

# Parameter Estimation of DC Motor Using Chaotic Initialized Particle Swarm Optimization

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**Abstract:** Parameter estimation plays an important role in system modelling and control. This paper presents a parameter estimation strategy for separately excited DC motor using a chaotic initialized particle swarm optimization algorithm. The parameter estimation problem is converted into an optimization problem using an objective function. The presented strategy is significant in estimating the motor parameters accurately when compared to standard particle swarm optimization portrayed by low mean square error between actual and estimated speed.

## 1 INTRODUCTION

DC motors have wide applications ranging from small home appliances to complex industrial control systems for the reason that they are easy in modelling and control. Sometimes precise parameters of a DC motor are needed for analysis and design of control system and optimization. The information given by manufacturer may not be sufficient in this situation. This scenario led to the application of numerical techniques for the parameter estimation. In particular, various techniques have been applied to parameter estimation of electric motors such as least squares (Cirrincione et al. 2003), equation error method (Petrovas, Pitrenas & Savickiene 2017), inverse problem method (Hadeif & Mekideche 2009), Nelder-Mead simplex method (Dub & Jalovecký 2010). Recently, evolutionary algorithms have gained much attention in parameter estimation problems (Mughal, Ma & Xiao 2017). Many evolutionary algorithms have been applied to parameter estimation of electric machines in particular to DC motors. Bosco et al. (Bosco et al. 2017) applied differential evolution (DE) algorithm for parameter estimation and PI control tuning of a permanent magnet DC motor. (Puangdownreong 2017) applied flower pollination algorithm to parameter estimation of a DC motor. (Udomsuk et al. 2010) applied an adaptive tabu search (ATS) algorithm to parameter estimation of a separately excited DC motor. (Kumpanya, Thaiparnat

& Puangdownreong 2015) applied ATS and intensified current search techniques to parameter estimation of a brushless DC motor. Among various evolutionary algorithms, Particle Swarm Optimization is relatively prominent due to its simple structure and ease in implementation (Zhang et al. 2015). PSO has found numerous applications in solving engineering optimization problems; (Mohammadi et al. 2014) used PSO for parameter estimation of a three-phase induction motor. In this paper, an improved PSO known as chaotic initialized PSO (CIPSO) was applied to parameter estimation of a separately excited DC motor. The accuracy of the estimation was evaluated by the degree of agreement between the actual motor speed response and the estimated speed response and also by comparing the results with standard PSO (SPSO).

## 2 MODELLING OF DC MOTOR

In this section a separately excited DC motor is modelled as a transfer function (*DC Motor Speed: System Modeling* n.d.) that relates the input voltage (volts) and output rotational speed (rad/sec) as expressed in (1):

$$G(s) = \frac{\dot{\theta}(s)}{\vartheta(s)} = \frac{K}{(Js + B)(Ls + R) + K^2} \quad (1)$$

where  $G(s)$  is the transfer function,  $\theta$  is the rotational direction and  $\vartheta$  is the input voltage. All other parameters are defined in Table 1 with their actual values and units.

Table 1: Actual parameter values with units.

Parameter	Value
Moment of inertia ( $J$ )	0.01 Kg.m <sup>2</sup>
Viscous friction ( $B$ )	0.1 N.m.s
Electromotive force constant ( $K$ )	0.01 V/rad/sec
Torque constant ( $K$ )	0.01 N.m/Amp.
Resistance ( $R$ )	1 Ohm
Inductance ( $L$ )	0.5 H

$X = [J \ B \ K \ R \ L]$  is the parameter vector to be estimated by time-varying PSO

### 3 PARAMETER ESTIMATION PROBLEM FORMULATION

The DC motor parameter estimation problem was converted to an optimization problem by using an objective function. A mean square error (MSE) is used in this paper as objective function as expressed in (2):

$$\min J = \frac{1}{N} \sum_{i=1}^N [\theta_{act.}(i) - \theta_{est.}(i)] \quad (2)$$

where  $J$  is the objective function  $N$  is the number of speed data samples,  $i$  is the index term whereas  $\theta_{act.}$  and  $\theta_{est.}$  represent the actual and estimated speed, respectively. The purpose of the optimization algorithm is to optimize (minimize) this error and output the corresponding parameters. Figure 1 shows the block diagram of the DC motor parameter estimation.

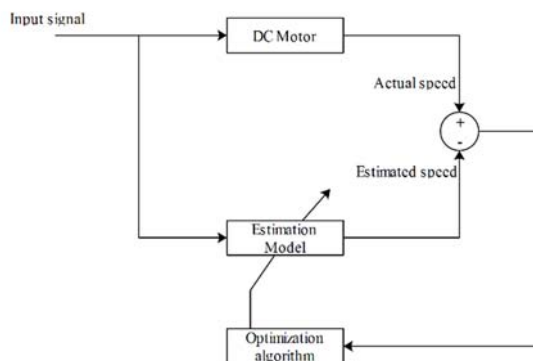


Figure 1: DC motor parameter estimation block diagram.

### 4 CHAOTIC INITIALIZED PSO

Particle Swarm Optimization is a well-known evolutionary algorithm which takes its inspiration from food search behaviour of bird flocks. A swarm of particles (initial solutions) is initialized randomly with normal distribution. Each particle in the swarm is evaluated against an objective function like the one expressed in (2); best solution of each particle called the personal best and best solution among all the particles called the global best is retrieved. The velocity of each particle is updated using (3) and position is updated using (4)

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (pBest_i - X_i) + \dots + c_2 r_2 (gBest_i - X_i) \quad (3)$$

where  $V$  is the velocity,  $X$  is the particle vector,  $\omega$  is the inertia weight,  $c_1$  is the personal acceleration coefficient,  $c_2$  is the social acceleration coefficient,  $pBest$  is the personal best,  $gBest$  is the global best,  $r_1$  and  $r_2$  are the random numbers distributed between 0 and 1.

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (4)$$

The  $pBest$  and  $gBest$  are updated using following (5) and (6).

$$pBest_i^{k+1} = \begin{cases} pBest_i^k, & \text{if } J(pBest_i^k) \leq J(X_i^k) \\ X_i^k, & \text{if } J(X_i^k) < J(pBest_i^k) \end{cases} \quad (5)$$

$$gBest_i^{k+1} = pBest_i^k, \text{ if } \max[J(pBest_i^k)] \quad (6)$$

#### 4.1 Chaotic Initialization

Chaos can be termed as bounded nonlinear system; it is generated by iterating some deterministic equation with an element of regularity (Tian 2017). In this paper a tent chaotic map is utilized for initialization of the swarm. The tent map is expressed by (7)

$$z_{i+1} = \begin{cases} 2z_i, & z_i \in (0, 0.5) \\ 2(1 - z_i), & z_i \in (0.5, 1) \end{cases} \quad (6)$$

where  $z_i$  is the chaotic amplitude,  $i$  is the iteration counter and  $z_0 \in (0, 1)$ . Figure 2 shows the chaotic variables generated for 50 iterations between 0 and 1.

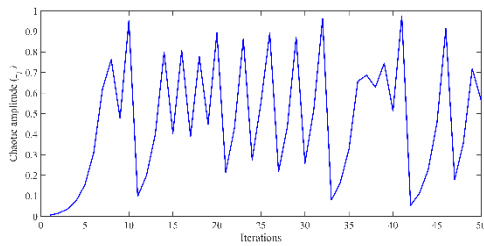


Figure 2: Chaotic variables generated for 50 iterations.

Following is the pseudo code for chaotic tent map generation

1. Begin
2. Randomly initialize chaotic variables
3. while(maximum iterations)
  - Update the variables by (6)
4. End while
5. Normalize the chaotic variables into the problem search space
6. End

Algorithm 1: Pseudo code for tent map generation.

1. Begin
2. Initialize position of particles using the chaotic map (6)
  - { $X_i | i = 1, 2, \dots, N$ };
3. Calculate the objective value of  $X_i$ ;
4. while (number of iterations)
5.     for  $i = 1$  to the number of particles
  - find  $pBest$
  - find  $gBest$
6.     for  $d = 1$  to number particle dimensions
  - Update the velocity of particles by (3)
  - Update the position of particles by (4)
7.     end
8.     end
9.     Next generation until stopping criterion
10.    end
11. End

Algorithm 2: Pseudo code for the CIPSO.

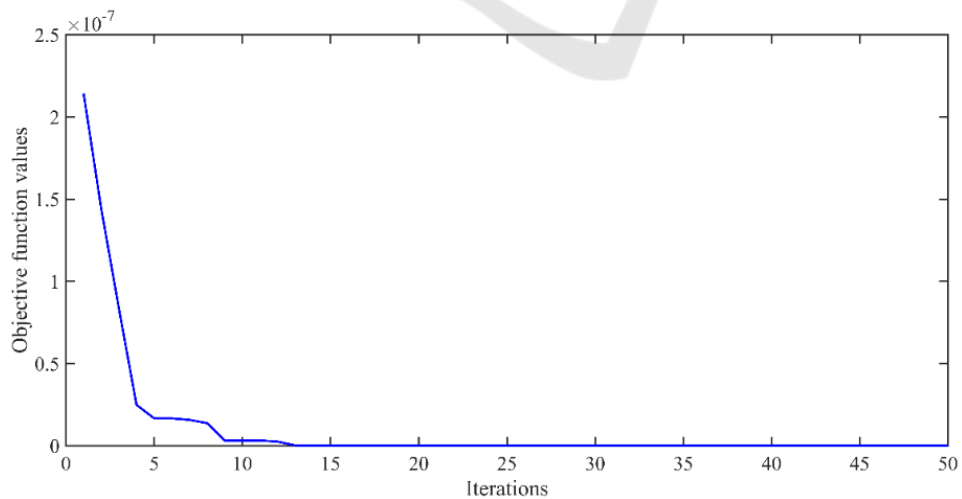


Figure 3: Convergence curve for CIPSO.

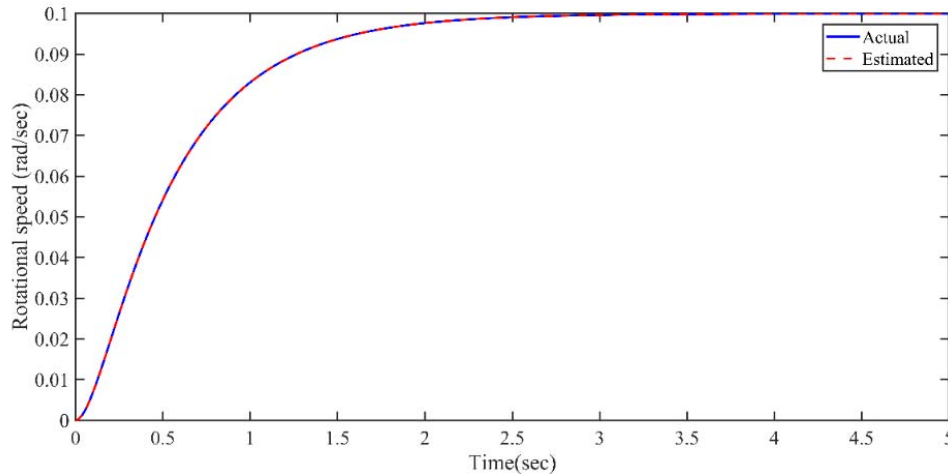


Figure 4: Actual and estimated speed response

## 5 COMPUTATIONAL RESULTS AND DISCUSSION

### 5.1 Algorithm Parameter Settings

Table 2 displays the parameter settings for the CIPSO and SPSO. The CIPSO was initialized with chaotic tent map based particles whereas the SPSO was initialized with random numbers scaled in problem range.

Table 2: Algorithm parameter settings.

Parameters	Setting
Swarm size	30
Number of iterations	50
$\omega$	0.9
$c_1$	2
$c_2$	2

### 5.2 Computational Results

A unit-step signal was applied to the transfer function model of the DC motor to record the speed response (termed as actual speed) for a time period of 5 seconds. The CIPSO was then applied to minimize the difference between the actual speed response and the estimated speed by using (2). The parameters estimated by CIPSO were compared with the standard PSO (SPSO) and the actual parameters of the DC motor. Table 3 tabulates the estimation results obtained by the algorithms with the actual motor parameters. It can be observed from Table 3 that the CIPSO has outperformed the SPSO in terms of less MSE values and accuracy in estimating the motor parameters. CIPSO has achieved a MSE value of 1.399E-12 which is far less than the MSE achieved by SPSO. The parameters estimated by CIPSO are in close proximity with the actual motor parameters. Figure 3 shows the convergence of the CIPSO. It is clear from Figure 3 that the CIPSO converged to a stable value in less than 15 iterations. Figure 4 plots the actual speed response and the speed response estimated by CIPSO; it can be seen that the speed response estimated by CIPSO tracks the actual speed response with high accuracy and close proximity

Table 3: Actual and estimated parameters with MSE.

Parameters	$J$	$B$	$K$	$R$	$L$	MSE
Actual	0.01	0.1	0.01	1	0.5	
CIPSO	0.0102	0.1	0.0101	1.007	0.503	1.399E-16
SPSO	0.0110	0.104	0.014	1.0901	0.508	2.080E-12

## 6 CONCLUSIONS

A chaotic initialized particle swarm optimization (CIPSO) algorithm was applied to parameter estimation of a DC motor. The DC motor was modelled using transfer function. Five parameters of the DC motor namely moment of inertia, viscous friction, electromotive force constant, resistance and inductance were estimated optimally using the CIPSO. The initial population swarm was generated by using a chaotic tent map. The estimated parameters were compared with the actual parameters and the parameters estimated by the standard PSO. The CIPSO was accurate in estimating the parameters with less mean square error, comparatively.

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