# Performance Evaluation of Multivariable Optimal and Predictive Controllers on an Aircraft Roll Control System

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**Abstract—** The paper proposes an advanced aircraft roll control system based on design an autopilot that controls the roll angle of an aircraft. Firstly, modeling phase begins with a derivation of suitable mathematical model to describe the lateral directional motion of an aircraft. Then, the Linear Quadratic Controller (LQR) and Model Predictive Controller (MPC) are developed for controlling the roll angle of an aircraft system. Simulation results of roll controllers are presented in time domain and the results obtained with MPC are compared with the results of LQR. Finally, the performances of roll control systems are analyzed in order to decide which control method gives better performance with respect to the desired roll angle. According to simulation results, it is showed that MPC controller deliver the best performance than LQR Controller.

**Index Terms—** Aircraft, Roll control, LQR, MPC.

## I. INTRODUCTION

The development of automatic control systems has played an important role in the growth of civil and military aviation [1]. The Sperry brothers developed an autopilot that is sensitive to the movements of an aircraft. When an aircraft deviated from a particular flight route, this autopilot adjusted the pitch, roll and heading angles of an aircraft. Then, in 1914, the Sperry brothers demonstrated this autopilot at the Paris air-show. To demonstrate the effectiveness of their design, Lawrence Sperry trimmed his airplane for straight and level flight and then engaged the autopilot [1]. Since then, the fast advancement of high performance military, commercial and general aviation aircraft design has required the development of many technologies; these are aerodynamics, structures, materials, and propulsion and flight controls [2]. Currently, the aircraft design relies heavily on automatic control systems to monitor and control many of the aircraft subsystems [2].

Modern aircrafts are much more complex and includes a variety of automatic control system. Generally, an aircraft is controlled by three main surfaces. These are elevator, rudder and ailerons. Pitch control can be achieved by changing the lift on either a forward or aft control surface. If a flap is used, the flapped portion of the tail surface is called an elevator. Yaw control is achieved by deflecting a flap on the vertical tail called the rudder and roll control can be achieved by deflecting small flaps located outboard toward the wing tips in a differential manner [1].

These flaps are called ailerons. The two ailerons are typically interconnected and both ailerons usually move in opposition to each other. The ailerons are used to bank the aircraft.

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The banking creates an unbalanced side force component of the large wing lift force which causes the aircraft's flight path to curve [3].

Thus, when the pilot applies right push force on the stick, as the aileron on the right wing is deflected upward, the aileron on the left wing is deflected downward. As a result of this, the lift on the left wing is increased, while the lift on the right wing is decreased.

So, the aircraft performs a rolling motion to the right as viewed from the rear of the aircraft. The rolling motion of an aircraft is controlled by adjusting the roll angle.

In this study, for this situation an autopilot is designed to control the roll angle of an aircraft. In aircraft modeling phase, the aerodynamic forces (lift and drug) as well as the aircraft's inertia are taken into account [4]. This is a third order, nonlinear system which is linearized about the operating point [4]. Lucio [2] has proposed a new autopilot controller in order to meet the desired performance. In (Atlas, 2011), an intelligent fuzzy logic controller (FLC) is developed for the roll control of an aircraft system. Performances of this controller are analyzed with respect to the desired roll angle [7]. A comparative analysis between LQR and fuzzy controller was proposed by Nurbaiti Wahid et.al [4].Generally these are all approaches which won't handle constraints and optimal control. So in order to handle to the constraints of the system, Predictive strategy is used.

In this work, Constrained Model predictive controller (MPC) has been proposed for aircraft roll control system and its performance is compared with unconstrained MPC. The simulation test studies have been carried out to illustrate the performances of the constrained and unconstrained MPC in an aircraft roll system.

The paper is organized as follows. Next section presents the modeling of the aircraft roll system. Preliminaries are given in section 3. The simulation results and discussion is given in section 4. Finally some conclusions are drawn in section 5.

## II. MODELING OF AIRCRAFT SYSTEM

The equation governing the motion of an aircraft are very complicated as a set of six nonlinear equations. Under certain assumptions, these equations can be decoupled and linearized into the longitudinal and lateral equations. Roll control is achieved by deflecting small flaps located outboard toward the wing tips in a differential manner. It is controlled by controlling the roll angle of an aircraft to stabilize the system when an aircraft performs the rolling motion. The roll control system is shown in Fig.1.

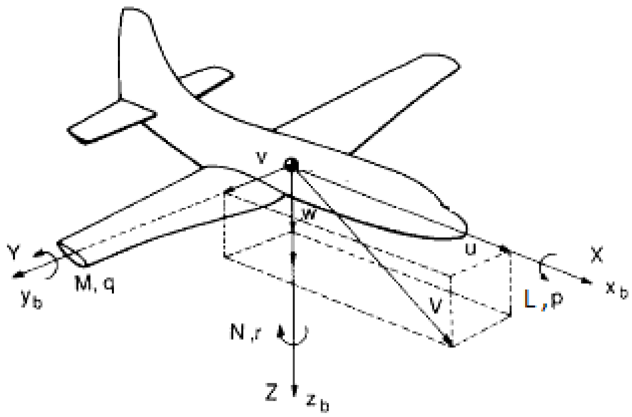


Fig.1.Definition of forces, moments and velocity components in a body fixed coordinate

In this figure, X, Y and Z represents the aerodynamic force components, ϕ and $\delta_a$ represent the orientation of aircraft (roll angle) in the earth-axis system and aileron deflection angle respectively. The forces, moments and velocity components in the body fixed coordinate of an aircraft system are shown in Figure 3 where *p*, *q* and *r* represents the angular rate 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 term *L*, *M* and *N* represent the aerodynamic moment components.

Referring to figure.1, the rigid body equations of motion are obtained from Newton's second law. But, a few assumption and approximation need to be considered before obtaining the equations of motion. Assume that the aircraft is in steady-cruise at constant altitude and velocity, thus, the thrust and drag cancel out and the lift and weight balance out each other. Also, assume that change in pitch angle does not change the speed of an aircraft under any circumstance. Under these assumptions, the lateral directional motion of an aircraft is well described by the following kinematic and dynamic differential equations.

$$X - mgS_{\emptyset} = m(\dot{u} + qw - rv) \quad (1)$$

$$Y + mgC_{\theta}S_{\theta} = m(v + r\dot{u} - pw) \quad (2)$$

$$Z + mgC_{\theta}C_{\emptyset} = m(\dot{w} + pv - qu) \quad (3)$$

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

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

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

Equation (1), (2), (3), (4), (5) and (6) are nonlinear and they can be linearized by using small-disturbance theory. According to small-disturbance theory, all the variables in the equation (1), (2), (3), (4), (5) and (6) are replaced by a reference value plus a perturbation or disturbance, as given in equation (7-10).

$$u = u_0 + \Delta u \;\; v = v_0 + \Delta v \; w = w_0 + \Delta w \quad (7)$$

$$p = p_0 + \Delta p \; q = q_0 + \Delta q \; r = r_0 + \Delta r \quad (8)$$

$$Y = Y_0 + \Delta Y \; L = L_0 + \Delta L \; M = M_0 + \Delta M \quad (9)$$

$$\delta = \delta_0 + \Delta\delta \quad (10)$$

For convenience, the reference flight condition is assumed to be symmetric and the propulsive forces are assumed to remain constant. This implies that,

$$V_0 = p_0 = q_0 = r_0 = \emptyset_0 = \Psi_0 = 0 \quad (11)$$

After linearization the lateral rigid body equations of motion are obtained as

$$\left(\frac{d}{dt} - Y_v\right)\Delta v - Y_p\Delta p + (u_0 - Y_r)\Delta r - (g\cos\theta_0)\Delta\emptyset = Y_{\delta r}\Delta\delta_r$$

$$-L_v\Delta v + \left(\frac{d}{dt} - L_p\right)\Delta p - \left(\frac{I_{xz}}{I_x}\frac{d}{dt} + L_r\right)\Delta r = L_{\delta a}\Delta\delta_a + N_{\delta a}\Delta\delta_r$$

$$-N_v\Delta v - \left(\frac{I_{xz}}{I_x}\frac{d}{dt} + N_p\right)\Delta p + \left(\frac{d}{dt} - N_r\right)\Delta r = N_{\delta a}\Delta\delta_a + N_{\delta a}\Delta\delta_r$$

The lateral directional equations of motion consist of the side force, rolling moment and yawing moment equations of motion. It is sometimes convenient to use the sideslip angle $\Delta\beta$ instead of the side velocity $\Delta v$ . These two quantities are related to each other in the following way

$$\Delta\beta \approx tan^{-1}\frac{\Delta v}{u_0} = \frac{\Delta v}{u_0} \quad (12)$$

Using this relationship and if the product of inertia of pitch axis $I_{xz}$=0, then the lateral equations of motion can be rearranged and reduced into the state space form in the following manner.

$$\begin{bmatrix}\Delta\dot{\beta}\\ \Delta\dot{p}\\ \Delta\dot{r}\\ \Delta\dot{\emptyset}\end{bmatrix} = \begin{bmatrix}\frac{Y_\beta}{u_0} & \frac{Y_p}{u_0} & -\left(1 - \frac{Y_r}{u_0}\right) & \frac{g\cos\theta_0}{u_0}\\ L_\beta & L_p & L_r & 0\\ N_\beta & N_p & N_r & 0\\ 0 & 1 & 0 & 0\end{bmatrix}\begin{bmatrix}\Delta\beta\\ \Delta p\\ \Delta r\\ \Delta\emptyset\end{bmatrix} + \begin{bmatrix}0 & \frac{Y_{\delta r}}{u_0}\\ L_{\delta a} & L_{\delta r}\\ N_{\delta a} & N_{\delta r}\\ 0 & 0\end{bmatrix}\begin{bmatrix}\Delta\delta_a\\ \Delta\delta_r\end{bmatrix}$$

For this system, the input will be the aileron deflection angle and the output will be the roll angle. In this study, the data from General Aviation Airplane: $NAVION^a$[1] is used in system analysis and modeling. The lateral directional derivatives stability parameters for this airplane are given Table I.

Table.I.The lateral directional derivatives stability parameters

| General Aviation Airplane: $NAVION^a$ | The Dynamic Pressure | | |
|---|---|---|---|
| | $Q = 36.8\frac{Ib}{ft^2}$ $QS^-c = 38596\, ft.Ib$ $QS = 6771\;\; Ib\frac{c}{2u_0} = 0.016\, s$ | | |
| | Components | | |
| | Y-Force Derivatives | Yawing Moment Derivatives | Rolling Moment Derivatives |
| Pitching Velocities | $Y_V$= - 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 | $Y_P = 0$ | $N_P = -0.349$ | $L_P = -8.395$ |
| Yawing Rate | $Y_r = 0$ | $N_r = -0.76$ | $L_r = 2.19$ |
| Rudder Reflection | $Y_{\delta r} = 12.433$ | $N_{\delta r} = -4.613$ | $L_{\delta r} = 23.09$ |
| Aileron Reflection | $Y_{\delta a} = 0$ | $N_{\delta a} = -0.224$ | $L_{\delta a} = -28.916$ |

## III. DESIGN PROCEDURES FOR LQR AND MPC

### A. *Linear Quadratic Regulator (LQR)*

Linear quadratic regulator (LQR) is a method in modern control theory and it is an alternative and very powerful method for flight control system designing. The method is based on the manipulation of the equations of motion in state space form and makes full use of the appropriate computational tools in the analytical process [6]. LQR control system for the lateral directional control of an aircraft is shown in Fig. 1.

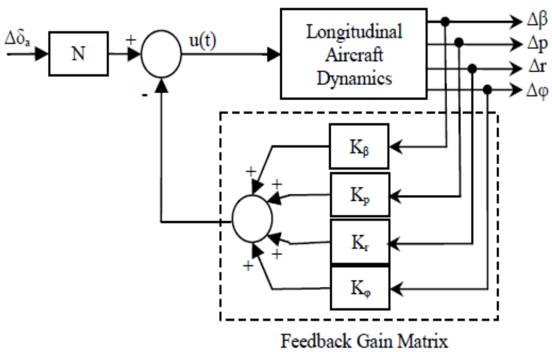



Fig.1. Full-state feedback controller with reference input for the roll control system.

In this work, the closed loop optimal control of linear systems with quadratic performance measure are presented. This leads to state regulation and set point tracking.

The state and output matrix equations describing the lateral directional equations of motion can be written as the following equation.

$\dot{x}(t) = Ax(t) + Bu(t)$ (13)

$y(t) = Cx(t)$ (14)

Where $x(t)$is the state vector, u(t) is the input vector, A and B indicate the constant system model parameters. The pair (A, B) is assumed to be stabilizable. The performance index as

$J = \frac{1}{2}\int_0^{\infty}\left[x^{`}(t)Qx(t) + u^{`}Ru(t)\right]dt$

(15)

Where Q is a nonnegative definite matrix that penalizes the departure of system states from the equilibrium and R is a positive definite matrix that penalizes the control input.

The solution is

Step 1: Solve the matrix algebraic Ricatti equation

$-\bar{P}A - A^{`}\bar{P} - Q + \bar{P}BR^{-1}B^{`}\bar{P} = 0$ (16)

Where P$\in R^{n\times m}$ is a non negative definite matrix satisfying the matrix Riccati Equation,

Step 2: Estimated the state using an Extended Kalman Filter (EKF)

$\hat{X}(t) = A\hat{x}(t) + Bu(t) + K(t)(y(t) - C\hat{x}(t))$ (17)

$K(t) = P(t)C^{`}(t)V^{-1}(t)$ (18)

Kalman gain

$V(t) = C(t)P(t)C(t)^{`} + R$ (19)

Step3: To find Optimal control

$u^{*}(t) = -\left(R^{-1}B^{`}P(t)\right) * \hat{x}(t)$ (20)

The error is

$e(t) = z(t) - y(t)$ (21)

Where z(t) is the desired signal(set point)

The performance index taken as

$\lim_{t_f\to\infty} J = \lim_{t_f\to\infty}\frac{1}{2}\int_0^{\infty}[e'(t)Q\,e(t) + u'(t)R\,u(t)]\,dt$

(22)

To find $\bar{P}$

$-\bar{P}A - A'\bar{P} + \bar{P}BR^{-1}B'\bar{P} - C'QC = 0$ (23)

To find $\bar{g}$

$\dot{\bar{g}}(t) = [\bar{P}E - A']\bar{g}(t) - Wz(t)$ (24)

Where$E = BR^{-1}B^{`}$ and $W = C^{`}Q$

Optimal control

$u(t) = -R^{-1}B'[\bar{P}x(t) - \bar{g}(t)]$ (25)

The weighting matrices Q and R are important components of an LQG optimization process. The compositions of Q and R elements have great influences on system performance [3]. The number of matrices Q and R elements are dependent on the number of state variable (n) and the number of input variable (m), respectively. The diagonal-off elements of these matrices are zero for simplicity. If diagonal matrices are selected, the quadratic performance index is simply a weighted integral of the squared error of the states and inputs. The designer is free to choose the matrices Q and R, but the selection of matrices Q and R is normally based on an iterative procedure using experience and physical understanding of the problems involved. Commonly, a trial and error method has been used to construct the matrices Q and R elements. This method is very simple and very familiar in LQG application. For this study, R=1 and Q= $C^T \times C$ where C is the matrix from state equation and $C^T$ is the matrix transpose of C. For designing LQR controller, the value of the feedback gain matrix, K, must be determined. The following block is shown how to determine the values of K.

K= [0.5284, -0.5349, -0.0917 -8.6567] values are obtained by using MATLAB. To obtain the desired output in other words to reduce steady-state error, we must use a feed-forward scaling factor called N. Because, the full-state feedback system does not compare the output to the reference, it compares all states multiplied by the feedback gain matrix to the reference [5]. The reference must be scaled by scaling factor N. The scaling factor N is obtained from MATLAB function that is a designer-defined function in m-file code. In this case, N=-8.6603 is determined.

### B. *Model Predictive Control (MPC)*

The model predictive control is a strategy that is based on the explicit use of some kind of system model (eqn. 1 and 2) to predict the controlled variables over a certain time horizon, the prediction horizon. The block diagram of a model predictive controller is shown in Fig 2. At any sampling instant k, the model predictive control problem is formulated as a constrained optimization problem whereby the future manipulated input moves, denoted as $\{m(k|k, m(k+1|k) \ldots m(k+N_p|k)\}$ are determined by minimizing an objective function involving the predicted controller errors. Typical objective function used in a MPC formulation is of the form:

$J = J_e + J_{\Delta u}$ (26)

$J_e = \sum_{i=1}^{m} e_f(k+i|k)^T\, W_e e_f(k+i|k)$ (27)

$$J_{\Delta u} = \sum_{i=1}^{n-1} \Delta u(k+i|k)^T W_u \Delta u(k+i|k) \quad (28)$$

Where,

$$e_f(k+i|k) = y_r(k+i) - \hat{y}(k+i|k) \quad (29)$$

$$\Delta u(k+i|k) = u(k+i) - u(k+i-1|k) \quad (30)$$

Subject to the following constraints:

$$u^i \leq u(k+i|k) \leq u^N \quad (31)$$

Where, $i \in [0\ m]$. Here $m$ represents prediction horizon and $n$ represents control horizon, $y_r$ represents the future set-point trajectory and $\hat{y}$ represents the vector of controlled outputs.

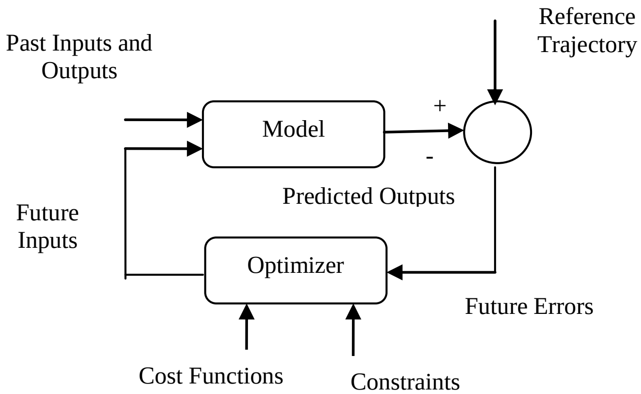



Fig.2. Structure of MPC controller

As the control variables in a MPC controller are calculated based on the predicted output, the model thus needs to be able to reflect the dynamic behavior of the system as accurately as possible. The control strategy can be described as follows [6].

(1). At each sampling time, the value of the controlled variable y(t+i) is predicted over the prediction horizon i=1,……$N_2$. This prediction depends on the future values of the control variable u(t+i) within a control horizon k=1,…Nu, where $N_u \leq N_2$. If $N_u < N_2$, then u(t+i)=u(t+$N_u$), i=$N_u$+1,…$N_2$.
(2). A reference trajectory r(t+i), i=1,….N is defined which describes the desired system trajectory over the prediction horizon.
(3). The vector of future controls u(t+i) is computed such that a cost function, usually a function of the errors between the reference trajectory and the predicted output of the model, is minimized.
(4). Once minimization is achieved, the first optimized control action is applied to the plant and the plant outputs are measured. Use this measurement of the plant states as the initial states of the model to perform the next iteration.
Steps 1 to 4 are repeated at each sampling instant; this is called receding horizon strategy.

Table.II. Initializing parameters of MPC

| | |
|---|---|
| Model length (N) | 100 |
| Prediction horizon (m) | 2 |
| Control horizon (n) | 1 |
| Weighting factor We | 10 |
| Weighting factor Wu | 10 |
| Sample time | 1sec |
| Time of set point change | 2 |
| Final simulation time | 100 |

## IV. Results and Discussions

### A. Adaptive aspects

Since the computation of the gain matrices in the case of the predictive controller is simpler than the resolution of the Riccati equation to be solved in the LQR controller, the predictive controller seems better suited for adaptive aspects. In this case the gain matrices can be computed frequently when the operating conditions have changed.

### B. Robustness

According to the above presented simulations, both controllers prove a satisfactory robustness to model degradation. It seems that the LQR controller is slightly more robust than the MPC one, but additional simulations must be done.

### C. Simplified Solutions

One advantage of the optimal LQR controller is to allow the simplified asymptotic solution obtained when the time horizon is infinite. The predictive controller allows a simplified solution consisting of considering a weighting coefficient only on the final time step and a constant control sequence over the prediction interval.

This option was not tested in this paper. It will be tested in the future, but a priori it appears more restrictive than the asymptotic solution of the LQR controller.

### D. Computational Efforts

Since a significant time horizon as to be selected in order to include roll control effects, the computation efforts of the predictive controller are bigger than in the case of the asymptotic solution of the LQR controller. They could be reduced using the above quoted simplifications, but probably with a degradation of the controller performance.

### E. Results

Results obtained with both controllers are very close in terms of performance indicators. Tuning of the predictive controller seems easier and leads to less variability in the weighting coefficients (Matrices Q and R).

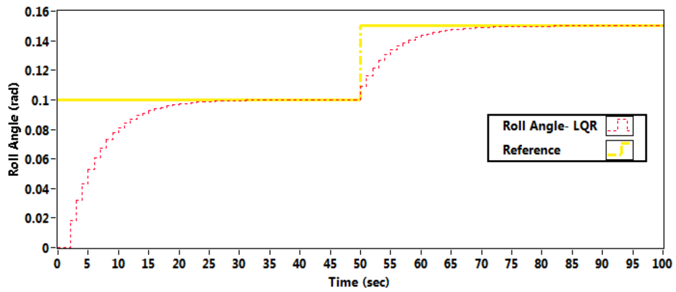
### F. Performance Index

In order to assess the performance of the controller, Integral Square Error (ISE) is used as performance index to evaluate the performance of the controllers proposed. Table 3 shows the comparative study.

Table.III. Comparison between conventional MPC and LQR

| Controller/ Performance index | ISE |
|---|---|
| MPC | 9.3404 |
| LQR | 13.5121 |

From Table 3, it is clear that the MPC shows better performance than the LQR whether the measurement noise is considered or not. Moreover it shows that MPC has better




noise suppressing capability.

Fig.2. Closed Loop Performance of LQR Controller

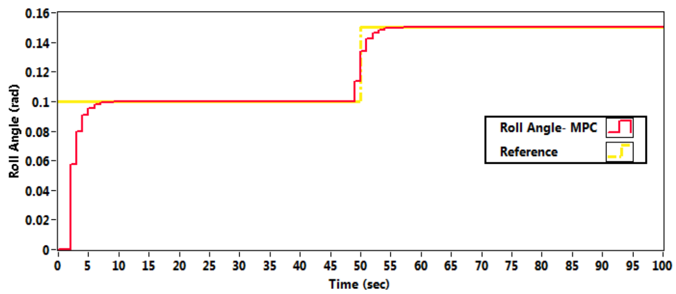



Fig.2. Closed Loop Performance of MPC Controller

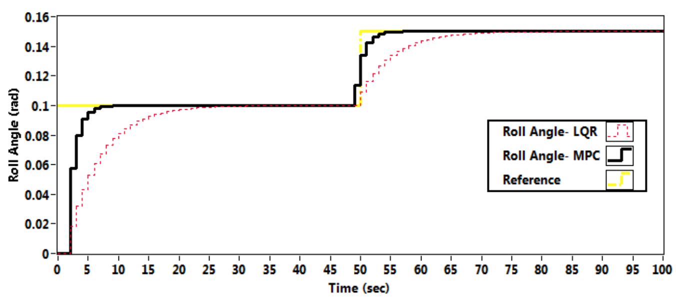



Fig.2. Comparative Analysis of LQR and MPC Controller

## V. Conclusion

In this paper, the model of an aircraft rolls control system that is helpful in developing the control strategy for an aircraft system. There are two advanced control methods developed for this system. The results from MPC are compared with those obtained using LQR controller. MPC has good and acceptable performances according to the results from simulation and analysis. Practically obtained results show that MPC controller relatively gives the best performance in comparison to LQR and using such controller increases speed of the time response.

## VI. References

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

[2]. Lucio R. Riberio and Neusa Maria F. Oliveira, "UAV Autopilot Controllers Test Platform Using Matlab/Simulink and X-Plane", *40th ASEE/IEEE Frontiers in Education Conference*, October 27-30, 2010, Washington, DC.

[3]. www.nasa.gov (01.03.2011)

[4]. Nurbaiti Wahid and Mohd Fua'ad Rahmat, "Pitch Control System Using LQR and Fuzzy Controller", 2010 IEEE Symposium on Industrial Electronics and Applications (ISIEA 2010), October 3-5, 2010, Penang, Malaysia

[5]. http://www.engin.umich.edu/class/ctms/index.htm (01.03.2011)

[6]. Mıchael V. Cook, 2007, *Flight Dynamics Principles*, Elsevier, Second Edition.

[7]. I. H. Altas and A. M. Sharaf, "A Generalized Direct Approach for Designing Fuzzy Logic Controllers in Matlab/Simulink GUI Environment", Accepted for publication in *International Journal of Information Technology and Intelligent Computing*, Int. J. IT&IC no.4 vol.1.

[8]. G. K. Venayagamoorthy, and R. G. Harley, "Swarm Intelligence for Transmission System Control, *Proceedings of the IEEE Conference on Power Engineering*, (2007).

[9]. Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," *in Proc. IEEE Int. Congr.* Evolutionary Computation, vol. 3, pp. 101–106, (1999).

[10]. J.Hamidi, "Control System Design Using Particle Swarm Optimization", International Journal of Soft Computing and Engineering (IJSCE, ISSN: 2231-2307, Volume-1, Issue-6, January (2012).

[11]. Ker-Wei, Yu, Zhi-Liang, Huang, "LQ Regulator Design Based on Particle Swarm Optimization", Proceedings of the IEEE Conference on *Systems, Man, and Cybernetics, October*, (2006).

[12]. A.P. Engelbrecht, "Particle swarm optimization: where does it belong?" in Proc. of the IEEE Swarm Intelligence Symposium 2006 (SIS'06), pp. 48-54, (2006).

[13] A. J. Alos, "Stabilization of a class of plants with possible loss of outputs or actuator failures," *IEEE Trans. Automat. Contr.*, vol. 28, pp. 231–233, 1983.

[14] D. Kim and Y. Kim, "Robust variable structure controller design for fault tolerant flight control," *Journal of Guidance, Control and Dynamics*, vol. 23, no. 3, pp. 430–437, 2000.

[15] J. Stoustrup and V. D. Blondel, "Fault tolerant control: A simultaneous stabilization results," *IEEE Trans. Automat. Contr.*, vol. 49, no. 2, pp. 305–310, 2004.

[16] M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki, *Diagnosis and Fault-Tolerant Control*. Springer-Verlag, 2003.

[17] H. Noura, D. Sauter, F. Hamelin, and D. Theilliol, "Fault-tolerant control in dynamic systems: Application to a winding machine," *IEEE Control Syst. Mag.*, vol. 20, no. 1, pp. 33–49, 2000.

[19] Manikandan P, Geetha M, et. al.,"Performance Analysis and Control Design of Two Dimension Fuzzy PID Controller", *International Journal of Electrical Engineering and Technology*, Vol.4 (5),pp. 47-55, 2013.

[20] Manikandan, Pandiyan and Mani Geetha. "Takagi Sugeno fuzzy expert model based soft fault diagnosis for two tank interacting system. "*Archives of Control Sciences* 24, no. 3 (2014).

[21] Manikandan, P., M. Geetha, and Jovitha Jerome. "Weighted fuzzy fault tolerant model predictive control." In *Fuzzy Systems (FUZZ-IEEE), 2014 IEEE International Conference on*, pp. 83-90. IEEE, 2014.

[22] Geetha, M.; Manikandan, P.; Jerome, J., "Soft computing techniques based optimal tuning of virtual feedback PID controller for chemical tank reactor," *Evolutionary Computation (CEC), 2014 IEEE Congress on* , vol., no., pp.1922,1928, 6-11 July 2014