Hybrid DE-TLBO Based Robotic Arm Controller

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Abstract

A New effective optimization Technique called ‘Hybrid DE-TLBO’ is proposed in this paper by clubbing of Differential Evolution¹⁰ and Teacher learning Based optimization algorithms⁹ for optimization of motion control of one degree of freedom of Robotic arm consisting of a DC Motor. This algorithm is used to control the PID gains namely Kp, Ki, Kd to get the optimized values of desired specifications that is to optimize the Rise time, settling time, steady state error, Maximum Peak Overshoot. This can be achieved through developing the model of DC Motor of Robotic Arm in Simulink and simulate with the algorithm and comparing with DE and TLBO algorithms.

Keywords: DC Motor, Differential Evolution, Hybrid DE_TLBO, PID Controller, Teacher Learning Based Optimisation

1. Introduction

Process control industry has seen many developments in the previous two decades in terms of controller design method and its execution method⁸. In spite of these developments PID Controller is the highly popular control since its humble structure and robust performance in several functioning situations. The speed of DC motor can be optimized to excessive amount as to provide controllability easy and great performance. To implement the PID Controller efficiently, alteration of its parameter is to be done. In 1942, Ziegler Nicholas¹ presented a tuning formulae based on the time responses and experiences. As it lags choice of parameters and extensive rise time, still releases way of tuning parameters.

Over the years many metaheuristic and stochastic techniques have been developed which are being applied in every discipline of life. These techniques are nature inspired depending upon the swarm intelligence, evolutionary, or foraging behavior of different species. Some of the widely used techniques are Genetic Algorithm (GA)², Particle Swarm Optimization (PSO)⁷, Teacher Learning Based Optimization (TLBO) and Differential Evolution(DE)⁴. Hybridization of algorithms has become common practice in the past few years as not only does this increase the converging capabilities of both the algorithms, it combines the characteristics of the two to give more desirable characteristics. In this case, we combine two relatively young algorithms, namely differ-
Differential evolution is known for its ability to converge at the global minima no matter what initial parameters are assigned to it. This process, however, can take large number of iterations in computationally expensive functions. On the other hand, TLBO is an efficient algorithm which converges to the local minima rather quickly in lower dimension problems. Hybridizing the two algorithms can yield better results in less computational time. In this paper, the hybrid algorithm is tested upon ‘Robot Arm with DC-Motor’.

2. Robot Arm Mathematical Modelling

In modelling to simplify, design and analysis linear approximated calculations are being used as long as the results produce a good approximation to the reality. This DC motor system is distinctly exited DC motor frequently used to speed, position tuning and torque adjustment. The motor has the field coil current independent of the armature coil current which helps in excellent speed and
position control. The armature voltage control to control the DC motor velocity, as the flux fixed is also a field current fixed. The control equivalent circuit of the DC motor by armature voltage control method is shown in Figure 1 and 2:

Now we derive the equations of the system in order to obtain a model suitable for control tasks. For this aim, let us consider each physical component of the system.

2.1 Gear Box
1. The angle turned by motor and load are related by

\[ \theta_m r_1 = \theta_1 r_2 \]  

Where, \( r_1, r_2 \) = Wheel Radii
\( \theta_m \) = Angle rotated by the motor shaft
\( \theta_1 \) = Angle rotated by the Robot Arm

2.2 Parameters of Robotic Arm
The parameters that are being used throughout this paper.

2.3 Modelling of Robotic Arm
The Gravitational Torque acting on the arm can be stated as the

\[ M g x Lcm x \sin(\theta) \]

Where \( M \) = Mass of the Robotic arm
\( Lcm \) = Distance of the centre of mass from the centre of rotation

![Image of a control equivalent circuit of the DC motor by armature voltage control method.](image)

Table 1.

| Parameters of Robotic Arm         | Symbol | Values and Units       |
|-----------------------------------|--------|------------------------|
| Armature Voltage                 | \( V_a \) | 1.57079 volts          |
| Armature Resistance              | \( R_a \) | 1 ohm                  |
| Armature Inductance              | \( L_a \) | 0.023 henry            |
| Armature current                 | \( i_a \) | ampere                 |
| Back emf constant                | \( K_b \) | 0.023 volt/(rad/sec)   |
| Torque Constant                  | \( K_t \) | 0.023 N-m/Ampere       |
| Angular Displacement of Shaft    | \( \theta \) | radians               |
| Net Moment of inertia            | \( J \) | 0.127 Kg-m2/rad        |
| Gear Ratio                       | \( n \) | 1(for Simplicity)      |
| Frictional constant of motor and load | \( B \) | 0.12 N-m/(rad/sec)    |
| Back emf                         | \( e(t) \) | volts                 |
| Torque developed by Motor        | \( T_m \) | N-m                   |
Theta = θ = Angle prepared by the arm with Y-axis (axis normal to the ground surface)
g = acceleration due to gravity

The remaining torque acting on the Robotic arm is given by:

\[
T_m = M g \times L cm \times \sin(\theta) = \frac{d^2(\theta)}{dt^2} + B \frac{d(\theta)}{dt}
\]

We need the motor to improve the Robot arm to a desired angular position (say 90 degrees) for a given value of DC input.

### 2.4 DC Motor Armature Control

Based on Newton’s law combined with Kirchhoff’s law the mathematical model can be formulated.

\[
V_a = i_a R_a + L_a \frac{di_a}{dt} + e_b
\]

\[
T_m = K_i i_a(t)
\]

\[
e_b(t) = K_b
\]

On Solving above Equation (1) to Equation (6) we obtain:

\[
V_a = i_a R_a + L_a \frac{di_a}{dt} + K_b \frac{d(\theta(t))}{dt} + K_i i_a(t) = \frac{d^2(\theta(t))}{dt^2} + B \frac{d(\theta(t))}{dt} + M g \times L cm \times \sin(\theta)
\]

### 2.5 State Space Model

By setting up \( x = [\theta \ \dot{\theta} \ i_a \ \dot{i_a} \ \theta \ \dot{\theta} \ i_a \ \dot{i_a} ] \), the system can be described by the following state-space form:

\[
\dot{x}_p = \begin{bmatrix} 0 & \frac{1}{J} & 0 & \frac{1}{J} \\ 0 & \frac{-B}{J} & \frac{-B}{J} & \frac{-B}{J} \\ 0 & \frac{-K_i}{J} & \frac{-K_i}{J} & \frac{-K_i}{J} \\ 0 & \frac{-K_p}{J} & \frac{-K_p}{J} & \frac{-K_p}{J} \end{bmatrix} x + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} u
\]

### 3. Control System Selection, Design Analysis

#### 3.1 Simulink Model of the DC Motor

A negative feedback closed loop control system with PID control and corresponding Simulink model shown in Fig. are to be used. Our design goal is to design, model, simulate and analyze a control system so that a voltage input in the range of 0 to 1.5707 volts agrees linearly of a Robot arm output angle range of 0 to 90, that is to move the robot arm to the desired output angular position, \( \theta_l \).

### 4. Results

Proportional Integral Derivative (PID) controllers provide control signals that exist proportional to the error between the reference signal and the actual output (proportional action), to the integral of the error (integral action), and to the derivative of the error (derivative action), namely:

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

Where \( u(t) \) and \( e(t) \) indicate that control and the error signals respectively, and \( K_p, K_i \), and \( K_d \) are the parameters These functions have been sufficient to the utmost control processes. As the structure of PID controller is simple, The PID controller is principally to adjust an appropriate proportional gain (Kp), integral gain (Ki), and different-
tial gain ($K_d$) to attain the optimum control performance. Transfer function can also be expressed as:

$$U(s) = K_p + \frac{K_i}{s} + K_d s$$

The block diagram of Complete Robot arm is shown in the Figure 4.

The above mentioned Sub System is the DC motor Simulink Shown in Figure 3.

5. Control Strategy of Robotic Arm

Consecutively the Simulink model of the robot arm closed loop system without controller committed Using Ziegler-Nichols Tuning (The Traditional Method) is used to find the approximate range of the PID Controller Constants and the Parameters Rise time, settling time, Maximum Peak Overshoot, Steady State error are being calculated.
and the response obtained is given in Table 1 which clearly does not meet our specifications.

In four different Nature Inspired Heuristics were applied to DC Motor and it is found that these strategies may be more or less meeting our desired specifications. The designer essentially selects the best one to increase, the system stability the parameters specified are to be optimized to the better extent. Through suitable selection the of the PID parameter gains, various characteristics of the motor response are controlled. To achieve a fast response of above mention specifications the Nature Inspired algorithms mentioned above will be used to control the PID gains and the desired parameters of Robot arm are calculated and compared.

6. Principle of Optimisation Algorithm

6.1 Differential Evolution

6.1.1 Mutation

This operation creates a mutant vector \( u_i \) by selecting components from an arbitrarily nominated vector \( x_a \) and the variance of two other arbitrarily generated vectors \( x_b \) and \( x_c \). Mathematically,

\[
u_i = x_a + \beta \cdot (x_b - x_c)
\]

Where, \( a \neq b \neq c \neq i \). \( \beta \) is a random number used to control the perturbation size of the mutation. Here, \( x_a \) is known as Base Vector.

6.2 Crossover

This operator creates a trial vector \( v_i \) by crossing over mutant vector and Target Vector (Another randomly generated vector). In other words, trial vector is generated by randomly selecting components from mutant vector \( (u_i) \) and Trial Vector \( (x_i) \) using a probability factor \( (p_{cr}) \). Mathematically,

\[
v_{ij} = \begin{cases} u_{ij} & \text{if } rand \leq p_{cr} \text{ or } j = j_0 \\ x_{ij} & \text{otherwise} \end{cases}
\]

The probability factor \( (p_{cr}) \) controls the diversity of the population and assists the algorithm to out of from local minima. \( j_0 \) is a randomly generated index between \( \{1, 2, 3, \ldots, Np\} \). This guarantees that \( v_i \) has at least one component from \( u_i \).

6.3 Selection

This operator chooses the better offspring among \( v_i \) and \( x_i \) using their fitness. Mathematically,

\[
x_i = \begin{cases} u_i & \text{if } \text{fitness}(u_i) > \text{fitness}(x_i) \\ x_i & \text{otherwise} \end{cases}
\]

This operator guarantees that each iteration’s solution is better than the solution obtained in the previous iteration.

6.4 Teacher Learning Based Optimisation

TLBO is a new algorithm by R.V. Rao, V.J. Savsani, and D.P. Vakharia. It is inspired by the classroom environment and can be termed as a simulation of modern education; it can be divided into two phases.

6.5 Teacher Phase

A teacher can be considered to be the most educated individual in the society. Hence, the student with the highest marks acts as a teacher during the teacher phase. The teacher efforts to boost the mean of the class to her/his level. However, depends on the learning proficiency of the class. This is expressed as:

\[
x_{i_{temp}} = x_i + \text{rand} \cdot (\text{Teacher - TF} \cdot \text{Mean})
\]

Where, \( \text{TF} = \text{Ceil}(0.5 + \text{rand}) \) is the teaching factor, Mean is the mean of the class. The New solution, \( x_{i_{temp}} \) is accepted only if it is better than the previous solution, that is,

\[
x_i = \begin{cases} x_{i_{temp}} & \text{if } f(x_{i_{temp}}) > f(x_i) \\ x_i & \text{otherwise} \end{cases}
\]
6.6 Learner Phase
Teaching is not the only education students receive, they also learn by interacting among each other. This is simulated in the learner phase. In each iteration two students $x_m$ and $x_n$ interact among each other, with the smarter one enhancing the others marks. It can be formulated as:

![Diagram](image-url)
The temporary solution is accepted only if it is better than the previous solution, that is,

\[
x_m = \begin{cases} 
    x_m^{\text{temp}}, & f(x_m^{\text{temp}}) > f(x_m) \\
    x_m, & \text{otherwise} 
\end{cases}
\]

6.7 Hybrid DE-TLBO

This division discusses the rationale of the proposed hybrid algorithm. Both DE and TLBO are population based algorithms with individuals being considered as vectors in DE and learners in TLBO. Initially, DE is initialized with random vectors. TLBO is used as an intermediate algorithm to improve the worst results obtained using DE between generations. TLBO is initialized with lower half of the DE population and random particles between the best and worst results. The newly initialized learners undergo a certain number of TLBO iterations before being sorted and fed back to the DE iterations. The process might be better understood by the flowchart given in Figure 5.

7. Implementation of Proposed Algorithm for PID Tuning

PID tuning can be viewed as a 3-dimensional problem with the dimensions being the values of \( K_p \), \( K_i \), and \( K_d \). The proposed hybrid DE-TLBO can be used to find the global optimum, which, in this problem is the value of the PID gains for which minimum error is obtained.

7.1 Initialising the Solutions

The population \( P \) consists of \( N_p \) particles each having 3 elements. The first element represents the value of \( K_p \), the second element represents the value of \( K_i \), and the third element represents the value of \( K_d \). Any particle \( x_i \) can be represented as:

\[
x_i = [K_p, K_i, K_d]
\]

7.2 Applying the Algorithm

The values of \( K_p, K_i, \) and \( K_d \) have to be used to simulate a Simulink model each time, to calculate the fitness of any particle. There are various methods of calculating the fitness such as Integral-Absolute-Error (IAE), Integral-Square-Error (ISE), Integral-Time-Square-Error (ITSE), Integral-Time-Absolute-Error (ITAE) etc. In this paper, ITAE was used to calculate the fitness of the particles. Using the values obtained from the chosen method, the Simulink model can be optimized, in this case, a Robot arm with a DC Motor. The range of \( K_p, K_i, K_d \) estimated from the Ziegler Nicholas method are given in Table 2.

### Table 2.

| PID Constants | Maximum Range | Minimum Range |
|---------------|---------------|---------------|
| \( K_p \)     | 65            | 0             |
| \( K_i \)     | 11            | 0             |
| \( K_d \)     | 60            | 0             |

8. Results and Discussion

The results of \( K_p, K_i \) and \( K_d \) obtained using Hybrid DE-TLBO were used and the Rise Time, Settling Time, Maximum Overshoot and Steady State Error were calculated. These values were compared with those obtained from DE and TLBO.

The number of iterations that the algorithm runs is given by Table 3.

### Table 3.

| Algorithm       | Iterations |
|-----------------|------------|
| DE              | 30         |
| TLBO            | 30         |
| Hybrid DE-TLBO  | DE:30 TLBO:10 |
The results of PID controller and parameters are tabulated in Table 4 and 5 respectively.

9. Conclusion

Using the classical methods of PID tuning, Ziegler-Nichols, PID Controller was tuned by keeping the objective that the Rise time, Maximum Peak Overshoot, settling time, Steady state error to be optimized but it does not happen, rather than none of the DE and TLBO gave the desired results. The hybrid DE-TLBO gave the results which are extremely optimized. The results of $K_p$, $K_i$, and $K_d$ obtained using Hybrid DE-TLBO over a wide range gave the optimized parameters for the motion of Robot arm in one degree of freedom.

Table 4.

| Parameters of Robot Arm     | DE   | TLBO  | DE_TLBO | ZN    |
|-----------------------------|------|-------|---------|-------|
| Rise time                   | 0.33326 | 0.30666 | 0.24704 | 0.56778 |
| Settling time               | 4.9461 | 1.5754 | 1.8056 | 9.6695 |
| Maximum Overshoot           | 49.6667 | 16.1174 | -0.80913 | 199.7941 |
| Steady state Error          | 0.72743 | 0.049044 | 0.81573 | 53.827 |

Graph 1. Comparison of DE, TLBO, and hybrid DE_TLBO algorithms.
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