ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 7, Issue 1, July 2017

Roll Control System Design Using Auto Tuning LQR Technique

Abdulla I. Abdulla, Ibrahim K. Mohammed, Abdulhamed M. Jasim

Abstract— ***The aim of this study is to design an autopilot for an aircraft roll control system using optimal controller with auto tuning gain strategy. The dynamics of an aircraft roll system based on autopilot is modeled mathematically and then simulated using Matlab/Simulink to validate the proposed roll control system. The linear quadratic regulator (LQR) technique is adopted to implement the controller of the system. Three tuning algorithms, genetic algorithm (GA), particle swarm optimization (PSO), and artificial bee colony (ABC), are used to find the optimum values of the controller gain parameters. The performance of the GA, PSO and ABC-LQR controller for an airplane roll system is presented and compared based on maximum overshoot, rise time, settling time and steady state error stable parameters. The simulation results suggest that the ABC tuning algorithm-LQR controller can perform an efficient search for the LQR gain parameters than the PSO and GA algorithms. Consequently, the ABC-LQR controller can be used to implement a good performance aircraft roll control system.***

Index Terms— **Aircraft roll control, Artificial Bee Colony, Autopilot, Genetic Algorithm, Linear Quadratic Regulator,, Particle Swarm Optimization.**

I. INTRODUCTION

Autopilot system is used to adjust the pitch, roll and yaw angles of an aircraft by complex automatic control systems through three main control surfaces. These are elevator, ailerons and rudder. Pitch control can be achieved by flapped portion located at the back of an airplane called elevator. Roll control is achieved by deflecting small flaps called ailerons placed outboard toward the wing tips in a differential manner, while yaw control can be obtained by deflecting a flap fixed on the vertical tail called the rudder. These control surfaces, elevator, ailerons and rudder are depicted in Fig. 1 [1].

The control strategies of autopilot system of an aircraft can be grouped into two categories which are longitudinal and lateral control. In longitudinal control, pitch angle is controlled whereas both of roll and yaw angles are controlled in lateral control [1].

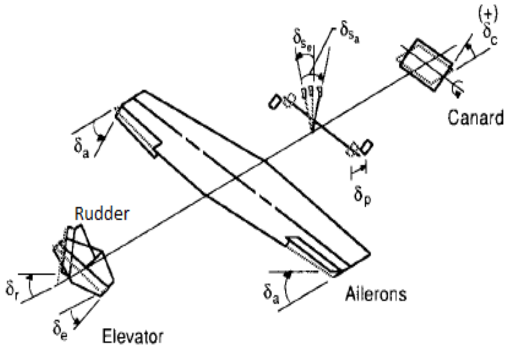

Fig. 1. Aerodynamics controls of an aircraft.

This paper focuses on the design of an autopilot system that controls the roll angle of aircraft, which can help airplane crew to lessen their workload during navigation and flight management. Roll control is a lateral control, therefore lateral model of an aircraft is used to design roll angle controller. During the last decades, there has been a considerable interest by many researchers in control the pitch, roll and yaw angles of an aircraft to achieve stable and accurate movement for airplane. However, this topic still even now remains a challenging issue for current and future research works [2]-[7].

In this study, a state feedback controller is used to design an autopilot system to control the roll angle of an aircraft.

Linear Quadratic Regulator (LQR) is a more common technique used in the control of roll angle for aircraft system which seeks basically a compromise between minimum energy (control input) and the best performance [8][9]. Non-linearity tolerance and superior disturbance compensation of the state feedback approach enables of using it in the autopilot control system, position control field and many industrial applications [10][11].

However, adopting this control method includes many drawbacks such as limitation of the state and control variable and using trial-and-error procedure to determine the control gain coefficients. Therefore, there is a considerable interest in optimization algorithms used to obtain optimum parameters values for state feedback controller techniques. For LQR controller design there are many computer-aided optimization methods can be used to find optimum weighting matrices elements such as genetic algorithm (GA) [12], particle swarm optimization (PSO) [13], and particle swarm inspired evolutionary algorithm (PS-EA) [14] and artificial bee colony (ABC) [15].

ABC method is one of the tuning algorithms that have been successfully applied to solve various types of optimization problems [16]. Basturk and Karaboga compared the performance of ABC optimization algorithm with those of PSO and PS-EA [17], GA [18] and DE, PSO and EA [19] on various test problems. In this study, the GA, PSO and ABC tuning algorithms, were developed for the roll control of an aircraft system using the LQR technique. Performance of the GA, PSO and ABC-LQR controller is analyzed with respect to the desired roll angle based on standard control criteria, which includes maximum overshoot, rise time, settling time, steady state error and control input.

The organization of this paper is as follow. In section II, the dynamics of the aircraft roll control system is modeled and then formulated in state space form. In section III, controller design technique is presented. LQR controller tuning methods are introduced in section IV. Section V, presents simulation

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 7, Issue 1, July 2017

results of the proposed roll control scheme and followed by conclusion and future works in section VI.

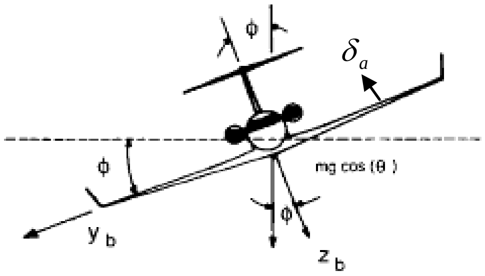

Fig. 2. Definition of the aircraft roll control.

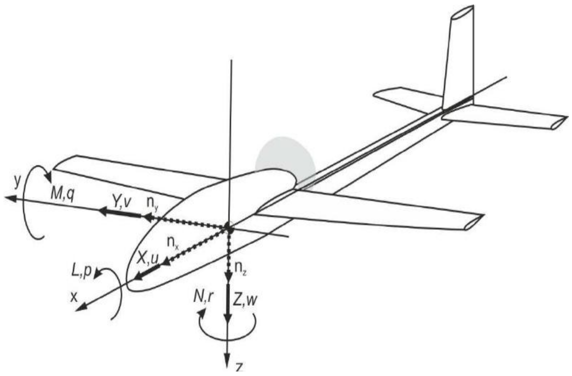

Fig. 3. Definition of forces, moments and velocity components in a body fixed frame.

II. MODELING OF ROLL CONTROL SYSTEM

The dynamic motion of an aircraft is governed by a system of six nonlinear coupled differential equations. However, with the consideration of certain assumptions, these complicated equations can be decoupled and linearized into the lateral and longitudinal equations. Roll control is a lateral problem and this study has been developed to control the aircraft roll angle so that it can perform stable rolling motion. The roll control system is shown in Fig. 2 where y_b and z_b represent the aerodynamics force components, ϕ and δ_a indicate the orientation angle (roll angle) and aileron deflection angle of an aircraft in the earth-axis system respectively [1]. The forces, moments and velocity components in the body fixed frame of an aircraft system are shown in Fig. 3 where *L*, *M* and *N* represent the aerodynamic moment components, the term *p*, *q* and *r* represent the angular rates components of roll, pitch and yaw axis and the term *u*, *v* and *w* represent the velocity components of roll, pitch and yaw axis.

The kinematic expressions relating angular rates to the airplane pitch (θ), roll (ϕ) and yaw (φ) angles and aerodynamic moment components are as follows:

$$p = \dot{\phi} - \dot{\varphi}\sin\theta \quad (1)$$

$$q = \dot{\theta}\cos\phi - \dot{\varphi}\sin\phi\cos\theta \quad (2)$$

$$r = -\dot{\theta}\sin\phi - \dot{\varphi}\cos\phi\cos\theta \quad (3)$$

$$L = I_x\dot{p} - I_{xz}\dot{r} + (I_z - I_y)qr - I_{xz}pq \quad (4)$$

$$M = I_y\dot{p} + (I_x - I_z)rp + I_{xz}(p^2 - r^2) \quad (5)$$

$$N = -I_{xz}\dot{p} + I_z\dot{r} + (I_y - I_x)pq + I_{xz}qr \quad (6)$$

For convenience, based on the steady state velocity component of roll axis u_o , the sideslip angle $\Delta\beta$ is used instead of the slip velocity Δv .These two quantities are related to each other in the following way;

$$\Delta\beta \approx \tan^{-1}\frac{\Delta v}{u_o} = \frac{\Delta v}{u_o} \quad (7)$$

To design linear LQR controller for an airplane roll control system, the system dynamics should be formulated in state space form and then linearized using Toylar series: let $\Delta X = [x_1, x_2, x_3, x_4]^T = [\Delta\beta, \Delta p, \Delta r, \Delta\phi]^T$ be the state vector of the system, the aileron deflection is considered the control input's vector such that, $\Delta u = [x_1] = [\Delta\delta_a]$ and the aircraft roll angle is considered the output's vector such that, $\Delta Y = [y_1, y_2, y_3, y_4]^T = [0,0,0,1]^T$. Where $\Delta v, \Delta p, \Delta r, \Delta\phi$ are perturbations about their corresponding steady state value (v_o, p_o, r_o, ϕ_o). The linearized state and output equations describing the lateral directional equations of motion can be written as follows [2]:

$$\Delta x^{\bullet}(t) = A\Delta x(t) + B\Delta u(t) \quad (8)$$

$$\Delta y(t) = C\Delta x(t) + D\Delta u(t) \quad (9)$$

Where *A* is the system matrix, *B* is the input matrix, *C* is the output matrix, and *D* is feed forward matrix, for the designed system. These matrices are given by

$$A = \begin{bmatrix} \frac{Y_\beta}{u_o} & \frac{Y_p}{u_o} & -(1-\frac{Y_r}{u_o}) & \frac{g\cos\theta}{u_o} \\ L_\beta & L_p & L_r & 0 \\ N_\beta & N_p & N_r & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ L_{\delta a} \\ N_{\delta a} \\ 1 \end{bmatrix},$$

$$C = \begin{bmatrix} 0 & 0 & 0 & 1 \end{bmatrix}, \quad D = [0]$$

The input of the proposed control system will be the aileron and rudder deflection angles and the output will be the roll angle of an aircraft. In this research, the data from General Aviation Airplane: NAVIONa [1] is used in system analysis and modeling.

The lateral directional derivatives stability parameters for this application are given Table I. Based on the parameters values stated in Table I [2], the state equation (8) can be written as follows:

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 7, Issue 1, July 2017

$$\begin{bmatrix} \dot{\Delta\beta} \\ \dot{\Delta p} \\ \dot{\Delta r} \\ \dot{\Delta\phi} \end{bmatrix} = \begin{bmatrix} -0.254 & 0 & -1 & 0.184 \\ -15.969 & -8.395 & 2.19 & 0 \\ 4.549 & -0.349 & -0.76 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\beta \\ \Delta p \\ \Delta r \\ \Delta\phi \end{bmatrix} + \begin{bmatrix} 0 \\ -28.916 \\ -0.224 \\ 0 \end{bmatrix} \Delta\delta_a \qquad (10)$$

TABLE I. THE LATERAL DIRECTIONAL DERIVATIVES STABILITY

Quantity	Y-Force deriv.	Yawing moment deriv.	Rolling moment deriv.
Pitching vel.	$Y_v = -0.254$	$N_v = 0.025$	$L_v = -0.091$
Side slip angle	$Y_\beta = -44.665$	$N_\beta = 4.549$	$L_\beta = 15.969$
Rolling rate	$Y_p = 0$	$N_p = -0.349$	$L_\beta = -8.395$
Yawing rate	$Y_r = 0$	$N_r = -0.76$	$L_r = 2.19$
Rudder def.	$Y_{\delta r} = 12.433$	$N_{\delta r} = -4.613$	$L_{\delta r} = 23.09$
Aileron def.	$Y_{\delta a} = 0$	$N_{\delta a} = -0.244$	$L_{\delta a} = -28.91$

III. CONTROLLER DESIGN METHOD

In this work, a more common technique LQR is adopted to implement the proposed controller for aircraft roll control system since it seeks basically a compromise between minimum control input and best performance. The LQR controller can be successfully implemented in this application as the proposed control system is observable and state controllable. The LQR control system for the lateral directional control of an aircraft is shown in Fig. 4 [2]. This approach involves applying the input vector:

$$u(t) = -Kx(t) + \Delta\delta_a N \qquad (11)$$

where $K = [K_\beta \quad K_p \quad K_r \quad K_\phi]$ is gain matrix, to achieve a stable performance while minimizing the following LQR quadratic cost function:

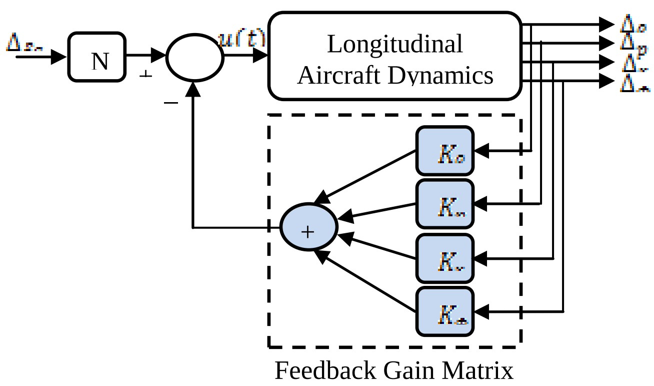

Fig. 4. Full state feedback LQR-controller for the roll system.

$$J = \int_0^\infty \left[x^T(t)Q(t)x(t) + u^T(t)R(t)u(t)\right]d(t), \qquad (12)$$

Where $Q(t)$ and $R(t)$ are called combined state and control penalty matrices respectively, $x^T(t)Q(t)x(t)$ is the state cost with weight $Q(t)$ and $u^T(t)R(t)u(t)$ is the control cost with weight $R(t)$.

It is worth considering that in this application, all of the four states $x(t)$ are available for the controller. In the proposed approach, optimization methods are employed to obtain best values for the weighting matrices R and Q, which are used to calculate optimum gain matrix required to achieve good control performance. The optimization methods will be presented in detail in the next section. In this research, based on the LQR weighting matrices and A and B matrices, the controller gain coefficients were calculated by using the Matlab command "*lqr*". In the proposed controller design, based on (11) a feed-forward scaling factor called N is involved in determination of the control input vector in order to achieve the desired output.

IV. LQR CONTROLLER TUNING METHODS

In this study, three optimization algorithms, GA, PSO and ABC, are adopted to implement tuning process for the LQR weighting matrices Q and R, which are used to calculate the feedback gain matrix K of the roll control system. A set of good control parameters *Q*, and *R*, can achieve a good output response for the system and result in minimization of performance criteria in the time domain including the settling time (t_s), rise time (t_r) maximum overshoot $(\%Mo)$ and steady state error (e_{ss}).

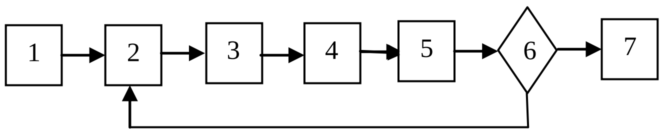

Fig. 5. Genetic algorithm loop.

A. *Genetic Algorithm (GA)*

GA is a stochastic global adaptive search optimization technique based on the mechanisms of natural selection. The GA consists of three main stages: selection, crossover and mutation.

This algorithm is repeated for many generations and finally stops when reaching individuals that represent the optimum solution to the problem. The graphical illustration of the GA loop is shown in Fig. 5 [11]. The application of these three basic operations allows the creation of new individuals which may be better than their parents.

The definition of the GA sequence is as follows:

1. Initial population.
2. Select individuals for mating.
3. Mate individuals to generate offspring.

4. Mutate offspring.
5. Insert new individuals into population.
6. Are criteria satisfied?
7. End of searching.

The implementation of the tuning procedure through genetic algorithms starts with the definition of the chromosome representation. Each chromosome represented in real valued form as shown in Fig.6, the chromosome is formed by five values that correspond to the weighting matrices Q and R to be adjusted in order to achieve a satisfactory behavior. The values q_{11}, q_{22}, q_{33}, q_{44} and *R* must be positive numbers and characterize the individual to be evaluated [13].

B. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) algorithm is used to find the global optimum values of the LQR parameters. Kennedy and Eberhart developed a PSO algorithm based on the behavior of individuals (i.e. particles or agents) of a swarm [8]. It has been perceived that members within a group seem to share information among them, a fact that causes to increased efficiency of the group. An individual in a swarm approaches to the optimum by its present velocity, previous experience, and the experience of its neighbors. In a physical n-dimensional search space, parameters of the PSO technique are defined as follows [9]:

$$v_i(t+1) = w.v_i(t) + c_1.rand.(pbest(t) - x_i(t)) + c_2.$$

$$rand(gbest(t) - x_i(t)) \quad (13)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (14)$$

Definition of the above equation parameters is as follows: $x_i(t+1)$ and $v_i(t+1)$ are the velocity and position of the i^{th} particle at $(t+1)$ iteration respectively. w: is the inertial weight factor (weighting function). c_1 and c_2: are acceleration constants called cognitive learning rate and social learning rate respectively. $rand$: is random number between 0 and 1. $pbest$: is the individual best position of the particle. $gbest$: is the global best position of the swarm of the particles.

The weighting function, (w) is responsible for dynamically adjusting the velocity of the particles, hence it is responsible for achieving a balance between local and global search. Applying a large inertia weight at the start of the algorithm and decaying to a small value through the PSO execution makes the algorithm search globally at the beginning and locally at the end of the execution. The weighting function (w) is calculated as follows:

$$w = w_{\max} - \frac{(w_{\max} - w_{\min})iter}{iter_{\max}}, \quad (15)$$

where, $w_{\max}$ and $w_{\max}$ are the initial and final weights respectively, $iter$ is the current iteration time and $iter_{\max}$ is the maximum number of iterations.

C. Artificial Bee Colony (ABC) Algorithm

In Bees Algorithm, the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. First half of the colony consists of the employed artificial bees and the second half includes the onlookers. For every food source, there is only one employed bee. In other words, the number of employed bees is equal to the number of food sources around the hive. The employed bee whose the food source has been abandoned by the bees becomes a scout. The position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees or the onlooker bees is equal to the number of solutions in the population [12].

The procedure of the ABC algorithm is as follows. Steps (pseudo-coding) to initialize the artificial BA:

1. Initialize the population of solutions xi,j, i = 1. . .SN,(SN is the number of food source) j = 1. . .D.(is the dimension of problem ,for optimization of LQR[namely q_{11} ,q_{22},q_{33},q_{44} and R] ,there is D=5.)
2. Evaluate the population.
3. Cycle=1
4. Repeat
5. Produce new solutions xi,j for the employed bees by using (4) and evaluate them.
6. Apply the greedy selection process.
7. Calculate the probability values Pi,j for the solutions xi,j by (4 & 3).
8. Produce the new solutions xi,j for the on looking from the solutions xi,j selected depending on Pi,j and evaluate them.
9. Apply the greedy selection process.
10. Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution xi,j by (4& 5).
11. Memorize the best solution achieved so far.
12. Cycle = Cycle+1.
13. Until Cycle = MCN (Maximum Cycle Number).

V. ROLL CONTROL SYSTEM DESIGN

In this study, the LQR controller is used to design the aircraft roll control system based on tuned gain parameters using optimization algorithms, GA, PSO and ABC. Matlab/Simulink environmental used to demonstrate the validation of the proposed airplane roll control system. The design characteristics required in the performance of the tuned LQR controller based on step input are rising time < 20 ms, settling time < 40 ms and percentage of overshoot < 1% for controlling the roll angle.

A. Simulation of GA-LQR Controller

The implementation of the tuning procedure through genetic algorithms starts with the definition of the chromosome representation. Each chromosome represented

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 7, Issue 1, July 2017

in real valued form as shown in Fig. 6, the chromosome is formed by five values that correspond to the weighting matrices Q and R to be adjusted in order to achieve a satisfactory behavior. The values q_{11}, q_{22}, q_{33}, q_{44} and R must be positive numbers and characterize the individual to be evaluated [13].

q_{11}	q_{22}	q_{33}	q_{44}	R

Fig. 6. Chromosome definition based on the GA method.

The Simulink model of the GA-LQR controller of the roll control system is shown in Fig. 7. The objective function is the calculation of its associated fitness. The fitness function (F) is the measure of the quality of chromosome and can be expressed as:

$$F = S.t_t.t_{r\max} + S.t_s.t_{s\max} + S.O.Mo \tag{16}$$

Where t_r is rise time (s) and t_s is settling time (s), S is closed loop transfer function of the aircraft roll system, $t_{r\max}$ is maximum rise time, $t_{s\max}$ is maximum settling time, O is the overshoot value and Mo is the maximum overshoot value.

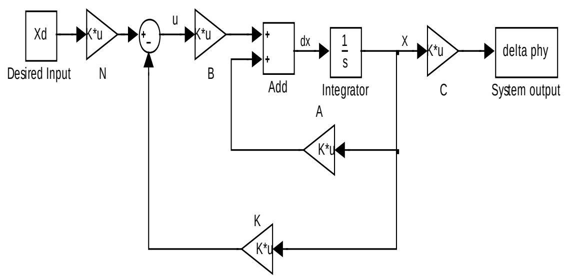

Fig. 7. Simulink model of the GA-LQR controller for the roll control system.

The control parameters of the GA optimization algorithm chosen for the tuning purpose are listed in Table II. The optimal weight vector Q and R obtained for the GA-LQR controller are:

Q = blkdiag(q_{11} , q_{22} , q_{33} , q_{44}) and R = 0.00195375.

Where q_{11} =2.76661 , q_{22} =0.010324 , q_{33} = 2.5977 and q_{44} = 155.767. The feedback gain matrix K is

K=[-5.3099 -4.7153 0.7398 -282.4066].

Fig. 8 presents the time response of the aircraft roll system based on the GA-LQR technique. Converging of the GA tuning approach through generations is shown in Fig. 9.

TABLE II. PARAMETERS VALUES OF THE GA METHOD

GA property	Value/Method
Population size	20
Max No. of generations	100
Selection method	Normalized geometric selection
Crossover method	0.05
Crossover probability	Scattering
Crossover probability	0.2
Mutation method	Uniform mutation
Mutation probability	0.01

The control input of the roll control system based on the GA-LQR controller is illustrated in Fig. 10. It can be noted from Fig. 8 that the controller based on the GA optimization succeeded to guide the roll angle through the desired trajectory with fast rise time, 0.0374 s, short settling time, 0.0618 s, small overshoot value, 2.4266%, and very small steady state error of 0.05 V. Regarding the control signal, Fig. 10 suggests the initial and the steady state control input of the controller system were within reasonable values. The initial value of the control input is 1.2 V, while its steady state value approximately is 0.95 V.

B. Simulation of PSO-LQR Controller

The proposed Fitness function (F) for the optimization of the PSO- LQR controller parameters is defined as:

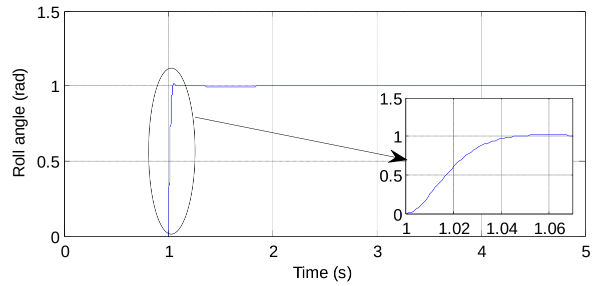

Fig. 8. Roll angle response based on the GA-LQR controller.

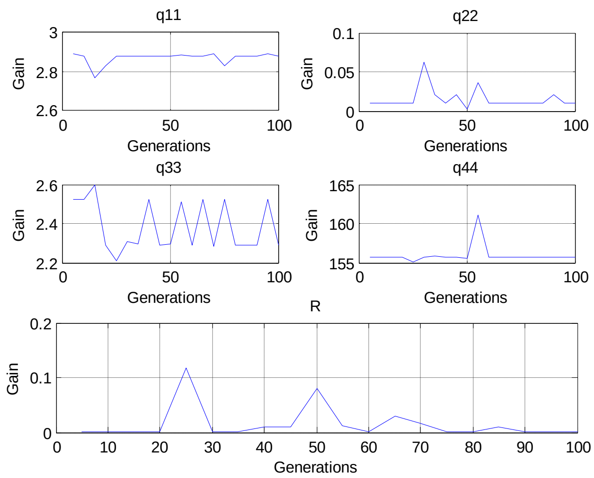

Fig. 9. Illustration of the GA converging through generations.

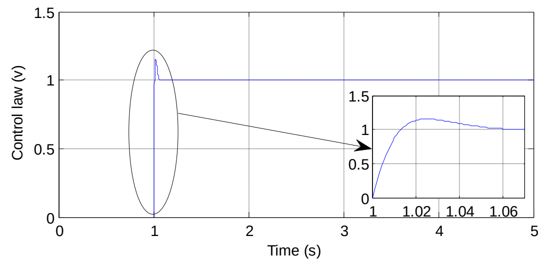

Fig. 10. Control law for the GA- LQR controller.

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 7, Issue 1, July 2017

$$F = w_{\max}(1 - e^{-1(Mo + e_{ss})}) + w_{\min} e^{-(t_s - t_r)} \quad (17)$$

The controller parameters Q and R composed an individual K by K =[q_{11}, q_{22}, q_{33},q_{44},R]; hence there are five members in an individual. These numbers are assigned as real values. The PSO-LQR controller for aircraft dynamic is the same design of the GA-LQR controller as previously shown in Fig. 7.

The flow chart depicting the implementation of the PSO algorithm for optimizing the parameters of the PSO- LQR controller for the aircraft roll control system is shown in Fig. 11. The tuning parameter values taken for running the PSO algorithm in Matlab environment is give in Table III.

TABLE III. PARAMETERS VALUES OF THE PSO ALGORITHM

Parameter	Value
Number of particles	20
Max No. of generations	100
Cognitive component c_1	2
Social component c_2	2
Maximum speed	10
Maximum inertia weight	0.9
Minimum inertia weight	0.4

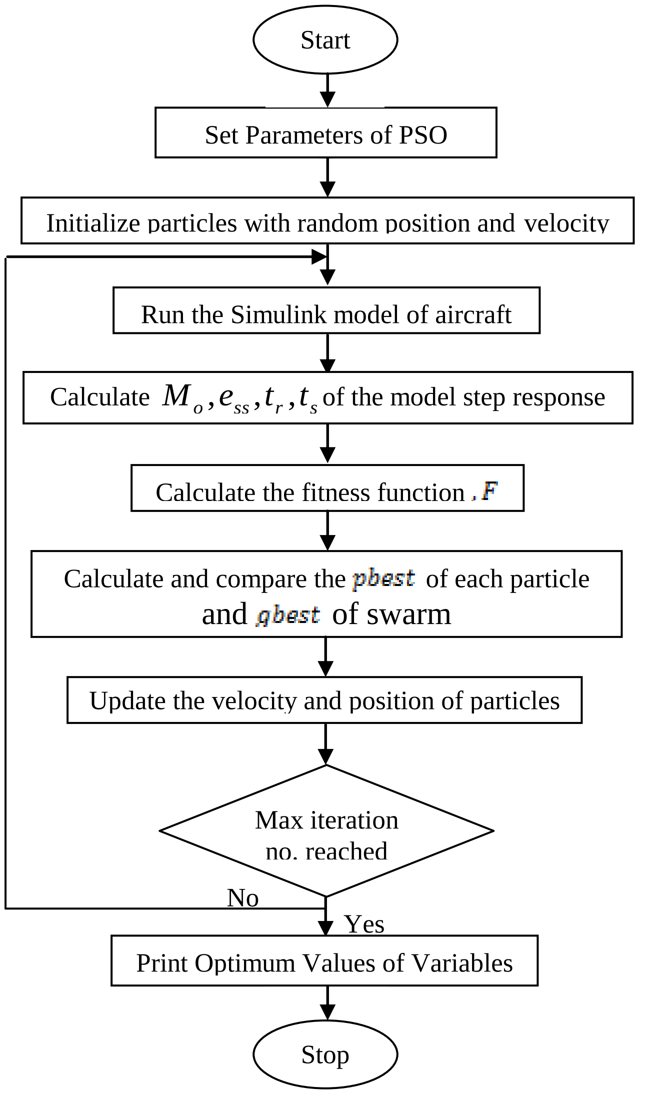

Fig. 11. Flow chart of basic PSO tuning algorithm.

The optimal weighting matrices Q and R obtained for the LQR controller using the PSO tuning algorithm are:
Q = blkdiag (q_{11} , q_{22} ,q_{33} , q_{44}) and R =0.0011896 .

Where, q_{11}=4.31164 , q_{22}=0.0117533, q_{33}=1.62006 and q_{44}=187.453. Based on the LQR controller weighting matrices Q and R, the feedback gain matrix K was calculated using the Matlab command " *lqr* " as follows:
K = [-5.0130 -5.8398 0.6268 -396.9634].

The time response of the airplane roll control system based on the PSO-LQR approach is shown in Fig. 12. Fig. 13 presents converging of the PSO tuning method through generations. The control input of the proposed roll control system based on the above PSO-LQR controller is illustrated in Fig. 14.

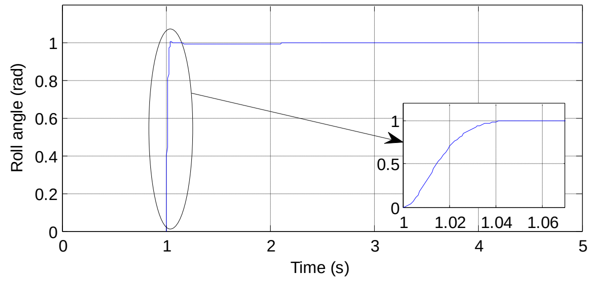

Fig. 12. Roll angle response based on the PSO-LQR controller.

Compared with the GA-LQR approach, the transient response of the heading angle based on the PSO-LQR controller is improved through keeping the stability and reduction of the rise time, settling time, maximum overshoot and steady state error, which are 0.0141 s, 0.0455 s, 1.461% and 0.096 V respectively. However, the maximum overshoot value is still not small enough.

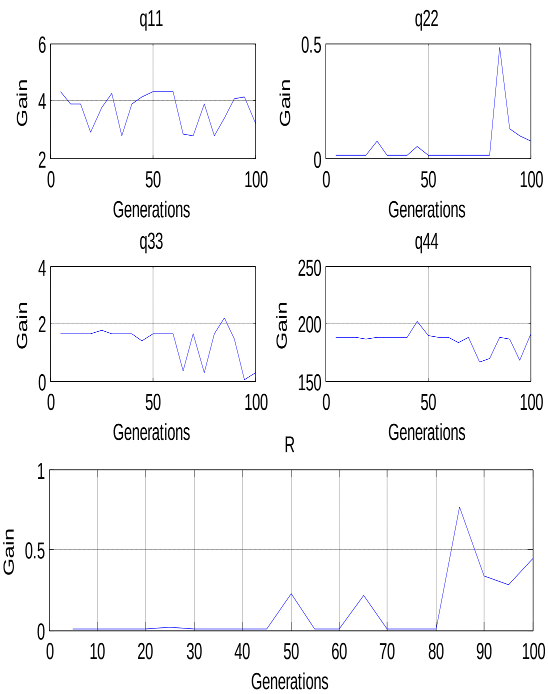

Fig. 13. Converging of the PSO algorithm through generations.

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 7, Issue 1, July 2017

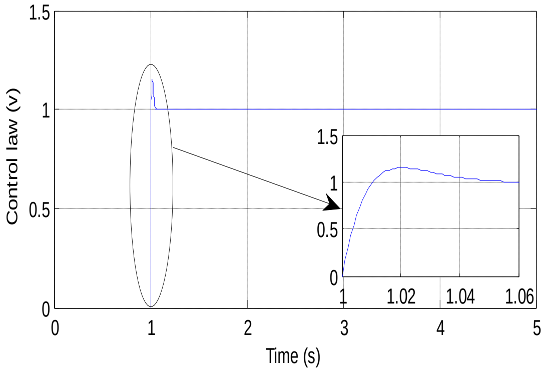

Fig. 14. Control law curve for the PSO-LQR controller.

Regarding the control effort, it can be seen from Fig. 14 that the steady state control signal of the system is reduced to 0.097 V with an initial value of 1.16 V. It is evident from Fig. 14 that, the control effort of the system was also within an acceptable range.

C. Simulation of ABC-LQR Controller

The optimal weighting vector Q and R obtained for the ABC-LQR controller are given by:

Q = blkdiag(q_{11} , q_{22} ,q_{33} , q_{44}) and R = 0.000149047.

Where q_{11} =3.64177 , q_{22} =0.000800173 , q_{33} = 1.36733 and q_{44}=135.344 . The feedback gain matrix K is given by K=[-15.1459 -8.2062 1.8045 -952.9548].

The time response for the roll angle based on the ABC-LQR controller is shown in Fig. 15. Fig. 16 presents converging of the ABC optimization method through iterations. The control input of the proposed roll control system based on the ABC-LQR controller is illustrated in Fig. 17.

Compared with the GA-LQR and PSO-LQR controllers, the system response based on the ABC-LQR controller is further improved through guide the heading angle to effectively follow the demand trajectory with a shorter transient response. Based on Fig. 15, the system has a rise time of 0.0136 s, a settling time of 0.0349 s, maximum overshoot of 0.84761% and a variance around the demand value of approximately 0.03 V. Regarding the control effort, it can be seen from Fig. 17 that the steady state control signal of the system is reduced to 0.04 V with an initial value of 1.1 V. Consequently, the ABC optimization technique can be adopted to obtain optimal values for the LQR controller parameters.

Table V shows comparison between the GA, PSO ABC-LQR controllers, based on rise time, settling time, maximum overshoot value and scaling factor parameters. The comparison reveals that the performance of the LQR controller based on the ABC tuning algorithm compared with the GA and PSO tuning methods has a faster rise time, shorter settling time and minimal overshoot value.

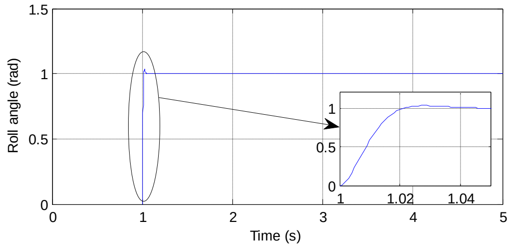

Fig. 15. Response of the roll angle based on the ABC-LQR controller.

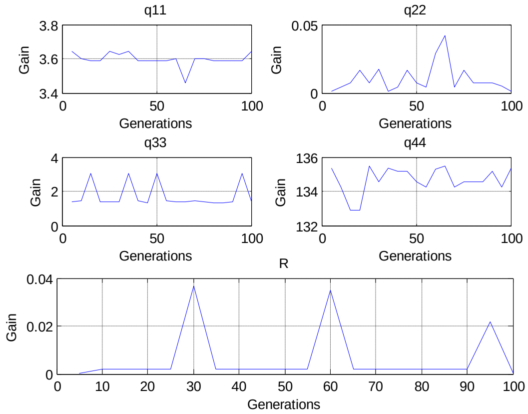

Fig. 16. Illustration of the ABC algorithm converging through generations.

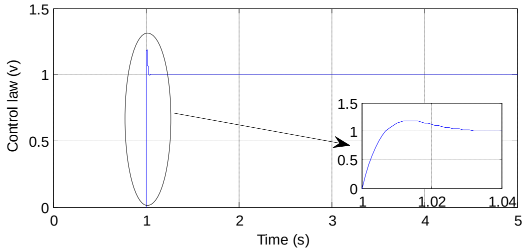

Fig. 17. Control law curve for the ABC-LQR controller.

TABLE V. RESULTS BY GA-LQR, PSO-LQR,AND ABC-LQR CONTROLLER FOR ROLL CONTROL SYSTEM

Parameter	GA-LQR	PSO-LQR	ABC-LQR
Rise time, $t_r(s)$	0.0374	0.0141	0.0136
Settling time, $t_s(s)$	0.0618	0.0455	0.0349
Max. overshoot, Mo%	2.4266	1.4610	0.8478
Scaling factor, N	-6.8712	-4.7621	-3.4562

VI. CONCLUSION AND FUTURE WORKS

In this study, an aircraft roll control system was designed based on the LQR controller technique. The controller was simulated using Matlab/Simulink environment under step input to validate the performance of the proposed control system. In this research, the LQR controller design was optimized through using tuning algorithms based on the GA, PSO and ABC methods, which were used to determine the optimum values for controller gain coefficients. The performance of the GA, PSO and ABC-LQR controller was evaluated based on the rise time, settling time, maximum overshoot value, steady state error and control input

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 7, Issue 1, July 2017

parameters. Simulation results suggests that the ABC tuning algorithm in comparison to GA and PSO methods has the ability to get efficiently out optimum values for state feedback LQR controller coefficients. Consequently, the ABC-LQR controller can be effectively employed to design an aircraft roll control system.

In the future, further research work could be carried out in field of autopilot system, pitch and yaw control system design based on robust optimized controller techniques for more perfect response. Moreover, enhance the realism of the simulation design of roll, pitch and yaw control system by including a realistic measurement and process noise in the Simulink model of the system in order to compensate the measurement errors of physical system variables and for the linearization process on non-linear system dynamics respectively.

REFERENCES

[1] R. C. Nelson, Flight Stability and Automatic Control, McGraw Hill, Second Edition 1998.

[2] M. A. Usta, O. Akyazi, and A. S. Akpinar, Aircraft roll control system using LQR and fuzzy logic controller, in: IEEE Conference on Innovations in Intelligent Systems and applications (INISTA), pp. 223-227, Istanbul, June 2011.

[3] N. Wahid, and N. Hassan, "Self-tuning fuzzy PID controller design for aircraft pitch control", Intelligent Systems, Modeling and Simulation (ISMS), Third International Conference on Intelligent Systems Modelling and Simulation, 2012 IEEE, pp 19-24.

[4] N. Wahid, and M.F. Rahmat, "Pitch control system using LQR and fuzzy logic controller", Industrial Electronics & Applications (ISIEA) ,IEEE Symposium on Industrial Electronics Malaysia,2010, pp.389-394.

[5] N. Wahid, M. F. Rahmat, and K. Jusoff, "Comparative assessment using LQR and fuzzy logic controller for a pitch control system". European Journal of Scientific Research, Vol 42, 2010, No 2, pp.184-194.

[6] A. Torabi, A. A. Ahari, A. Karsaz, and S.H. Kazemi "Intelligent pitch controller identification and design "Journal of Mathematics and Computer Science, 2014, pp.113-127.

[7]. V. G. Nair, M. V. Dileep, and V. I. George "Aircraft yaw control system using LQR and fuzzy logic controller" International Journal of Computer Applications, 45, (2012), no.9, 25-30.

[8] M. V. Cook, Flight Dynamics Principles, Elesvier, Second Edition, 2007.

[9] K. Ogata, 1997. Modern Control Engineering. Prentice-Hall International Upper Saddle River, NJ. 3333

[10] M. Safonov, and M. Athans, "Gain and phase margin for multiloop LQG regulators," IEEE Trans. Autom. Control, 22 (1977), n.2, 173–179.

[11] T. Tarczewski., and L. M. Grzesiak, "Constrained state feedback speed control of PMSM based on model predictive approach," IEEE Trans. Ind. Electron., (2015), IEEE Early Access Article, DOI: 10.1109/TIE.2015.2497302.

[12] I. Robandi , K. Nishimori, R. Nishimura, and N. Ishihara, "Optimal feedback control design using genetic algorithm in multimachine power system," Int. J. Elec. Power & En. Sys., 23 (2001), no.4, 263–271.

[13] J. Kennedy, and R. C. Eberhart, "Particle swarm optimization," In: Proceedings of the IEEE International Conference on Neural Networks, vol. 4, pp. 1942–1948. IEEE Service Center, Piscat away (1995).

[14] D. Srinivasan, and T. H. Seow, " Evolutionary Computation," CEC '03, 8–12 Dec. 2003, 4(2003), Canberra, Australia, pp. 2292–2297.

[15] D. Karaboga , and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," Journal of Global Optim., 39 (2007), no.3, 459-471.

[16] A. Yurtkuran, and E. Emel, "An enhanced artificial bee colony algorithm with solution acceptance rule and probabilistic multisearch," Journal of Computational Intelligence and neuroscience. 2016 (2016), no.41, 1-13.

[17] D. Karaboga, and B. Basturk, "A. powerful, A powerful and efficient algorithm for numerical function optimization: artificial bee colony (abc) algorithm," Journal of Global Optimization 39 (3) (2007) 459–471.

[18] B. Basturk, and D. Karaboga , "An artificial bee colony (abc) algorithm for numeric function optimization," in: IEEE Swarm Intelligence Symposium 2006, Indianapolis, Indiana, USA, May 2006. Specially

[19] D. Karaboga, and B. Basturk, "On the performance of artificial bee colony (abc) algorithm," Applied Soft Computing 8 (1) (2008) 687–697.