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Comparison of Classical PD and Fuzzy PD Controller Performances of an Aircraft Pitch Angle Control System

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ABSTRACT

Aircraft dynamics are in general nonlinear, time varying, and uncertain. A control system (classical control systems) designed for a flight condition, may not provide the desired stability and performance characteristics in case of deviation from the equilibrium point. There are numerous studies regarding flight control in the literature. One of them is fuzzy flight control system Fuzzy Logic Controllers (FLCs) from their inception have demonstrated a vast range of applicability to processes where the plant transfer function is not defined but the control action can be described in terms of linguistic variables. FLCs are also being used with improved performance instead of "classical" controllers where the plant transfer function is known. Most of the applications about the design of fuzzy flight control are in simulation level. In this study, the design of classical and fuzzy PD controller for the pitch angle control system is analyzed and the results are compared for a very large, four-engine passenger jet aircraft.

Key Words**:** *Aircraft, Classical PD controller, Flight control, Fuzzy PD controller.*

1. INTRODUCTION

The aim of a flight control system (FCS) of an aircraft is to maintain a safe and economic operation. Thus, the desired flight missions can be accomplished even under unexpected events. In the early days of flight, safety was the main concern of a flight control system. Since the number of flights and number of people using planes for travel has increased, safety is even more important.

Aircraft dynamics are in general nonlinear, time varying, and uncertain. Generally, the dynamics are linearized at some flight conditions and flight control systems are designed by using this linearized mathematical model of the aircraft. However, some aerodynamic effects are very difficult to model resulting to uncertainties in the aircraft dynamics and the dynamic behavior of an aircraft may change in a short period of time as a result of internal and/or external disturbances. Thus, a control system designed for a specific flight condition may not be suitable if the conditions change from this flight condition. In this case, the performance of the aircraft may be unsatisfactory. Moreover, unexpected situations such as changing weather conditions and system failures are difficult to model and thus difficult to translate into appropriate classical control designs [1-2-3].

As the complexity of aircrafts increase, classical methods become unsatisfactory to yield acceptable performance [2] and come to its limits when controllers for Multi-

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Input Multi-Output (MIMO) systems with high internal coupling are to be designed. For a higher-number passenger aircraft or a new supersonic commercial transport, powerful and robust techniques are required [4].

There are numerous studies regarding flight control in the literature such as adaptive control [5-6], μ synthesis control [7-8-9], H∞ control [10-11-12], multi model control [13-14], neural control [15], adaptive neural control [16-17], gain scheduling control [18], control system with a genetic algorithm optimization process [19-20] and fuzzy control [21-22].

These methods have many different features. A common feature is that each of them is developed to achieve advantages over classical techniques. The classical approach in which each mode and flight condition is treated as a separate problem has led to mode proliferation and the need for complex algorithms. To avoid functional integration at the end of the FCS design, which is too late, an all-encompassing and consistent design strategy is necessary. Throughout the design process a "systems approach" strategy should be applied, supported by good requirements, design tools and design models. Application of advanced techniques promises a significant reduction of design time because it would remove the time-consuming classical "one-loop-at-a-time" approach and reduce the number of design points for which a controller has to be designed [4].

Among these methods, fuzzy systems have different kinds of applications (regulating the velocity of a freight train, optimization trip time and energy consumption of a high-speed railway, helicopter flight control system, control of heating, ventilating and air conditioning systems, hi-tech filming devices (photo and recording cameras), washing machines, microwave devices, industrial control systems, high performance medical instruments, railway vehicle control systems, autonomous vehicle control, such as trajectory tracking, or obstacle avoidance etc.) in many areas [23-24-25-26-27].

Fuzzy control depends on the fuzzy algorithm between the information of process and control input. Fuzzy controllers from their inception have demonstrated a vast range of applicability to processes where the plant transfer function is not defined but the control action can be described in terms of linguistic variables. Fuzzy controllers are also being used to improve the performance of a system where the plant transfer function is known [28-29].

In the literature, there are different applications of fuzzy systems in aviation. Most of the applications about the design of fuzzy flight control are in simulation level.

NASA developed a training simulator where a fuzzy control is used for STA (Shuttle Training Aircraft) that is modified from a Gulf Stream II business jet. When the STA was first developed in 1975 conventional linear control systems were used. Although these systems performed well, there were areas that could be improved. The use of fuzzy control was investigated with the conclusion that implementing it in the STA would improve the control system performance. It also allows for a design based on the physical characteristics of the plant, or STA, as opposed to the previous design based on an approximate mathematical model of the plant. This, plus the inherent structure of fuzzy control, allows for an easier implementation of a complex nonlinear control system. The nonlinear characteristic of fuzzy control systems is the biggest advantage over the old linear control system. In the end, the fuzzy control system's overall performance is better; it is more than the original linear control system. The fuzzy control has improved the simulation fidelity of the STA and consequently astronaut training [21].

An approach based on a fuzzy logic controller was implemented to control and regulate the atmospheric plasma spray processing parameters (arc current intensity, total plasma gas flow, hydrogen content) to the in-flight particle characteristics (average surface temperature and velocity) [22].

Researchers at the U.S. Bureau of Mines, University of Alabama, and the U.S. Army, have developed a fuzzy system for controlling the flight of UH-1 helicopters through various maneuvers. A genetic algorithm is used to discover rules for effective control of the helicopter. The performance of the controller is tested both in simulation and in actual flight. The developed fuzzy controller architecture is general enough to be applicable to a variety of rotorcraft. Moving the controller to a new helicopter simply requires discovering rules for the fuzzy controller [24].

Schram and Verbruggen, members of the Group for Aeronautical Research and Technology in Europe (GARTEUR) designed a fuzzy controller for the landing control of a two-engine civil aircraft and got successful simulation results [3]. A fuzzy controller is designed for landing of an unmanned aircraft [30]. A fuzzy-logic "performance control" system, providing envelope protection and direct command of airspeed, vertical velocity, and turn rate, was evaluated in a reconfigurable general aviation simulator (configured as a Piper Malibu) at the FAA Civil Aerospace Medical Institute. Performance of 24 individuals (6 each of high-time pilots, low-time pilots, student pilots, and non-pilots) was assessed during a flight task requiring participants to track a 3-D course, from take-off to landing, represented by a graphical pathway primary flight display. Baseline performance for each subject was also collected with a conventional control system. All participants operated each system with minimal explanation of its functioning and no training. Results indicated that the fuzzy-logic performance control reduced variable error and overshoots, required less time for novices to learn (as evidenced by time to achieve stable performance), required less effort to use (reduced control input activity), and was preferred by all groups [31].

Pitch angle which is one of the most important parameters of a flight control system that was used in [32] was evaluated by using a fuzzy PD controller. A quite good system performance was obtained previously from a fuzzy PD controller. In this paper, our intention is to compare the former results with classical PD controller.

The structure of the paper is as follows. Following first introductory section, Section 2 and 3 presents some basic knowledge about fuzzy PD and classical PD control, respectively. Section 4 describes an aircraft pitch angle control system. In Section 4 analyses and comparisons of some simulation results obtained by Matlab are given. Finally, Section 5 presents conclusions and highlights the scope for future work.

2. FUZZY PD CONTROL

FLCs can be used to realize the closed-loop control actions directly, i.e. replace conventional closed-loop controllers, or they can complement and extend conventional control algorithms via supervision, tuning or scheduling of local controllers [4]. A general fuzzy controller consists of four modules: a fuzzy rule and data base, a fuzzy inference engine, and fuzzification /defuzzification modules. The interconnections among these modules and the controlled process are shown in Figure 1. Most of the systems use fuzzy controller is PD type controller. In this type of controller, error and change of error knowledge is used in fuzzification and rule base modules.

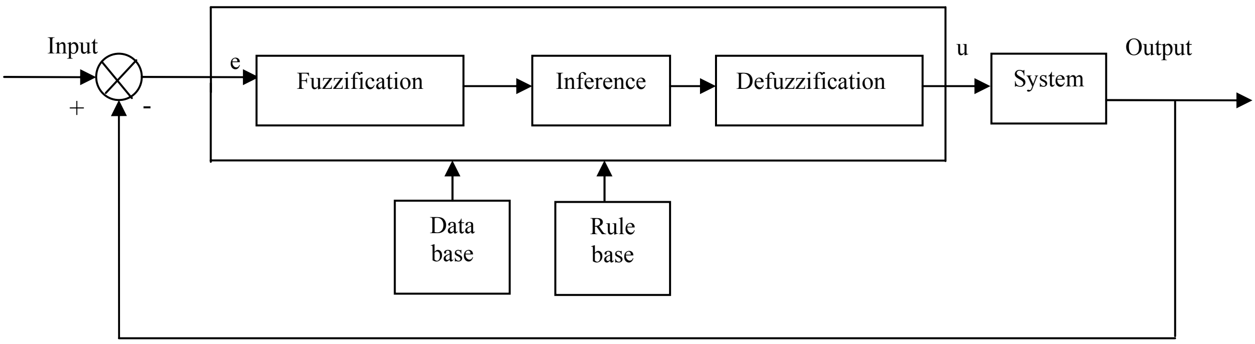


Figure 1. Closed loop fuzzy controller.

Fuzzy PD controller calculates the appropriate control at the input of the system according to the error and change of error at the input. While developing such a system the most important process is encoding the knowledge base of fuzzy controller. The knowledge base of the fuzzy PD controller consists of data and rule bases. Membership function distributions of system input and output variables are defined in data base.

Membership functions may be selected as a triangular, trapezoid or other appropriate forms. The number of membership functions changes depending on the problem. The number of these linguistic variables specifies the quality of control, which can be achieved using fuzzy controller. As the number of linguistic variables increases, the quality of control increases at the cost of increased computer memory and computational time [28-33-34-35].

3. CLASSICAL PD CONTROL

Classical PD type controller used in this study because the D effect ensures a rapid response, increases damping and decreases rise time and settling time. As shown in Figure 2 the controller output is equal to

$$U(s) = (K_p + K_d s)E(s) \tag{1}$$

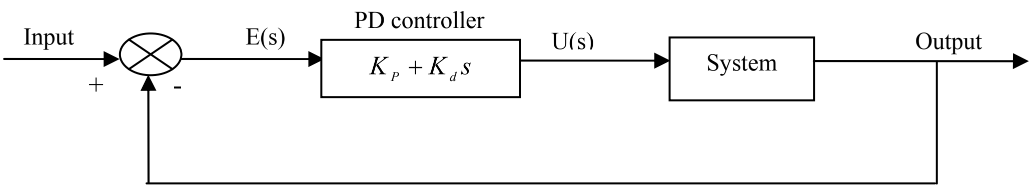


Figure 2. Classical PD Control system.

Classical Control methods are also rigorously analyzable, and therefore they can be readily certified, and since they contain relatively few components, the effects of failure of some of those components can be assessed relatively easily. There is a great deal of experience concerning their use and implementation available within most vendors and airframe manufacturers.

Their principal disadvantage is the time taken to perform the design process. It is common in industry for an existing autopilot design to be modified to suit a new aircraft, as opposed to a completely new design being performed, and this reduces the design time. A significant amount of knowledge concerning aircraft and their characteristics is also required to support the design procedure since the optimization of the controller depends on the knowledge and intuition of the designer and not a computer algorithm [4].

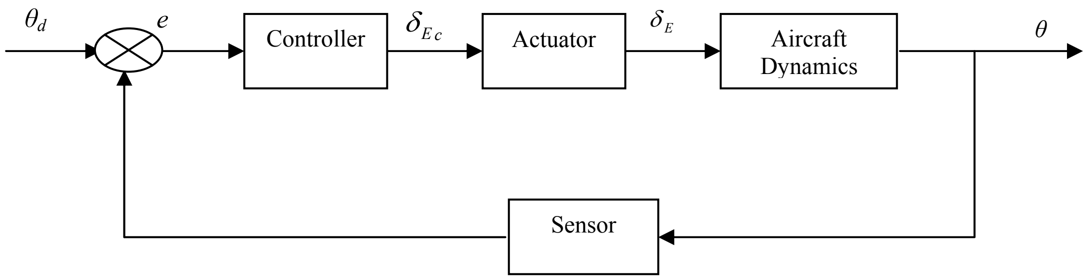


Figure 3. Aircraft pitch angle control system.

4. AIRCRAFT PITCH ANGLE CONTROL SYSTEM

Aircraft pitch angle control system shown in Figure 3. It can be seen from the Figure 3 that, elevator angle (δ_{Ec}) at the output of the controller is calculated such that the output of system pitch angle (θ) follows the reference pitch angle value (θ_d). The input of actuator δ_{Ec} provides the change of elevator angle of the input of aircraft dynamic via actuator transfer function. Controller calculates the appropriate elevator angle at the input of the actuator. In this study, fuzzy PD controller for the pitch angle control system is designed and the simulation results for a very large, four-engine passenger jet aircraft are compared with the results of a classical PD controller in a MATLAB coded program.

5. SIMULATION RESULTS

The proposed fuzzy PD controller and classical PD controller applied to four-engine passenger jet aircraft data. The flight parameters of different flight conditions of selected aircraft are given in Table 1 [36].

Table 1. Flight condition parameters .

Parameter	Flight Condition 1	Flight Condition 2	Flight Condition 3
Altitude (m)	6100	6100	12200
Mach no	0.5	0.8	0.8
$U_0\left(ms^{-1}\right)$	158	250	250
$\overline{q}\left(Nm^{-2}\right)$	8667	24420	9911
$\alpha_0(\text{degree})$	6.8	0	4.6
$\gamma_0(\text{degree})$	0	0	0

In Table 1, U_0 is the forward equilibrium velocity, $\overline{q}$ is the dynamic pressure, α_0 is the equilibrium angle of attack, γ_0 is the equilibrium flight path angle. Also in Figure 3, actuator and sensor dynamics are chosen as $\frac{1}{1+0.1s}$. Aircraft dynamics for the above three flight condition are given in Equations 2, 3 and 4 respectively.

$$\frac{\theta(s)}{\delta_E(s)} = \frac{1.087s + 0.441}{s^3 + 0.917s^2 + 1.13s} \tag{2}$$

$$\frac{\theta(s)}{\delta_E(s)} = \frac{2.072s + 1.257}{s^3 + 1.467s^2 + 1.666s} \tag{3}$$

$$\frac{\theta(s)}{\delta_E(s)} = \frac{1.161s - 0.351}{s^3 + 0.756s^2 + 0.857s} \tag{4}$$

In this study, type of the designed fuzzy controller is Sugeno. So there are 25 weight values. According to intuition method, list of linguistic rules is shown in Table 2. In Table 2 error and change of error membership functions are denoted with NVS (negative very small), NS (negative small), ZE (zero), PB (positive big) and PVB (positive very big). Units of values are given in degree but these values are converted to radian in coded program.

Table 2. Rule weight values.

δ_{E_c}			e			
		NVS	**NS**	**ZE**	**PB**	**PVB**
	NVS	-20	-17	-18	-12	0
$\dot{e}$	**NS**	-16	-15	-10	0	10
	ZE	-3	-8	0	17	15
	PB	-10	0	13	16	19
	PVB	0	14	20	19	20

In fuzzy PD controller, five triangular membership function forms for error and five triangular membership function forms for change of error are determined which are shown in Figure 4 and Figure 5. Borders of both function varies between ±3 rad.

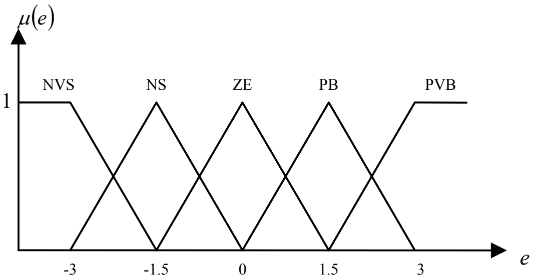


Figure 4. Error membership functions.

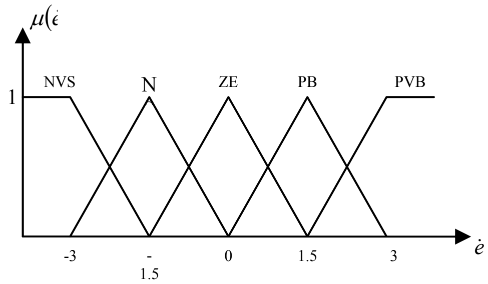
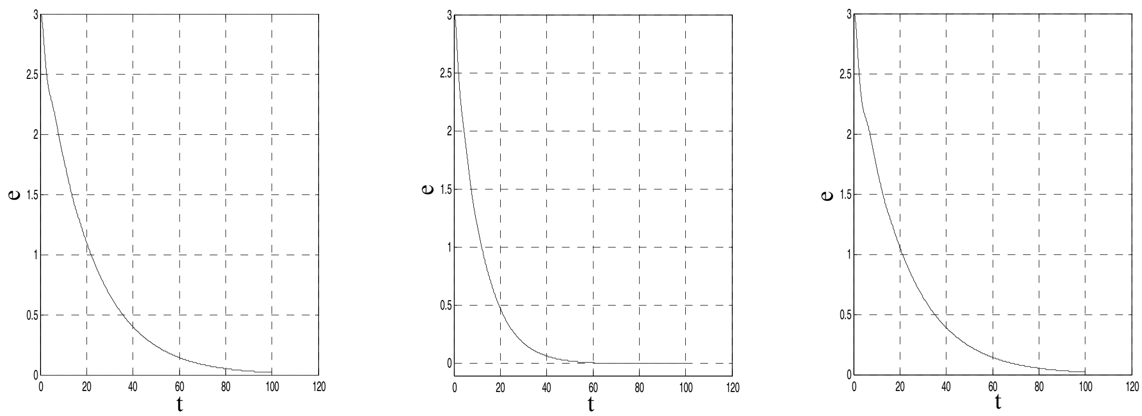


Figure 5. Change of error membership functions

In coded MATLAB 7.0 based program, fuzzy PD controller simulation results ($f(t,e), f(t,\theta)$) shown in the Figures 6-7 respectively are obtained in case of reaching 3 rad pitch angle from 0 rad in different flight conditions shown in Table 2 (first flight condition:6110 m, second flight condition:6100 m, third flight condition:12200 m). Time axes scaled where responses reach steady state values.

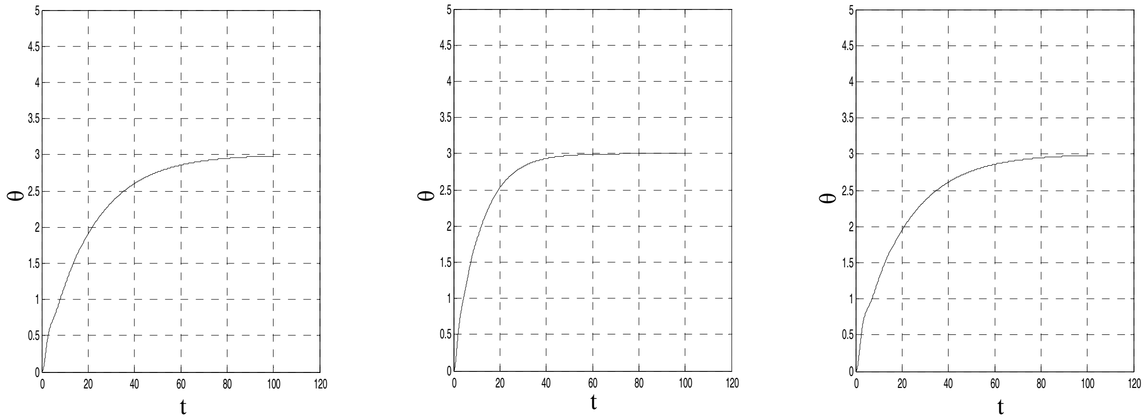


First flight condition

Second flight condition

Third flight condition

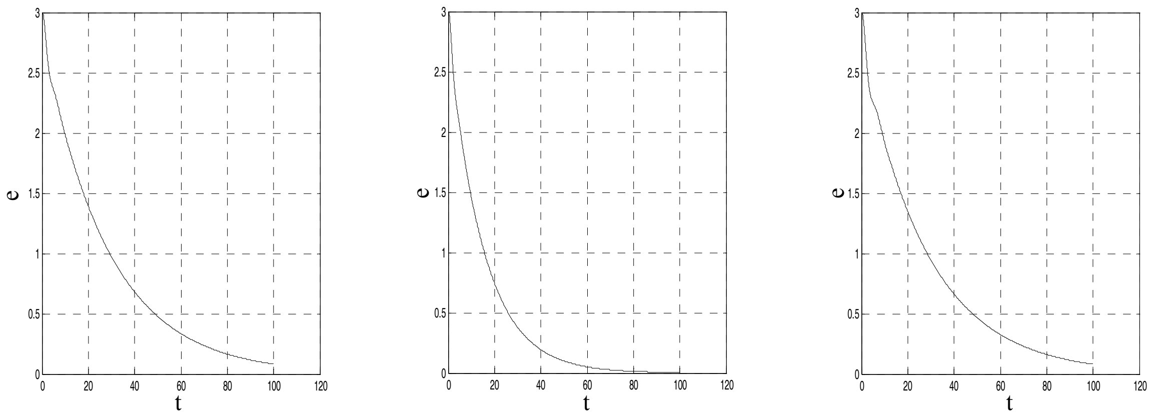
Figure 6. Time vs error.



First flight condition Second flight condition Third flight condition

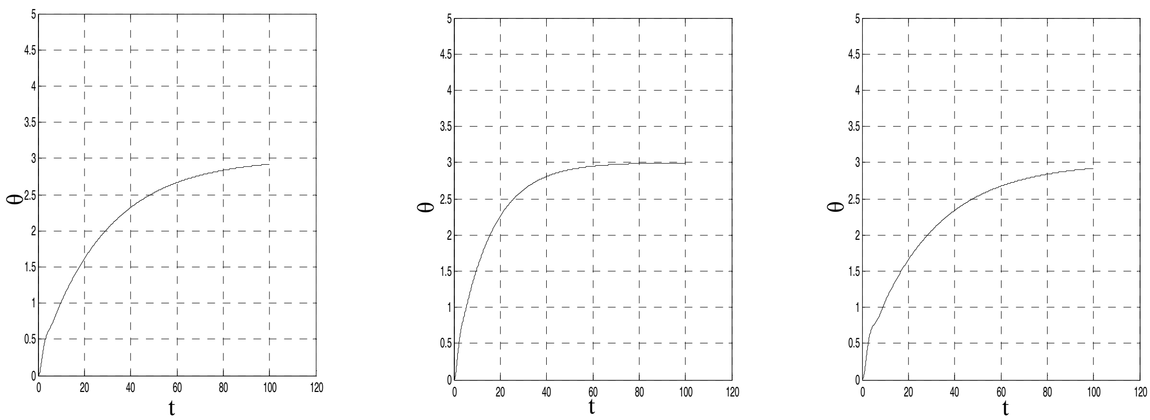
Figure 7. Time vs Pitch angle.

Classical PD Controller In classical PD controller K_p=0.1 and K_d=0.1 are chosen and the simulation results ($f(t,e), f(t,\theta)$) shown in the Figures 8-9 respectively are obtained in case of reaching 3 rad pitch angle from 0 rad.



First flight condition Second flight condition Third flight condition

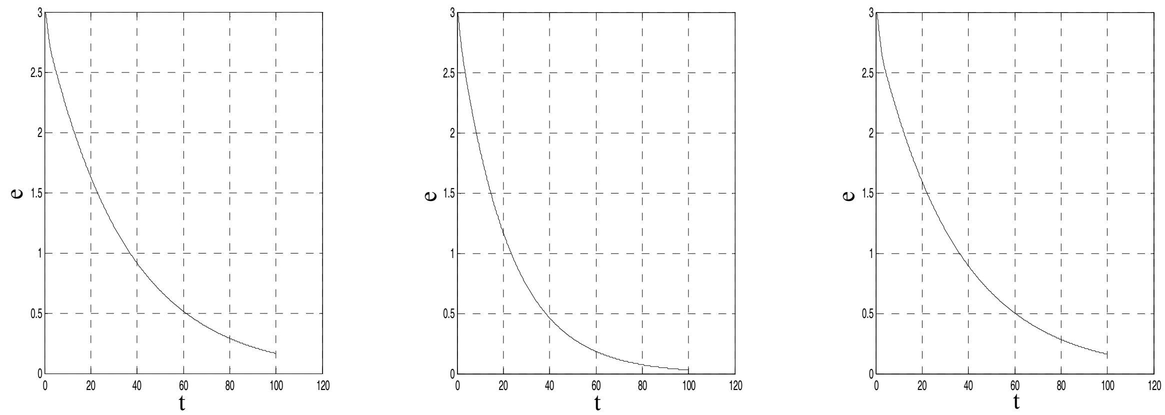
Figure 8. Time vs error.



First flight condition Second flight condition Third flight condition

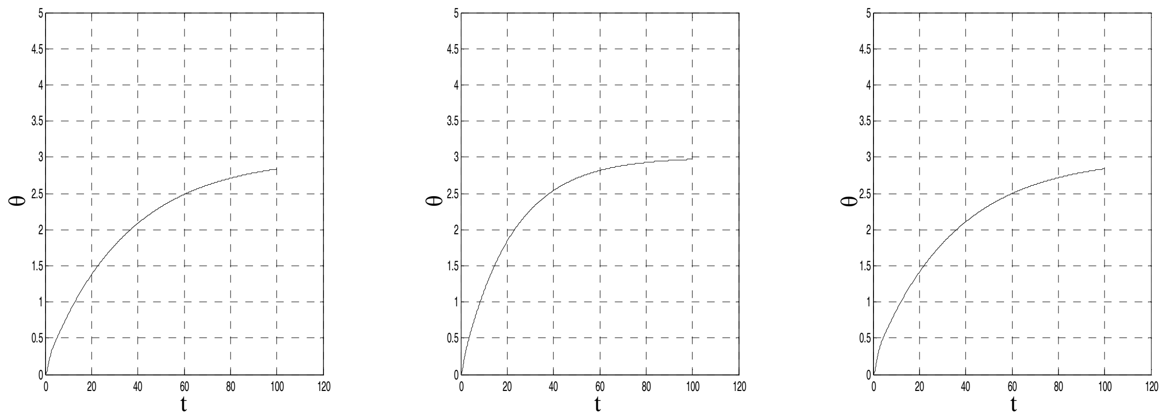
Figure 9. Time vs Pitch angle.

As shown in Figures 8-9, settling time is long and the response is not smooth. So it is pointed out that a classical PD controller designed for a specific flight condition doesn't provide same performance characteristics under another flight condition. Different K_p and K_d values are tested for the third flight condition and as shown in Fig. 10-11, better output responses obtained when K_p=0.1 and K_d=0.8 are chosen.



First flight condition — Second flight condition — Third flight condition

Figure 10. Time vs error.



First flight condition — Second flight condition — Third flight condition

Figure 11. Time vs pitch angle.

6. CONCLUSION

In this paper, classical PD controller and fuzzy PD controller are used respectively to control pitch angle which is a main control parameter of a flight control system. Designed controllers are applied to a very large, four-engine, passenger jet aircraft parameters to compare the results of classical PD and fuzzy PD controllers. Simulation results, as shown in figures, show that responses are quite similar in both cases. Furthermore when fuzzy PD controller applied, the settling time of responses is shorter than classical PD controller.

In classical controller, different K_p and K_d parameter values are tried to reach a smooth elevator angle deviation versus time. Also for the same aircraft, different flight condition parameters are analyzed to evaluate performance characteristics of controllers.

Using different methods such as intuitions, inference, rank ordering, angular fuzzy sets, neural networks, genetic algorithms, inductive reasoning, soft partitioning, meta rules and fuzzy statistics in developing membership functions and rule weights, performance of the fuzzy controller can be improved.

REFERENCES

[1] Kahvecioglu, A., "Flight control system design using multi-model approach and genetic algorithm", Phd. Thesis, University of Anadolu, Eskisehir, (2000).

[2] Savran, A., Tasaltin, R., Becerikli, Y., "Intelligent adaptive nonlinear flight control for a high

performance aircraft with neural networks", ***ISA Transactions***, 45(2): 225–247 (2006).

[3] Verbruggen, H.B., Zimmerman, H.J., Babuska, R. , "Fuzzy Algorithms for Control", ***Kluwer Academic Publishers***, Massachusetts, U.S.A, (1999).

[4] Robust Flight Control, A Design Challenge, Lecture Notes in Control and Information Sciences, Springer Berlin-Heidelberg, (224/1997).

[5] Aström, K.J., Wittenmark, B., "Adaptive control", Addison Wesley, ***Lund Institute of Technology***, U.S.A, (1989).

[6] Experience with the X-15 adaptive flight control system, http://www.nasa.gov/centers/dryden/pdf/87785main_H-618.pdf

[7] Enns, D.F., "Robustness of dynamic inversion vs. Mu synthesis: Lateral-directional flight control example", Proceedings of the AIAA Conference on Guidance, Navigation, and Control, Portland, Oregon, (1990).

[8] Hayes, J.R., Bates, D.G., "LFT-based uncertainty modeling and mu-analysis of the HIRM+RIDE flight control law", Proc. of the IEEE International Symposium on Computer Aided Control Systems Design (CACSD'02), Glasgow, 242–247, (2002).

[9] AI-Malki, M.F., Wei, G.D., "Advantages of using μ-synthesis for fault-tolerant flight control system", IFAC Fault Detection, ***Supervision and Safety of Technical Processes***, Beijing, Elsevier IFAC publication (2006).

[10] Nichols, R.A., Reichert R.T., "Gain Scheduling for H-Infinity Controllers: A Flight Control Example", ***IEEE Transactions on Control Systems Technology***, 1(2): 69-79 (1993).

[11] Kung, C.C., "Nonlinear H∞ robust control applied to F-16 aircraft with mass uncertainty using control surface inverse algorithm", ***Journal of the Franklin Institute***, 345: 851–876 (2008).

[12] Postlethwaitea, I., Prempain, E., Turkoglu, E., Turnera, M.C., Ellisb, K., Gubbelsb, A.W., "Design and flight testing of various H∞ controllers for the Bell 205 helicopter", ***Control Engineering Practice***, 13: 383–398, (2005).

[13] Ackermann, J., "Multi-Model Approaches to Robust Control System Design", Lecture Notes in Control and Information Science, ***Springer Verlag*** ,70 (1985).

[14] Magni, J.F., "Multimodel eigenstructure assignment in flight control design", ***Aerospace Science and Technology Elseiver Science***, 3(3): 141-151 (1999).

[15] Li, Y., "Neuro-controller design for nonlinear Fighter aircraft maneuver using fully tuned RBF networks", ***Automatica***, 37: 1293-1301 (2001).

[16] Vijaya, K.M., "A direct adaptive neural command controller design for an unstable helicopter", ***Engineering Applications of Artificial Intelligence***, 22: 181–191 (2009).

[17] Savran, A., "Intelligent adaptive nonlinear flight control for a high performance aircraft with neural networks", ***ISA Transactions***, 45(2): 225–247 (2006).

[18] Wu, S.L., Chena, P.C., Hsu, C.H. , Chang, K.Y., "Gain-scheduled control of PVTOL aircraft dynamics with parameter-dependent disturbance", ***Journal of the Franklin Institute***, 345: 906–925 (2008).

[19] Yang, C.D., Luo, C.C, Shiu-Jeng, L., Chang, Y. H., "Applications of Genetic-Taguchi Algorithm in Flight Control Designs", ***Journal of Aerospace Engineering***, 18(4): 232-241 (2005).

[20] Fantinutto, R., Guglieri, G., Quagliotti, F.B., "Flight control system design and optimization with a genetic algorithm", ***Aerospace Science and Technology***, 9: 73–80 (2005).

[21] Jamshidi, M., Titli, A., Zadeh, L., Boverie, S., "Applications of fuzzy logic towards high machine intelligence quotient systems", ***Prentice Hall PTR***, New Jersey, (1997).

[22] Kantaa, A.F., Montavon, G., Planche, M.P., Coddet, C., "In-flight particle characteristics control by implementing a fuzzy logic controller", ***Surface & Coatings Technology***, 202: 4479–4482 (2008).

[23] Cordon, O., Gamide, F., Herrera, F. , Magdelen, H.L.,, "Ten Years of Genetic Fuzzy Systems Current Framework and New trends", ***Fuzzy Sets and Systems***, 141(1): 5-31 (2004).

[24] Sanchez, E., Shibata, T., Zadeh, L.A., "Genetic Algorithms and Fuzzy Logic Systems, Soft Computing Perspectives", ***World Scientific***, Singapore, (1997).

[25] Kim, M.S., "Fuzzy Controller Design with the Degree of Non-uniformity for the Scaled Active Steering Testbed in the Railway Vehicle", ***Wseas Transactions on Systems and Control***, 4(7): 306-315 (2009).

[26] Popescu, M.C., Petrisor, A., Drighiciu, A., "Fuzzy Control of the Position for the Piston of an Industrial Robot", ***12th Wseas International Conference on Systems***, Heraklion, Greece, 222-226 (2008).

[27] Susnea, I., Vasiliu, G., Filipescu, A., "Real-time, embedded fuzzy control of the Pioneer3-DX robot

for path following", ***12th Wseas International Conference on Systems***, Heraklion, Greece, 334-338 (2008).

[28] Kiyak, E., "Flight control applications with fuzzy logic method", MSc. Thesis, University of Anadolu, Eskisehir, (2003).

[29] Rotton, S.K., Brehm, T., Sandhu, G. S., "Analysis and Design of a Proportional Fuzzy Logic Controller", Department of Electrical Engineering Wright State University, Dayton, Ohio (2005).

[30] Livchitz, M., Abershitz, A., Soudak, U., "Development of an automated fuzzy-logic- based expert system for an unmanned landing", ***Fuzzy Sets and Systems***, 93(2): 145-159, (1998).

[31] Beringer, D. B., Applying Performance-Controlled Systems, Fuzzy Logic, and Fly-By-Wire Controls to General Aviation, Civil Aerospace Medical Institute Federal Aviation Administration Oklahoma City, 2002, http://www.hf.faa.gov/docs/508/docs/cami/0207.pdf

[32] Işık, Y., Kahvecioğlu, A., Korul, H., "Bir uçağın yunuslama açısı kontrolünde bulanık PD denetleyici performansının incelenmesi", Kayseri VI. Havacılık Sempozyumu, Nevşehir, Türkiye, 434-438 (2006),

[33] Topuz, V., "Fuzzy genetic process control", PhD. Thesis, University of Marmara, Istanbul, (2002).

[34] Ross, T.J., "Fuzzy Logic with engineering applications", ***McGraw-Hill***, U.S.A., (1995).

[35] Dubey, M., Mastorakis, N.E., "Tunning of Fuzzy Logic Power System Stabilizers using Genetic Algorithm in Multimachine Power System", ***Wseas Transactions on Power Systems***, 4(3): 105-114 (2009).

[36] McLean, D., "Automatic Flight Control Systems", ***Prentice Hall***, New York, U.S.A, (1990).