Pitch Rate Damping of an Aircraft by Fuzzy and Classical PD Controller

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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. FLC's 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 fuzzy and classical PD controller for the pitch rate damping system is analyzed and the results for a two-engined jet fighter aircraft are evaluated in a MATLAB coded program.

Key-Words: - Aircraft, flight control, pitch rate, classical PD control, fuzzy and fuzzy PD control.

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 in 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 MIMO (Multi-Input Multi-Output) 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].

"Fly by Wire" allows the pilot to control the aircraft states, as an alternative to the conventional direct control of the engines and control surfaces. It gives new opportunities to increase the overall level of safety through the flexibility offered by the control laws. For example, error-tolerant control laws provide flight envelope protection, and help the pilot to recover from unusual attitudes and successfully achieve critical manoeuvres. The use of modern FCS can be beneficial from an economic point of view. For certain types of aircraft, fuel consumption can be reduced by allowing relaxed static stability, counteracted by the application of active control. Another advantage related to fuel consumption is that for large aircraft the weight of Fly by Wire systems is smaller than that of conventional systems. Most importantly, modern FCS has contributed to improved dynamical behavior. For civil aircraft, performance can be increased by application of active systems, for example to provide gust suppression and auto-trimming, in order to achieve improved ride quality. The performance benefits achieved have the penalty of tremendous costs involved in the development of an advanced FCS [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 sytem, control of heating, ventilating and air conditioning systems, hi-tech filming devices (photo and recording cameras), washing machines, micro wave 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].

2 Fuzzy PD Control

Fuzzy logic is a method of rule-based decision making used for expert systems and process control that emulates the rule-of-thumb thought process used by human beings. The basis of fuzzy logic is fuzzy set theory which was developed by Lotfi Zadeh in the 1960s. Defining a fuzzy controller, process control can be implemented quickly and easily. Many such systems are difficult or impossible to model mathematically, which is required for the design of most traditional control algorithms. In addition, many processes that might or might not be modeled mathematically are too complex or nonlinear to be controlled with traditional strategies. However, if a control strategy can be described qualitatively by an expert, fuzzy logic can be used to define a controller that emulates the heuristic rule-of-thumb strategies of the expert. In other words, fuzzy controllers allows imprecise and qualitative information to be expressed in a quantitative manner. Therefore, fuzzy logic can be used to control a process that a human can control manually with expertise gained from experience. The linguistic control rules that a human expert can describe in an intuitive and general manner can be directly translated to a rule base for a fuzzy logic controller. [25,32]

Fuzzy Logic Controllers 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 controller, error and change of error knowledges are used in fuzzification and rule base modules.

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. Determining of appropriate knowledge base is a rather difficult process. For most applications, personal intuition, logic and experiences are used to constitute knowledge base.

At this point, it is necessary to have adequate and proper knowledge. However, in some situations, it is impossible to get enough knowledge. At this time, it can be based on some algorithmic or logical operations. The following list provides some of the methods described in the literature to assign membership values or functions to fuzzy variables. Intuitions, inference, rank ordering, angular fuzzy sets, neural networks, genetic algorithms, inductive reasoning, soft partitioning, meta rules and fuzzy statistics.

Membership functions of error and change of error are shown in Figure 2 and 3, respectively. Membership functions may be selected as a triangular, trapezoid or other appropriate forms. Base values of these forms must be intersected with each other. The reason of selecting triangular form is that these membership functions can be identified with minimum parameters. These parameters are the projection of bases and top points of triangle on the e and $\dot{e}$ axes. 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.

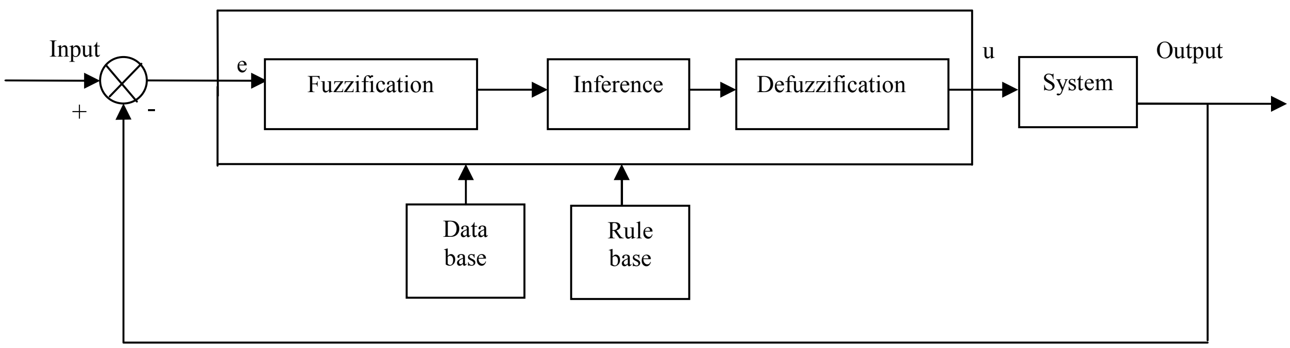

Fig. 1 Closed loop fuzzy controller

Therefore, a compromise between the quality of control and computational time is needed to choose the number of variables. In Table 1, for Sugeno type controller, as the A_1, A_2………..A_n values are real numbers and shows rule weight values, error and change of error membership functions are denoted with, C_2,….C_n, D_1, D_2,….D_n. According the table, number of rules will be n^2 [28,33,34,35]. These rules are;

If = C_1 and = D_1 then = A_1
If = C_1 and = D_2 then = A_{n+1}

If = C_n and = D_n then = A_n^2

Table. 1 Rule weight table

u	e				
$\dot{e}$		C_1	C_2	…	C_n
	D_1	A_1	A_2	…	A_n
	D_2	A_{n+1}	A_{n+2}	…	A_{2n}
	…	…	…	…	…
	…	…	…	…	…
	D_n	…	…	…	A_n^2

3 Classical PD control

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 4 the controller output is equal to

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

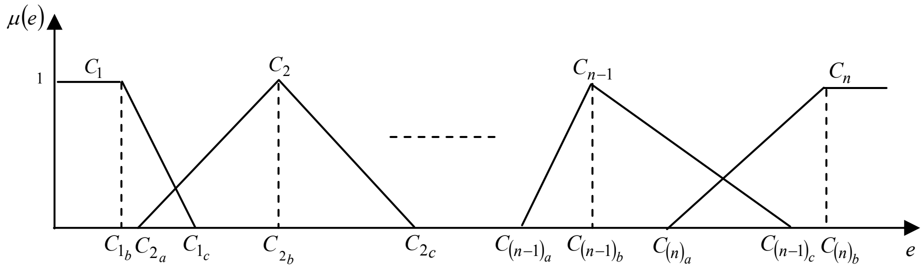

Fig. 2 Error membership functions

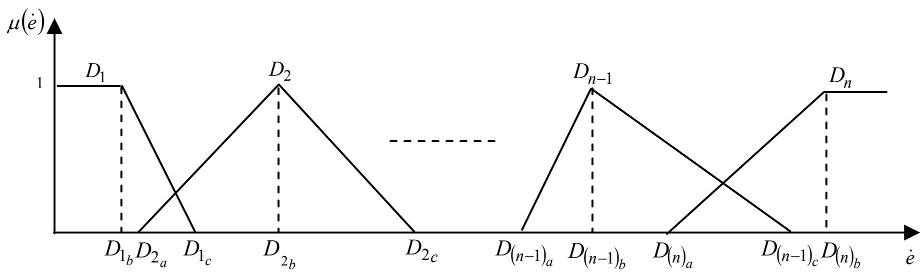

Fig. 3 Change of error membership functions

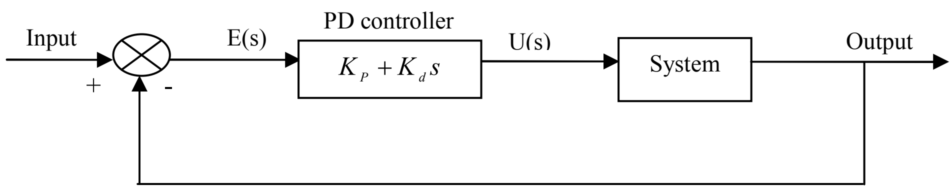

Fig. 4 Classical PD Control system

Classical Control methods are also rigorously analysable, 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 optimisation of the controller depends on the knowledge and intuition of the designer and not a computer algorithm [4].

4 Aircraft Pitch Rate Damping System

Aircraft pitch rate control system shown in Figure 5. It can be seen from the Figure 5 that, elevator angle (δ_{Ec})(deltaec) at the output of the controller is calculated such that the output of system pitch rate (q) follows the reference pitch rate value (qd). The input of actuator 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, the design of fuzzy and classical PD controller for the pitch rate damping system is analyzed and the results for a two-engined jet fighter aircraft are evaluated in a MATLAB coded program.

5 Fuzzy PD Controller Application and Simulation Results

The proposed fuzzy PD controller applied to a two-engined jet fighter aircraft data. The flight parameters of selected aircraft are height 10650 m, Mach no 1.2, the dynamic pressure ($\overline{q}$) 24090 Nm^{-2}. Also in Figure 5, actuator dynamic is 0.01745, sensor dynamic is 5.73, and aircraft dynamic for the above flight condition is given in Equation 1 [36].

$$\frac{q(s)}{\delta_E(s)} = \frac{-12.73(1+s1.618)}{s^2+1.76s+29.49} \qquad (1)$$

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, for Sugeno type controller, as the A_1, A_2..........A_n values are real numbers and shows rule weight values, 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). According the table, number of rules will be 25.

Table. 2 Rule weight values

δ_{Ec}		e				
		NVS	**NS**	**ZE**	**PB**	**PVB**
$\dot{e}$	**NVS**	2	1.7	1.8	1.2	0
	NS	1.6	1.5	1	0	-1
	ZE	0.3	0.8	0	-1.7	-1.5
	PB	1	0	-1.3	-1.6	-1.9
	PVB	0	-1.4	-2	-1.9	-2

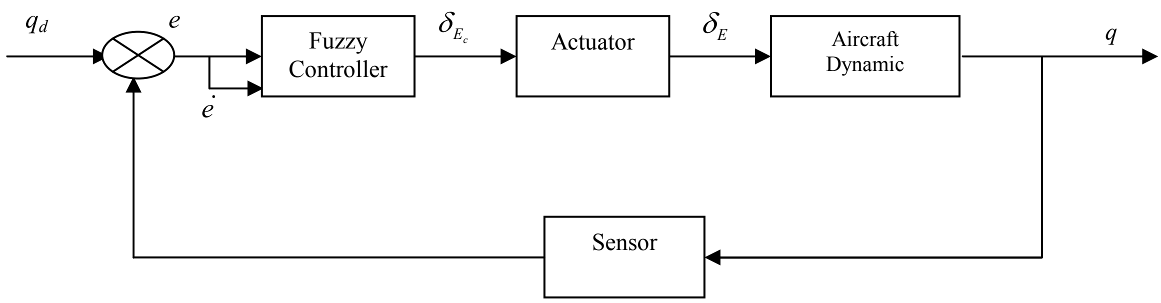

Fig. 5 Pitch rate damping system

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 6 and Figure 7. Borders of both function varies between ±5 rad/sn.

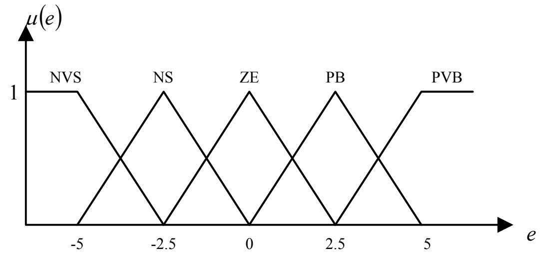

Fig.6 Error membership functions

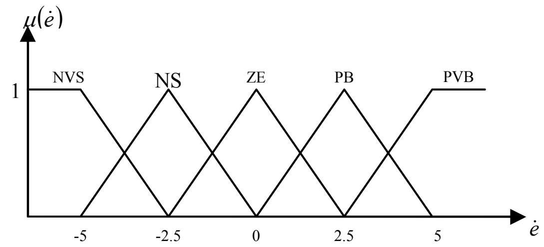

Fig.7 Change of error membership functions

In coded MATLAB 7.0 based program, in fuzzy PD controller simulation results ($f(t,e), f(t,\delta_{Ec}(deltaec)), f(t,q), f(t,\dot{q})$) shown in the Figures 8-15 respectively are obtained in case of ±1 rad/sn pitch rate change.

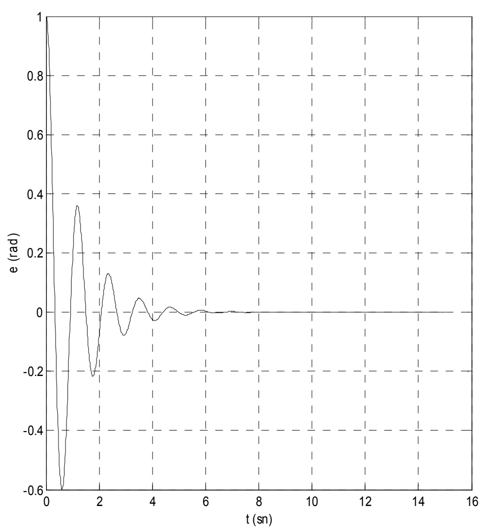

Fig. 8 time vs. error

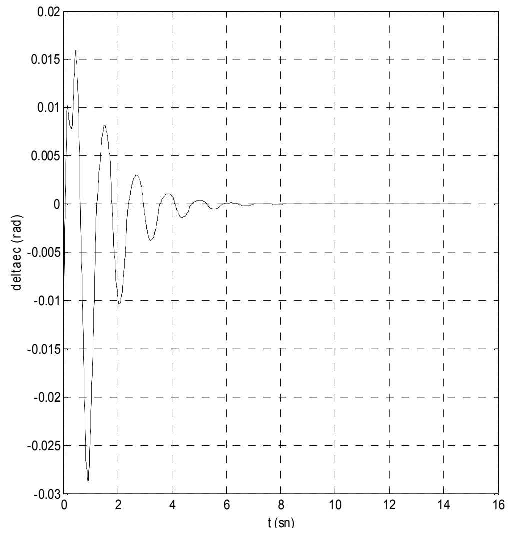

Fig. 9 time vs. elevator angle

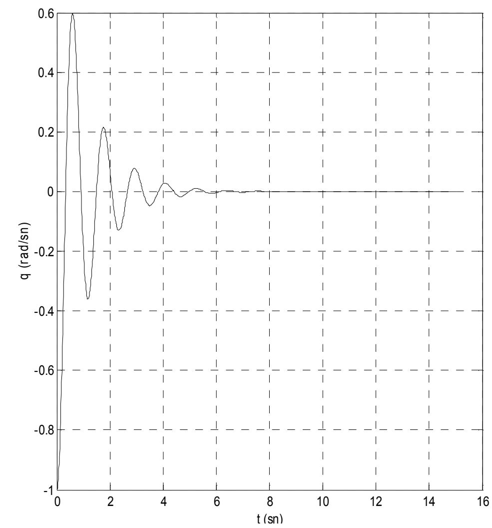

Fig. 10 time vs. pitch rate

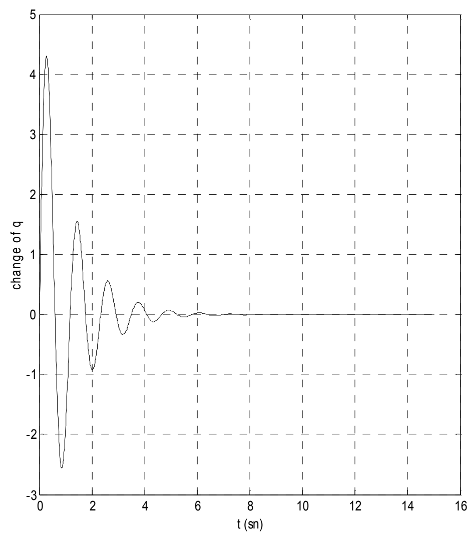

Fig. 11 time vs. change of pitch rate

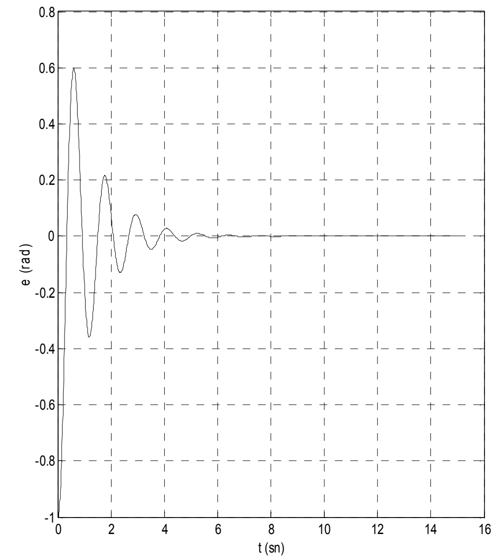

Fig. 12 time vs. error

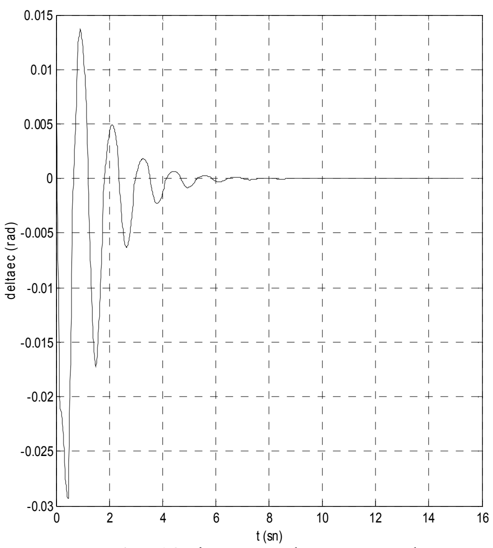

Fig. 13 time vs. elevator angle

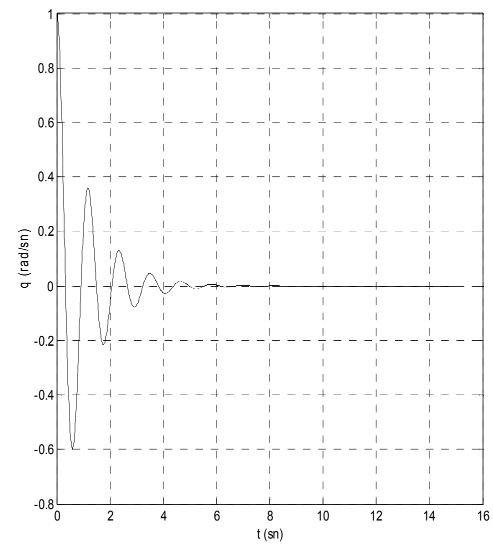

Fig. 14 time vs. pitch rate

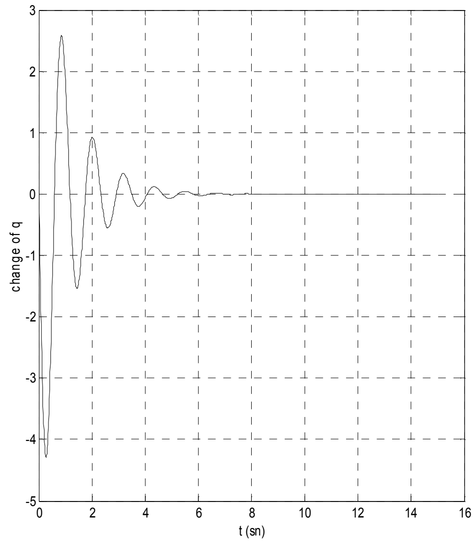

Fig. 15 time vs. Pitch rate change

As shown in Figures 8-15, responses obtained with a fuzzy PD controller for the pitch rate have some oscillation, overshoot is not short but rise times and settling times of responses are also short. By changing the rule weights in rule table and borders of membership functions, it is possible to get different responses.

4 Classical PD Controller Application and Simulation Results

In classical PD controller K_p=-0.0008 and K_d=-0.0005 are chosen and the simulation results ($f(t,e), f(t,\delta_{Ec}(deltaec)), f(t,q), f(t,\dot{q})$) shown in the Figures 16-23 respectively are obtained in case of ±1 rad/sn pitch rate change.

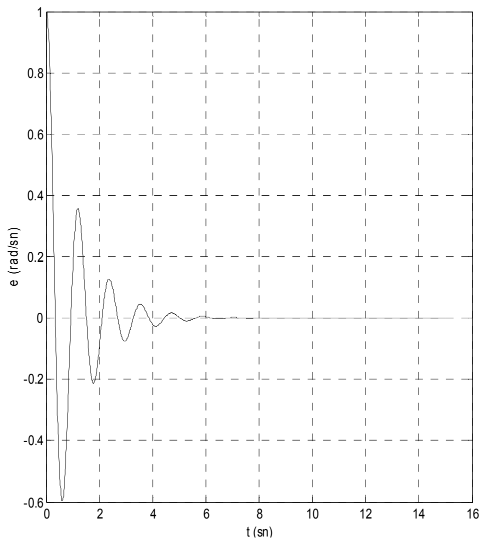

Fig. 16 time vs. error

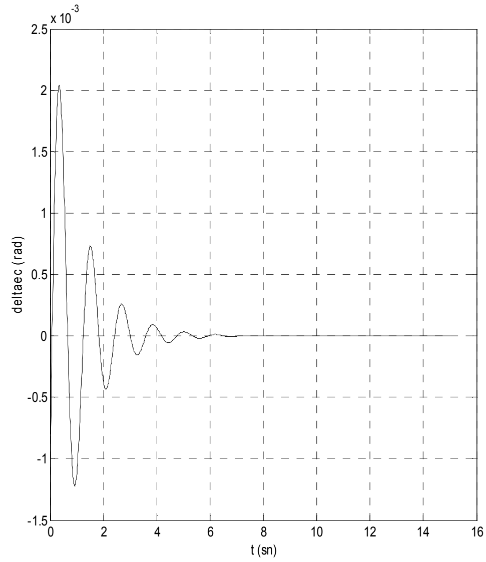

Fig. 17 time vs. elevator angle

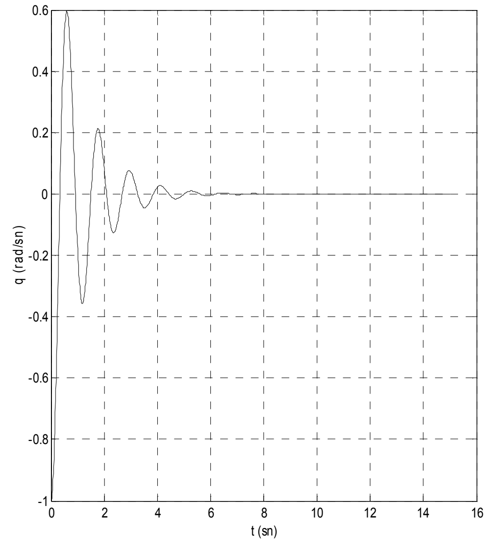

Fig. 18 time vs. pitch rate

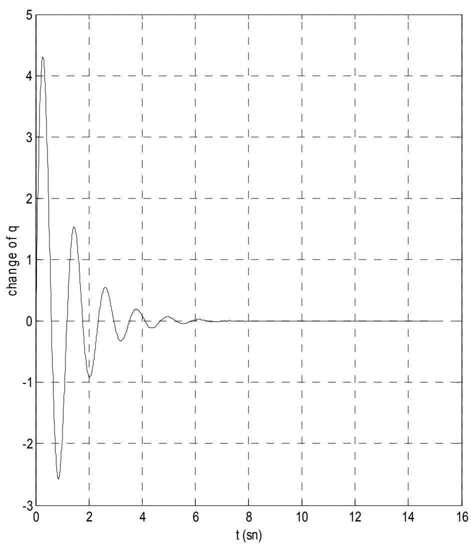

Fig. 19 time vs. change of pitch rate

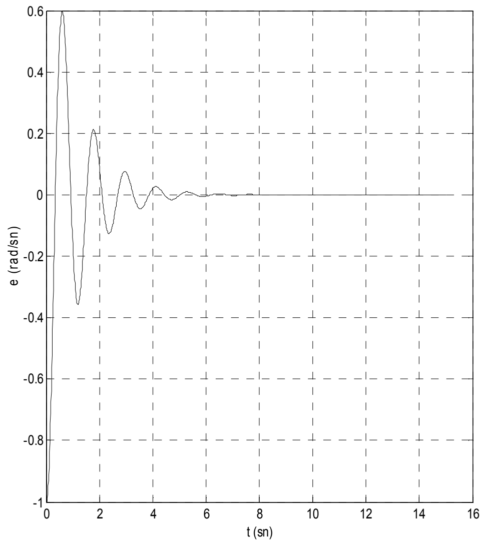

Fig. 20 time vs. error

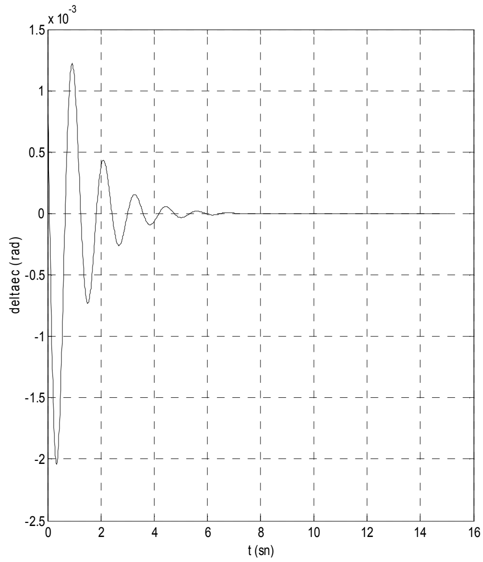

Fig. 21 time vs. elevator angle

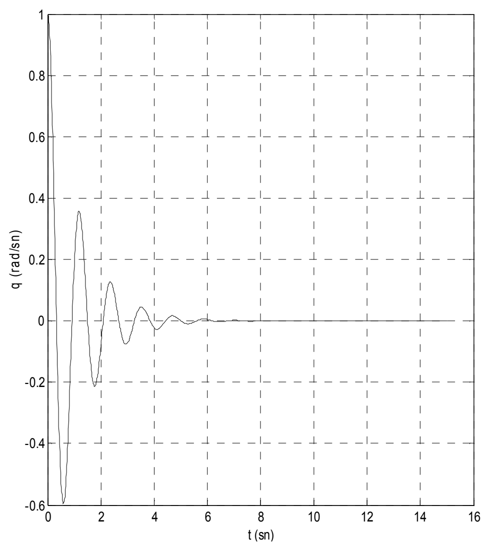

Fig. 22 time vs. pitch rate

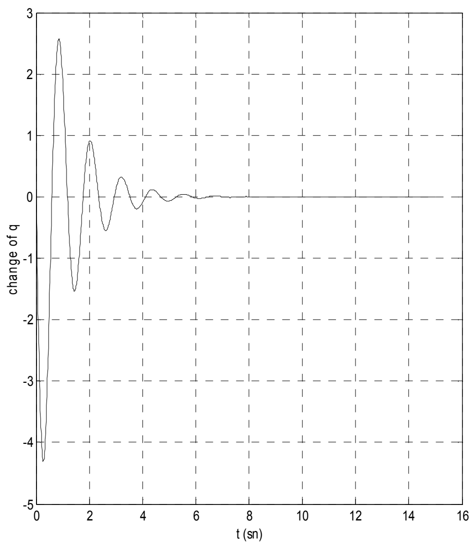

Fig. 23 time vs. change of pitch rate

5 Conclusion

In this paper, the design of fuzzy and classical PD controller for the aircraft pitch rate damping system is analyzed and the results for an aircraft are evaluated in a MATLAB coded program. As shown in simulation results, responses obtained with fuzzy and classical PD controller are a good bit smooth and quite similar in both cases. Furthermore when fuzzy PD controller applied, the settling time of responses is shorter than classical PD controller and overshoot is smaller. 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. Using different methods (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.

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