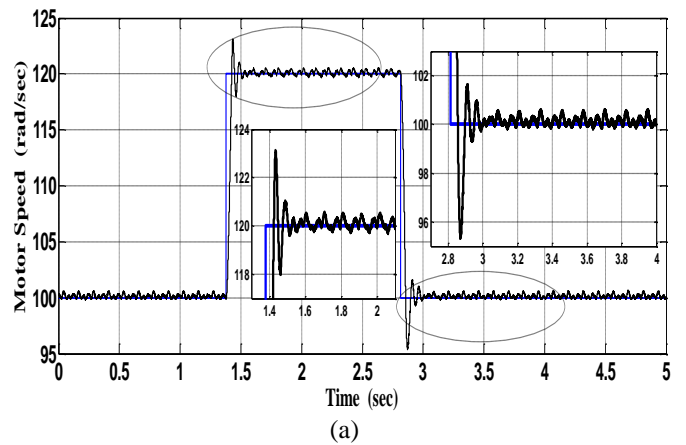


Fig. 14 Experimental results of PI controller with hand tuning gains: (a) Motor Speed, (b) Motor Speed Error.

**B. PI controller with PSO optimal gains**

The experimental results of motor speed and motor speed error in case of using PI controller with PSO optimal gains are shown in Fig. 15. It is noted that, overall dynamic performances of the motor when operated at PI controller with optimal gains with PSO is better than the hand tuning, it has zero steady-state error of speed response, the overshoot and undershoot is low when speed change. It can show the difference between them through Figs. 14 and 15.

It seems that results of Fig.14 are better in some aspects, e.g. lower speed ripples.

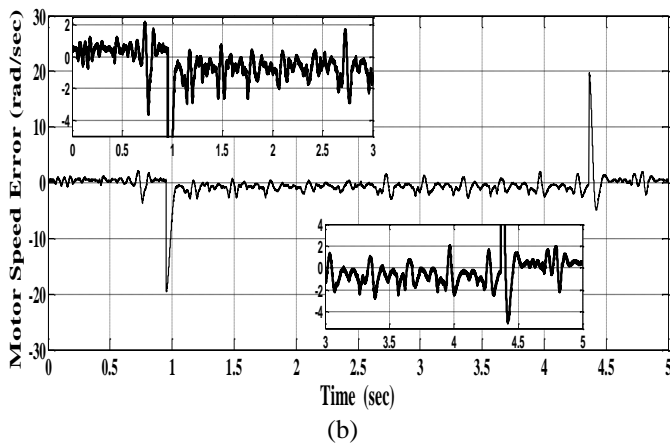
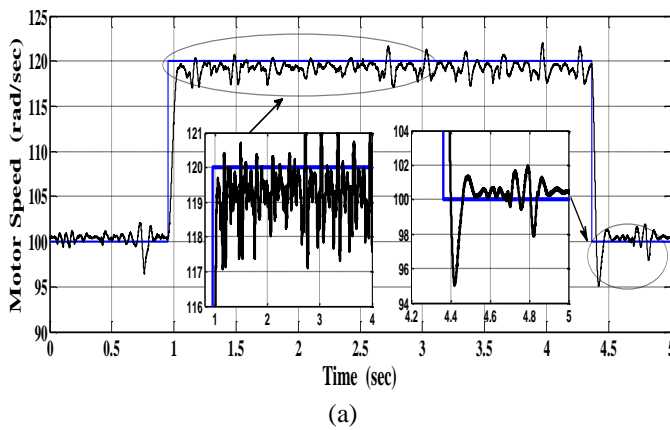


Fig. 15 Experimental results of PI controller with PSO optimal gains: (a) Motor Speed, (b) Motor Speed Error.

**C. Fuzzy Logic controller**

Fig.16 shows the experimental results of motor speed and motor speed error responses of the motor, when operate with FL speed controller. At full load, there is no speeds overshoot when change speed from 100 to 120 rad/sec. and ripples are negligible, but it has speed error (disadvantageous of this controller). We can observe that FL controller stills better than PI controller with and without optimal tuning of gains.

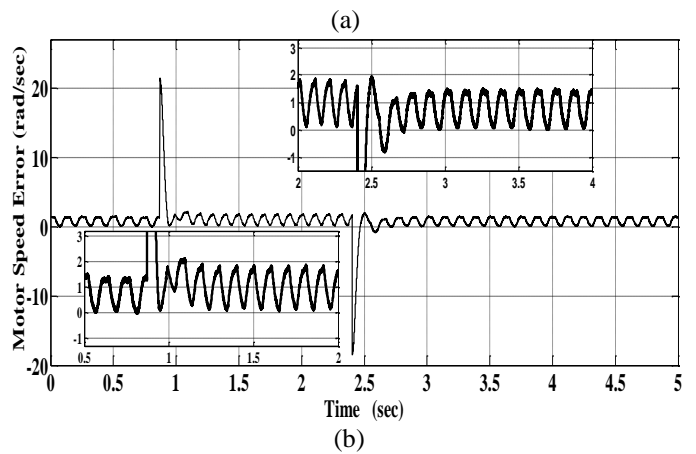
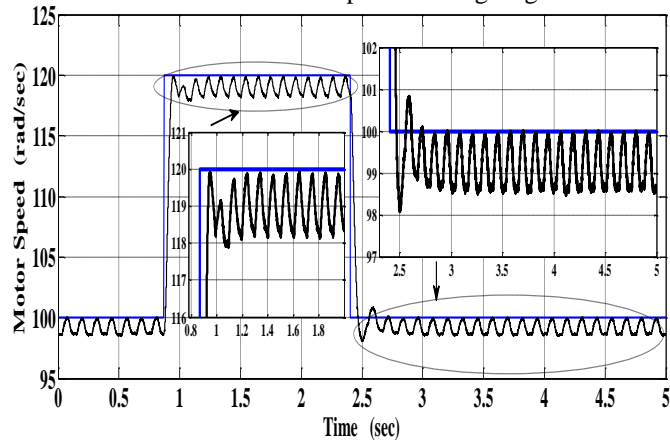
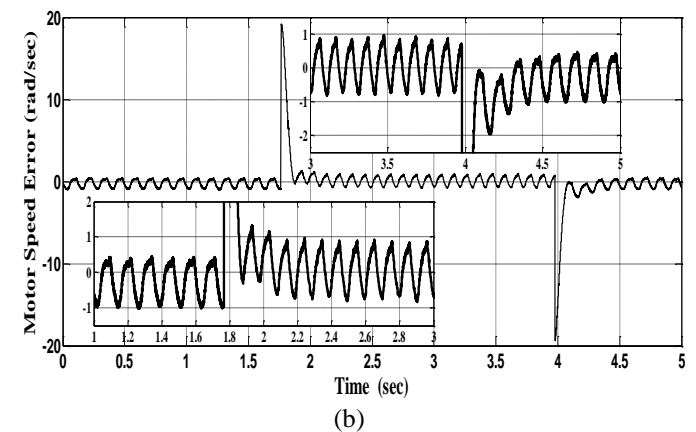
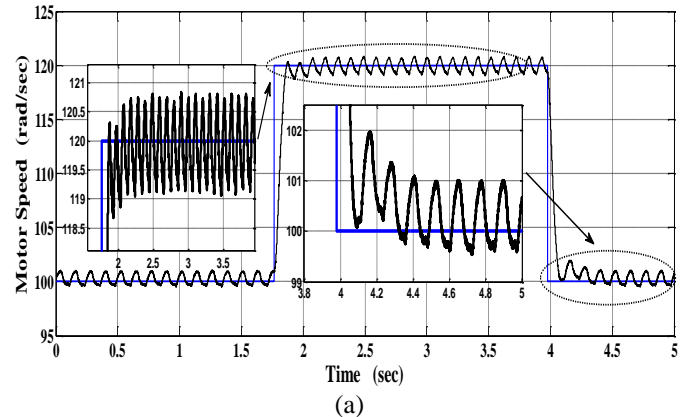


Fig. 16 Experimental results of Fuzzy Logic controller: (a) Motor Speed, (b) Motor Speed Error.

**D. Hybrid speed controller with PSO optimal gains**

It is clear from the Fig.17 of the experimental results of hybrid speed controller (HC) with PSO optimal gains of motor speed and motor speed error responses when loaded is better than PI and FL controllers. There is a negligible ripple in speed response at HC in comparison with PI and FL controller. It has no overshoot, no undershoot, no steady-state error and settles faster when speed change from 100 to 120 rad/sec.



**Fig. 17** Experimental results of hybrid speed controller with PSO optimal gains: (a) Motor Speed, (b) Motor Speed Error.

### VIII. CONCLUSIONS

A modern approach of speed controller for 3 phase IM using PSO algorithm to optimize the parameters of the PI and Fuzzy-PI controllers has been presented in this paper. From the simulation studies, comparison between different controllers is achieved using PI and fuzzy-PI controllers which are tuned by two methods, manually and using PSO technique. HC of PI and FL controller PSO-based for the speed control of given motor is also performed to eliminate the drawbacks of PI controller (overshoot, undershoot), FL controller (steady-state error). It produced better performances in terms of rise time, overshoot, undershoot and settling time. The use of PSO as an optimization algorithm makes the drive system robust, with faster dynamic response, higher accuracy and insensitive to load variation. For practical implementation, the values of PI gains obtained from PSO at different speed and torque commands can be stored in the memory of a digital signal processor and used to operate the motor with optimal gains according to desired speed and torque. Finally the system is tested under a change in the load and a step change in the speed reference. From these results, the PSO succeeds in tuning the (PI and Fuzzy-PI) controllers more efficiently than the traditional method, and shows a more dynamic response.

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### APPENDIX (A)

The simulation and the experimental results for the proposed method are taken with the following specifications:

#### The induction motor parameters are as follows:

Rated power	1.5 HP
Rated line voltage	380 V
Rated current	2.8 A
No. of poles	4
Stator resistance	7.4826Ω
Rotor resistance	3.834Ω
Mutual inductance	0.4114 H
Stator leakage inductance	0.0221 H
Rotor leakage inductance	0.0221 H
Rated speed	1400 rpm
Moment of inertia	0.035 kg.m <sup>2</sup>
Rated torque	7.5 N.m

#### Parameter settings for the PSO algorithm

Inertia weight ( $\omega$ ): linearly decreasing (0.9–0.4).

Acceleration constants PSO parameter:  $\rho_1 = \rho_2 = 2.0$ .

$n = 30$  Size of the swarm "no of birds" particles.

Bird-step = 150. Max Noof " birds steps" iteration.