Enhancing Genetic Algorithms using a Dynamic Mutation Value Approach: An Application to the Control of Flexible Robot Systems

Sarah Deif, Hanan A. Kamal and Mohammad Tawfik

***Abstract*---**This paper presents an investigation into a new optimization technique based on genetic algorithm (GA). A dynamically-changed mutation value approach is introduced to increase the diversity in the search space and avoid premature convergence caused by simple genetic algorithm (SGA). The enhanced genetic algorithm (EGA) is used to tune the feedback gains of a PD controller which controls both the position and vibration of a single-link flexible arm. The dynamic model of the system is derived using Hamilton’s principle and modeled using the finite element method (FEM). A multi-objective function is defined and altered to reach a range of specified system responses and therefore it is shown to be able to satisfy different objectives. Adaptive Genetic Algorithm (AGA) and Cloud Model Based Adaptive Genetic Algorithm (CAGA) techniques are used to challenge the proposed technique. Results obtained show that EGA creates significant improvement in the speed of convergence compared to other techniques. Moreover, the obtained solutions are of higher average fitness values. EGA succeeded to consistently reach a global solution for an objective function that needs rigorous search mechanism which encourages for further application to various control problems, complex mathematical functions and real time applications.

***Keywords*---**Adaptive Genetic Algorithm (AGA), Cloud Model Based Adaptive Genetic Algorithm (CAGA), Enhanced Genetic Algorithm (EGA), Genetic Algorithms (GA), Multi-Objective Optimization, PD Controller, Single-Link Flexible Manipulator.

I. INTRODUCTION

OVER the past few decades, the need of high speed manipulation and high payload capability in robot manipulators have drawn a thorough attention to the modeling, control and development of flexible manipulators. Flexible-link robot arms exhibit many advantages over their rigid counterparts including lighter weight, higher speed operation, better maneuverability, lower energy consumption, requirement of smaller actuators, less manufacturing cost and higher payload to manipulator weight ratio. However, the dynamic analysis of flexible robots and the design of their control system are more challenging problems. Several applications to flexible manipulators make use of their high performance and necessary characteristics [1]. In space applications, a light weight space manipulator is used to reduce the cost of launching it. Medical and nursing robots are required to be flexible in order to interact with humans. Other applications include collision control, contouring control, trajectory tracking, pattern recognition and many others.

Despite the favorable characteristics, the main disadvantage of flexible robots is the vibration problem due to low stiffness. These oscillations make the precise positioning of the tip of the arm a difficult task. Therefore, the design of the control system must take into account not only the precise angular positioning but also suppressing the vibration developed at the tip due to the high structural flexibility of the manipulator. Several studies have been conducted worldwide in the area of dynamic analysis and control of flexible robot arms presented by the surveys of Dwivedy and Eberhard [1] and Benosman and Vey [2]. These studies have put effort into adopting good control mechanisms that would eliminate structural vibrations.

Many feedback control schemes have been investigated in the literature regarding both the precise positioning and the vibration control of single-link flexible manipulators. Examples include Linear Quadratic Gaussian controllers [3], adaptive control [4], Lyapunov-based control [5], robust control [6], sliding-mode control [7], integral resonant control (IRC) [8] and Regulator-based controllers [9]. Most of these classic or modern controllers assume the exact knowledge of the system dynamics and therefore unsatisfactory for real applications. Therefore, research has been directed towards intelligent-based control such as fuzzy-logic algorithms [10], neural network based techniques [11], [12]. However, these methods require complex design methodologies.

Despite the growing research towards studying and designing a sophisticated control algorithm, Proportional Integral Derivative (PID) controllers are still widely used in most industrial control applications. This popularity is due to their structural simplicity, robustness, reliability and broad applicability. The only limitation of PID controllers is the improper choice of the PID parameters which may affect the stability of the system. Therefore, it has become necessary to tune the control parameters to achieve good performance. Several conventional tuning methods were presented in literature including Ziegler-Nichols, pole placement,

---

Manuscript received on November 28, 2011, review completed on December 07, 2011 and revised on December 31, 2011.

Sarah Deif is a Teaching Assistant at the Engineering Mathematics and Physics Department, Cairo University, Giza, Egypt. E-Mail: sarah_deif@hotmail.com.

Hanan A. Kamal is an Associate Professor at the Electronics and Communication Engineering Department, Cairo University, Giza, Egypt. E-Mail: hanan_ak2003@yahoo.com.

Mohammad Tawfik is an Assistant Professor at the Aeronautical and Aerospace Engineering Department, Cairo University, Giza, Egypt. E-Mail: mohammad.tawfik@gmail.com.

Digital Object Identifier No: AIML012012002.

continuous cycling and more [13]. Moreover, intelligent tuning techniques were used and compared to conventional techniques. These include, but not limited to, Genetic Algorithm (GA), Evolutionary Programming (EP), and Particle Swarm Optimization (PSO). They were found to prove excellence in obtaining better results by improving steady state response and performance indices in contrast to classical methods [14]. Genetic Algorithm (GA) has been successfully applied in various research areas such as optimization, design, image processing, machine learning and many other computational intelligence applications [15]. One of the reasons of its broad applicability is that it offers an effective way to search for global solutions. It is also a robust and data-independent search technique. GA was successfully used in tuning the controller parameters for an optimal tip performance of a single-link flexible manipulator [16], [17].

The main drawback of the simple genetic algorithm (SGA) is that it may converge to a sub-optimal solution. This means it may lead to both slow and premature convergence. Researchers proposed many ideas to solve this problem: all are based on increasing the diversity of the search space. One of these techniques is based on the concept of adaptive genetic algorithm (AGA). In AGA, the probabilities of the crossover and mutation can be adaptive. This has proven to increase the diversity of the search space leading to faster convergence and obtaining better results. Different formulas of adaptive operators were presented in literature where the probabilities of crossover and mutation are represented as a function of the fitness values of the solutions, the average fitness and the maximum fitness at each generation [18]-[22]. In [18], the crossover and mutation probabilities are varied depending on the fitness values of the solutions. Although this technique significantly improves the speed of convergence, it also has higher possibility to get stuck at a local optimum because the probability of crossover and mutation of the best solution with the largest fitness value will both equal zero, which means crossover and mutation cannot occur for best solution and thus causes premature convergence. In [19], a different genetic operator was presented that is varied depending on the average fitness value in each generation. Furthermore, AGA that is based on a Cloud Model was presented in [20], [21]. As far as this survey is concerned, AGA hadn't been applied before in the control problem of a single-link flexible manipulator until it was presented by Sarah Deif et.al in [22].

This work presents an enhanced genetic algorithm (EGA) technique that is used to tune the feedback gains of a PD controller which is designed to control the hub angle position and the vibration developed on the single-link flexible manipulator. EGA is based on a new dynamic mutation operator designed to overcome the deficiencies of SGA which is thoroughly explained in this paper. The dynamics of the flexible arm is derived using the Hamilton's principle and modeled using the finite element method (FEM). A multi-objective function is altered to meet a range of specified system responses. The effectiveness of this proposed technique has been shown by comparing the results obtained with SGA and two other AGA techniques.

This paper is organized as follows. The dynamics of the single-link flexible robot is introduced in Section II. . The PD controller is presented in Section III. In section IV, the new mutation operator that is used to tune the controller's feedback gain is discussed. Section V presents two adaptive GA techniques that are used for comparison with the proposed technique. Section VI shows the results and discussion of simulation experiments demonstrating the effectiveness of the new proposed genetic algorithm. Finally, some conclusions and suggestions for future work are given in Section VII.

II. THE SINGLE-LINK FLEXIBLE MANIPULATOR MODEL

Fig. 1 shows a single-link flexible robot arm which rotates in the horizontal plane. The mechanical properties of the flexible link are shown in Table I. Starting from Hamilton's principle:

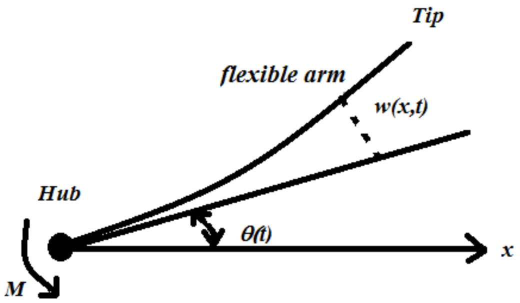

Fig. 1 Schematic Diagram of a Single-Link Flexible Robot Arm

TABLE I
MECHANICAL PROPERTIES OF FLEXIBLE MANIPULATOR

Parameter (Units)	Value
Length (m)	1.0
Width (m)	0.02
Thickness (m)	0.001
Material	Steel
Density (kg/m^3)	7800
Modulus of elasticity (Pa)	207×10^{9}
Second moment of area (m^4)	1.6667×10^{-12}

$$\int_{t_1}^{t_2} \delta(U - T - W)\, dt = 0, \qquad (1)$$

where U is the potential energy, T is the kinetic energy, and W is the work done by the external forces. The potential energy of the beam moving in a horizontal plane may be written as:

$$U = \frac{1}{2}\int EI \left(\frac{d^2 w}{dx^2}\right)^2 dx, \qquad (2)$$

where EI is the beam bending stiffness and w is the displacement of the beam measured from the rigid body line as shown in Fig.1. Meanwhile, the kinetic energy can be written as:

$$T = \frac{1}{2}\int \rho A\,(\dot{\theta}^2 x^2 + 2\dot{\theta}\dot{w}x + \dot{w}^2)\,dx, \qquad (3)$$

where θ is the angular displacement of the rigid beam measured from the x-axis. The external work done by the servo motor can be written as:

$$W = M\theta, \qquad (4)$$

where M is the moment provided by the motor. Using the standard finite element modeling techniques, we may write the displacement of any element in the form:

$$w(x,t) = \lfloor N_1(x) \;\; N_2(x) \;\; N_3(x) \;\; N_4(x) \rfloor \begin{Bmatrix} w_1(t) \\ w_1'(t) \\ w_2(t) \\ w_2'(t) \end{Bmatrix}, \qquad (5)$$

where N_i is the shape function; and w_i and w_i' are the nodal displacement and the slope respectively. The above equation may be written in compact form as:

$$w(x,t) = \lfloor N(x) \rfloor \; \Delta(t) \;. \qquad (6)$$

Applying Hamilton's principle and using the above equation, we may write the equation of motion as:

$$\begin{pmatrix} M_B & M_t \\ M_t & J \end{pmatrix}\begin{pmatrix} \ddot{w} \\ \ddot{\theta} \end{pmatrix} + \begin{pmatrix} K_B & 0 \\ 0 & 0 \end{pmatrix}\begin{pmatrix} w \\ \theta \end{pmatrix} = \begin{pmatrix} 0 \\ M \end{pmatrix}, \qquad (7)$$

where M_B is the assembled mass matrix, M_t is the assembled coupling mass matrix, J is the rigid beam mass moment of inertia around the hub and K_B is the assembled bending stiffness matrix. On the other hand, the element mass matrix may be written as $\int_{x_1}^{x_2} \rho \lfloor N(x) \rfloor \; N(x) \; dx$ where ρ is the beam mass per unit length, the element coupling mass matrix $\int_{x_1}^{x_2} \rho x \lfloor N(x) \rfloor dx$, the element bending stiffness matrix $\int_{x_1}^{x_2} EI \lfloor N_{xx}(x) \rfloor \; N_{xx}(x) \; dx$ and the beam moment of inertia is $\rho\ell^3/3$ where ℓ is the element length. The structural and environmental damping coefficients are neglected to solely study the effect of the designed control scheme on the system performance. The time integration has been performed using the Newmark method which approximates the time response using the algorithm in [23].

III. The PD Controller

The feedback control scheme is shown in Fig.2 including a Proportional Derivative (PD) feedback controller and an enhanced genetic algorithm (EGA). PD is widely used in industrial applications and its algorithm can be described as:

$$M(t) = -k_p \theta_{hub}(t) - k_d \frac{d\theta_{hub}(t)}{dt}, \qquad (8)$$

where $\theta_{hub}(t)$ is the hub angle measured at the output and $M(t)$ is the control signal which defines the input torque to the system. Negative feedback adds stiffness and damping effect to the system and therefore the negative signs are put in the controller equation with the controller gains (k_p, k_d) resulting in positive values.

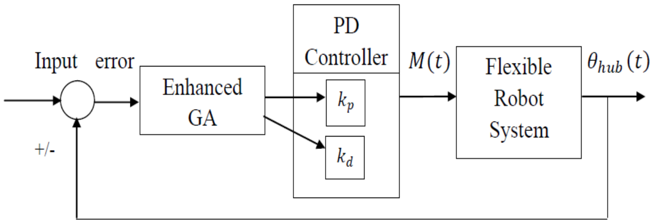

Fig. 2 The Feedback Control Scheme Based on Enhanced GA

IV. The Enhanced Genetic Algorithm (EGA)

The basic principles of the genetic algorithm (GA) were first proposed by John Holland [24]. GA uses operations found in natural genetics based on the Darwinian Theory. In the beginning, a random population of chromosomes of size N_{pop} is generated to represent the PD gain values (k_p, k_d) in the given bounds. A real-coded GA [25] is used to represent the values of the genes. Then, these values are applied to the flexible manipulator system and a corresponding fitness value is calculated for each chromosome by evaluating the fitness function. Based on the fitness value of each individual, a group of chromosomes are selected to propagate into the next generation. The higher the fitness the more probable it will survive. The selected chromosomes are then mated together to recombine the best features of the parent chromosomes to produce better offspring. A mutation operator is then introduced to ensure diversity in the search space.

A. *Genetic Operators*

Three genetic operators are applied to the current population in order to create a new generation of chromosomes of the same population size. These operators are reproduction, crossover and mutation respectively. The choice of both the crossover and mutation operators is of a great importance and can determine the performance of the whole genetic algorithm. By using different probabilities of both operators, the speed of convergence and the accuracy of the solution can be controlled.

1) *Reproduction:* The reproduction operator is the element that performs the “Survival of the Fittest” or natural selection function in a GA. “Roulette Wheel Selection” method is used [26]. Power-law fitness scaling is performed prior to the selection process in order to avoid premature convergence.

2) *Crossover:* The crossover operator recombines genetic information from the two selected parents to produce offspring with characteristics from both at a probability of crossover p_c. An arithmetic crossover operator for real (decimal) numbers called weighted average operator [16] is used.

3) *Dynamic Mutation Value Approach:* A new mutation value approach is proposed to increase the diversity in the search space and avoid the premature convergence of SGA. The algorithm is based on dividing the chromosomal population into two groups and assigning different mutation operators to each one of them. The algorithm can be logically explained as follows:

In a given population, let f_i be the fitness value of any chromosome i and f_{avg} be the average fitness value. Then, the mutation probability p_m and the mutation value added to each gene can be defined as:

***For Group 1:* (**$f_i \geq f_{avg}$**)**

The mutation probability is: $p_m = 0.8$

***For Group 2:* (**$f_i < f_{avg}$**)**

The mutation probability is: $p_m = 0.1$

***Mutation Value Added*:**

*Let r_1 be a random percentage value in the range $0 \rightarrow 75\%$ for **Group 1** and $0 \rightarrow 200\%$ for **Group 2**.*

Let Pert= $\pm\ (r_1 \times r_2)$ be a random perturbation value with a maximum value of perturbation = r_1 where r_2 is a random value in the range (0,1). Therefore, the mutated gene value can be defined as:

New mutated gene value = current value of the gene + (pert × current value of the gene).

If the new mutated gene value exceeds the defined bound of the gene, then the perturbation term is reduced as follows:

Pert= Pert $\times\ 0.5$

The value of Pert continues to be reduced by a factor of 0.5 as long as the bound is exceeded.

This algorithm is based on dynamically changing the mutation value added to the genes. For high fitness chromosomes whose fitness values are higher than the average fitness, p_m is set to a high value to increase the diversity of the search space and to prevent the solution getting stuck at a sub-optimal point. This technique may lead to the loss of the “good featured” chromosomes unless the concept of *Elitism* is utilized [25]. The gene is perturbed by a random value of a maximum 75% of the current gene value. If this perturbation term violates the bound limit, then it is reduced each time by a factor of 0.5 until the new mutated value is within the bound. The factor 75% is chosen to be small so as not to lose the good features of the high fitness chromosomes. Similarly, for chromosomes with fitness below the average fitness, a low standard mutation probability is used and a high maximum perturbation factor of 200% is defined. A high factor of perturbation is set to push the low fitness genes into the vicinity of the best chromosomes.

B. Fitness Function

One of the most crucial steps in applying GA is to choose the objective function that is used to evaluate the fitness of each chromosome. The objective of the optimization problem is to have better control over angular position vibration of a single-link flexible robot, i.e. to obtain optimal values of the feedback gains with which the PD controller can drive the hub angle and the tip deflection to predefined values as fast as possible with minimal oscillation. A multi-objective function is defined based on the Integral of Absolute Magnitude of the Error (IAE) where $IAE = \int_0^T |e(t)|\,dt$ and $e(t)$ is the output error function to be minimized. In order to reach the objective of controlling both the position and vibration of the arm, a multi-objective function based on the *“sum of weighted cost functions”* is introduced [27]. This Multi-Objective IAE (MOIAE) is defined as:

$$MOIAE = \left(\alpha \times \int_0^T \left| w_{tip}(t) \right| dt \right) + \int_0^T \left| \theta_{hub}(t) \right| dt \qquad (9)$$

where α is a weighting factor. The first term satisfies the first objective of minimizing the error in tip deflection w_{tip}. The error is defined as the difference between the measured tip deflection and the predefined set point which is set to zero. Similarly, the second term satisfies the second objective of minimizing the hub angle θ_{hub} for the same set point. For this defined function, the weighting factor is multiplied by the first term while keeping the second term with a weighting factor unity. The value of α has a profound effect on the system performance as it will be discussed in Section VI.

V. ADAPTIVE GENETIC ALGORITHM TECHNIQUES

In order to challenge the proposed enhanced genetic algorithm, two different adaptive genetic algorithm techniques presented in literature are used for comparison.

A. Adaptive GA (AGA)

This technique is based on varying the probabilities of crossover and mutation in order to increase the diversity of the population and thus avoid the problem of premature convergence that commonly exists in simple GA [19]. Define the diversity level (DL) as:

$$DL = \frac{best\ population\ fitness\ value}{average\ population\ fitness\ value}. \qquad (10)$$

It can be used to vary the probabilities of crossover and mutation as follows:

$$Pb_{crossover} = \frac{1}{1 + e^{(1-DL)}}, \qquad (11)$$

$$Pb_{mutation} = \frac{e^{(1-DL)}}{1 + e^{(1-DL)}}. \qquad (12)$$

The value of *DL* ranges from unity to positive infinity. When *DL* equals unity, all the chromosomes in the population have the same fitness value, and the diversity level is the lowest. In this circumstance, the evolution tends to prematurity. By (11) and (12), the probability of crossover will be close to 0.5, while the probability of mutation will increase significantly to diversify the population. If *DL* approaches positive infinity, the population has the highest diversity level. The probability of mutation is near zero and that of crossover tends to 1, which is the normal condition of evolution.

B. Cloud-Model-Based AGA (CAGA)

In CAGA, the choice of p_c and p_m is created from a cloud crossover/mutation rate generator. The stable tendency of normal cloud guarantees CAGA can improve convergent speeds, while the randomness of normal cloud model can, to a large extent, prevent CAGA from getting stuck at a sub-optimal solution. A normal cloud is defined with three digital characteristics, expected value E_x, entropy E_n and hyper entropy H_e [20]. p_c and p_m are calculated using the following algorithm [21]:

In any given population, let f_i *be the fitness value of any chromosome i,* f_{max} *be the best fitness value and* f_{avg} *be the average fitness value. Then,*

$$E_x = f_{avg}\ ,\ E_n = C_n * (f_{max} - f_{avg})\ \text{and}\ H_e = E_n * C_e$$

```
For each chromosome i ,
1) If ( $f_i \geq f_{avg}$ )
        $E_n' = Cloud\ Generator\ (\ E_n , H_e\ )$
        $P_m = C_m *\ Cloud\ Generator\ (\ E_x , E_n'\ )$
        $P_c = C_c *\ Cloud\ Generator\ (\ E_x , E_n'\ )$
2) If ( $f_i < f_{avg}$ )
        $P_m = P_{fm}'$
        $P_c = P_{fc}'$
```

where the $Cloud\ Generator\ (\ x, y\ )$ *gives a normal random number from a normal distribution with mean x and standard deviation y.*

In this algorithm, for the individual whose fitness is higher than the average fitness of the population, an adaptive crossover rate and an adaptive mutation rate are produced using a cloud generator. For the individual whose fitness is lower than the average fitness, fixed crossover and mutation rates are given. From [20], $C_n = 1/3$ and $C_e = 1/10$ are adjustment factors that directly affects the diversity and randomness of the cloud model, $P_{fm}' = 0.5$ and $P_{fc}' = 1$ are the fixed crossover and mutation rates respectively and $C_m = 0.5$ $C_c = 1$ are constants.

VI. SIMULATION RESULTS AND DISCUSSION

Numerical simulations were carried out using MATLAB to verify the effectiveness of the proposed controller. In order to obtain more persuasive results, the plant is simulated with a 5 element finite element model. The robot starts with an initial tip displacement $w_{tip} = 0.01\ m$ and an initial hub angle $\theta_{hub} = \frac{\pi}{2}\ rad$. The objective is to force the arm to reach set points $w_{tip} = 0$ and $\theta_{hub} = 0$ in the least possible time and resulting in a precise angle position and minimal oscillations. A population size $N_{pop} = 10$ and a maximum number of generations $G_{\max} = 100$ are used for all algorithms. Also, a crossover probability $p_c = 0.9$ is used for SGA and EGA. As for the probability of mutation, $p_m = 0.05$ is used for SGA.

A. Effect of α on the Performance of the EGA

First, the influence of α, defined Section IV, on the settling time of the hub angle (defined as reaching 5% of the final set point) and the vibration amplitude (at time=5 sec) is studied. For small values of α, θ_{hub} tends to have a higher effect on MOIAE while as α grows larger w_{tip} has a stronger effect on the objective function and thus prevails over the effect of θ_{hub} on MOIAE. Fig.3, Fig. 4 and Table II show the settling time of the hub angle, the tip deflection amplitude and sample readings recorded in a table respectively. The settling time is at its best at $\alpha = 0$ (MOIAE only controls θ_{hub}) and it increases as the weighting factor increases. As for the tip deflection, it shows poor response at low values of α until it reaches a point where MOIAE sense the presence of w_{tip} .

TABLE II
THE EFFECT OF α ON THE HUB ANGLE SETTLING TIME AND THE TIP DEFLECTION

α	Settling Time (sec)	Tip Deflection (at time=5 sec)
0	0.9	0.05
6	2.3	0.004
12	2.9	0.001
22	3.55	0.00036
38	4.18	0.00084
50	4.58	0.001

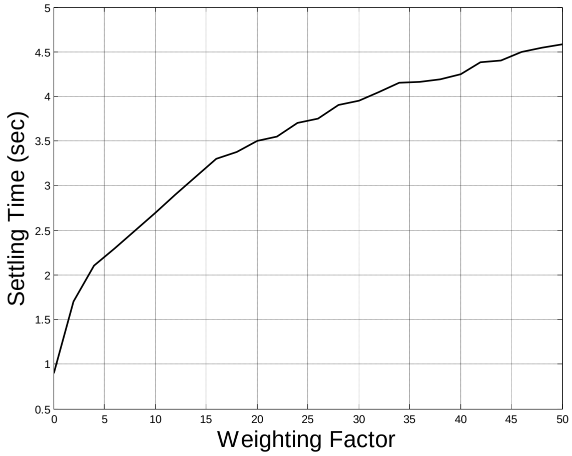

Fig. 3 Settling Time of the Hub Angle for Different Values of α

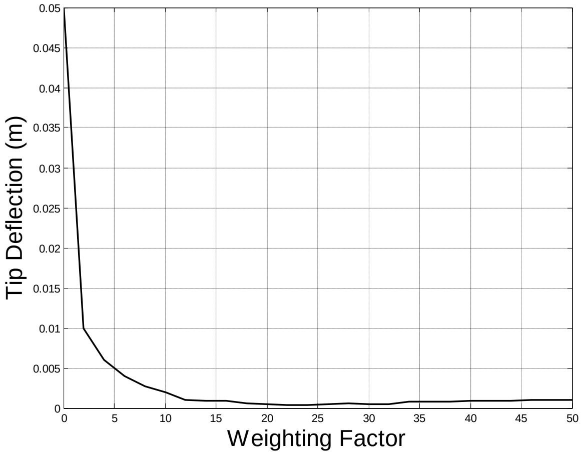

Fig. 4 Tip Deflection at Time= 5 Sec for Different Values Of α

The minimum tip deflection value reached was recorded at $\alpha = 22$ as shown in Table II. The choice of the optimal value of α depends on the application. Some applications favor higher control on tip vibration whereas other applications need a very small settling time. Therefore, a compromise between position control and vibration can be done using different values of α.

B. Effect of α on the Hub Angle and the Tip Deflection

The position and vibration control results are compared and analyzed for the best solutions resulted from EGA for three different values of α . The values of (k_p, k_d) used are shown in Table III. Obj1 defines the response for $\alpha = 0$, Obj2 for $\alpha = 12$ and Obj3 for $\alpha = 22$. From Table III and Fig.5, Obj1 gives the smallest settling time which outperforms Obj2 by 69% and Obj3 by 74.6%. As for the vibration in Fig. 6, Obj1 shows the worst performance while a major improvement in vibration damping is shown by Obj2 and Obj3 where they appear as fine lines compared to the high oscillations resulted from Obj1. Fig. 7 shows a comparison between Obj2 and Obj3 regarding the tip deflection. Obj3 shows an improvement by 64% over Obj2.

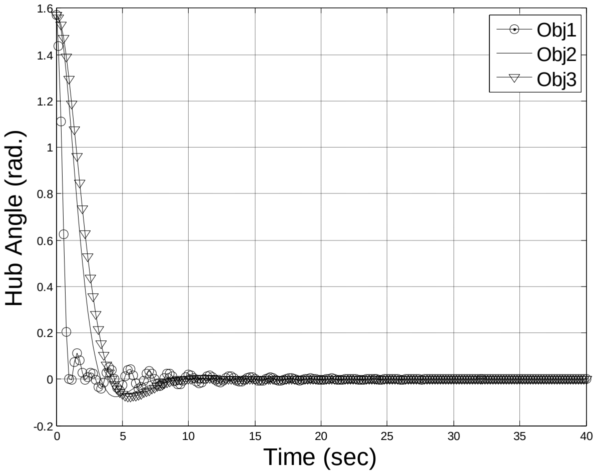

Fig. 5 Hub Angle for Obj1, Ob2 and Obj3 using EGA

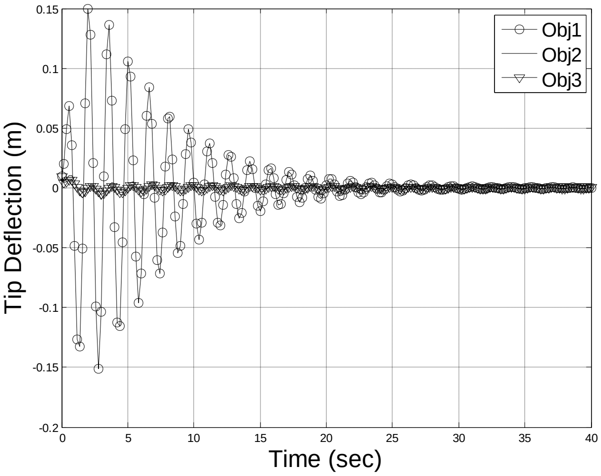

Fig. 6 Tip Deflection for Obj1, Ob2 and Obj3 using EGA

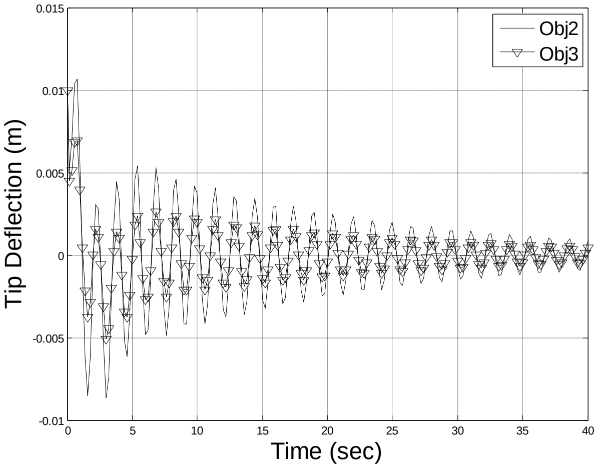

Fig. 7 Comparison between Obj2 and Obj3 for Tip Deflection

TABLE III
CONTROLLER GAINS

Objective Function	α	k_p	k_d
Obj1	0	0.3997	0.2681
Obj2	12	0.0497	0.0808
Obj3	22	0.0342	0.0671

C. Comparing SGA, EGA, AGA and CAGA

In order to test the effectiveness of the EGA, a comparison is done with SGA, AGA and CAGA for $\alpha = 12$. MOIAE is a multi-peak function that needs a rigorous search mechanism in order to successfully reach the global solution. It has a global minimum at 17.8182 for $k_p = 0.0497$ and $k_d = 0.0808$ that is reached only using EGA. Table IV shows the comparison results of the four algorithms for 50 executions. SGA, AGA and CAGA fail to reach the global solution while EGA successfully reaches it multiple times which shows the consistency of EGA compared to the other algorithms. EGA shows significant improvement in speed of convergence over SGA by 87.9%, AGA by 86.5% and CAGA by 84.7%. Also, EGA results in the best average optimal value compared to all other algorithms. Fig.8 is a sample of the objective function convergence. Apparently, EGA converges very quickly to the global solution whereas CAGA takes more number of iterations to reach an optimal solution followed by AGA and finally the slowest in convergence is SGA. All four algorithms are further compared to study their effect on hub angle settling time and tip deflection as shown in Table V. The corresponding controller gain values are recorded to each optimal value and then the hub angle settling time and the tip deflection is measured. As shown, EGA gives the best results out of the four algorithms.

TABLE IV
COMPARISON BETWEEN SGA, EGA, AGA AND CAGA

Algorithm	Average Generations	Average Optimal Value	Optimal Value	Improvement in number of generations
SGA	58	27.3655	18.0074	
EGA	7	17.8196	17.8182	87.9%
AGA	52	20.4664	17.8616	10.3%
CAGA	46	20.0214	17.8901	20.7%

TABLE V
HUB ANGLE SETTLING TIME AND TIP DEFLECTION FOR SGA, EGA, AGA AND CAGA

Algorithm	k_p	k_d	Settling Time (sec)	Tip Deflection (at time=5 sec)
SGA	0.0586	0.0865	2.9	0.00624
EGA	0.0497	0.0808	2.9	0.001
AGA	0.0502	0.0784	3.0	0.004646
CAGA	0.0546	0.0868	3.1	0.005566

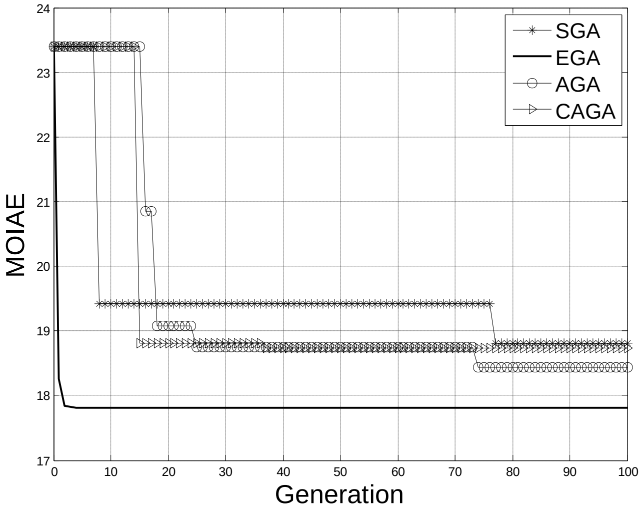

Fig. 8 Sample Convergence of MOIAE to the Optimal Solution

VII. CONCLUSION AND FUTURE WORK

A new enhanced genetic algorithm (EGA), which is based on a dynamically-changed mutation value approach, has been thoroughly defined and successfully applied to the problem of position and vibration control of a single-link flexible robot arm. A multi-objective function was designed to meet different objectives resulting in specified system response. Two adaptive algorithms (AGA and CAGA) have been used to challenge the new proposed technique and were for the first time applied to this problem. Simulation results have shown significant improvement of EGA over SGA, AGA and CAGA regarding the speed of convergence and the accuracy and consistency in finding the global solution. EGA outperforms SGA in speed of convergence by 87.9%, AGA by 86.5% and CAGA by 84.7%. Moreover, EGA shows consistency and accuracy in reaching the global solution compared to SGA, AGA and CAGA where it results in the best average optimal value reached. Therefore, the combination of EGA with the concept of multi-objective optimization resulted in a significantly faster convergence, a higher accuracy in the resulted optimal value and a better control over the hub angle positioning and vibration damping. Future work may include applying EGA to complex mathematical functions that require a rigorous search mechanism and to a wide range of systems such as multiple link rigid robots and multiple link flexible robots. Also, it can be applied to on-line control applications for its fast convergence and high accuracy.

REFERENCES

[1] S.K. Dwivedy and P. Eberhard, "Dynamic Analysis of Flexible Manipulators: A Literature Review," Mech. Mach. Theory, vol.41, pp. 749-777, 2006.

[2] M.Benosman and G.Le.Vey, "Control of Flexible Manipulators: A Survey," Robotica, vol.22, pp. 533-545.

[3] R.H.Cannon Jr., E. Schmitz, "Initial Experiments on the End-Point Control of a Flexible One-Link Robot," Int. J. Rob. Res., vol.3, no.3, pp. 62-75, 1984.

[4] V. Feliu, K.S.Rattan and H.B.Brown Jr., "Adaptive Control of a Single-Link Flexible Manipulator," IEEE Control Syst. Magazine, vol.10, no.2, pp. 29-33, 1990.

[5] K.Takahashi and M.Sasaki, "Remarks on Tip Angular Position Control of a Single-Link Flexible Robot Arm Using Modified Lyapunov Function," in Proc. IEEE Int. Conf. Mechatron. Autom., 2010.

[6] I.A.Mahmood, S.O.R.Moheimani and B.Bhikkaji, "Precise Tip Positioning of a Flexible Manipulator Using Resonant Control," IEEE/ASME Trans. Mechatron., vol.13, no.2, 2008.

[7] Y.P.Chen and H.T.Hsu, "Regulation and Vibration Control of an FEM-Based Single-Link Flexible Arm Using Sliding-Mode Theory," J. Vibration Control, vol.7, no.5, pp. 741-752, 2001.

[8] E.Pereira, S.S. Aphale, V.Feliu and S.O.Moheimani, "Integral Resonant Control for Vibration Damping and Precise Tip-Positioning of a Single-Link Flexible Manipulator," IEEE/ASME Trans. Mechatron., vol.16, no.2, 2011.

[9] M.Baroudi, M.Saad, W.Ghie, A.Kaddouri and H.Ziade, "Vibration Controllability and Observability of a Single-Link Flexible Manipulator," in Proc. IEEE Conf. Syst. Signals Devices, 2010.

[10] I.H.Akyuz, S.Kizir, Z.Bingul, "Fuzzy Logic Control of Single-Link Flexible Joint Manipulator," in Proc. IEEE Int. Conf. Ind. Tech., 2011

[11] Z.Su and K.Khorasani, "A Neural-Network-Based Controller for a Single-Link Flexible Manipulator Using the Inverse Dynamics Approach," IEEE Trans. Ind. Electron., vol.48, no.6, 2001.

[12] T.Mansour, A.Konno and M.Uchiyama, "MPID Control Tuning for a Flexible Manipulator using a Neural Network," J.Rob. Mechatron., vol.22, no.1, pp.82-90, 2010.

[13] P.Cominos and N.Munro, "PID Controllers: Recent Tuning Methodsand Design to Specification," in Proc. IEE Control Theory and Applications, vol. 149, no.1, pp. 46-53, 2002.

[14] B.Nagaraj, S.Subha and B.Rampriya, "Tuning Algorithms for PID Controller Using Soft Computing Techniques," Int. J. Computer Science and Network Security, vol.8, no.4, 2008.

[15] D.Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley, 1989.

[16] S.S.Ge, T.H.Lee and G.Zhu., "Genetic Algorithm Tuning of Lyapunov-Based Controllers: An Application to a Single-Link Flexible Robot System," IEEE Trans. Ind. Electron., vol.43, 1996.

[17] B.Zain, M.O.Tokhi and S.F.Toha, "PID-Based Control of a Single-Link Flexible Manipulator in Vertical Motion with Genetic Optimisation," in Proc. IEEE UKSim Computer Modeling and Simulation, 2009.

[18] M.Srinivas and L.M.Patnaik, "Adaptive Probabilities of Crossover and Mutation in Genetic Algorithms," IEEE Trans. on Systems, Man and Cybernetics, Vol.24, No.4, pp. 656-667, April 1994.

[19] L.Lu, W.Cai, Y.C.Soh and L.Xie, "Global Optimization for Overall HVAC systems- Part II," Energy Conversion and Management, vol.26, pp.1015-1028, 2005.

[20] C.H.Dai, Y.F.Zhu and W.R.Chen, "Adaptive Probabilities of Crossover and Mutation in Genetic Algorithms Based on Cloud Model," in Proc. IEEE Information Theory Workshop, 2006.

[21] J.Yue, T.C.Jie, Z.H.Chun, L.Chuan, C.Yu, WU Jiang and W.D.Lei, "Adaptive Gene Expression Programming Algorithm Based on Cloud Model," in Proc. IEEE Int. Conf. BioMedical Engineering and Informatics, 2008.

[22] Sarah Deif, Mohammad Tawfik and H. A. Kamal, "Optimal Tuning of a PD Controller for a Single-Link Flexible Robot Arm Using Adaptive Genetic Algorithm," in Proc. 14th Int. Conf. on Aerospace Sciences and Aviation Technology, Military Technical College, 2011.

[23] M.Tawfik, "Dynamics and Stability of Stepped Gun Barrels with Moving Bullets," Advances in Acoustics and vibration, 2008

[24] J.H.Holland, Adaptation in natural and articial systems. Ann Arbor, The University of Michigan Press, 1975.

[25] S.N.Sivanadam and S.N.Deepa, Introduction to Genetic Algorithms. Springer, 2008.

[26] K.F.Man, K.S.Tang and S.Kwong, "Genetic Algorithms: Concepts and Applications," IEEE Trans. Ind. Electron., vol.43, pp. 519-534, 1996.

[27] R.L. Haupt and S.E.Haupt, Practical Genetic Algorithms. Wiley, 2004.

Sarah Deif acquired her B.Sc. in Electronics and Communication Engineering from the Faculty of Engineering of Cairo University with first class honors. Since her graduation in 2006, she held teaching and research positions first at the British University in Egypt, then at Cairo University where she is currently working as a Teaching Assistant at the Engineering Mathematics and Physics Department and is also pursuing her M.Sc. degree. She received an undergraduate grant for Outstanding Achievements as well an "Order of Merit" for the ideal student in 2002-2003. Her research interest lies in the area of Control and Optimization in which she is developing new Genetic Algorithms for controlling the position and vibration of robot systems, an area in which she contributed a number of publications. Deif is also a Cisco-certified network engineer and a member of the IEEE.

Hanan Ahmed Kamal was born in Cairo, Egypt, in 1959. She received her B.Sc. in Electronics and Communications Engineering, Cairo University, July 1982 with honor. M.Sc. in Electrical Engineering, Cairo University, February 1986. PhD. in System Engineering, Cairo University, September 1991. Associate Professor in System Engineering and Control, September 2003. She has been involved in the area of Improvement of Control Systems by applying Evolutionary techniques. Previous research includes work on Genetic Algorithm, Genetic Programming, Fuzzy Logic Control and Hybrid Genetic Fuzzy Control System. Current research includes work in Optimal Control of linear and nonlinear system and swarm intelligence.

Mohammad Tawfik has obtained his B.Sc. from the Aerospace Engineering Department of Cairo University with Honors in 1993, then M.Sc. from the Aerospace engineering Department of Old Dominion University in 1999 followed by a Diploma in Computer Science from Cairo University in 2001 and a MEng from the Mechanical Engineering Department of the University of Maryland in 2002 and PhD from the same department in 2003. He worked since then as an Assistant Professor in the Mathematics department and Material Science and Engineering Department of the German University in Cairo then in the Mechanical Engineering Department of the British University in Egypt and in the Aerospace Engineering Department in Emirates Aviation College in UAE and in Cairo University in Egypt. In 2006 he was awarded the Distinguished Lecturer Award from the German University in Cairo and in 2008 he was awarded the Encouragement Research Award from the Egyptian Government and in 2010 he was cited in the Who's Who in the World book. Dr. Tawfik has 13 papers published in international journals and 20 published in international conferences. Tawfik's research is mainly involved in the vibrations and controls of structures specially those of Aerospace vehicles.