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Fuzzy Logic Controlled Landing of a Boeing 747

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Abstract—**In this research, the simulation of the landing and descent of a Boeing 747 in its linearized landing configuration model are controlled using fuzzy logic controllers (FLCs). The rule bases for the FLCs are functions of the linearized model's inputs, the Boeing 747's vertical velocity and altitude. The crisp FLC outputs, as determined by the centroid method, are the elevator and throttle deflections. Different types of membership functions are tested with the FLCs to determine the efficacy of the tested membership types for the given application for landing an aircraft. Future work will involve comparing the FLCs to more conventional controllers.**

I. INTRODUCTION

FUZZY logic was first developed by Lotfi Zadeh in the 1960s and 1970s. In 1965 Zadeh first introduced fuzzy sets [1]. He later continued his work with fuzzy sets with linguistic variables in [2]-[4]. Fuzzy logic and sets differ from classical two valued logic, "on" and "off," in that fuzzy sets utilize varying degrees or gray shades of membership. "By construction, fuzzy logic has a much higher level of generality than bivalent logic. It is the generality of fuzzy logic that underlies much of what fuzzy logic has to offer."[5] This allows for highly complex systems or unknown systems to be controlled using natural language computation or a series of linguistic rules that describe how the system operates and is controlled, for instance by an experienced operator.[5] Fuzzy control can then successfully be implemented on partially known or complex systems quickly and without developing complex controllers. A typical feedback control system using a fuzzy logic controller is shown in Fig. 1, where r is the external input, u is the plant input, y is the output, FLC is the fuzzy logic controller, and $G(s)$ is the plant.

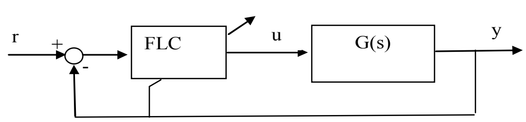

Fig. 1. Fuzzy logic control system

Intelligent control using artificial neural networks (ANNs) and fuzzy logic has been extensively studied in various applications such as autopilots [6]-[14], process control [15]-[18], robotics [19]-[24], and modeling [25]-[26]. In this research, the simulation of the landing and descent of a Boeing 747 in its linearized landing configuration model are controlled using FLCs. In addition, ANNs have been used in intelligent automatic landing control. Juang and Cheng developed four ANN controllers to land a simulated aircraft in the presence of turbulence [6]. The authors Juang and Chio next developed a fuzzy neural controller (FNC) for a commercial aircraft linearized inverse model [7]. The FNC was tested with varying turbulence conditions as well. The FNCs outperformed the ANN controllers developed in [6]. Juang, Chin, and Chio studied FNCs where the gains were determined by genetic algorithms [8]. Another area entails system or model identification. Failer and Schreck used neural networks to develop nonlinear reference models of aircraft [25]. Putro *et al.* employed neural networks for identification of rotorcraft unmanned aerial vehicles [26].

Small model planes and UAVs have been controlled using fuzzy controllers [9]-[11]. For instance, Doitsidis *et al.* developed altitude as well as latitude-longitude FLCs [11]. Other examples of automatic control of air vehicles include [13], [14], [27], [28]. Liguni *et al.* developed a controller utilizing a nonlinear mapping to represent the human expert responses for a simplified aircraft model [13]. On the other hand in [27], the authors use H_∞ control with stable inversion to control the simulated landing of a linearized model for a Boeing 747. Tao, Chen, and Joshi study adaptive controllers for actuator failures [28]. In this research, the simulation of the landing and descent of a Boeing 747 in its linearized landing configuration model are controlled using FLCs. Different types of membership functions are tested with the FLCs to determine the efficacy of the tested membership types for the given application for landing an aircraft. In addition, the FLC is tested for partial elevator actuator failure.

The rest of the paper is organized as follows: Section II. Fuzzy Logic Landing Control System, Section III. Landing Simulation Results, and Section IV. Discussion and Conclusions.

II. FUZZY LOGIC LANDING CONTROL SYSTEM

A. Boeing 747 Linearized Model

In this work, the simulation of the landing and descent for a 747 using FLCs is described. Much research exists in the literature utilizing a linearized model for the 747. In particular, this work investigates the control of the linearized steady state equations for the Boeing 747 longitudinal motions in the landing configuration that are as follows from [29], [30].

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$$\begin{bmatrix} \dot{u} \\ \dot{w} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} -0.021 & 0.122 & 0.000 & -0.322 \\ -0.209 & -0.530 & 2.210 & 0.000 \\ 0.017 & -0.164 & -0.412 & 0.000 \\ 0.000 & 0.000 & 1.000 & 0.000 \end{bmatrix} \begin{bmatrix} u-u_w \\ w-w_w \\ q \\ \theta \end{bmatrix} + \begin{bmatrix} 0.010 & 1.0 \\ -0.064 & -0.044 \\ -0.378 & 0.544 \\ 0.000 & 0.000 \end{bmatrix} \begin{bmatrix} \delta_{ELE} \\ \delta_{THR} \end{bmatrix} \quad (1)$$

where
u = velocity perturbation (forward, x_B axis),
w = velocity perturbation (z_B axis),
q = pitch rate,
θ = pitch angle,
u_w and w_w = wind velocity perturbation (x_B and z_B axis components),
δ_{ELE} = elevator deflection,
δ_{THR} = throttle deflection,
$\dot{u}, \dot{w}, \dot{q}, \dot{\theta}$ = first derivatives,
and the units are in feet, seconds, and centiradians.

Given a reference starting altitude *h* and displacement *x*, changes in altitude *h* and displacement *x* can be calculated using

$$\begin{bmatrix} \dot{x} \\ \dot{h} \end{bmatrix} = \begin{matrix} (u+V_o)\cos\theta + w\sin\theta \\ (u+V_o)\sin\theta - w\cos\theta \end{matrix} \quad (2)$$

where V_o = 221 ft/s [29], [30]. Fig. 2 depicts the above relationships.

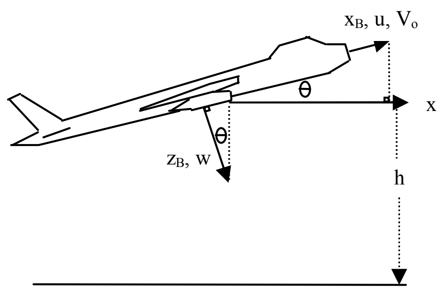

Fig. 2. Boeing 747 Parameters [29], [30]

B. *Fuzzy Logic Control*

A general fuzzy logic system is depicted in Fig. 3. Fuzzy systems fuzzify the crisp inputs. Membership functions are utilized to determine how much each input belongs to each membership set. The fuzzy inputs are then combined using a fuzzy operation, such as OR or max, according to a rule base. The rule base is a series of IF condition THEN action statements describing, in linguistic terms, the control. Using the output membership functions, the output of each rule is fuzzified using a fuzzy operation, such as AND or min.

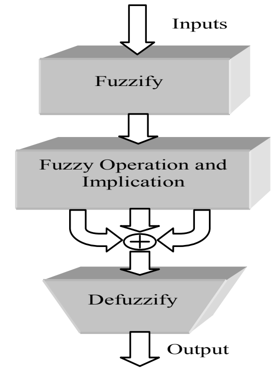

Fig. 3. Fuzzy logic system

These fuzzy output sets are then combined using a fuzzy operation, such as OR or max. This combined fuzzy output set is then defuzzified into a crisp output. A common method used in defuzzification is to use the centroid method [31]-[33].

Membership functions and rule bases can be tuned by using numerous methods such as neural networks [34], genetic algorithms, evolutionary strategy [35], expert knowledge/ systems, Kalman filters [36], or numerical optimization [37]. In this research, the fuzzy logic membership functions for the FLC and its associated rule base were determined *heuristically*. The input membership functions used in this work are triangular and trapezoidal for the two cases. The input membership functions are given in Fig. 4-5. Both cases have been scaled between 0 and 1.

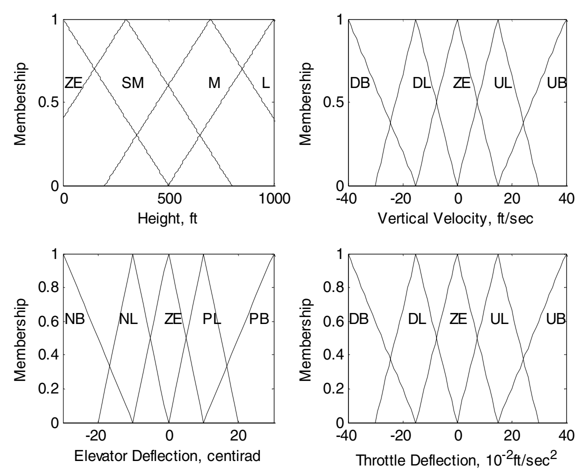

Fig. 4. Triangle membership functions

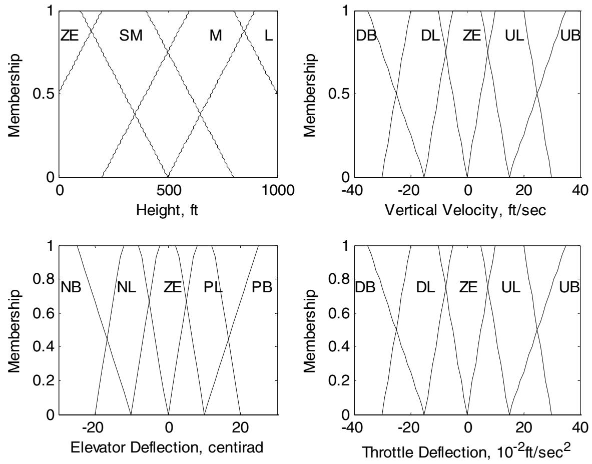

Fig. 5. Trapezoid membership functions

where the vertical velocity ranges are

UB = Up Big	UL = Up Little
DB = Down Big	DL = Down Little
ZE = Zero,	

the height input ranges are

NZ = Near Zero	SM = Small
MD = Medium	LG = Large,

the elevator deflection outputs are

ZE = Zero	PB = Positive Big
PL = Positive Little	NB = Negative Big
NL = Negative Little, and	

the throttle deflection outputs are

ZE = Zero	UB = Up Big
UL = Up Little	DB = Down Big
DL = Down Little.	

The rules bases are given in the following Tables I, II. The same designations for the ranges as defined above are used. Specifically, the elevator deflection rule base is given in Table I while the throttle deflection rule base is shown in Table II.

Table. I. Rule Base for Elevator Deflection

Velocity (Vert.) \ Height	NZ	SM	MD	LG
UB	PB	PB	PB	PB
UL	PL	PL	PL	PB
ZE	ZE	PL	PL	PL
DL	NL	ZE	ZE	ZE
DB	ZE	ZE	ZE	ZE

Table. II. Rule Base for Throttle Deflection

Velocity (Vert.) \ Height	NZ	SM	MD	LG
UB	DL	DL	DB	DB
UL	ZE	DL	DB	DB
ZE	ZE	ZE	DL	DB
DL	ZE	UL	ZE	DL
DB	UL	UB	UL	ZE

To illustrate how to read Table I or II, the rule bases can also be written in the form of IF –THEN statements. For example, the first two entries in Table 1 are

1. If (height is Near Zero) and (Vertical Velocity is Up Big) then (Elevator Deflection is Pos Big)
2. If (height is Near Zero) and (Vertical Velocity is Up Little) then (Elevator Deflection is Pos Little).

III. Landing Simulation Results

The fuzzy logic landing control system described in Section II was utilized in the landing simulations. The initial velocity was given as 221 ft/s for the model. The first case utilized triangular membership functions for the input and output memberships as depicted in Fig. 4 for the FLC. The inputs were fuzzified and combined according to the rule base given in Tables I and II. The centroid method was employed to defuzzify the output for both the throttle and elevator deflections. Figs. 6 and 7 are the fuzzy logic control surfaces for the elevator and throttle deflections obtained for the simulation model. As can be seen in Fig. 8, the simulated Boeing 747 was started at an altitude of 1400 ft. The plane descended and landed in 8 minutes 5 seconds in a distance of 107,500 ft with a final vertical velocity of -5 ft/s and a pitch angle θ of 0 radians to slightly more than -0.0215 radians. Fig. 9 shows the throttle and elevator deflections generated by the FLC to control the flight parameters. The case was simulated for different starting altitudes with similar results. With an initial altitude of 1000 ft, the plane descended and landed in 6 minutes 50 seconds in a distance of 90,600 ft with a final vertical velocity of -5 ft/s and a pitch angle of 0 radians to slightly more than -0.0215 radians. The controller will not adequately control the simulated Boeing 747 if the initial altitude is well above the membership input limits. There are oscillations in the pitch and velocity. In Fig. 8, the oscillatory pitch angles and vertical velocities are small. These oscillations may be due to the fuzzy logic controller overshooting the necessary control input to achieve a smooth response. This can be alleviated by slowing down the fuzzy controller response or by modifying the membership functions. The oscillations seen in Figs. 9-11 are a result of the controller reacting to the oscillations in the pitch and velocity previously mentioned.

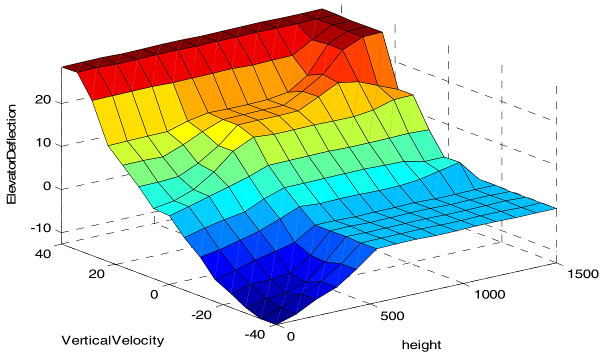

Fig.6. Elevator deflection control surface for the triangular membership functions case

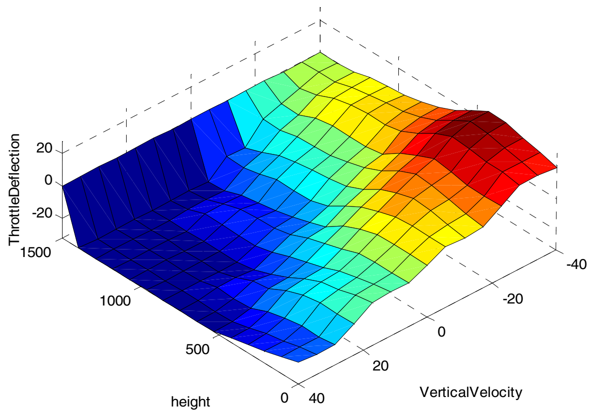

Fig.7. Throttle deflection control surface for the triangular membership functions case

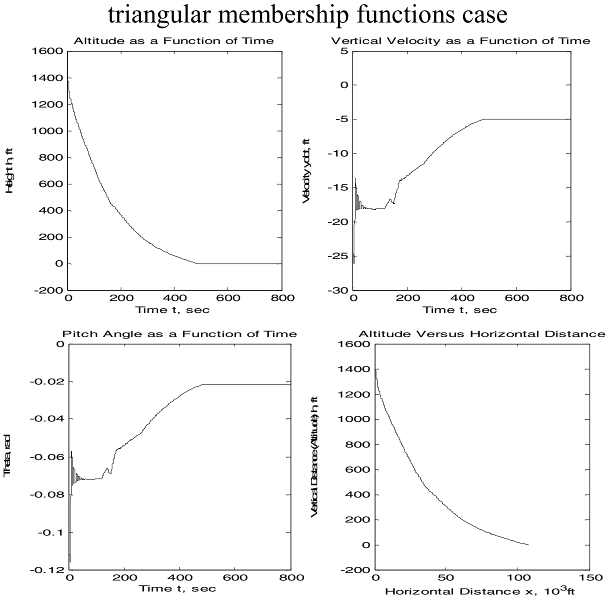

Fig.8. Altitude, vertical velocity, and pitch angle

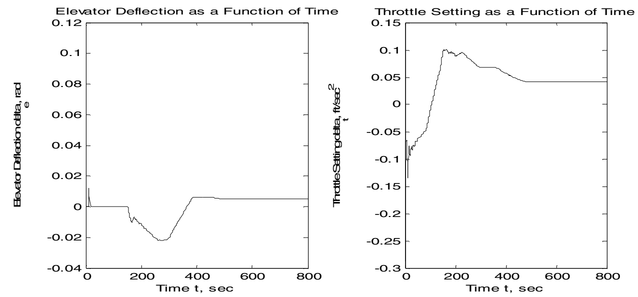

Fig 9. Crisp elevator and throttle deflections, initial altitude 1400 ft

With an initial altitude of 500 ft, the plane descended and landed in 4 minutes 45 seconds in a distance of less than 65,000 ft with a final vertical velocity of slightly less than -5 ft/s and a pitch angle of 0 to -0.0215 radians. As can be seen in Figs. 10 and 11, the output control deflections are more oscillatory initially for both of these lower initial altitude test cases. The altitude, vertical velocity, and pitch angle graphs for these two cases were very similar to the case shown in Fig. 8, and therefore have been omitted.

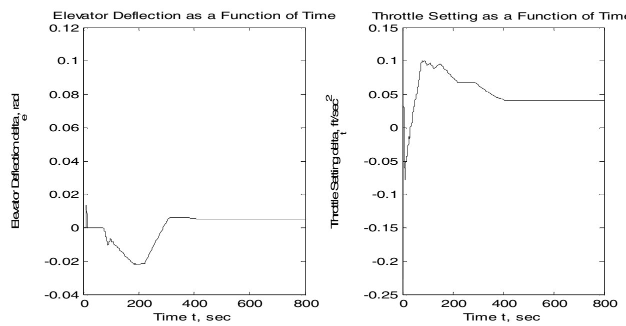

Fig 10. Crisp elevator and throttle deflections, initial altitude 1000 ft

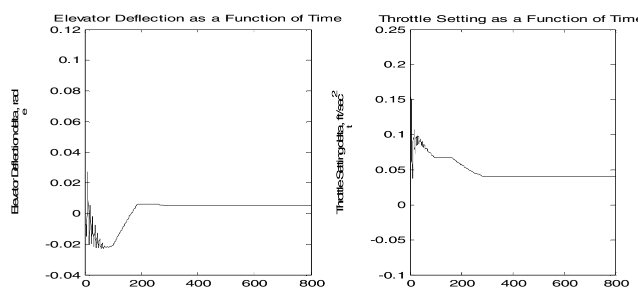

Fig 11. Crisp elevator and throttle deflections, initial altitude 500 ft

The second tested case utilized trapezoidal membership functions for the input and output memberships as depicted in Fig. 5 for the FLC. The inputs were fuzzified and combined according to the rule base given in Tables I and II. The centroid method was employed to defuzzify the output for both the throttle and elevator deflections. Figs. 12 and 13 are the fuzzy logic control surfaces for the elevator and throttle deflections for the case utilizing the trapezoidal membership functions. The simulated Boeing 747 was again started at an altitude of 1400 ft. The plane descended and landed in 8 minutes 48 seconds in a distance of 117,000 ft with a final vertical velocity of -4.74 ft/s and a pitch angle of 0 radians to slightly more than -0.0205 radians as seen in Figs. 14. Fig. 15 shows the throttle and elevator deflections generated by the FLC to control the flight parameters. The case was simulated for different starting altitudes with similar results. With an initial altitude of 1000 ft, the plane descended and landed in 7 minutes 30 seconds in a distance of 100,000 ft with a final vertical velocity of -4.74 ft/s and a pitch angle of 0 radians to slightly more than -0.0205 radians.

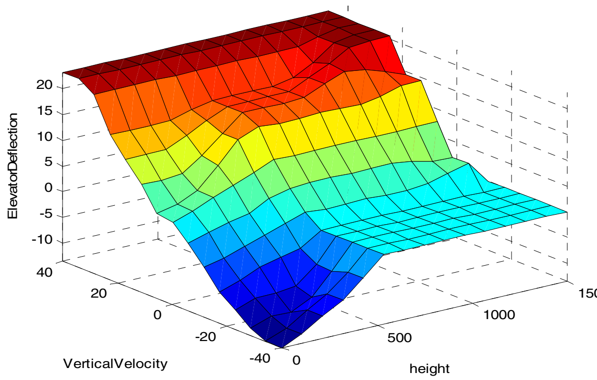

Fig.12. Elevator deflection control surface for the trapezoidal membership functions case

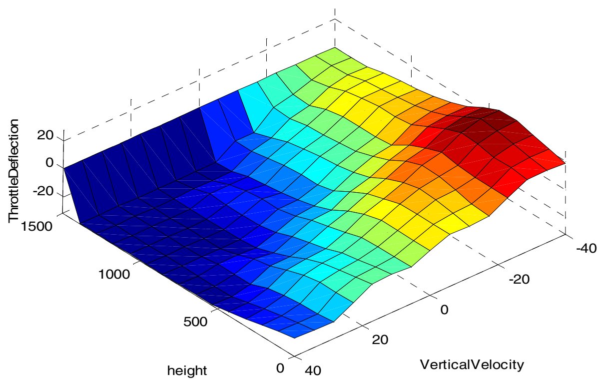

Fig.13. Throttle deflection control surface for the trapezoidal membership functions case

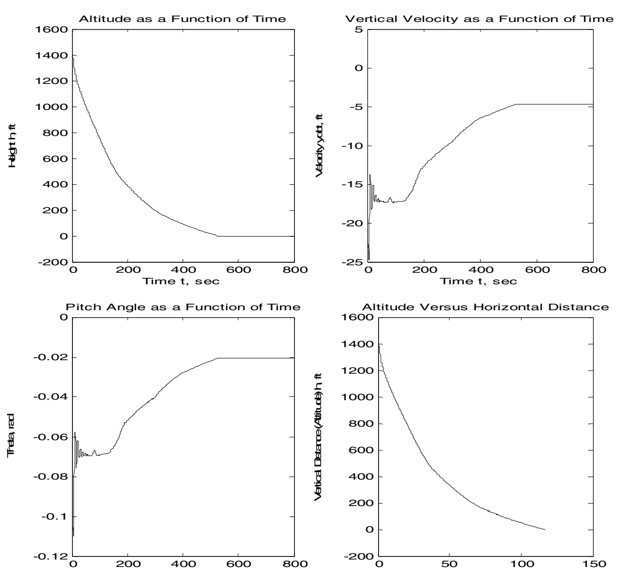

Fig.14. Altitude, vertical velocity, and pitch angle, for the trapezoidal membership functions case

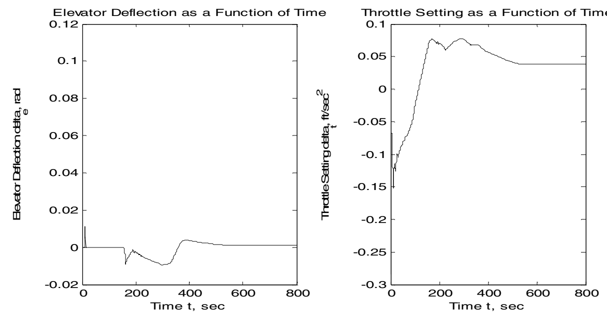

Fig 15. Crisp elevator and throttle deflections for trapezoidal membership functions case

With an initial altitude of 500 ft, the plane descended and landed in 4 minutes 45 seconds in a distance of less than 65,000 ft. The final vertical velocity was slightly less than -5 ft/s and the pitch angle was between 0 and -0.0215 radians. As can be seen in Fig. 16, the output control deflections are again more oscillatory initially for the lower initial altitude test case. The altitude, vertical velocity, and pitch angle graphs for these cases were again very similar to the case shown in Fig. 14, and therefore have been omitted. The oscillations in Figs. 14-16 in the pitch, velocity, elevator and throttle deflections are again a function of the FLC overshooting the control input required for an overdamped response. This underdamped response can be alleviated by slowing down the fuzzy controller response or by modifying the membership functions.

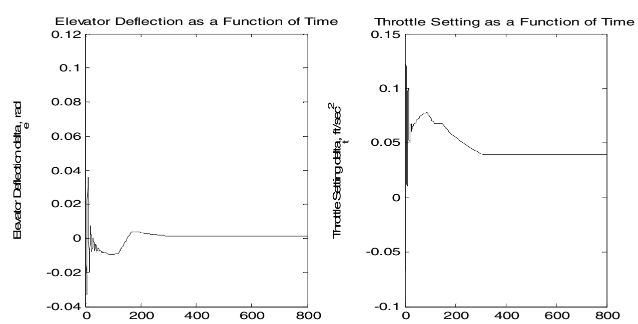

Fig 16. Crisp elevator and throttle deflections for trapezoidal membership functions case, initial altitude 500 ft

As can be seen in Figs. 17 and 18, if the fuzzy logic controller experiences a partial elevator actuator failure, the FLC can still compensate for the reduced control. For example, in the tests the failure occurs at 100 s. One can see that the system responses are not as smooth and continuous as

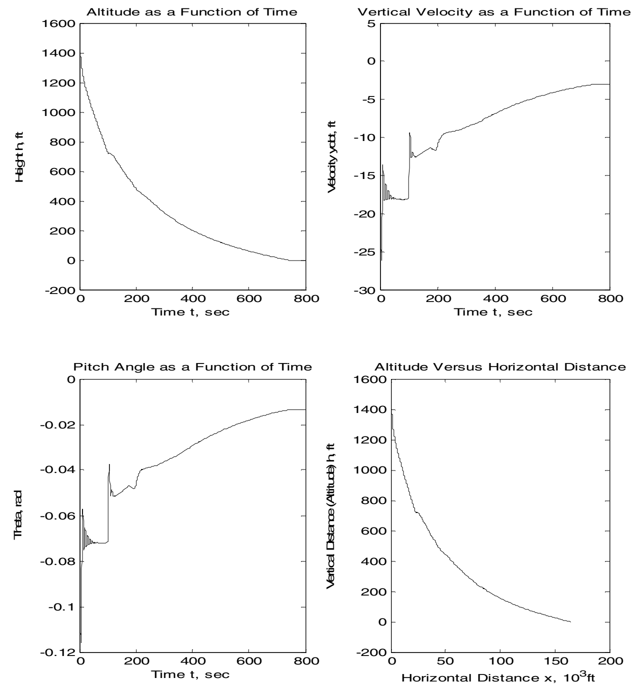

Fig.17. Altitude, vertical velocity, and pitch angle, with triangular membership functions, and a partial elevator actuator failure at t=100 s

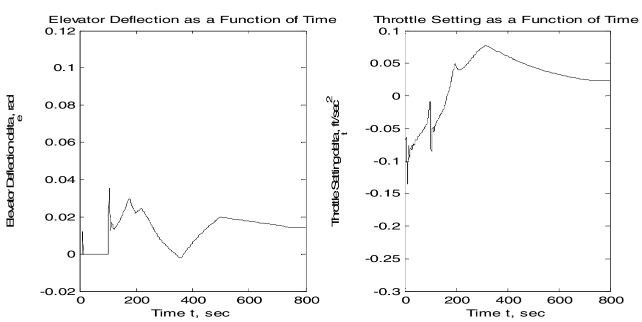

Fig 18. Crisp elevator and throttle deflections with triangular membership functions, and a partial elevator actuator failure at t=100 s

those seen in Fig. 8. Similar results can be obtained for partial throttle failure as well. In the case of near total failure of elevator deflection control, the plane will oscillate unacceptably as seen in Fig. 19.

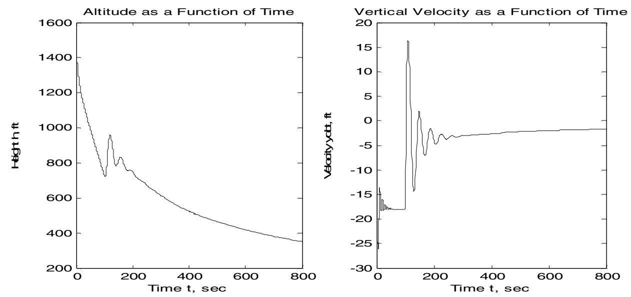

Fig.19. Altitude, vertical velocity, with triangular membership functions, and a near total elevator actuator failure at t=100 s

IV. Discussions and Conclusions

The fuzzy logic membership functions for the FLC and its associated rule base were determined heuristically. In addition, the trapezoidal membership functions give a smoother controlled landing although with longer landing times. This would be due to more overlap in the trapezoidal input membership functions for the FLC. The initial altitude also affects the initial oscillatory descent response. At lower altitudes the FLC causes more oscillation although the overall response is similar to tests for higher initial altitudes.

Further research would involve optimizing the membership function parameters. In addition, whether more membership functions would improve system performance should be investigated. Another area of research would entail testing more types of membership functions in the search for more optimal membership function types. Further work will also involve comparing the FLCs to more conventional controllers.

Acknowledgment

The author would like to acknowledge the contributions of Dr. Robert A. McLauchlan, and the research detailed here is dedicated to his memory. Dr. Robert A. McLauchlan will always be remembered.

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