



Differential evolutionary algorithm for optimization of pid controller parameters applied to electromagnetic levitation system

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ARTICLE INFO

Article history:

Received: 22 August 2011;

Received in revised form:

26 August 2011;

Accepted: 31 August 2011;

Keywords

Actuator,
Differential Evolutionary Algorithm,
Electromagnetic levitation,
ITAE.

ABSTRACT

Differential Evolutionary Algorithm is a simple but powerful computing tool for real parameter optimization. This article describes the application of this technique for designing a PID controller for Electromagnetic levitation system (EMLS). EMLS is inherently unstable and strongly non-linear in nature. Classical controllers designed for this system give no satisfactory performance. Little change in the operating air gap position deteriorates the controller performance making the system unstable. Therefore a need arises to make one controller such that it will give the optimum performance in the sense of changing gap positions. To that end Differential Evolutionary Algorithm (DEA) is used to fulfil this goal. The analysis is performed within the mathematical programming environment of MATLAB using both DEA and Conventional Genetic Algorithm (CGA) and a detailed comparative study is presented.

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Introduction

Electromagnetic levitation is getting much attention now a days due to its ability to be applied in several critical field of science.

It was utilized for aerodynamic testing in wind tunnels in 1954 in France [14]. Also it is being used in high speed trains, vibration isolation, frictionless bearings, Magnetic Resonance Imaging (MRI) for medical application [15] etc. It basically applies the magnetic force generated by the current flowing through the coils wound on it to levitate an object against the gravitational force but without any physical contact between the magnet and the levitated object. It may use attraction type magnetic force or repulsion type magnetic force. In Electromagnetic Levitation system (EMLS in short), levitation is produced due to the attractive forces between the magnet and a ferromagnetic object.

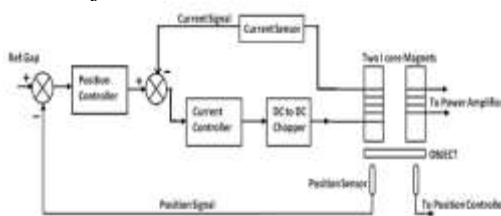


Fig.1. Schematic block diagram of individual unit for the proposed EMLS

Details about the closed-loop system design are discussed in references [2] & [10]. The transfer-function of the levitated system can be written in the following form while taking controlled current source as the excitation to the magnet-coil [11]

$$G_p(s) = - \frac{\left(\frac{K_i}{m} \right)}{\left(s^2 - \frac{K_z}{m} \right)} \quad (1)$$

Where, K_i and K_z are respectively the slope at the operating point of the force-current and force-distance characteristics of

the electromagnetic suspension system, 'm' is the mass of the cylindrical rod.

One pole at the right half side of the s-plane makes system unstable.

Here the inner current control loop gain is taken to be 1 as it makes no appreciable difference in the performance because of its faster characteristic (less time constant) than the outer loop position control (larger time constant). An important aim of this controller design is to find such a controller which will make the system to perform satisfactorily under varying air gap positions. Several types of classical controllers were applied to this system to make it perform satisfactorily. They are PD, Lead, PID, Lead-Lag, outer loop (not shown here) PI and PID position controller, outer PI plus Lead, outer PI plus Lead-Lag etc. It is seen that PD-type of control leads to noise amplification. While using Lead controller steady state error cannot be minimized. Lead-lag controller cannot eliminate the steady state error but it improves the margin of stability [2].

The thumb rule is applied in all the case for initially getting the classical controller parameters mentioned above.

The transfer-function of the PID controller is given as: $G_c(s) = (K_p + sK_D + \frac{K_I}{s})$, where K_p , K_D and K_I are the

proportional, derivative and integral gain respectively. The transfer-function can be written in other way as:

$$G_c(s) = \frac{K(s+z_{c1})(s+z_{c2})}{s}; z_{c1} \text{ and } z_{c2} \text{ are the two zeros of}$$

this controller to be placed on the negative real axis of the s-Plane, $K_p = K(z_{c1}+z_{c2})$, $K_D = K$ and $K_I = K * z_{c1} * z_{c2}$. Locations of these two zeros are dependent on the system pole locations. It is, z_{c2} is placed very near (at the right side) to the stable pole of the plant and z_{c1} is placed near to the origin. Choosing these two the value of the gain is found to meet

desired performance. It must be noted here that Ziegler-Nichols tuning rule for PID controller tuning, is not applicable for this system since the linearized model has one positive pole.

Overview of differential evolutionary algorithm and genetic algorithm

As more and more difficult engineering problems appear, always with objective functions being non-differentiable, non-continuous, non-linear, noisy and multi-dimensional or having many local minima and complex constraints because of various practical requirements, practicable and effective approaches to solve such problems are becoming unsatisfactory and insufficient[6].

DEA is a simple yet powerful population-based stochastic search technique originally introduced by Storn and Price in 1995 for solving global optimization problems. It employs real-coded variables and mainly relies in mutation as the major search operator [1].

GAs are a subclass of evolutionary algorithms. The genotypes are used in the reproduction operations whereas the values of the objective functions are computed on basis of the phenotypes in the problem space which are obtained via the genotype-phenotype mapping. The encoding scheme and objective function are the two most important aspects to be noticed while using GAs.

The major similarity between these two types of algorithm is that they both maintain populations of potential solutions and use a selection mechanism for choosing the best individuals from the population. The main differences are as follows [3]:

- DEA operates on floating point vectors while GA relies mainly on binary strings.
- GA mainly relies on the recombination operator to explore the search space while DEA on mutation.

• DEA is an abstraction of evolution at individual behavioral level stressing the behavioral link between an individual and its offspring, while GA maintains the genetic link.

The advantages of DEA as summarized by Price are [4]:

- Ability in many cases to find the true global minima regardless of the initial parameter values.
- Fast and simple with regard to application and modification. Requires few control parameters.

With these advantages DEA has many disadvantages as follows:

- DEA does not always produce an exact global optimum (premature convergence).
- Requires a tremendously high-computation time.

DEA works with both old and new generation populations. The population consists of real valued vectors with dimension D that equals the number of decision parameters. It is randomly initialized within its parameter bounds. Like GA it also has three main operators: mutation, recombination and selection. In each generation individuals of the current population become the target vectors. For each target vector the mutation operator generates a mutant vector by adding the weighted differences between two randomly selected vectors to a third vector. The crossover operator helps to increase the diversity among the mutant vectors. It generates trial vector by mixing the parameters of the mutant vectors and the target vectors. If this trial vector obtains a better fitness value than the target vectors, then the trial vector replaces the target vector in the next generation. The operators are described below [12]:

A. Initialization: For each parameter j with lower bound X_j^l and upper bound X_j^u , the initial parameters are selected randomly with uniform distribution in the interval $[X_j^l, X_j^u]$.

B. Mutation: For a given parameter vector $X_{i,G}$ (G :current generation), three vectors ($X_{r1,G}$, $X_{r2,G}$, $X_{r3,G}$) are selected such that the indices $r1, r2, r3$ are mutually exclusive. The mutant vector is created as:

$V_{i,G+1} = X_{r1,G} + F \cdot (X_{r2,G} - X_{r3,G})$ where F is a constant in $(0,2)$.

C. Crossover: Three parents are chosen for this and a child is perturbation of one of them. The trial vector is generated as follows:

$U_{j,i,G+1} = \begin{cases} V_{j,i,G} & \text{if } \text{rand}_{j,i} \leq CR \text{ or } j = \text{rand} \\ X_{j,i,G} & \text{otherwise} \end{cases}$

Where CR is the user defined crossover rate. Here initially it is taken to be 1 and then as the generation passes crossover rate is lowered up to 0.5 using some simple equation [5].

D. Selection: The target vector is compared with the trial vector $V_{i,G+1}$ and the one with better fitness is taken. It can be written as:

$X_{i,G+1} = \begin{cases} U_{i,G+1} & \text{if } f(U_{i,G+1}) \leq f(X_{i,G}) \\ X_{i,G} & \text{otherwise} \end{cases}$

The brief outline of the DEA used in this project is given below:-

Begin

$G=0$

Initialization

For $G=1$ *to* G_{max}

For $j=1$ *to* N_p

Select random integers $r1 \neq r2 \neq r3 \neq j$ *in* $(1, N_p)$

Generate a random integer i_i *in* $(1, D)$

For $i=1:D$

If $\text{rand} < CR$ *or* $i = i_i$

$V_{i,j,G+1} = X_{i,r1,G} + F \cdot (X_{i,r2,G} - X_{i,r3,G})$

Else

$V_{i,j,G+1} = X_{i,r1,G}$

End if

End for

If $V_{i,G+1}$ *is better than* $X_{j,G}$

$X_{j,G+1} = V_{i,G+1}$

Else

$X_{j,G+1} = X_{j,G}$

End if

End for

End for

end

Control parameter values and methods used in tuning PID controller

In this work the termination criteria has been considered to be the maximum number of iterations for DEA and maximum achievable fitness value ($=1/(1+ITAE)$) for CGA. For the proposed PID controller the required declarations are as follows:

For DEA

Population size: 30

Number of generations: 300

$F=0.002$

For CGA

Population size: 100

Number of generations: 60

Crossover type: Single-point crossover

Mutation type: Binary mutation

Crossover rate: 0.9

Mutation rate: 0.001

Mass of object rod: 0.122Kg.

Objective Function for CGA & DEA

Several available performance indices are there. Here Integral of Time multiplied by Absolute Error (ITAE) as defined by the following expression is used:

$$ITAE = \int_0^{\tau} t|e(t)|dt$$

The limits for the equation from time, $t = 0$ to $\tau = Ts$, where Ts is the settling of the system. The value of $Ts = 0.433s$.

Result and discussion

The system under study here is 10mm gap plant which by experiment is found as:

$$\frac{13.98}{(s^2 - 727.38)}$$

The classical PID controller transfer function (trial and error) for 10mm air gap is given below:

$$0.0145 \frac{(s + 21)(s + 5)}{s}$$

The DEA-based PID controller designed for 10mm air gap position found experimentally as:

$$0.1979 \frac{(s + 24.09)(s + 0.9475)}{s}$$

The CGA-based PID controller designed for 10mm air gap position as found from the simulation run as:

$$0.16188 \frac{(s + 24.94)(s + 0.99)}{s}$$

The following table summarizes the results obtained with the designed controller for 10mm gap position:

Fig.2 shows the unit step response of the 10mm plant given above with classically tuned and CGA-tuned PID controllers.

With CGA-based PID controller the system behavior is satisfactory compare to the classically tuned controller.

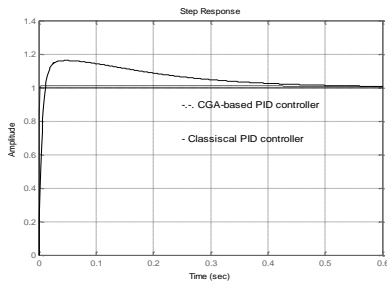


Fig.2: Unit-step response of 10mm plant with conventional PID and CGA-based PID controller applied separately.

Fig.3 shows the unit step response of the 10mm plant given above with classically tuned and DEA-tuned PID controllers. With DEA-based PID controller the system becomes fast with satisfactory performances.

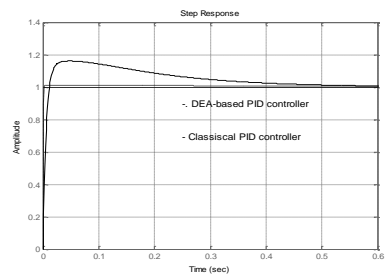


Fig.3: Unit-step response of 10mm plant with conventional PID and DEA-based PID controller applied separately.

Fig.4 shows the iteration vs. objective function plot. It clearly shows DEA's ability to find the minimum function value.

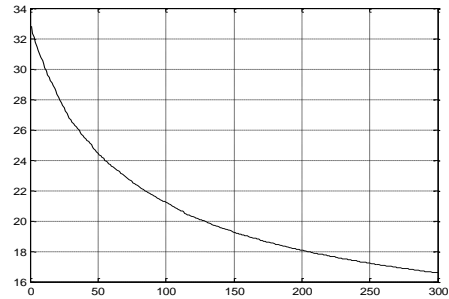


Fig.4: Iteration vs. objective function value plot

This designed controller when used for other gap positions gives satisfactory results.

Fig.5 shows the result when the same controller is applied to a 3mm air gap plant.

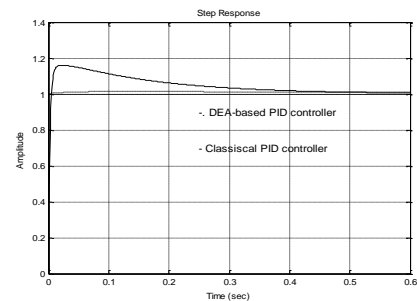


Fig.5: Unit-step response of 3mm plant with conventional PID (designed for 3 mm gap) and the 10mm DEA-based PID controller applied separately.

Fig.6 shows the system response when this 10mm designed DEA-based PID controller is applied to a 20mm air gap plant.

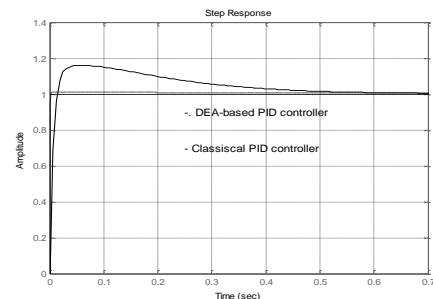


Fig.6: Unit-step response of 20mm plant with conventional PID (designed for 20 mm gap) and the 10mm DEA-based PID controller applied separately

Conclusion

In this study PID tuning method for EMLS based on DEA is developed and compared to both classical tuning and CGA-based tuning techniques. DEA working with real parameters outweigh the other methods discussed in this paper although it requires high computation time compare to the CGA.

Here PID tuning is discussed which gives low margin of stability although it completely eliminates the steady state error. For enhancing the stability margin cascade compensation like Lead-Lag controller can be thought of. This remains a subject for further study

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Table: 1

Techniques used	Peak Overshoot (%)	Rise time(sec)	Settling time(sec)	Steady State Error
Classical controller(trial and error)	16	0.00813	0.433	0
CGA	1.23	0.00102	0.00163	0
DEA	1.03	0.000722	0.00148	0

Table: 2 shows the details results

Method used	Operating Distances in mm	Peak Overshoot (%)	Rise time in sec.	Settling time in sec.	Steady State Error
CGA	3	1.7	0.0011	0.00135	0
	5	1.39	0.00077	0.00095	0
	7	1.24	0.00068	0.00129	0
	12	1.25	0.00108	0.00162	0
	15	1.31	0.00116	0.00182	0
	17	1.48	0.00129	0.0021	0
DEA	20	1.57	0.00135	0.0022	0
	3	1.43	0.00085	0.00104	0
	5	1.17	0.00065	0.0008	0
	7	1.04	0.00066	0.001	0
	12	1.03	0.00081	0.00151	0
	15	1.07	0.00093	0.00155	0
DEA	17	1.18	0.0011	0.00167	0
	20	1.25	0.00117	0.00185	0