Genetic-Fuzzy Inverse Controller for a Robot Arm Suitable for On Line Applications

Abduladheem A. Ali, and Easa A. Abd

***Abstract*—**The robot is a repeated task plant. The control of such a plant under parameter variations and load disturbances is one of the important problems. The aim of this work is to design Geno-Fuzzy controller suitable for online applications to control single link rigid robot arm plant. The genetic-fuzzy online controller (indirect controller) has two genetic-fuzzy blocks, the first as controller, the second as identifier. The identification method is based on inverse identification technique. The proposed controller it tested in normal and load disturbance conditions.

***Keywords*—**Fuzzy network, genetic algorithm, robot control, online genetic control, parameter identification.

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

I. INTRODUCTION

THE problem of self-adjusting the parameters of the controller to compensate for the plant parameters variations and disturbances was the origin of adaptive systems [1]. Adaptive control system can be solved using fuzzy control technique by neural-fuzzy system [2] or genetic-fuzzy model [3]. Generally, in adaptive control system, identification is an essential part to determine, online, the disturbances through either explicit or implicit techniques.

The Identification is the process of constructing a mathematical model of a dynamic system using experimental data from that system [3]. Identification is an important and integral part in the control of dynamic systems. There are two types of identification methods, the first is the forward identification, and the second is the inverse identification [4]. The problem of identification consists of setting up a suitably parameterized identification model and adjusting the parameters of the model to optimize a performance function. Two forms of identification are currently used in modern adaptive systems: The forward identification and inverse identification. Based on the form of identification used, there exist two techniques of control: The parallel model following scheme and the inverse model following scheme.

In this work inverse identification method is previewed with its simulation results. Genetic-fuzzy inverse online control is structured with simulation results.

Manuscript received May 20, 2005.

A. A. Ali is with the Department of Computer Engineering, college of Engineering, University of Basrah, Basrah, Iraq (e-mail: abduladem1@yahoo.com).

E. A. Abd is with the Department of Electrical Engineering, College of Engineering, University of Basrah, Basrah, Iraq (e-mail: easaahmed1980@yahoo.com).

II. DYNAMIC MODEL OF ROBOT ARM MANIPULATORS

The type of robot arm model which is presented in this paper is a Single Link Rigid Robot Arm (SLRA) as shown in Fig. 1. Little works took the actuator dynamics and friction into consideration [5]. All these phenomena are considered in this work.

The relation between the input voltage to the motor and position angle as follows:

$$V = C_3\,\dddot{\theta} + C_2\,\ddot{\theta} + C_1\,\dot{\theta} + C_0 \tag{1}$$

in witch:

$$C_3 = K_l\, L_a (m d^2 + J).$$

$$C_3 = K_l\, L_a (m d^2 + J).$$

$$C_2 = K_l\, R_a (m d^2 + J) + K_l L_a B.$$

$$C_1 = K_l\, L_a\, m\, g\, d \cos(\theta) + K_l\, R_a\, B + K_e.$$

$$C_0 = K_l\, R_a\, m\, g\, d \sin(\theta).$$

where

$V =$ The armature voltage.

$K_l = {}^{1}\!/\!{}_{K_{pm}}$ and K_{pm} the torque constant of the motor.

$g =$ The gravity acceleration

The parameters of this plant that we take in our work are as in Table I.

III. THE USED GENETIC ALGORITHM

Simple Genetic Algorithm (SGA) is used here, where the entire population is generated for each generation on the basis of the previous generation [6, 7].

This kind of evolution resembles the evolution of population of fruit flies where a large part of the population is replaced simultaneously with new offspring. We will concentrate on the aspects of this approach:

- **Representation:** In this work real-valued representation is used. This is for many reasons; first the values that deal with are real, then to prevent encoding of the floating point values

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

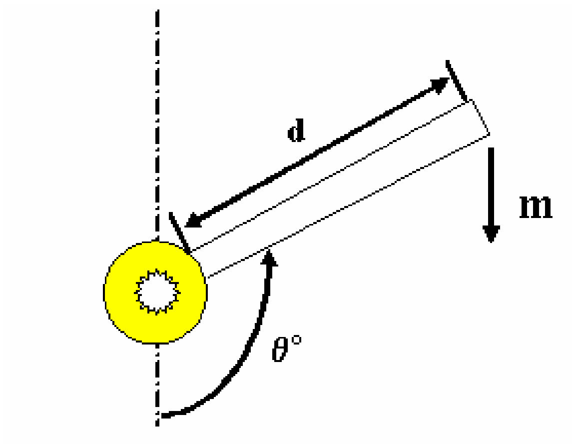

Fig. 1 Sketch of single link robot arm

with a binary encoding and this need more genes, second, the precision, and third, the processes of encoding and decoding take much time. Then, for these reasons the real-valued representation is more suitable for this problem.

- **Initialization**: Producing the initial population of solutions is the second step in GAs, 50 individuals with real values is generated; each individual has center, width, and center of outputs for fuzzy system. This number (50 individuals) remained constant for each generation.
- **Fitness Evaluation**: The fitness function is very important in order to develop a good GAFL approach. The fitness function that is used :

$$Fitness\ Function(E) = \frac{1}{2}(y_r(k) - y_p(k))^2 \qquad (2)$$

this fitness function is called mean square error function, where $y_r(k)$ is the output of reference model and $y_p(k)$ is the plant output.

- **Selection operators**: A Roulette Wheel Selection (RWS) is used. It is used to select those parents that have a higher fitness with a higher probability [8]. This method is used usually with SGA. There is an important point in this method that may be one individual which has a much higher fitness than all the other individuals. This highly fit individual could very quickly dominate the whole population (premature convergence) since it would be chosen for selection extremely often [9]. In our work we select 10 individuals from the initial population for next generation and to make crossover on these individuals, then from selection and crossover and mutation the population remained constant for each generation.
- **Recombination operators**: Because the used of real encoding (i.e. the parameters that use in the GA remained as real valued), then one of the real-valued crossovers is used which is called intermediate crossover. This method only applicable to real variables and it can be performed many ways. One of that is offsprings are produced in form:

$$offspring_1 = parent_1 + \alpha_1(parent_2 - parent_1) \qquad (3)$$

$$offspring_2 = parent_1 + \alpha_2(parent_2 - parent_1) \qquad (4)$$

α_1, α_2 are generated randomly for each generation between [-1.1,1.1]. The above rules used to each parameter that need optimization in fuzzy system.

TABLE I
THE ROBOT PARAMETERS VALUES

d : Link length.	$d=1$	m
m : Initial total mass.	$m=2$	Kg
R_a : Armature resistance.	$R_a=1$	Ω
L_a : Armature inductance.	$L_a=1$	H
K_e : Electric motive force constant.	$K_e=1$	$V/krpm$
K_{pm} : Torque constant of motor.	$K_t=1$	$in.-oz_f/A$
J : Rotor inertia.	$J=0.5$	$Kg\cdot m^2$
B : Rotor friction.	$B=0.5$	$N\cdot m\sec/rad$

- **Mutation operator**: When using real encoding it is quite easy to control the mutation, for instance by adding a random value to the existing chromosome that to be mutated. Since there are three parameters in the chromosome then, ($p_m = 0.3$).
- **Replacement** (Reinsertion) operators: weak parent replacement is used. A new child replaces the weaker parent, 40 weaker parent is replaced with 40 child come from the recombination and mutation operators.
- **Termination**: After several generations the best individuals of the population are then tested to determine if they satisfy the problem. The problem in this work is the tracking between the desired and the output curves or may be the tracking between the input or output of the plant with the output of identification model.

IV. THE USED FUZZY LOGIC CLASSIFIER

The defuzzyfier formula:

$$f_j(\overline{u}) = \frac{\sum_{L=1}^{R} \overline{y}_j^L * \mu_{B^L}(\overline{u})}{\sum_{L=1}^{R} \mu_{B^L}(\overline{u})} \qquad (5)$$

this defuzzyfier formula is called " Center-Average Defuzzyfier ".

where:

$R =$ The number of rules.

$j =$ The number of output.

$\overline{u} =$ The total input.

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

$y_j^L =$ The center of output.

and,

$$\mu_{B^L}(\bar{u}) = \left[\prod_{i=1}^{n} \mu_{F i^L}(u_i)\right]$$

$F i^L =$ Denote linguistic values defined by fuzzy sets.

$n =$ The number of input.

Because the triangle membership function is simple, it is used in this work. The mathematical eqn. for this membership function is:

$$\mu(u) = \left[|u-c| - \frac{2}{w}\right] + 1 \qquad if\ c - \frac{w}{2} \le u \le c + \frac{w}{2}$$
$$= 0 \qquad elsewhere \qquad (6)$$

When this membership function is used and substituted in eqn. (5), the following formula is found:

$$f(\bar{u}) = \frac{\sum_{L-1}^{R} \bar{y}^L * \left[\prod_{i=1}^{n}\left[\left[\left|u - c_i^L\right| - \frac{2}{w_i^L}\right] + 1\right]\right]}{\sum_{L=1}^{R}\left[\prod_{i=1}^{n}\left[\left[\left|u - c_i^L\right| - \frac{2}{w_i^L}\right] + 1\right]\right]} \qquad (7)$$

where

$c_i^L =$ The center of triangle membership function at input i and rule L.

$w_i^L =$ The width of triangle membership function at input i and rule L.

$\bar{y}^L =$ The centers of the output at rule L.

The c_i^L, w_i^L, and $\bar{y}^L$ are the fuzzy parameters that have to be found using GA.

One can generalize eqn. (7) for each chromosome as:

$$f_q(\bar{u}) = \frac{\sum_{L=1}^{R} y_q^L * \left[\prod_{i=1}^{n}\left[\left[\left|u - c_{iq}^L\right| - \frac{2}{w_{iq}^L}\right] + 1\right]\right]}{\sum_{L=1}^{R}\left[\prod_{i=1}^{n}\left[\left[\left|u - c_{iq}^L\right| - \frac{2}{w_{iq}^L}\right] + 1\right]\right]} \qquad (8)$$

where

$q =$ Refer to the sequence of the chromosome

V. SERIES-PARALLEL IDENTIFICATION MODEL

The Series-Parallel model is obtained by feeding back the past values of the plant output as shown in Fig. (2). This implies that in this case the identification model has the form:

$$\hat{y}_p(k+1) = f[y_p(k),...,y_p(k-m+1), u(k),....,u(k-n+1)] \qquad (9)$$

The Series-Parallel model has several advantages over that of parallel model [10]. As in the Fig. 2 the input to the plant denoted by $u(k)$ and the plant output by $y_p(k)$

where TDL represents a Time Delay Line of (Z^{-1}) discrete time delay element.

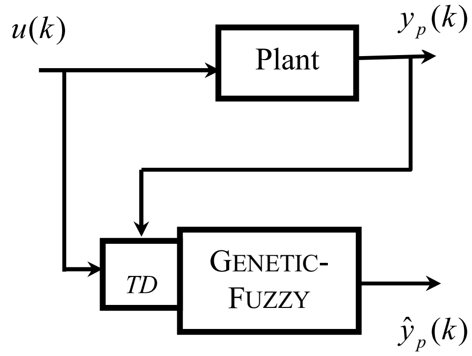

Fig. 2 Series-Parallel identification model

VI. ROBOT ARM IDENTIFICATION SYSTEM

It is well known that the response of a nonlinear plant like robot arm generally can not be shaped into a desired pattern using a linear controller. Consequently, a nonlinear controller is required to satisfactorily the control of such plants. Nonlinear controller design may be viewed as a nonlinear function approximation problem [11]. Two concepts can specify the identifier structure: the type of identifier and the plant dynamics. In this papers genetic-fuzzy identifier is used as inverse identifier. But after then the inverse identifier will be used for control applications.

Inverse Identification

When the plant output is used as the GAFL system input and the GAFL system output is compared with the plant input, the inverse transfer function of the unknown plant is obtained in the GAFL system.

In the inverse identification, the learning process must be accurate, this mean that the identifier must be identical to the plant inverse model in view of the fact that if it is not identical the inverse control system may diverge.

Rewriting eqn. (9) to express the inverse plant model:

$$y_m(k) = f[y(k), y(k-1), y(k-2), y(k-3), u(k-2), u(k-3)] \qquad (10)$$

where $y_m(k)$ denote identifier output.

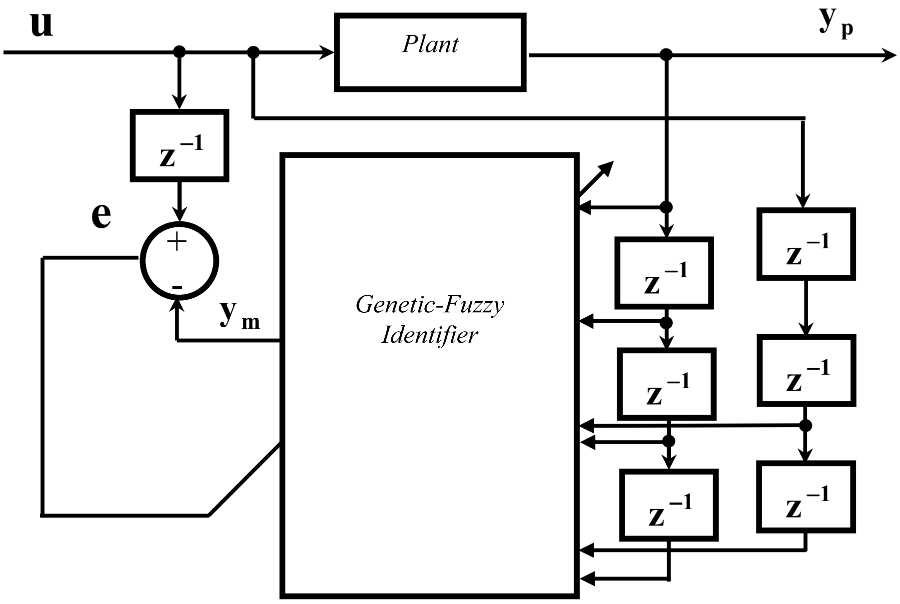

Fig. 3 Genetic-Fuzzy inverse identification block diagram

The structure of the inverse identification is illustrated in Fig. 3 in which all the output time delay plus the output are entered to the identifier as inputs, on the other side one of the inputs is compared with the identifier output and the rest is entered to the identifier as inputs.

VII. Genetic-Fuzzy Inverse Control Scheme (Indirect)

The suggested Genetic-Fuzzy inverse control is shown in the Fig. 4, in which two GAFL systems are present, one for the identification and the other for the controller.

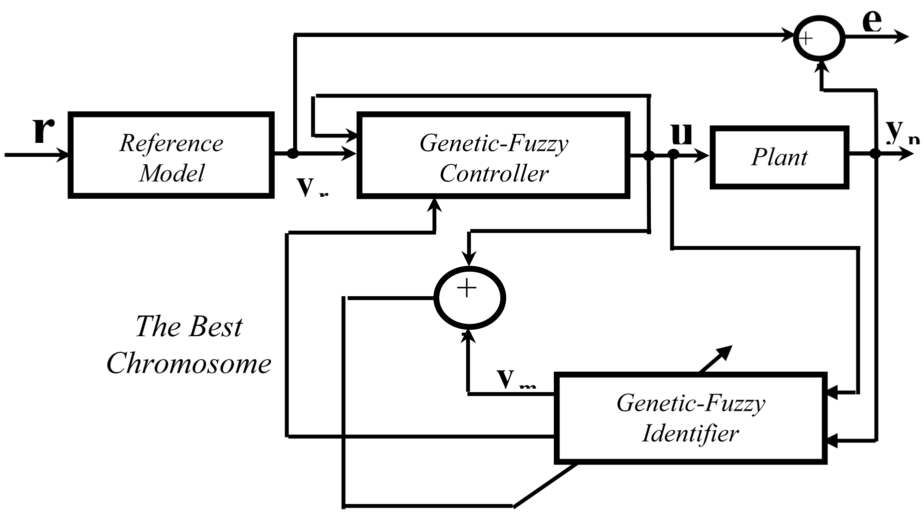

Fig. 4 Genetic-Fuzzy Inverse Control block diagram

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

The simple concept of the inverse controller is the controller block that represents the inverse transfer function of the plant, so the product result of the two blocks (plant and controller) must equal to unity. Hence, the output of the plant will be equal to the desired input of the controller as in Fig. 5.

In the control system, the parameters of the inverse identifier will be taken from the online learning that is achieved in previous section. So the purpose of the identification process is to overcome the changes that may occur in the system parameters.

The developed identifier has 50 chromosomes to construct the population. The optimal chromosome is the chromosome that has the minimum fitness function. The optimal identified model can be given as in equation 11.

$$y_{mop}(\overline{u}) = \frac{\sum_{L=1}^{R} y_{op}^{L} * \left[\prod_{i=1}^{n} \left[\left[\left| u - c_{iop}^{L} \right| - \frac{2}{w_{iop}^{L}} \right] + 1 \right] \right]}{\sum_{L=1}^{R} \left[\prod_{i=1}^{n} \left[\left[\left| u - c_{iop}^{L} \right| - \frac{2}{w_{iop}^{L}} \right] + 1 \right] \right]} \qquad (11)$$

where

$y_{mop}(\overline{u}) =$ The defuzzyfied output for identifier model in the optimal chromosome.

$R =$ The number of rules.

$n =$ The number of input.

$c_{iop}^{L} =$ The center of triangle membership function at input i and rule L for optimal chromosome.

Fig. 5 Illustration of the Inverse Controller

$w_{iop}^{L} =$ The width of triangle membership function at input i and rule L for optimal chromosome.

$y_{op}^{L} =$ The center of the output at the optimal chromosome.

The online genetic-fuzzy controller uses the parameters of the optimal identifier to structured an inverse controller using the following control algorithm:

$$u(k) = f[y_r(k), y_r(k-1), y_r(k-2), y_r(k-3), u(k-2), u(k-3)] \qquad (12)$$

One can see that the eqn. of the inverse controller is similar to that of the inverse identifier eqn. (10) when replacing the plant output y_p with the reference model output y_r.

VIII. Simulation Results

In order to demonstrate the validity of genetic algorithm as an identification system, a single link robot arm identification scheme is simulated.

The inverse identification scheme is considered. The genetic algorithm employed in this simulation is similar to that employed previously except for the fitness function.

The fitness function is the average of sum square error between the delayed plant input $u(k-1)$ and the identifier output $y_m(k)$ as in Fig. 3.

The initial values for fuzzy system are selected to be 60 equally spaced membership functions. The identification process is done on the input to the plant as shown in the initial response Fig. 6. After 20 iterations the response is as in Fig. 7. The final response is (after 1800 iteration) as in Fig. 8. In this response one can observe the tracking for this input. The variation of fitness function with generations is shown in Fig. 9.

The control system is showed in Fig. 4. The reference input to the control system is step input between 1 and -1. The control problem is to make the plant output track the reference model. This system has two important blocks; identification block and control block. When the system is suffered from disturbances, the parameters of control block could not be able to control the output and an error appears between plant output and model output. In this case the identifier try to adjust itself to identify the disturbances effect, hence, best chromosome will again be taken to the controller, modify the controller to overcome the disturbances. Two forms of disturbances are considered: The first is to add another mass and the second to lift some mass from the initial mass. Fig. 10 shows the response curve at initial mass ($m = 2$ Kg). Fig. 11 shows the response when the mass is modified to ($m = 3$ Kg). One can see in this curve, initially there is bad tracking between plant output and reference model output. The identifier starts to identify the disturbances. Fig. 12 shows the response after the convergence of the identification process, when the identifier is identical to the plant, the controller also converges and compensates for the variations in mass. The same results can be found in Fig. 13, Fig. 14, Fig. 15, and Fig 16.

IX. Conclusions

In this work, genetic-fuzzy online controller is structured. It is indirect controller because the parameters of plant are identified by identification model and then used by controller to control this plant.

The identification process is continuing in the normal conditions or disturbance conditions. The work identifier in the normal conditions to make the tracking is more accurate as well as for the small variations in some plant parameters.

The suddenly changing in the load on the robot arm at it is work make the arm diverge from a suitable path, therefore, it is need number of iterations (that depend on the value of load) that make the controller control the system and it converges to accurate path.

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

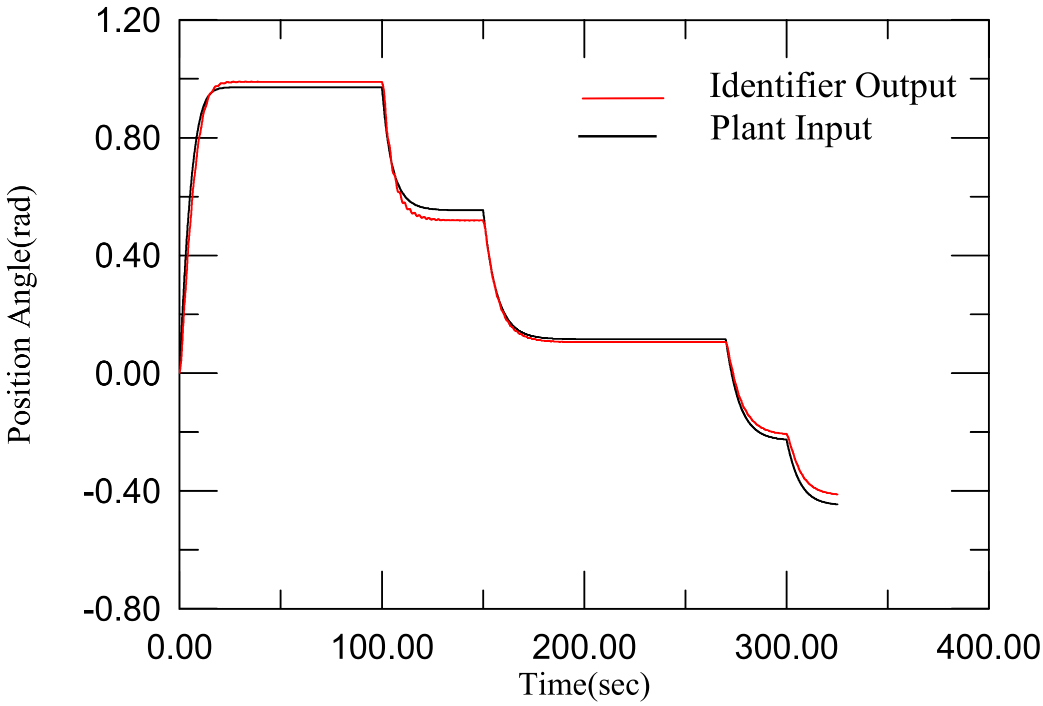

Fig. 6 Initial Position angle (after 5 iteration)

Inverse identifier

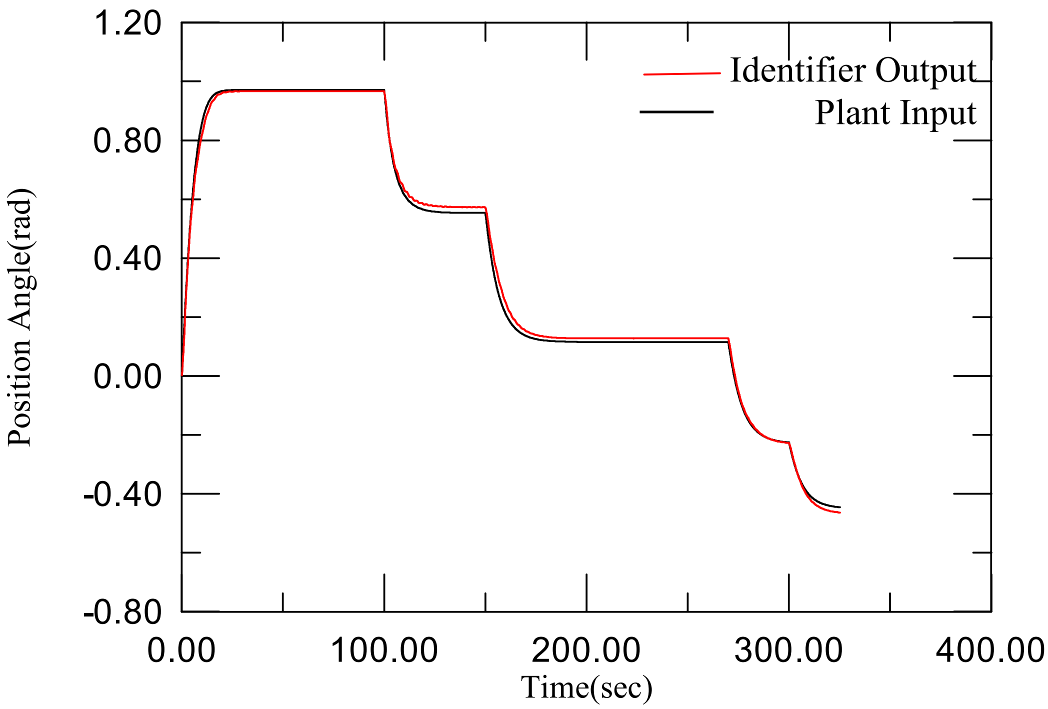

Fig. 7 Position angle after 20 iteration

Inverse identifier

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

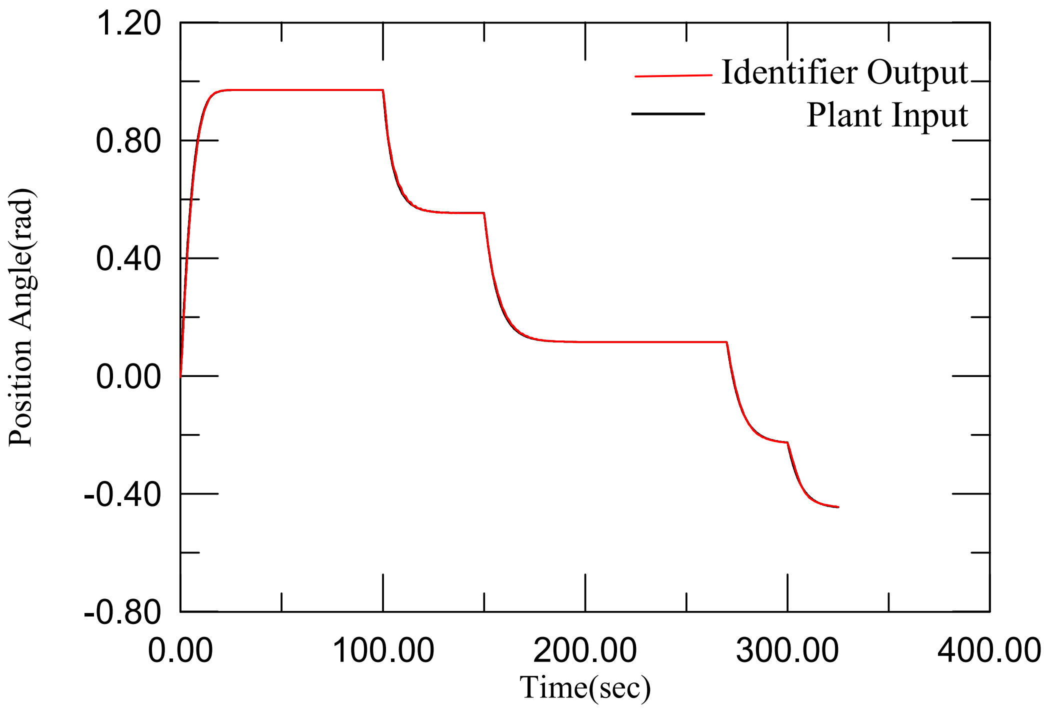

Fig. 8 Position angle after 1800 iteration

Inverse identifier

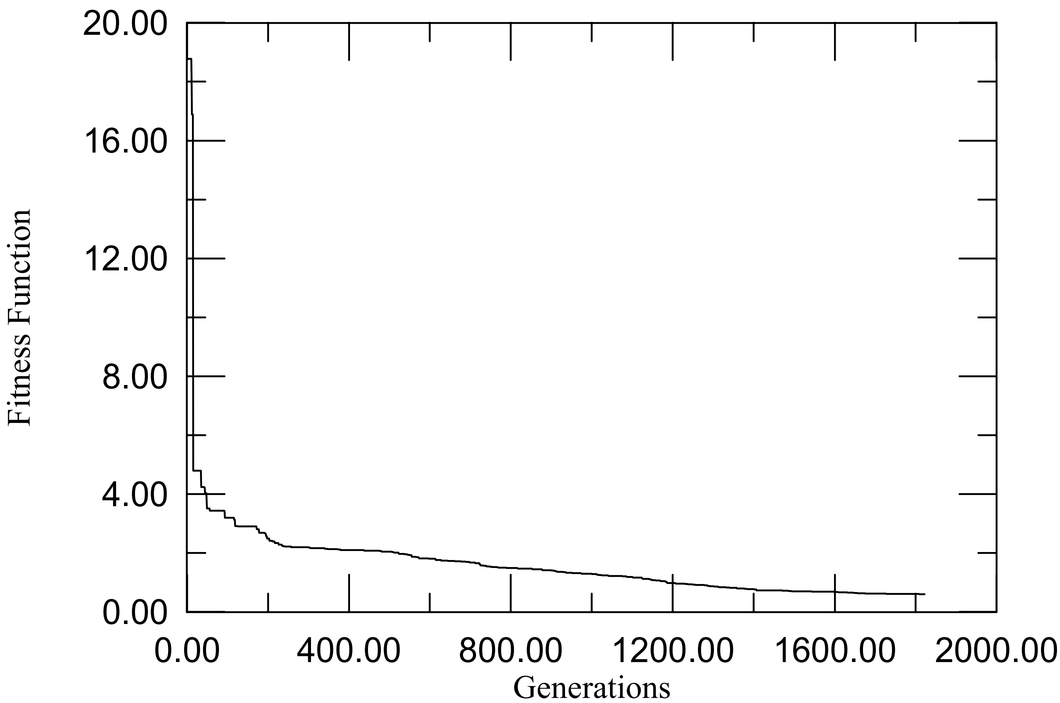

Fig. 9 Fitness function

Inverse identifier

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

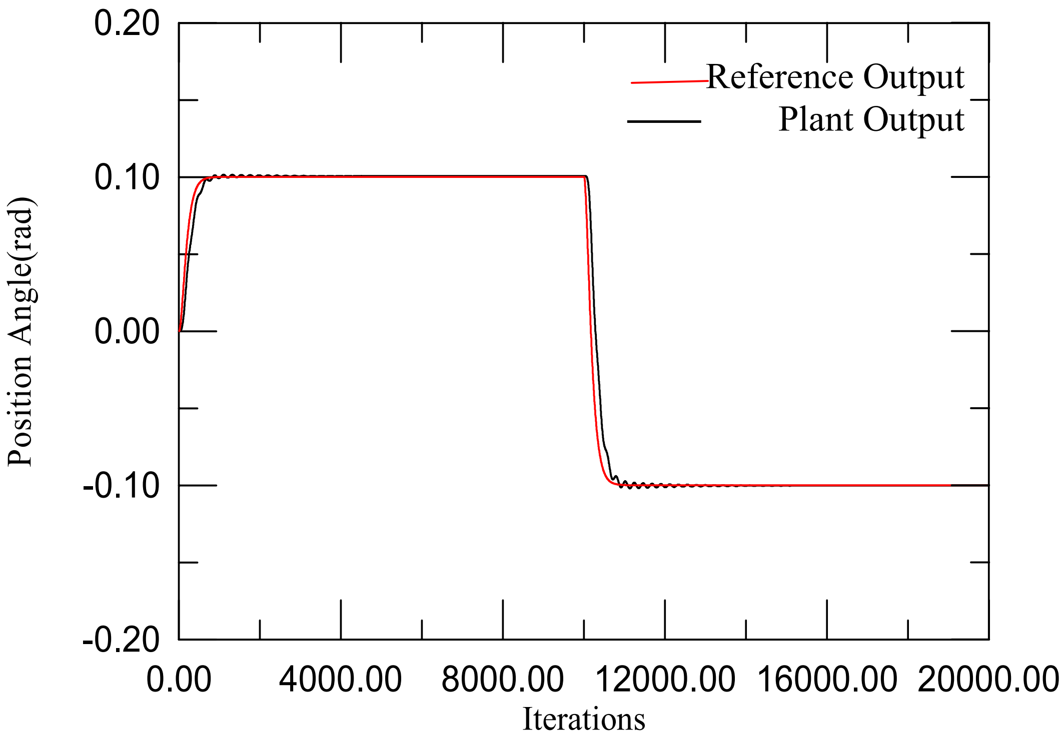

Fig. 10 Position angle at (m=2Kg)

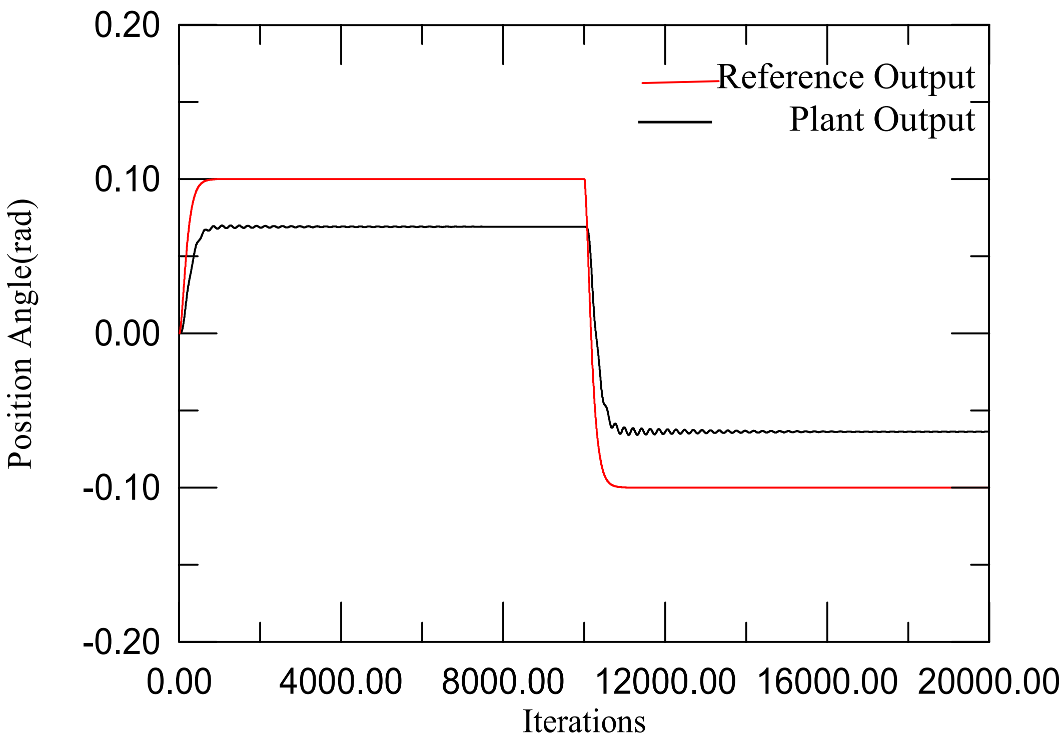

Fig. 11 Position angle at (m=3Kg)

Immediately after application of load

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

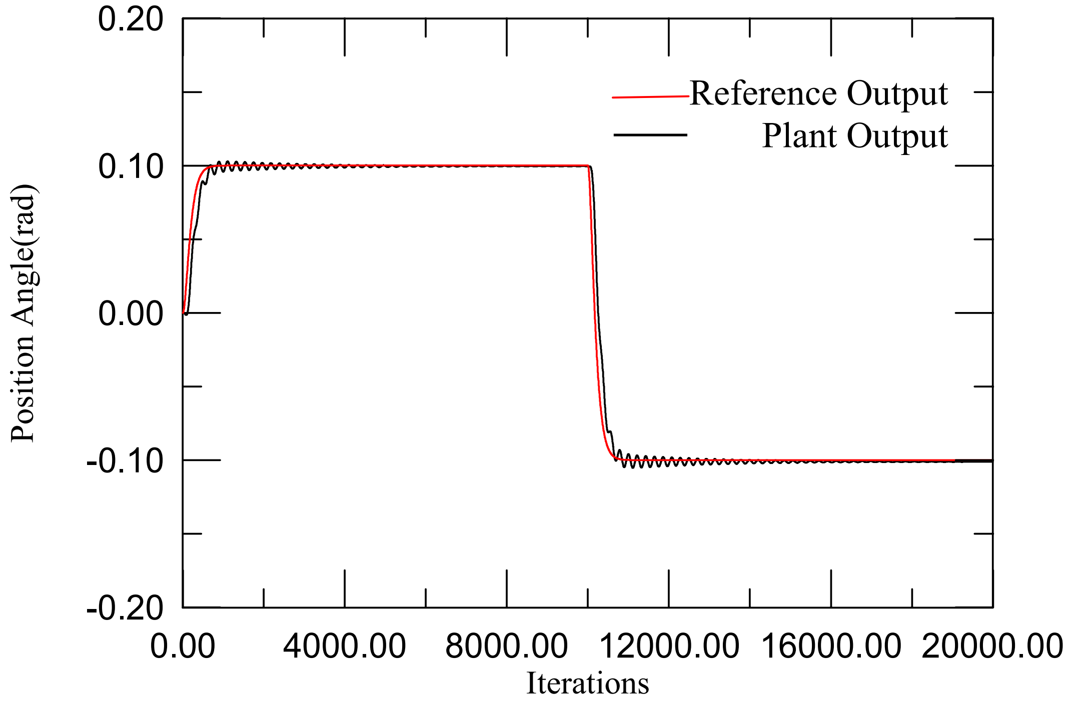

Fig. 12 Position angle at (m=3Kg) after convergence

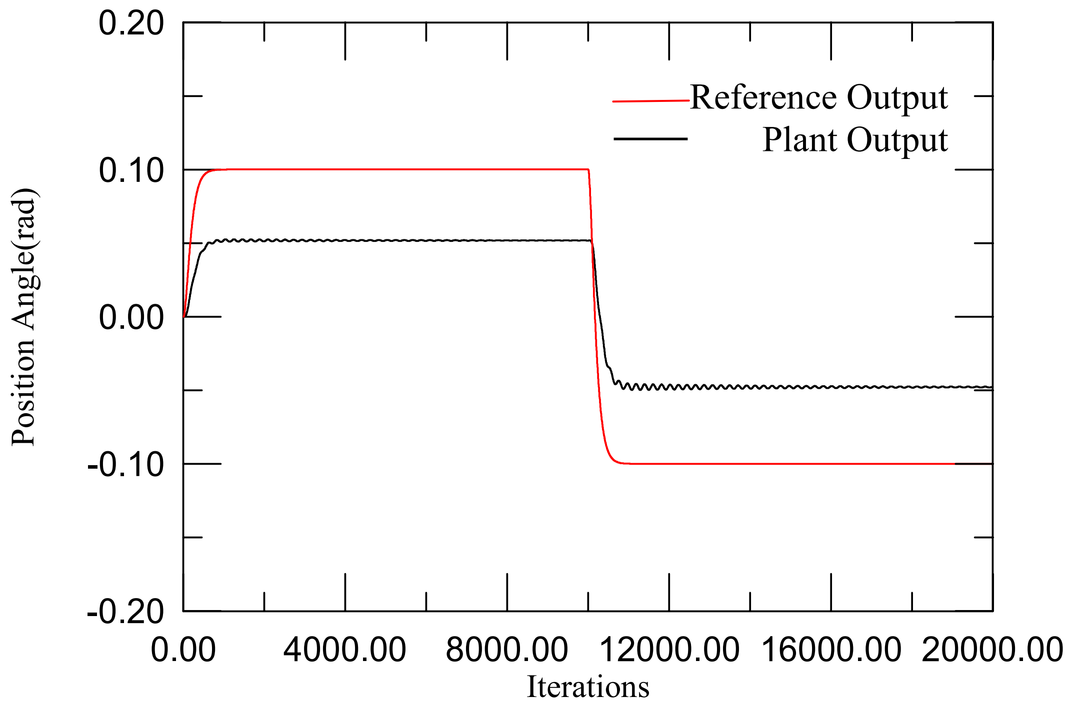

Fig. 13 Position angle at (m=4Kg)

Immediately after application of load

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

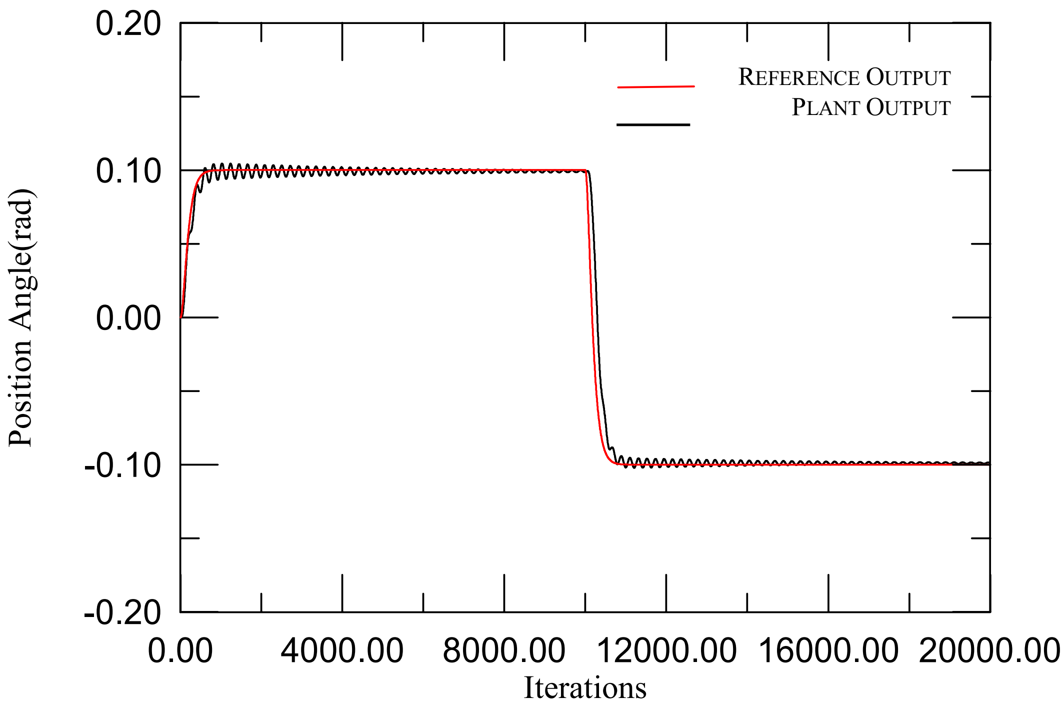

Fig. 14 Position angle at (m=4Kg) after convergence

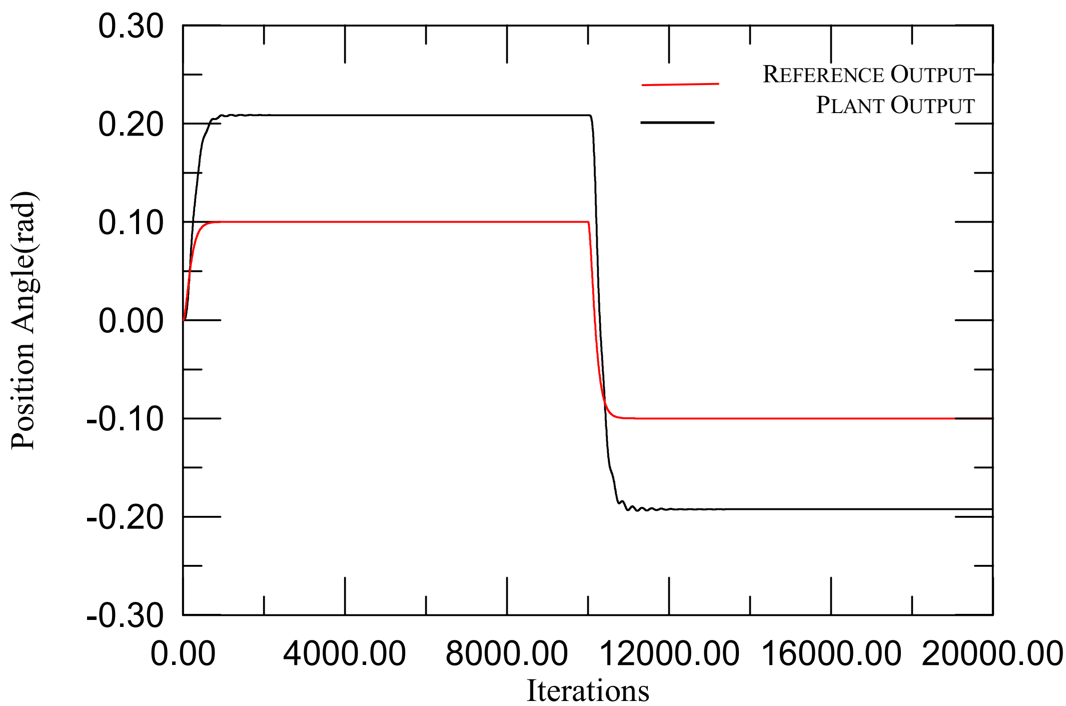

Fig. 15 Position angle at (m=1Kg)

Immediately after application of load

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063

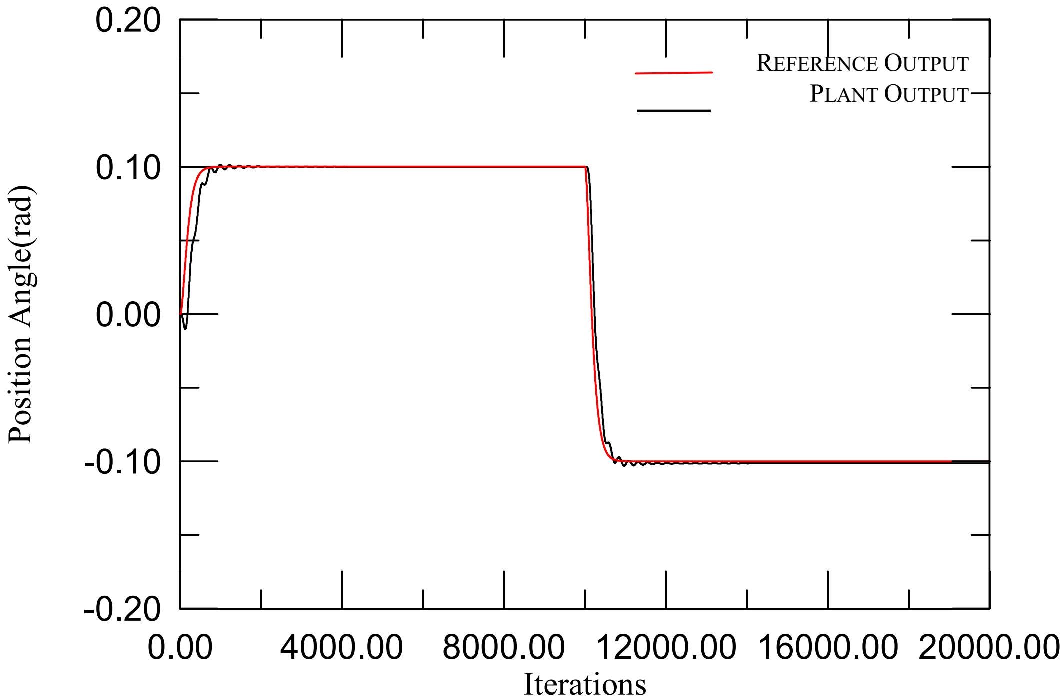

Fig. 16 Position angle at (m=1Kg) after convergence

REFERENCES

[1] K. J. Astrom, B. Wittenmark, "Adaptive Control", Addison Wesley, 1989.

[2] T. L. Seng, M. Khalid, R. Yusof, S. Omatu, "Adaptive Neuro-Fuzzy Control System by RBF and GRNN Neural Networks", Intelligent and Robotic System Journal, vol. 23, PP.267-289, 1998.

[3] K. M. Passino, S. Yurkovich, "Fuzzy Control", Addison Wesley Longman, Inc., 1998.

[4] J. G. Kuschewski, S. Hui, S. H. Zak, "Application of Feedforward Neural Networks to Dynamical System Identification and Control", IEEE Transaction on Control System Technology, vol.1, No.1, March 1993.

[5] J. N. Abdulbaqi, "Neuro-Fuzzy Control of Robot Arm", M.Sc. Thesis, Department of Electrical Engineering, Basrah University, 2004.

[6] J. M. Herrero, X. Blasco, M. Martinez, J. V. Salcedo, "Optimal PID Tuning with Genetic Algorithms for Nonlinear Process Models", 15th Triennial World Congress, Barcelona, Spain, 2002.

[7] M. Mitchell, "An Introduction to Genetic Algorithms", Aisradford Book, The MIT press, Cambridge, Massachusetts, London, England, 1998.

[8] H. A. Younis, "Attacking Stream Cipher Systems Using Genetic Algorithm", M.Sc. Thesis, Department of Computer Science, Basrah University, 2000.

[9] M. Schmidt, T. Stidsen, "Hybrid Systems: Genetic Algorithms, Neural Networks, and Fuzzy Logic", Aarhus University, Denmark, 1996.

[10] G. Lightbody, G. W. Irwin, "Nonlinear Control Structures Based on Embedded Neural System Models", IEEE Transactions on Neural Networks, vol.8, No.3, May 1997.

[11] M. S. Ahmed, "Neural-Net-Based Direct Adaptive Control for a Class of Nonlinear Plants", IEEE Transactions on Automatic Control, vol.45, No.1, January 2000.

Abduladhem A. Ali was born in Basrah 1956. Received his BSc , PG. Diploma, MSc. and PhD Degrees in 1978, 1981, 1983 and 1996 respectively all from Department of Electrical Engineering University of Basrah, Basrah Iraq, in computer and control specialization.

He worked with Hartha power station, Basrah, Iraq as operation and control engineer from 1978 to 1980. He Joins The Department of Electrical Engineering, University of Basrah from 1984 to 1997 Later joins the Department of Computer Engineering at the same university in which he is working till now as a professor of computer control. His industrial experience includes the design and implementation of many industrial projects related to North Iraq Electrical Generation Company, Iraqi petrochemical complex, Basrah Steel Company and many other industrial firms.

Prof. Ali primary interest is in adaptive systems including neural, fuzzy and genetic systems with applications to control, signal processing and online industrial control. He supervised numerous PhD and MSc projects in these fields and published more than fifty papers. Also he is the editorial board chairman for Iraqi Journal of Electrical and Electronics Engineering (IJEEE) and member of the editorial board for Basrah Journal for Engineering Science (BJES).

Easa A. Abd was born in Basrah Iraq in 1980. Recived his BSc. and MSc. Degree from Department of Electrical Engineering, University of Basrah, Iraq in 2002 and 2005 respectively in computer and control engineering.

He worked with Department of Electrical Engineering University of Basrah since 2003.

Mr. Abd primary inteerest is in Genetic algorithims, Fuzzy systems, nural networks and Robotics.

Open Science Index, Electrical and Computer Engineering Vol:1, No:9, 2007 waset.org/Publication/9063