A Novel Particle Swarm Optimization PSO Tuning Scheme for PMDC Motor Drives Controllers

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ABSTRACT — The paper presents the novel application of Particle Swarm optimization PSO for the optimal tuning of PID controller for high performance permanent magnet PMDC industrial motor drives. This will smooth the starting torque; enhance acceleration and dynamic tracking of the reference speed. The permanent magnet PMDC motor drive is fed from a 3-phase AC supply via a six pulse thyristor controlled rectifier. The proposed Dynamic tri-loop controller utilizes the motor speed error ($e_\omega$), the armature current deviation ($e_I$) from its maximum or "specified" allowable current level and dynamic current ripple error ($e_R$) as inputs to the PSO gain search algorithm. The control voltage signal is used to regulate the firing delay angle $\alpha$ of the 3-phase controlled rectifier bridge. The proposed Tuned PID controller is based on the minimization of the absolute of total Error.

INDEX TERMS — PMDC Motor Drive, Particle Swarm Optimization PSO, Tuning PID gains, total error minimization.

1. INTRODUCTION

DC motors have long been the primary means of Electrical Traction. DC motor has at torque/speed characteristics compatible with most mechanical loads. The speed control methods of a dc motor are simpler and less expensive than those of A.C Motor and speed control over a large range both below and above rated speed can be easily achieved [1]. High performance permanent magnet dc (PMDC) motor drives (10-1000 KW) are currently used in a multitude of industrial applications such as in process control, traction, pulp and paper, steel mills, robotics, guided vehicles, mining and smelting plants. Precise, fast and dynamic speed reference tracking with minimum overshoot/ undershoot and small steady state tracking error are the main control objectives of such a drive system [2]. In a typical electric drive controller, there are usually several nested control loops for the control of current/torque, speed and position, each of which may use a separate proportional-integral- Derivative (PID) controller. Although many alternative optimal control techniques have been proposed, the PID controller continues to be the most popular controller used in industrial processes [3-4]. The main advantage of this kind of controller is its simplicity. It is not easy to find another controller with such a simple structure that is both effective, robust and comparable in its dynamic performance. A very important step in the use of PID controllers is the controller parameters tuning process. In a PID controller, each mode (proportional, integral and derivative mode) has a gain to be tuned, giving as a result three variables involved in the tuning process. PSO algorithm is used to select optimal control gains that dynamically minimize the total controller error $e_c$.

There have been a lot of methods to search the parameters of PID controllers, including time response tuning [5], time domain optimization [6], frequency domain shaping [7] and genetic algorithms [8]. The speed response of the drive with PID controllers designed with the above techniques may be satisfactory but not necessarily be the best, since they do not pose any constraint on settling time, overshoot / undershoot etc. Despite the known method of Zeigler-Nichols (ZN) ultimate cycle tuning scheme, the control parameters can also be optimally and dynamically obtained via Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) based on control error criterion. GA is an iterative search and optimization algorithm based on natural selection and genetic mechanism. However, GA is very fussy; it contains selection, copy, crossover and mutation scenarios, and so on. Furthermore, the process of coding and decoding not only impacts precision, but also increases the complexity of the genetic algorithm. Particle swarm optimization (PSO) is a novel emerging intelligence which was flexible optimization algorithm proposed in 1995. There are many common characteristics between PSO and GA. First, they are flexible optimization technologies. Second, they all have strong universal property independent of any gradient information. However, PSO is much simpler than GA, and its operation is more convenient, without selection, copy and crossover.

In this paper, an optimally tuned PID controller for PMDC motor drive systems is developed using Particle Swarm optimization Technique PSO. The novel time decoupled time scaled tri-loop error driven PID Controller is also proposed for speed regulation under parametric variations and sudden load excursions. The proposed Tuned PID controller is based on the minimization of the Total error ($e_t$) that equals to the summation of ($e_\omega$, $e_I$, $e_R$). There is no constraint in the search space of the optimally selected PID parameters. The computer simulations results demonstrate that the effectiveness of the PID tuning algorithm using PSO based on minimization of absolute of the total error.

2. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is an evolutionary computation optimization technique (a search method based on a natural system) developed by Kennedy and Eberhart [9]-[12]. The system initially has a population of random selective solutions. Each potential solution is called a particle. Each particle is given a random velocity and is flown through the problem space. The particles have memory and each particle keeps track of its previous best position (called the $P_{\text{best}}$) and its corresponding fitness. There exist a number of $P_{\text{best}}$ for the respective particles in the swarm and the particle with greatest fitness is called the global best ($G_{\text{best}}$) of the swarm. The basic concept of the
PSO technique lies in accelerating each particle towards its Pbest and Gbest locations, with a random weighted acceleration at each time step. The main steps in the particle swarm optimization and selection process are described as follows:

(a) Initialize a population of particles with random positions and velocities in d dimensions of the problem space and fly them.

(b) Evaluate the fitness of each particle in the swarm.

(c) For every iteration, compare each particle’s fitness with its previous best fitness (Pbest) obtained. If the current value is better than Pbest, then set Pbest equal to the current value and the Pbest location equal to the current location in the d-dimensional space.

(d) Compare Pbest of particles with each other and update the swarm global best location with the greatest fitness (Gbest).

(e) Change the velocity and position of the particle. According to equations (1) and (2) respectively.

\[ V_{id} = \omega_t \times V_{id} + C_1 \times \text{rand1} \times (P_{id} - X_{id}) + C_2 \times \text{rand2} \times (P_{id} - X_{id}) \]  
\[ X_{id} = X_{id} + V_{id} \]  

Where: \( V_{id} \) and \( X_{id} \) represent the velocity and position of the i\(_{th}\) particle with d dimensions, respectively. \( \text{rand1} \) and \( \text{rand2} \) are two uniform random functions, and \( \omega_t \) is the inertia weight, which is chosen beforehand.

(f) Repeat steps (a) to (e) until convergence is reached based on some desired single or multiple criteria.

The PSO search and minimization algorithm has many parameters and these are described as follows: \( \omega_t \) is called the inertia weight that controls the exploration and exploitation of the search space because it dynamically adjusts velocity. \( V_{\text{max}} \) is the maximum allowable velocity for the particles (i.e. in the case where the velocity of the particle exceeds \( V_{\text{max}} \) then it is limited to \( V_{\text{max}} \)). Thus, resolution and fitness of search depends on \( V_{\text{max}} \). If \( V_{\text{max}} \) is too high, then particles will move beyond a good solution. If \( V_{\text{max}} \) is too low, particles will be trapped in local minima. The constants \( C_1 \) and \( C_2 \) in (1) and (2), termed as cognition and social components, respectively. These are the acceleration constants which changes the velocity of a particle towards Pbest and Gbest (generally, somewhere between Pbest and Gbest). Fig (1) shows the general flow chart of the PSO algorithm based on total error iterative minimum search.

3. DC MOTOR MODELING
The PMDC motor torque, \( T \), is related to the armature current, \( i \), by a constant factor \( K_t \): \( T = K_t \cdot i \). The back emf, \( e \), is related to the rotational velocity by: \( e = K_h \omega_r \). In SI units \( K_t \) (armature constant) is equal to \( K_h \) (motor constant). The PMDC motor equations based on Newton's law combined with Kirchhoff's law:

\[ J \frac{d\omega_r}{dt} + B \omega_r = K_t i_a - T_L \]  
\[ L_a \frac{di_a}{dt} + R_a i_a = V_a - K_h \omega_r \]  

where: \( J \) the moment of inertia, \( B \) damping coefficient of the mechanical system, \( K_t \) the electrical resistance of the armature circuit, and \( L_a \) the electrical inductance of the armature circuit. In the state-space form, the equations above can be expressed by choosing the rotational speed and electric current as the state variables and the voltage as an input. The output is chosen to be the rotational speed.

\[ \frac{d}{dt} [\omega_r] = \begin{bmatrix} -\frac{B}{J} & \frac{1}{J} \\ \frac{K}{K_p} & -\frac{R_a}{L_a} \end{bmatrix} [\omega_r] + \begin{bmatrix} 0 \\ \frac{1}{L_a} \end{bmatrix} V_a \]  
\[ \omega_r = [1 \ 0] [\omega_r] \]  

The PID controller has the following form in the time domain:

\[ u(t) = K_p e(t) + K_i \int_0^t e(t) dt + K_d \frac{de(t)}{dt} \]  

Where \( e(t) \) is the selected system error, \( u(t) \) the control variable, \( K_p \) the proportional gain, \( K_i \) the integral gain, and \( K_d \) the derivative gain. Each coefficient of the PID controller adds some special characteristics to the output response of the system. Because of this, choosing the gains becomes a crucial decision for putting into practice this controller.

4. DYNAMIC ERROR DRIVEN CONTROLLER
Fig. 2 shows the general block diagram of the proposed PMDC drive system using the Particle Swarm Optimization PSO tuning. The PMDC motor drive shown in figure 2 comprises a DC motor, AC/DC full wave 6-pulse rectifier and the proposed novel tri-loop error driven PID controller. The AC-DC converter voltage is controlled by the phase angle \( \alpha \) using the proposed dynamic controller based on Particle Swarm Optimization PSO. The proposed Tri Loop Error Driven PID controller, developed by the First Author and given in Fig. 3, is a novel advanced regulator concept that operates as an adaptive dynamic type multi-purpose controller capable of handling sudden parametric changes and load and/or source excursions.

By using the Tri Loop Error Driven PID controller, it is expected to have a smoother, less dynamic overshoot, fast and more robust speed controller when compared to those of classical control schemes. The proposed general PMDC Motor Drive Model with the novel Tri Loop Error Driven PID speed controller are fully validated in this paper for effective reference speed trajectory tracking under different loading conditions and parametric variations; such as temperature changes while driving a complex mechanical load with non-linear parameters and/or torque-speed characteristics. The novel Tri Loop Error Driven PID Controller is used to keep the motor armature voltage between specified operational limits and ensure excellent speed reference tracking under source, load excursions and parametric variations. The Tri Loop Error Driven PID Controller scheme inherently allows any dynamic excursions or parameter variations to be taken into account so that the PID controller regulator is dynamically adapted for reducing error changes. The novel error driven controller is validated for effective reference speed tracking under normal conditions as well as parameter load changes and sudden excursions. The tri loop Error Driven PID Controller was very effective and capable of handling all excursions and parameter variations, especially with dynamically tuned (\( K_p, K_i, K_d \)) gains using the PSO
dynamic search and optimization criterion based on total error minimization. Other criteria based on maximum overshoot, settling time, rising time, total error squared, and integral error squared minimization can also be utilized.

The dynamic supplementary control loops utilizes the (per-unit) three dimensional-error vector \((e_o, e_i, e_r)\) governed by the following equations:

\[
e_{o}(k) = e\omega(k) - e\omega_{ref}(k) \left( \frac{1}{1 + sT_1} \right)
\]

\[
e_{i}(k) = I_{mref}(k) - I_{m}(k) \left( \frac{1}{1 + sT_1} \right)
\]

\[
e_{r}(k) = I_{m}(k) \left( \frac{1}{1 + sT_1} \right) - I_{m}(k) \left( \frac{1}{1 + sT_2} \right)
\]

The total error \(e_t(k)\) at a time instant:

\[
e_t(k) = \gamma_o e_o(k) + \gamma_i e_i(k) + \gamma_r e_r(k)
\]

This is the error to be minimized using PSO algorithm.

5. SIMULATION RESULTS

The full unified motor drive with novel controller model was simulated using the MATLAB. The parameters of the PMDC motor are given in Appendix. The control parameters were tuned and the simulation results are shown on the following pages. Table (1) shows the results of PSO algorithm running. The table shows the main objective function (Minimum Total error) versus the Tuned PID Gains at different iteration counts. The PSO Gain tuning algorithm was used to minimize the absolute of controller total error as shown in fig.1

Motor Drive response with change in the reference speed:
The controller effectiveness in tracking different speed reference trajectories were tested for step reference. Per-unit error excursions are depicted. The PMDC motor starting under 0.5 PU load Torque, for a unit step change in the reference speed equals 0.25 PU from 0.5 to 0.75 PU. The value of \(K_p\), \(K_i\), and \(K_d\) corresponding to the best solution obtained is in the block diagram shown in Fig (3). Even though the design of \(K_p\), \(K_i\), and \(K_d\) is carried out assuming that there is no change in reference speed, the values of \(K_p\), \(K_i\), and \(K_d\) obtained through PSO are now used to study the system's response when there is a step change in reference speed. The response of speed track (step change) is shown in Fig. (4).

Motor Drive response with load disturbance:
With a step-load disturbance of 0.5 PU, variation of \(\omega_o\) is shown in the Fig (5). It can be inferred from this figure that settling time and maximum overshoot is well within the stipulated limits.

6. CONCLUSION

The paper presented the application of Particle Swarm Optimization PSO for the tuning of the error-driven self-adjusting multi loop PID speed regulator for large industrial PMDC motor drives. The proposed dynamic controller utilizes speed, current and current dynamic ripple errors as inputs to vary the firing delay angle \(\alpha\) of the 6-pulse controlled Thyristor rectifier. The self-adjusting error driven regulator ensures an effective control signal as required by the per-unit three-dimensional total error \((e_o, e_i, e_r)\). The selection of optimal control gains is essential for effective robust tracking of different speed reference trajectories. The Computer simulation results show that an optimized dynamic speed response is always obtained with load torque disturbance and change reference speed, as well demonstrate that the excellent performance of the optimal PID controller. The tri loop Error Driven PID Controller was very effective and capable of handling all load excursions and sudden parameter variations. PSO dynamic search and optimization criterion is based on total error minimization. Other search criteria based on the maximum overshoot, settling time, rising time, total error squared, and integral error squared minimization can also be utilized.

7. APPENDIX

PMDC Parameters
125 HP, 230 V, 120.4 rad/sec, armature circuit Resistance (\(R_a\)) 0.0125 \(\Omega\), Armature circuit Inductance (\(L_a\)) 0.065 H, Moment of Inertia (\(J\)) 3.0 Kgm², Coefficient of friction (\(B\)) 0.60 N.M.sec/rad, Torque constant (\(K_T\)) 1.91 V.Sec/rad, Back-Emf constant (\(K_b\)) 1.91 V/sec/rad

6 Pulse Rectifier:
Functional Model: \(V_f \cong 1.35 V_{LL} \cos \alpha - \frac{3 X_c}{\pi L_s} \), \(3^\circ \leq \alpha \leq 87^\circ\), \(V_c=230\) V (LL), \(X_c=X_s+X_T=0.3160 \Omega\), \(X_T\) Transformer Leakage Reactance; \(X_s\) AC system Thévenin’s reactance.

Interface Transformer:
11 KV/0.23 KV; 500 KVA; \(X_t=5\%\)

Controller Loops Gains:
\(\gamma_o = 1.0; \gamma_i = 0.60; \gamma_r = 0.40\)

Controller Loops delay Time:
\(T_o=20\) ms, \(T_i=10\) ms, \(T_r=10\) ms,

PID Controller Gains:
\(5 \leq K_P \leq 150, 1 \leq K_I \leq 50, 0.1 \leq K_D \leq 10\)

DC Side Filter(smoothing reactor):
\(R_f=0.05 \Omega, L_f=15\) mH

PSO Minimization:
find the optimal controller gains to minimize the absolute of the total current. The optimum selected gains are: \(K_p=124.789; K_i=35.17; K_d=27.623\); and best value of the absolute of the total error is \(e_t=0.01820959\)

Fig. 1 the general flow chart of PSO for minimizing the absolute of controller total error.
Table (1) the main objective function (Minimum Total error) versus the Tuned PID Gains at different iteration counts

<table>
<thead>
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<th>Iteration count</th>
<th>Tuned PID Gains</th>
<th>Minimum Total error</th>
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<td>$K_P$</td>
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<tr>
<td>300</td>
<td>124.789456453732</td>
<td>35.170331225515</td>
</tr>
</tbody>
</table>

PMDC

\[ \omega_r \]

PSO Tuning of Dynamic Controller Scheme

\[ \omega_{\text{ref}} \]

\[ I_m \]

\[ I_{\text{mref}} \]

AC Utility Transformer

11 KV / 550 V

11 KV / 550 V

PMDC

Mechanical Load

Fig (2): PMDC motor drive system

Fig (3): Unified PMDC motor drive scheme with multi-loop dynamic controller
Fig (4) the response of the control system for the first speed track based on total error \( e \), minimization

(a) Load Torque,  (b) Speed track response,  
(c) The armature current,  (d) The armature voltage,  
(e) Speed error curve,  (f) Current Error curve,  
(g) Ripple Error curve,  (h) Total Error curve, and  
i) Speed-Torque curve.
Fig (5) the response of the control system for the load torque disturbance based on total error \( e_{t} \) minimization

(a) Load Torque, (b) Speed track response, (c) The armature current, (d) The armature voltage, (e) Speed error curve, (f) Current Error curve, (g) Ripple Error curve, (h) Total Error curve, and (i) Speed-Torque curve.

8. REFERENCE


