ISSN: 2320-8090

Available online at http://www.journalijcst.com

International Journal of Current Science and Technology
Vol.5, Issue, 1, pp. 376-384, April, 2017

RESEARCH ARTICLE

DESIGN ASPECTS FOR OPTIMAL TUNING OF CONTROLLERS BY AI TECHNIQUES

Jagadish Pati[1]., Panigrahi C.K[2] and Mandal S.K[3]

[1,2] School of Electrical Engineering, KIIT University
[3]Department of Electronics & Telecommunication Engineering., Centurion University of Technology and Management

ARTICLE INFO

Article History:
Received 5th January, 2017
Received in revised form 18th February, 2017
Accepted 4th March, 2017
Published online 28th April, 2017

Key words:
Genetic algorithms, Differential evolution, Approximate model matching, Reference model & cost function.

ABSTRACT

In this paper a comparative study on the use of Genetic algorithms (GA) and Differential evolution (DE) for control systems design have been presented. GA and DE are used for offline design of control schemes for continuous-time linear time invariant systems both in complex domain and time domain formulations. In the complex domain controller design, the design philosophy is based on approximate model matching in which a reference model is parameterized from time, frequency and complex domain specifications which ensure both stability and performance margin. The nominal plant model is known; the problems become to search the controller parameters through minimization of a scalar objective function, so that the augmented plant with controller matches the reference model. In time domain design, the sub-optimal control problem is considered in which the coefficients of the gain matrix is searched through minimization of a cost function developed on control input and state vector. GA and DE are used in both the design methods and applied in the single input single output (SISO) systems, Multi input and single output (MIMO) systems and systems with time delays.

INTRODUCTION

The rapid advancement of science and technology and the advent of low cost, reliable and high speed digital computers have led to extensive research in the area of computer aided control system analysis and design. The aim is to solve some problems in identification, modeling and controller design by applying the genetic algorithm & differential evolution.

The application of artificial intelligent has been in wide use in many areas in system and control for the last two decades. Genetic algorithms (GA) [1] are search procedures inspired by the laws of natural selection and genetics. They can be viewed as a general-purpose optimization method and have been successfully applied to search, optimization and machine learning tasks. GA has the ability to solve difficult, multi-dimensional problems with little problem-specific information and hence has been chosen as the optimization technique to solve various problems in control systems.

In GAs, candidates' solutions to a problem are similar to individuals in a population. A population of individuals is maintained within the search space of GAs, each representing a possible solution to a given problem [28]. The individuals are randomly collected to form the initial population from which improvement is sought [27, 28]. The individuals are then selected according to their level of fitness within the problem domain and breed together.

Corresponding author: Jagadish Pati
School of Electrical Engineering, KIIT University

The breeding is done by using the operators borrowed from the natural genetic, to form future generations (offspring's). The population is successively improved with respect to the search objective. The least fit individuals are replaced with new and fitter offspring [23, 1] from previous generation.

Over the recent years, GAs has been at the centre of researches. Especially in the optimization problems where GAs provides better solutions with simpler techniques than other optimization methods. According to Goldberg in [1], GAs differs from other optimization methods in four ways:

1. GAs search from a population of points in parallel, no single point
2. GAs use probabilistic transition rules, not deterministic ones
3. GAs work on encodings of parameters set rather than the parameter set itself (except where real - valued individuals are used)
4. GAs do not require derivative information or other auxiliary knowledge; only the objective function and corresponding fitness levels influence the directions of the search.

DE [30] is parallel direct search method that uses a differential mutation scheme and greedy selection process (the better one of new solution and its parents wins the competition) to direct its search toward the prospective regions of search space. In DE, all solutions have the same chance of being selected as parents regardless of their fitness value. DE is known to use the greedy selection process whereby the better one of the new solution and its parents wins the competition. This principle provides a better convergence performance over GAs [29]. DE encodes parameters in floating - point regardless of their type [30]. This encoding offers a great malleability with arithmetic operators and provides significant advantages over the other optimizations methods, including [30]:

- Fast convergence
- Finds true global minimum regardless of the initial parameters
- Ease of use
- Efficient memory utilization
- Lower computational complexity

DE is used to tune the parameters by optimizing a frequency domain objective function. The objective function consists of finding, shifting the poorly damped or unstable poles into the left side of the s-plane (stability plane).

The mathematical procedures of modeling practical systems lead to descriptions of the process in the form of complex high -order transfer functions or states space models. These high-order models are difficult to use for simulation, analysis or controller synthesis, and it is not only desirable but also often necessary to obtain satisfactory reduced order representations of such high order models. A need exists for design methods that may be used to arrive at simple low-order implement able controllers that can adequately control plants or processes regardless of their order, complexity or stability.

Often the need arises to implement a digital controller in place of an existing analog controller. One may redesign a new controller in the digital domain or may discretize the existing continuous-time controller. Advanced controller design techniques such as LQG, H_∞ [11] etc., often lead to controllers whose order may be equal to or even exceed the order of the plant. A suitable low-order controller that retains the dominant characteristics of the original high-order controller is desired in such cases.

Control System Design

A new GA[1] & DE[30] based method is proposed for the design of rational continuous-time controllers for linear time-invariant single-input single-output (SISO) and multi-input multi-output (MIMO) systems. The design method is comprehensive in nature and is applicable to a wide range of plant models. Selection of an appropriate reference model extends the usefulness of the method to controller design for unstable systems and non-minimum-phase plants. The method relies on the concept of approximate model matching and yields implement able low-order rational controllers using only output feedback. Increase in the computational burden with increase in the order of the plant model is negligible thus obviating the need for order reduction of the plant transfer function. The validity of the method is illustrated by some examples from the literature.

The problem of model matching control consists of designing a controller to compensate a given plant so that the resultant controlled system has a pre-specified transfer function (reference model). The obvious advantage of this approach is that the design specifications (time and frequency domain) that are implicated through the reference model will be met by the controlled system. Design techniques for exact model matching as well as approximate model matching have been proposed for systems described by both state-space and transfer function models [Chen (1970)]. Exact model matching, however, is known to bring about certain practical difficulties. It requires overly complicated implementations. System configurations typically involve both feed forward and feedback compensation [Chen (1987)], in addition, the compensator TFs are generally of roughly the same order as the plant TF. Thus, for high-order plants, the controller implementation becomes impractical. The design of a control system is formulated as an approximate model -matching problem. That this problem is of great practical importance and provides a viable alternative for the design of effective, implement able controllers is evident from the number of publications in this area (given above). The objective of an approximate model matching type of control system design may be stated as: Given an open loop plant TF, P(s), design an overall closed-loop system so that the plant output y(t) will follow a given reference input as closely as possible. The design highly depends on the chosen reference input. Throughout the paper, we consider a step input. The closeness of the plant output tracking the reference step input is checked in terms of steady state and transient performances. In the steady state, we require the steady-state error to be zero and for good transient performance, we require a prescribed rise time, settling time, and overshoot. We also consider frequency-domain characteristics such as the gain and phase margins, bandwidth, cut-off rate etc. implicated through the reference TF as the desired design objectives. Thus, the controller design problem becomes: Given a plant and a reference input (step input), design an implement able dynamic controller that uses only output feedback and yields an overall closed-loop system to meet a given set of steady-state and transient performance criteria. One of the important aspects of controller design and implementation is the order of the controller and the subsequent hardware complexity. Practicing engineers prefer implement able controllers of low complexity. Various design methods have been proposed to obtain low-order compensators based on the Padé approximation technique Pal (1993), continued fraction expansion Chen (1970), least squares minimization Belanger (1976), and model reduction techniques Lepschy (1985) etc. Kreisselmeier and Mevenkamp (1988) proposed a method which involves an a-posteriori refinement of the controller that has been synthesized using a reduced-order model of the plant. In the model matching method of Sanathanan and Quinn (1987), frequency domain optimization is used to obtain a low-order approximate of the ideal controller given by the synthesis equation [D'Azzo (1981)]. In the proposed method, the controller parameters are obtained by minimizing a performance index (fitness function) using the GA and use the concept of approximate model matching. Selection of an appropriate reference model extends the usefulness of the method to controller design for unstable systems and non-minimum-phase (NMP) plants.

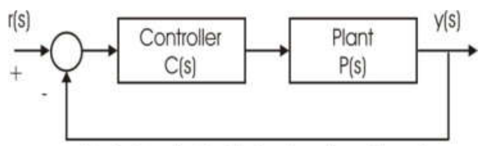


Fig. 1 Standard unity feedback configuration

Approximate Model Matching [16] Consider the continuous-time unity feedback control system configuration as shown in

Fig.1 P(s) and C(s) are respectively the plant and controller transfer functions and are given by

$$P_{m,n}(s) = \frac{\sum_{i=0}^{m} b_i s^i}{\sum_{i=0}^{n} a_i s^i}, \quad m \le n \tag{1}$$

$$C_{p,q}(s) = \frac{\sum_{i=0}^{p} \beta_i s^i}{\sum_{i=0}^{q} \alpha_i s^i}, \quad p \le q \tag{2}$$

The subscripts on the left-hand side of Eqn. (3.1) and Eqn. (3.2) indicate the orders of the numerator and denominator respectively. The closed loop transfer function F(s) is then given by

$$F_{m+p,n+q}(s) = \frac{\left(\sum_{i=0}^{m} b_i s^i \sum_{i=0}^{p} \beta_i s^i)\right)}{\left[\sum_{i=0}^{n} a_i s^i \sum_{i=0}^{q} \alpha_i s^i + \sum_{i=0}^{m} b_i s^i \sum_{i=0}^{p} \beta_i s^i\right]} \tag{3}$$

The denominator of (3) represents the characteristic polynomial of the closed-loop system and is of order $(n+q)$. The unknowns in (2) and (3) are the $\beta_i s$ and $\alpha_i s$ corresponding to the compensator $c(s)$. In the exact model-matching problem, it is desired to find the unknown parameters β_i and α_i of $c(s)$ such that closed-loop TF, F(s), exactly matches a general specification TF, M(s), given by

$$M_{k,l}(s) = \frac{\sum_{i=0}^{k} d_i s^i}{\sum_{i=0}^{l} c_i s^i}, \quad k \le l \tag{4}$$

Thus, for exact model matching, we have

$$F(s) = M(s)$$

$$or \quad \frac{P(s)C(s)}{[1+P(s)C(s)]} = M(s) \tag{5}$$

Solving for $c(s)$, we get

$$C(s) = \frac{M(s)}{[P(s)\{1-M(s)\}]} \tag{6}$$

Substituting for P(s) and M(s) from (1) and (4), we finally have

$$C(s) = C_{k+n,m+l}(s) = \frac{\sum_{i=0}^{k} d_i s^i \sum_{i=0}^{n} a_i s^i}{\left[\sum_{i=0}^{m} b_i s^i \sum_{i=0}^{l} c_i s^i - \sum_{i=0}^{m} b_i s^i \sum_{i=0}^{k} d_i s^i\right]} \tag{7}$$

This is also called the 'Synthesis Equation' or 'Truxal's method' for designing C(s) [D'Azzo and Houpis (1981)]. This controller has been termed as the 'Ideal Controller'.

In some cases, it is found that this design method may not lead to the simplest form of compensator. The resulting controller may be of high-order and/or unstable. Moreover $c(s)$ may not be realizable, i.e. improper. Further, the structure and order of the controller $c(s)$ cannot be fixed a-priori as has been done in Eqn. (2). In the case of Approximate Model Matching (AMM)[16], Eqn. (5) is only approximately satisfied, i.e.

$$F(s) \approx M(s) \tag{8}$$

Reference Model Selection

In the model-matching type of controller design followed in this thesis, the design goals are specified at the outset in the form of a reference model TF. The structure and complexity of the controller depends on the choice of the reference model TF. The reference model TF should be chosen to have a sufficiently rapid response; on the other hand, it should keep the high frequency gain of the controller small to avoid saturation in the actuators. The reference model might be required to satisfy some of the following design specifications.

The time-domain specifications e.g., the rise time, overshoot, settling time and steady state error. The frequency-domain specifications, e.g., the bandwidth, cut-off rate, gain margin and phase margin. The complex-domain specifications, e.g., the damping ratio,damping factor, undamped natural frequency.

Quadratic optimal criterion

Some representative model selection procedures are briefly given below. … (2.4)

Method 1. Let a model TF be specified as

$$M(s) = \frac{d_0 + d_1 s}{c_0 + c_1 s + s^2}$$

for steady-state matching, $d_0 = c_0$. Then

$$M(s) = \frac{c_0 + d_1 s}{c_0 + c_1 s + s^2} \tag{9}$$

Let the desired closed-loop specifications that M(s) has to satisfy be Velocity error constant: k_v

Crossover frequency: ω_c

Damping ratio: ξ

The second-order model M(s) of Eqn. (2.9) may be chosen to satisfy these specifications. The parameters c_0, c_1 and d_1 are determined by solving the following equations [Chen (1970)].

$$\omega_c^2 c_1^2 - 2\omega_c^2 c_1 d_1 - c_0^2 = -\omega_c^4$$

$$c_1 - \left(\frac{c_0}{k_v}\right) - d_1 = 0 \qquad (10)$$

$$c_1^2 - 4c_0\xi^2 = 0$$

For example,

When $k_v = 20, \omega_c = 4.5$ and $\xi = 0.785,$ Eqn. (3.10) gives,

$$M(s) = \frac{8.009 + 4.04265s}{8.009 + 4.4431s + s^2}$$

Method 2. Let the desired specifications be
Maximum overshoot: 10%
Time to first peak: 0.01s
Unity final value: no steady-state error,
Choosing M(s)

$$\frac{\omega_0^2}{s^2 + 2\xi\omega_n s + \omega_n^2},$$

and following the design rules of thumb of Shieh (1981);

$$\omega_n \approx \frac{\pi}{4} \approx 300\, rad/s, \quad M_p \approx \exp(-\xi\pi) \rightarrow \xi = 0.75$$

Then,

$$M(s) = \frac{90000}{90000 + 450s + s^2}$$

Method 3: A reference model M(s) that is optimal in the sense of minimizing a quadratic performance index may be chosen as given in Chi-Tsong (1990). For example, an optimal system TF may be chosen to minimize the quadratic performance index

$$J = \int_0^\infty \left[q(y(t) - r(t))^2 + pu^2(t)\right]dt, \quad where\ q, p > 0.$$

A certain value for q and p may be initially chosen and M(s) may be found out. If this model does not meet other requirements like control effort, then a different value each is chosen for q and p and the steps repeated to find another suitable M(s).

Method 4: A reference TF

$$M(s) = \frac{1}{(1 + sT)^2}$$

may be chosen Sanathanan (1987) and Quinn (1990). Certain features of this TF models are It has only real poles, It contains no numerator dynamics beyond those dictated by the loop type, It gives sufficient response speed, Reasonable robustness (in terms of gain and phase margins that can be imbedded in the TF model), It gives reasonable idea of the closed-loop time responses, Location of the real poles may be determined by the system specifications for bandwidth and response time.

Sub-Optimal Control

The optimal controller requires the feedback of all the states defined to describe the dynamics of the plant. In practical solutions, all the states may not be accessible /available for feedback purpose. The Kalman filter or the Luenberger observer, though necessary in such cases, increases the order and complexity of the controller. Using the method of this section GA, technique for tuning a commercially available 3-term controller for suboptimal control using output feedback may be easily devised.

Let the SISO linear time-invariant system be given by

$$\dot{x} = Ax + Bu$$

$$y = Cx$$

where, x(t) is an n-vector representing the state of the system, u(t) is the scalar control, and A and B are matrices of compatible dimensions. The objective is to find the control $u^*(t)$ that minimizes the performance index

$$J = \int_0^\infty (x^T Qx + ru^2)dt,$$

Where, $Q \geq 0$ and $r > 0$. The solution of this optimal control problem is well-known, and involves solving the matrix by Riccati equation:

$$A^T P + PA - PBr^{-1}B^T P + Q = 0$$

The optimal controller is a function of all the states x and is given by

$$u^*(t) = -r^{-1}B^T Px(t) = -k^T x(t)$$

The closed-loop transfer function with $u^*(t)$ is given by

$$M(s) = C^T(sI - A + Bk^T)^{-1}B$$

Controller Design using GA

The tuning process involves a number of steps, given below, to find the optimal parameters.

Step1: Set the minimum and maximum boundaries where the optimal values of the parameters will be found.

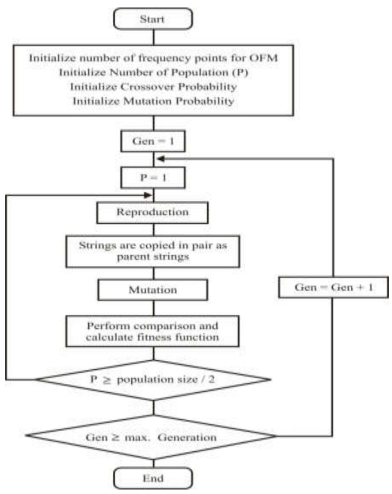
Step2: Obtain the system operating conditions and select the desired relative stability.

Step3: Generate an initial population within the constraints using GA.

Step4: Run for each individual to check if the system converges. If not, discards and then change the operating conditions.

Step 5: Repeat step 4 until maximum generation is reached

Step 6: Evaluate the objective function.



Controller Design Using DE

The tuning process involves a number of steps, given below, to find the optimal parameters.

Step1: Set the minimum and maximum boundaries where the optimal values of the parameters will be found.

Step 2: Obtain the system operating conditions and select the desired relative stability.

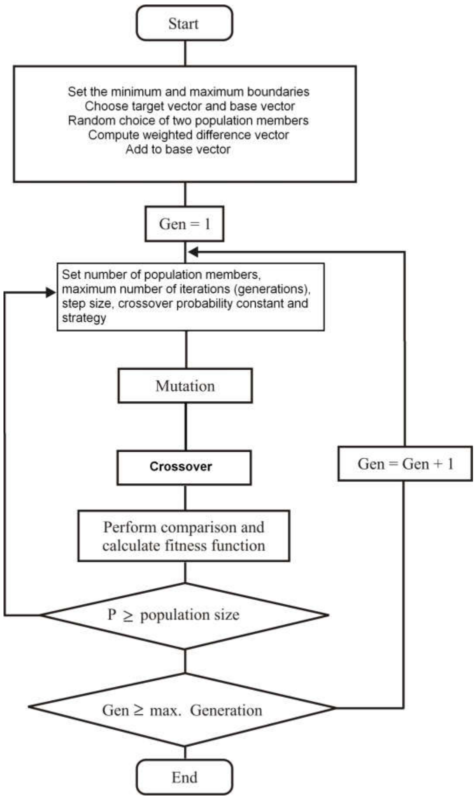
Step 3: Generate an initial population within the constraints using DE.

Step 4: Set number of population members, maximum number of iterations (generations), step size, crossover probability constant and strategy

Step 4: Run for each individual to check if the system converges. If not, discards and then change the operating conditions.

Step 5: Repeat step 4 until maximum generation is reached

Step 6: Evaluate the objective function.



Simulation Results

SISO

Example on PID Controller

For illustrating the methodology of the scheme, a simple plant is taken as:[3]

$$G_p(s) = \frac{3}{s^2 + 4s + 3}$$

The following model transfer function satisfies:

$$\omega_n = 5.0, \xi = 0.707$$

$$M(s) = \frac{4.242s + 25}{s^2 + 7.07s + 25}$$

We choose a PID type of pre-compensator:

$$C(s) = k_P + \frac{k_I}{s} + k_D s$$

The parameters of the compensator, obtained by minimizing the H_∞, are given in Table 1. The time responses obtained are shown in Figs. (2).

Table 1 Controller parameters

Fitness value	Range	Value In GA	Value In DE	parameter
	1,1.5	1.3612	1.3794	k_D
0.0121	9,11	10.0473	10.4600	k_p
	8,9	8.0576	8.8447	k_I

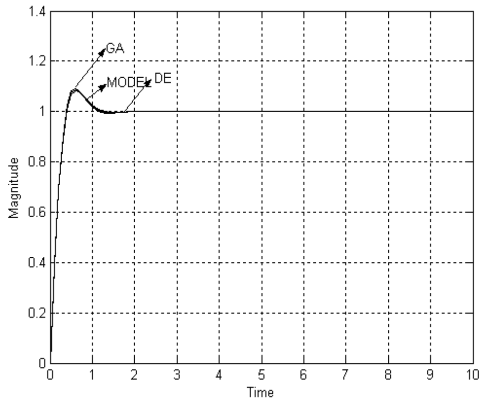


Fig 1

Table 2 Time response Specifications

Time response Specifications	Value In Model	Value In GA	Value In DE
Delay time(t_d)	0.1372	0.1388	0.139
Rise time(t_r)	0.3915	0.3793	0.3868
Peak time(t_p)	0.6	0.6	0.6
Maximum overshoot(m_p)	0.083	0.096	0.088
Settling time(t_s)	1.28	1.18	1.23

Phase Lead Controller

Let the plant be given by [4]

$$G_p(s) \frac{20(1+\frac{s}{1.5})}{s(1+\frac{s}{4.5})(1+\frac{s}{10})(1+\frac{s}{30})}$$

The desired performance specifications are:

Velocity error constant $K_v = 20$, damping ratio $\xi = 0.785$, crossover frequency $\omega_c = 4.5$. Following the method of Chen and Shieh (1970), the following model is obtained:

$$M(s) = \frac{4.04265s + 8.009}{s^2 + 4.4431s + 8.009}$$

A phase-lead type of pre-compensator is chosen:

$$C(s) = \frac{k(s+\beta)}{(s+\alpha)}$$

The parameters of the controller obtained by using the proposed method are included in Table 2. The time domain responses are given in Fig. (3).

Table 3 controller parameters.

Fitness value	Range	Value In GA	Value In DE	parameters
	0.07,0.1	0.0918	0.0957	k
0.6654	4,4.5	4.0053	4.3902	β
	0.3,0.5	0.4138	0.3281	α

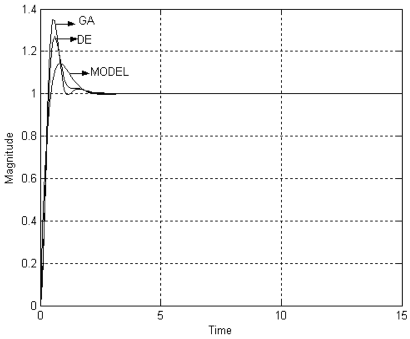


Fig 2

Table 4 Time response Specifications

Time response Specifications	Value In Model	Value In GA	Value In DE
Delay time(t_d)	0.1532	0.195	0.2124
Rise time(t_r)	0.4426	0.3253	0.3641
Peak time(t_p)	0.8	0.5	0.6
Maximum overshoot(m_p)	0.145	0.352	0.27
Settling time(t_s)	2.234	4.2961	4.458

Second Order Controller

Consider the following plant:[5]

$$G_p(s) = \frac{20}{s(1+\frac{s}{10})(1+\frac{s}{30})}$$

The following desired model satisfies the values of velocity error constant K_v=20, damping ratio ξ=0.7, crossover frequency $\omega_c = 5$.

$$M(s) = \frac{4.35s + 12.674}{s^2 + 4.984s + 12.674}$$

We choose pre-compensator of the following structure:

$$C(s) = \frac{s^2 + cs + d}{s^2 + as + b}$$

The parameters of the controller obtained by using the proposed method are included in Table 3. The time response is given in Fig. (4).

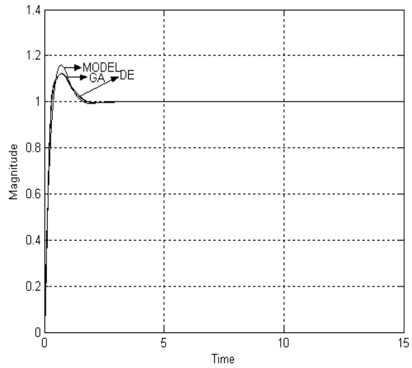


Fig 3

Table 5 controller parameters.

Time response Specifications	Value In Model	Value In GA	Value In DE
Delay time(t_d)	0.1375	0.1444	0.1426
Rise time(t_r)	0.3746	0.2909	0.2907
Peak time(t_p)	0.7	0.7	0.7
Maximum overshoot(m_p)	0.161	0.12	0.122
Settling time(t_s)	1.6054	1.1853	1.753

System with Time Delay

Consider a general second-order plant with time delay as:[6]

$$G_p(s) = \frac{200e^{-s}}{s^2 + 10s + 100}$$

We choose the same desired model as in Example 2, and incorporate a time -delay of 1sec, as shown below:

$$M(s) = \frac{(4.04265s + 8.009)e^{-s}}{s^2 + 4.4431s + 8.009}$$

We choose a PID controller as:

$$C(s) = k_P + \frac{k_I}{s} + k_D s$$

The parameters of the controller obtained by using the proposed method are included in Table 4. The time response is given in Figs. (5).

Table 7

Fitness value	Range	Value In GA	Value in DE	parameters
	22, 23	22.1188	22.7253	a
0.382	13,14	13.6543	13.6549	b
	6.5,7.5	7.1810	7.1546	c
	13,14	13.6687	13.0009	d

Fitness value	Range	Value in GA	Value in DE	Parameters
	0.92,0.93	0.9218	0.9297	x(1)
0.2443	0.17,0.18	0.1701	0.1743	x(2)
	0.016,0.05	0.0497	0.0363	x(3)

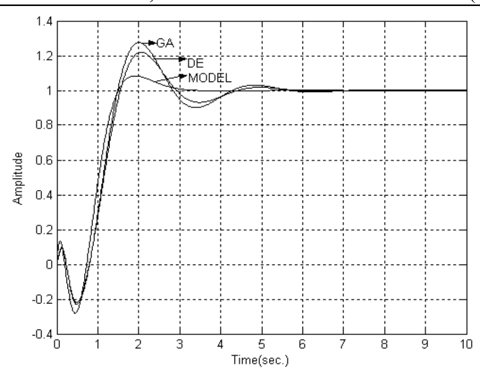


Fig 4

Table 8 Time response Specifications

Time response Specifications	Value In Model	Value In GA	Value In DE
Delay time(t_d)	1.01	1.12	1.16
Rise time(t_r)	1.501	1.485	1.562
Peak time(t_p)	1.9	2.01	2.08
Maximum overshoot(m_p)	0.084	0.275	0.221
Settling time(t_s)	3.44	2.834	2.955

MISO [15]

We consider the voltage-regulator example from Sannuti and Kokotovic (1969)

$$A=\begin{bmatrix}-0.2 & 0.5 & 0 & 0 & 0\\ 0 & -0.5 & 1.6 & 0 & 0\\ 0 & 0 & -14.29 & 85.715 & 0\\ 0 & 0 & 0 & -25 & 75\\ 0 & 0 & 0 & 0 & 10\end{bmatrix};\quad B=\begin{bmatrix}0\\0\\0\\0\\30\end{bmatrix};\quad C=\begin{bmatrix}1 & 0 & 0 & 0 & 0\end{bmatrix};$$

$$Q=diag(1,0,0,0,0);\quad r=1;\quad K_{optimal}=[0.9245\ \ 0.1711\ \ 0.0161\ \ 0.0492\ \ 0.2643];$$

$$K_{Pal}=\begin{bmatrix}0.9245221 & 0.1705645 & 0.0405198 & 0 & 0\end{bmatrix}$$

A suboptimal controller has to be designed by using the first three states for feedback purpose. We choose the following structure for the feedback matrix K.

$$K=[x(1)\quad x(2)\quad x(3)\quad 0\quad 0]$$

The controller parameters are given in Table 5.1, and the time-response comparisons are given in Fig (5).

Table 9

Fitness value	Range	Value In DE	Value in DE	parameters
	0.0003,0.005	0.0038	0.0040	k_D
0.7191	0.2,0.3	0.22993	0.2105	k_p
	0.3,0.6	0.48	0.4609	k_I

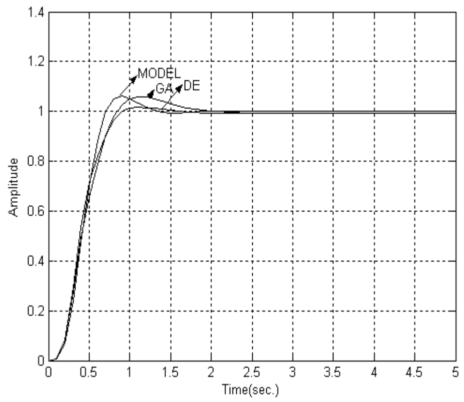


Fig 5

MIMO [13]

The numerical data refers to a Mach 2.7 flight condition of a supersonic transport aircraft [Markland, 1970].The system equations are:

$$A=\begin{bmatrix}-0.037 & 0.0123 & 0.00055 & -1\\ 0 & 0 & 0.08 & 0.804\\ -6.37 & 0 & -0.23 & 0.0618\\ 1.25 & 0 & 0.016 & -0.0457\end{bmatrix};\quad B=\begin{bmatrix}0.00084 & 0.000236\\ 0 & 0\\ 0.08 & 0.804\\ -0.0862 & -0.0665\end{bmatrix};$$

$$C=\begin{bmatrix}0 & 1 & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1\end{bmatrix};\quad Q=r=I;\quad K_{optimal}=\begin{bmatrix}1.8623 & -0.1798 & -0.7008 & -6.4075\\ -3.9387 & 0.9279 & 1.5541 & 2.9926\end{bmatrix}$$

A suboptimal controller has to be designed by using the last three states for feedback purpose. We choose the following structure for the feedback matrix K.

$$K=\begin{bmatrix}0 & x(1) & x(2) & x(3)\\ 0 & x(4) & x(5) & x(6)\end{bmatrix}$$

The controller parameters are given in Table 5.2, and the time-response comparisons are given in Fig (6).

Table 10

Fitness value	Range	Value in GA	Value in DE	Parameters
	-0.38, -0.35	-0.3689	-0.3715	x(1)
	-1.56, -1.5	-1.5297	-1.5318	x(2)
	-8, -6	-6.0248	-7.8704	x(3)
0.4617	1.2,1.5	1.2532	1.4965	x(4)
	3,4	3.0589	3.5828	x(5)
	4,6	5.4817	4.8470	x(6)

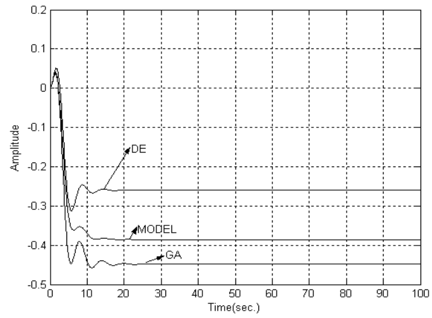


Fig 6 a MIMO U1-Y1

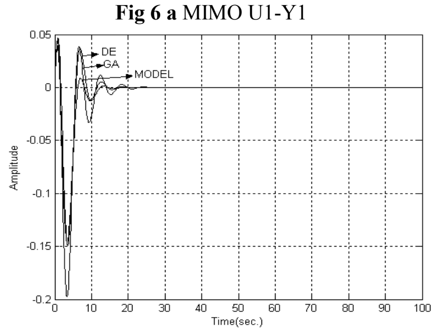


Fig 6 b MIMO U1-Y2

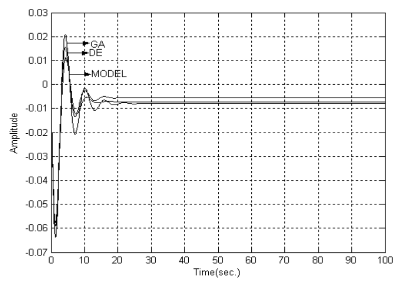


Fig 6 c MIMO U1-Y3

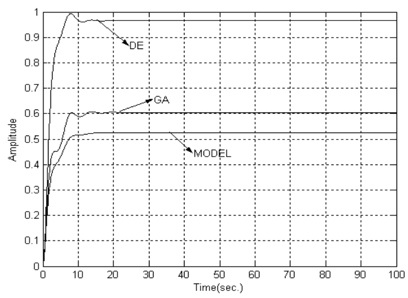


Fig 6 d MIMO U2-Y1

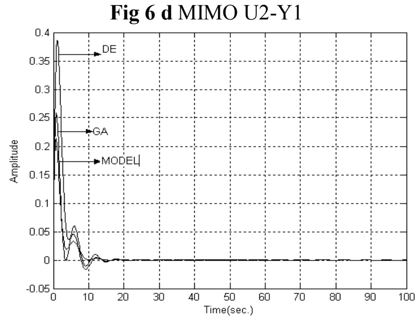


Fig 6e MIMO U2-Y2

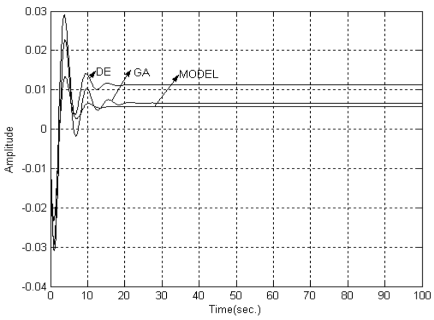


Fig 6 f MIMO U2-Y3

CONCLUSIONS

The present work has dealt with the development control system design using of GA and DE based techniques for solving various problems in single input and single output (SISO) control like, PID control, first order system control, second order system control, phase lead type control, multiple input and single output (MISO) control and multiple input and multiple output (MIMO) sub optimal control in continuous-time systems. The main advantages of the proposed techniques are in their general applicability, simplicity of the resultant controller / model, ease of formation of different fitness functions, no strict requirement of the initial guess vector, flexibility to work with fitness functions framed in the time or frequency domain, flexibility to work with a transfer function or state-space description and a general guarantee to arrive at (sub) optimal results. In spite of the several problems considered in this work, many important areas in control like adaptive controller tuning, adaptive control, identification of multivariable nonlinear systems etc. may be taken up by future researchers.

References

1. D. E. Goldberg, *Genetic Algorithms in Search, Optimisation, and Machine Learning* (Addison Wesley, 1989).
2. 29. A. Varsek, T. Urbancic & B. Filipic, Genetic Algorithms in Controller Design and Tuning, *IEEE transaction on Systems, Man and Cybernetics, 23*(5), 1993,1330-1339.
3. B. Porter & D. L. Hicks, "Genetic tuning of digital PID controllers, *Electronics Letters, 28*(9), 1992, 843-844.
4. B. Porter & D.L. Hicks, Genetic design of unconstrained digital PID controllers, *Proc. IEEE National Aerospace and Electronics Conference,* 1995, 478-485.
5. A.H. Jones, D. Moura & P.B. Oliveira, "Genetic auto tuning of PID Controllers", Proc.1st International Conference on Genetic Algorithms in Engineering systems, 1995, 141-145. Proc.1st International Conference on Genetic Algorithms in engineering systems, 1995, 141-145.
6. S.M. Badran & H.N. Al-Duwaish, "Optimal output feedback controller based on genetic algorithms", Electric Power Systems Research 50, 1999, 7-15.
7. Y.J. Cao & Q.H. Wu, "Optimization of control parameters in genetic algorithms: a stochastic approach", *International Journal of System Science*, *30*(2), 1999, 551-
8. Aoki, M., "Control of large scale dynamic system by aggregation," IEEE Trans. Automatic Contol, vol. AC-13, pp. 246-253, 1968.
9. Appiah, R. K., "Linear model reduction using Hurwitz polynomial approximation," *International journal of Control,* vol. 28, pp. 477-488, 1978.
10. Belanger, P. R. and Chuang, R., "Design of low-order compensators by gain matching," IEEE Transactions on Automatic Control, vol. AC-21, pp. 627-629, 1976.
11. Bernstein, D. S. and Haddad, W. M., "LQG control with an H_∞ performance bound: a Riccati equation approach," IEEE Transactions on Automatic Control, AC-34, pp. 393-305, 1989.
12. Bistritz, Y., "A direct Routh stability method for discrete system modeling," Systems and Control letters, vol. 2, no. 2, pp. 83-87, 1982.
13. Chen, C. F., and Shieh, L. S., "An algebraic method for control system design," *International Journal of Control*, vol. 11, no. 5, pp. 717-739, 1970.
14. Chi-Tsong Chen and Byunghak Seo, "The inward approach in the design of control systems," IEEE Transactions on Education, vol. 33, no. 3, pp. 270-278, 1990.
15. Sanathanan, C. K., and Quinn, S. B., "Design of set point regulators for processes involving time-delay," *AIChE Journal*, vol. 33, no. 11, pp. 1873-181, 1987.
16. Pal J., "Control system design using approximate model matching," *System Science (Poland),* vol. 19, no. 3, pp. 5-23, 1993.
17. Sanathanan, C. K., and Quinn, S. B., "Design of set point regulators for processes involving time-delay," *AIChE Journal*, vol. 33, no. 11, pp. 1873-181, 1987.
18. Sanathanan, C. K. and Stanley B. quinn Jr., "Controller design via the synthesis equation," *Journal of the Franklin Institute*, vol. 324, no. 3, pp. 431-451, 1987.
19. Shieh, L. S., Wei, Y. J. P., and Yates, R. E., "A modified direct-coupling method for multivariable control system designs," IEEE Transactions on Industrial Electronics and Control Instrumentation, vol. IECI-28, no.1, pp. 1-9, 1981.
20. Sridhar, B. and Indorff, P. D., "Pole-placement with constant gain output feedback," International Journal of Control, vol. 18, pp. 993-1103, 1973.
21. Ubaid M. Al-Saggaf, "An approximation technique to tune PID controllers," Computers and Elect. Engg., vol. 17, no. 4, pp. 313-320, 1991.
22. Xu, J. H. and Mansour, M., "Design of H_∞ optimal controllers: stability, asymptotic regulation and disturbance rejection," in Proceedings: 25th IEEE Conference on Decision and Control, 1986.
23. Adrian Andreou: "On power system stabilizers: Genetic algorithms based tuning and Economic worth as ancillary services", Department of Electrical Engineering, Chalmers University of Technology, Sweden 2004.
24. A. M.D. Ferreira, J.A.L. Barreiros, W. Barra Jr., J.R.B.d. Souza, "A Robust adaptive LQG/LTR TCSC controller applied to damp power system oscillations". Elsevier, Science Direct, Electric Power Research, vol. 77, 2007, pp. 956 - 964.
25. S. Panda, N.P. Padhy, "Coordinated Design of TCSC Controller and PSS employing Particle Swarm

Optimization Technique", *international journal of computer and information science and engineering*, volume 1, number 1, 2007, pp.1307 - 4164.

26. S. Panda, N. P. Padhy, "Power system with PSS and FACTS controller: Modelling, simulation and simultaneous tuning employing Genetic Algorithm", *International Journal of Electrical, computer and systems Engineering, volume* 1, num. 1, 2007, pp. 1307 - 5179.
27. Y. L. Abdel-Magid, M. A. Abido, S. Al-Baiyat, and A. H. Mantawy, "Simultaneous stabilization of multimachine power systems via genetic algorithms," IEEE Trans. Power Syst., vol. 14, Nov. 1999, pp. 1428-1439.
28. Hongesombut K., Mitani Y., Tsuji K. "An incorporated use of Genetic Algorithm and Modelica library for simultaneous tuning of Power System Stabilizers," Second International Modelica conference, Proceedings, pp. 89 - 98.
29. D. Karaboga, S. Okdem, "A simple and Global Optimization Algorithm for Engineering: Differential Evolution Algorithm," Turk Electrical Engineering, Vol. 12, No. 1, 2004.
30. K.V. Price, R.M. Storn, J.A. Lampinen, "Differential Evolution: A practical approach to global optimization" Springer - Verlag Berlin Heidelberg, 2005.