Intelligent Autolanding Controller Design using Neural Networks and Fuzzy Logic

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Abstract
Designing an intelligent controller for landing phase of a jet transport aircraft in presence of different wind patterns, in order to expand the flight safety envelope has been considered. There are some dangerous conditions like gusts and downbursts which may occur rarely in service life of aircraft, though, aircraft must be tested for these dangerous conditions. Then it is desired to design a controller that not only acts well in usual conditions but also has an acceptable performance in those hazardous conditions. Four different types of controllers have been designed named PID, Neuro, hybrid Neuro-PID and Anfis-PID (Adaptive Network-based Fuzzy Inference System) controllers. Simulation results show that the Anfis-PID which its inner loop is PID and outer loop is Anfis satisfies desired conditions in presence of very strong gust, however, the performance of Neuro-PID is also acceptable. To evaluate the performance of controllers two level of performance have been defined named level I (desired) and level II (acceptable). Also, in comparison with JFK airport gusts two strong wind patterns named strong and very strong winds have been applied.

1 Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>u</td>
<td>perturbed longitudinal velocity (ft/sec.)</td>
</tr>
<tr>
<td>w</td>
<td>perturbed vertical velocity (ft/sec.)</td>
</tr>
<tr>
<td>q</td>
<td>perturbed pitch rate (deg/sec.)</td>
</tr>
<tr>
<td>θ</td>
<td>perturbed pitch angle (deg.)</td>
</tr>
<tr>
<td>x</td>
<td>horizontal position of aircraft (ft)</td>
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<tr>
<td>h</td>
<td>altitude (ft)</td>
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<tr>
<td>h0f</td>
<td>flare initiation altitude (ft)</td>
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<tr>
<td>g</td>
<td>gravity (32.2 ft/sec²)</td>
</tr>
<tr>
<td>u0</td>
<td>normal speed (235 ft/sec.)</td>
</tr>
<tr>
<td>r₀</td>
<td>flight path angle (-3 deg.)</td>
</tr>
<tr>
<td>h0g</td>
<td>glide initiation altitude (ft)</td>
</tr>
<tr>
<td>𝛼s</td>
<td>stall angle of attack (deg.)</td>
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2 Introduction

On 24 June, 1975 in John F. Kennedy Airport a Boeing-727 aircraft had a hard crash, during its landing phase, due to a strong downburst gust (Fig. 1) and its 112 out of 124 passengers died. That was one of thousands of such crashes which have been occurred in the landing phase of the aircraft [1]. Strong downbursts such as the one shown in Fig. 1 are responsible for number of hard landing and crash each year [1].

Many research activities have been conducted on designing an automatic landing controller for different classes of aircraft, especially heavy jet transports. For example, Ref. [2] describes an automatic landing system (ALS) based on a human skill model. The model is expressed as a nonlinear I/O mapping from the aircraft state to the control command provided by a human expert; a gain adaptation technique has also been introduced for robustness. In Ref. [3], a mixed $H_\infty$ synthesis has been applied to the problem of designing a flare mode for automatic landing for a typical transport airplane. In Ref. [5], Linear Quadratic Gaussian with Loop Transfer Recovery (LQG/LTR) has been used to design an automatic landing controller for a typical commercial aircraft encountering a wind-shear. In Ref. [6], adaptive critic neural networks have been used to design a controller for a benchmark problem in aircraft autolanding. In Ref. [7], five different neural network structures are utilized to design intelligent autolanding controllers using linearized inverse dynamic model. In Ref.
[8], a Radial Basis Function Neural Network (RBFN) has been used in the control scheme to aid a conventional controller for aircraft autolanding procedure. In Ref. [9], a controller based on fuzzy logic methodology has been designed for a flight vehicle that enables it to track a predetermined flight path trajectory for safe landing. All of these works suffer from the point that they lack sufficient generality for a flight phase as landing phase is. Landing as a flight phase could vary considerably, due to its vicinity to the ground and existence of unknown pattern of wind and gust during the year and finally, the buildings surrounding an airport. Therefore, it is very desirable to develop a control system that can handle different climatic conditions in this regard, and neuro based control systems could be a solution.

Statistics show that landing phase of aircraft normally has the highest percentage of accidents and/or incident, hence this stage, is considered to be the most critical phase of a mission [10]. These accidents are normally due to several reasons that could be categorized into two different sets. The first set of reasons is related to the human errors such as error to estimate the altitude, runway condition and orientation. The second reason is due to the sudden changes in atmospheric conditions.

To prevent the first set of errors, we need controllers as well as pilots with the accumulated knowledge but without the usual human approximation. To prevent the second set of problems, we need an adaptive controller with the ability to adapt its parameters with regard to the changes in parameters during landing. Solving problems such as this, requires a flexible controller based on human knowledge. PID controller, on the other hand, has good capabilities to control the aircraft through-out the landing phase of a flight. However, these types of controllers need precise information about system dynamics. Knowing, that approximations in system dynamical model as well as its output parameters are inevitable, the primary objective of this paper is to present a methodology to practically, omit the need for switching between glide and flare modes with the help of neural networks technique by integrating the glide and flare controllers. The main objective of this paper is to design a controller with outstanding performance and stability during landing phase of flight in presence of very strong winds. At the end, classical, neural based and fuzzy based controllers will be compared to show that our goal has been achieved. The procedure has four major steps as follows:

a- First a PID controller is designed for a known trajectory, with dynamic of aircraft linearized in the vertical plane.

b- Then a neuro-controller is designed to control the aircraft through-out the glide and flare modes.

c- Then a hybrid neuro-PID controller has been designed to handle the aircraft in Very Strong wind pattern. In this controller the inner loop is PID based and the outer loop is neural based.

d- Finally a hybrid Anfis-PID controller has been designed. In this controller the inner loop is PID based and the outer loop is Anfis-based.

In this approach, the data and outputs generated by the PID controller are used to train the neuro-controller. Obviously, the PID controller is designed only for a single known trajectory in a specific set of conditions. However, it could be used for a wide range of flight conditions, based on the characteristics of neural networks. Omission of the switching mechanism between the glide and flare modes leaves out the selection of proper point to flare. In this way, uncertainties due to the so called "sensor errors" are no longer a concern. Different simulation conducted shows that with the help of hybrid neuro-PID technique acceptable landing performance & with Anfis-PID desired landing performance in severe atmospheric conditions are possible.

3 Problem Definition and Objectives

During complex maneuvers, such as landing and take-off; the dynamics of the aircraft is changing rapidly which leads to a complex design procedure as far as conventional controllers are concerned. The problem can become even more complex, while gusts and other natural climatic conditions are present. Two major modes of landing phase studied here are glide-slope hold and intercept and flare and touch down with regard to [14]. The following characteristics are usually observed, during landing phase of a flight:

1. A suitable altitude should be selected for the aircraft autopilot to start to glide mode or glide mode initiation.

2. At a height of about 15 meters (45 ft) AGL, the flare maneuver is started which results in nose being lifted, reducing the vertical speed of the aircraft and allowing the main gear to touch the ground firstly and smoothly. During this limited time interval the control law has to be adjusted continuously.

3. Through continuous decrease in the aircraft altitude, the ground effect starts to play a major role and the aircraft dynamics becomes affected accordingly.

4. Gust and downburst, which have an inevitable influence on the aircraft dynamics, do not follow a well-known pattern.

Based on design performance outlined in [11] and [13] and to evaluate the controllers’ performance, we consider two level of performance named level 1 and level 2.

In level 1, the controllers should satisfy the following conditions in any gust:

\[ |\dot{h}| \leq 17 \text{ fps} \]  
\[ |\alpha| \leq 7 \text{ deg} \]

In level 2, the necessary conditions are as follows:

\[ |\dot{h}| \leq 20 \text{ fps} \]  
\[ |\alpha| \leq 10 \text{ deg} \]

It is desired that the controllers achieve the level 1 of performance; however, Level 2 is also acceptable. It is further assumed that glide mode begins at 500 ft AGL and finishes at 45 ft AGL, which is the start point of flare
mode [14] (Fig. 2). The flare mode continues until a smooth touch down is achieved. During a glide-slope mode, an automatic landing system guides the aircraft along a straight line with a constant slope (with a constant glide angle, $\gamma$). Autopilot also attempts to prevent any changes in aircraft vertical and horizontal speeds, that is, during glide mode the sink rate is constant.

As flare mode starts, autopilot starts to nose up the aircraft by changing the glide angle to prepare aircraft for a smooth touchdown. The trajectory of aircraft during this mode is estimated by an exponential function. Through this mode the sink rate is reduced to the desired value of -1.5 fps.

Longitudinal control surfaces such as elevator in addition to the throttle are the usual controls during these modes.

4 Aircraft Equations of Motion and Turbulence Model

In this work, 3-DOF equations of motion in the vertical plane known as longitudinal dynamics have been used to design the controller, however, the procedure is very well extendable to a complete 6-DOF equations of motion. Based on [14], these equations are given by (1) through (9).

$$
\dot{u} = X_u (u - u_e) + X_v (w - w_e) + X_q q - g \left( \frac{\pi}{180} \right) \cos(\gamma_0) \theta + X_E \delta_E + X_T \delta_T
$$

$$
\dot{w} = Z_u (u - u_e) + Z_v (w - w_e) + (Z_q - \left( \frac{\pi}{180} \right) U_e) q
$$

$$
\dot{q} = M_u (u - u_e) + M_v (w - w_e) + M_q q + M_E \delta_E + M_T \delta_T
$$

$$
\theta = q
$$

$$
\ddot{x} = u \cos \theta + w \sin \theta
$$

$$
\dot{h} = u \sin \theta - w \cos \theta
$$

The initial conditions are assumed as:

$$
u(0) = w(0) = q(0) = \theta(0) = 0
$$

$$
h(0) = 500 \text{ ft} , \ x(0) = h(0) / \tan \gamma_0
$$

$$
\dot{x}(0) = U_0
$$

Wind disturbance, which are shown by $(u_g, w_e)$ consists of two components: constant velocity $(u_{gc}, 0)$ and turbulence $(u_{gt}, w_e)$. It is further assumed that the constant velocity component exists only in the horizontal direction, given by (10).

$$
u_{gc} = \begin{cases} 
- u_0 (1 + \ln(h/510) / \ln51) & \text{if } h \geq 10 \\
0 & \text{if } h < 10
\end{cases}
$$

Here $u_0$ is the wind speed at altitude 510 ft and its typical value is 20 ft/sec. Turbulence is represented by [2].

4.1 Aircraft Equations of Motion and Turbulence Model

5 Autoland Controller Design

As previously mentioned, a conventional PID controller, a modern neuro-controller and also a hybrid neuro-PID controller are designed to show the effectiveness of a hybrid system. To design a PID controller to train the Neuro-controller, longitudinal controls are throttle and elevator. Throttle is used in such a way that the aircraft speed during landing phase remains constant [2]. So:

$$
T = K_T (u_c - u) + K_T \omega_T \int_0^t (u_c - u) dt
$$

In this case: $u_c = 0$, $k_T = 3$, $w_T = 0.1$

The function of elevator is to control the pitch angle and pitch rate during landing phase, so:

$$
E = K_p (\hat{h} - \hat{h}) - K_q q
$$

And it is further assumed that, the desired pitch angle is a function of error in $h$ and $\dot{h}$, so

$$
\dot{\theta} = k_c (h - \hat{h}) + k_p \int (h - \hat{h}) dt + k_h \hat{h} + k_\theta \theta
$$

Where

$$
K_c = 0.3, \ W_h = 0.1, \ K_h = 0.3
$$

At Glide : $K_\theta = 3, \ K_q = 3, \ \theta_p = 0$

At Flare : $K_\theta = 12, \ K_q = 6.0, \ \theta_p = 0.0698$

The PID controller gains are estimated by applying the Linear Matrix Inequality (LMI) method, which is normally used to design PID controllers for MIMO systems. This method guarantees the stability of the designed system [15]. However, to achieve the desired performance one needs to optimize the gains through a trial and error process.
\[ \tan \gamma_0' = \frac{h}{x} \quad \Rightarrow \quad h_c = x \tan \gamma_0 \]  
(22)

At the flare mode the controller is applied to aircraft so that \( h \) is reduced smoothly to a desired value of -1.5 fps. It is assumed that the flare mode begins at \( t=t_0 \) and \( h_0 = h(t_0) = 45 \) ft and it ends at the main gear touch down point where \( t=T \) and \( h(T)=0 \), then:

\[ \dot{h}_c = \frac{h_0}{h_0 - \dot{h}_T}( h_0 e^{-(x-t_0)} - \dot{h}_T ) \]  
(23)

Where

\[ \dot{h}_T = \dot{h}(\tau) = -1.5(\text{ft/sec}) \]  
(24)

\[ \tau = \left[ -h_0 \times (t_0) \right] \left( h_0 - \dot{h}_T \right) \]  
(25)

Results of different simulations conducted by the authors show that setting the throttle command to zero results in much better trajectories. Therefore, the rest of the simulations, once the throttle setting was selected it was treated as a constant throughout the simulation.

6 Neuro-Controller Design

One neural network is designed for Elevator control. As previously mentioned the outputs of PID controller are used to train the neural network. The neural network used for Elevator control is a Multi Layer Perceptron (MLP) with 3 layers and 4 inputs (\( \theta, q, h \) and \( \dot{h} \)). The output of elevatormnet is the elevator setting. The hidden layer has 7 neurons (\( N_{4,7,1} \)). In this neural network, tangent-sigmoid function is used in input and hidden layers and pure-linear function is used in output layers. To train the network classical error back propagation method (Levenberg-Marquardt back propagation) is used. This method updates weight and bias values according to Levenberg-Marquardt optimization [16].

7 Hybrid Neuro-PID Controller Design

To achieve a better performance in the presence of very strong winds and gusts a new controller has been proposed. In this controller inner loop that provides stability of the system, is designed with the aid of classic methods (such as root locus plot), in other words, according to equations for elevator setting (20), we tune \( K_\theta \) and \( K_q \) by classical methods. The outer loop (\( \Theta_c \)) is estimated by a type of neural networks named General Regression Neural Networks (GRNN). A GRNN is often used for function approximation and has a radial basis layer as it hidden layer and a special linear layer as its output layer. [16]

8 Hybrid Anfis-PID Controller Design

Similar to the neuro-PID controller, the hybrid Anfis-PID controller has been designed to achieve a better performance; however, in this controller the outer loop is fuzzy based, using a mixed type of adaptive networks & fuzzy systems named ANFIS. In other words, Anfis acts like fuzzy systems and structurally is similar to adaptive networks (or Perceptron Neural Networks). Firstly, consider the following Sugno Type Fuzzy System, in which \( x \) and \( y \) are inputs of system and \( f \) is its output:

Rule 1: if \( x > A_1 \) and \( y > B_1 \), then \( f = P_1 x + Q_1 y + r_1 \)

Rule 2: if \( x < A_2 \) and \( y < B_2 \), then \( f = P_2 x + Q_2 y + r_2 \)

And

\[ f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \]  
(26)

Equivalent Anfis system for above fuzzy system is shown in Fig. 3 [17].

Layer 1 is membership layer in which the membership degree of \( x \) relative to \( A_i \) computes the output of layer 1 as follows:

\[ O_i^1 = \mu_{A_i}(x) \]  
(27)

where \( \mu \) is membership function of \( A_i \).

In layer 2, input signals are multiplied:

\[ w_i = \mu_{A_i}(x) \mu_{B_i}(y) \]  
(28)

That expresses the firing strength of each fuzzy rule. The output of each node in layer 3 is:

\[ \bar{w} = \frac{w_i}{w_1 + w_2} \]  
(29)

which is named normalized firing strength. Each node in layer 4 is a square node with node function:

\[ O_i^4 = \bar{w}_i f_i - \bar{w}_z (P_1 x + Q_1 y + r_1) \]  
(30)

Therefore, network acting like Sugno Type fuzzy system is provided by using the concept of adaptive (Perceptron) networks.

The \( \{P, Q, r\} \) parameters and parameters of membership functions are defined by training process, which is usually based on steepest descent method or least square error method.

As previously mentioned, in this controller the inner loop is designed by classic PID tuning method, the outer loop is designed by using Anfis. To train the Anfis Network, two error parameters are defined as follows:

\[ e_h = h_c - h \quad \text{and} \quad e_{\dot{h}} = \dot{h}_c - \dot{h} \]  
(31)

These two parameters \( (e_h, e_{\dot{h}}) \) are inputs to Anfis network and output of Anfis is \( \Theta_c \). In other words, Anfis network, based on these two error values \( (e_h, e_{\dot{h}}) \), estimates the desired pitch angle (\( \Theta_c \)) for compensation and correction. Each input \( (e_h, e_{\dot{h}}) \) has three bell-shaped membership function. Linguistic variables for these membership functions are Low, Medium and High. Consequently after 20 epochs training of Anfis, nine fuzzy laws are generated as follows [18]:

1. If \( (e_h \text{ is low}) \) and \( (e_{\dot{h}} \text{ is low}) \) then \( (\Theta_c \text{ is Very-Low}) \)
2. If \((eh\text{ is low})\) \(\text{and}\) \((eh\text{-dot is Medium})\) then \((\text{theta}_c\text{ is Very-Low})\)
3. If \((eh\text{ is low})\) \(\text{and}\) \((eh\text{-dot is High})\) then \((\text{theta}_c\text{ is Low})\)
4. If \((eh\text{ is Medium})\) \(\text{and}\) \((eh\text{-dot is Low})\) then \((\text{theta}_c\text{ is Low-Medium})\)
5. If \((eh\text{ is Medium})\) \(\text{and}\) \((eh\text{-dot is Medium})\) then \((\text{theta}_c\text{ is Medium})\)
6. If \((eh\text{ is Medium})\) \(\text{and}\) \((eh\text{-dot is High})\) then \((\text{theta}_c\text{ is Medium})\)
7. If \((eh\text{ is High})\) \(\text{and}\) \((eh\text{-dot is Low})\) then \((\text{theta}_c\text{ is High})\)
8. If \((eh\text{ is High})\) \(\text{and}\) \((eh\text{-dot is Medium})\) then \((\text{theta}_c\text{ is Very-High})\)
9. If \((eh\text{ is High})\) \(\text{and}\) \((eh\text{-dot is High})\) then \((\text{theta}_c\text{ is Very-Very-High})\)

9 Case Studies and Simulation Results

To train the networks, the M-files and Neural Networks Toolbox [16] of Matlab software have been used, and to simulate the system, Simulink Toolbox [19] of Matlab software has been used; also, suitable links between the M-files and Simulink environment have been provided. The initial conditions for all of the aforementioned controllers have been introduced in Equations (7) to (9). According to the Federal Aviation Administration (FAA) regulations (FAR 25) [20], environmental conditions considered in the determination of dispersion limits are: headwinds up to 25 knots (42.23 fps); tailwinds up to 10 knots (16.9 fps). The simulation result of the designed hybrid controller was found to be robust enough to properly handle all of the imposed turbulences proposed by the FAA in landing phase of flight.

Fig. 4 to 7, show the horizontal and vertical components of Strong and Very Strong winds applied to the controllers. With applying these wind patterns, the performance of the controllers have been discussed. Simulation results have been presented in two sections. In the first section, simulation results of the three controllers in presence of Strong wind and in the second section, the results in presence of Very Strong wind have been presented.

The profile of strong wind is depicted in Fig. 4 and 5. It can be compared with JFK gust, a strong Downburst, depicted in Fig. 1. Simulation results for applying Strong wind have been shown in Fig. 8 to 15. Followed and command trajectories of aircraft for all of four controllers are shown in Fig. 8 to 11. It is shown that for all of controllers, range of errors are acceptable. The sink rate variations for the controllers are shown in Fig. 12 to 15, which all of them satisfy the necessary conditions for level 2; moreover, the Anfis controller satisfy conditions for level 1. Variations of angle of attack during the landing phase of the aircraft, for the controllers, are not shown here, but its variations for all of the cases are in the acceptable range, with regard to angle of attack limitation (Stall angle, \(\alpha_s\)). Consequently, all of the controllers- PID, Neuro, Neuro-PID and Anfis-PID controller- have good capabilities to guide the aircraft throughout the landing phase in presence of Strong wind. To evaluate limitations of flight safety envelope, in the next section, we will discuss the aircraft performance with applying Very Strong wind.

Horizontal and vertical components of Very Strong wind have been depicted in Fig.6 and 7. Comparing these figures with JFK Airport Downburst, Fig. 1, it is seen that the wind named Very Strong wind is stronger than the JFK Airport Downburst. Since, JFK wind is known as a strong Downburst, if our controllers, in presence of Very Strong wind, show acceptable performance, our objective, which was the extension of flight safety envelope, have been achieved.

Fig. 16 to 23, show simulation results of the controllers in presence of Very Strong wind. Followed and command trajectories for the controllers, in presence of Very Strong wind, have been shown in Fig. 16 to 19. Fig. 16 shows that the classic controller follows the command trajectory well, but according to Fig. 17, the neuro controller hasn’t an acceptable behavior in following the command trajectory. Fig. 18 shows that the neuro-PID controller has a relative better performance. Fig. 19 shows that the Anfis controller has a good performance.

Desired and actual sink rates for the controllers have been shown in Fig. 20 to 23. Actual sink rate of classic controller (Fig. 20) exceeds -20 fps and doesn’t satisfy the conditions. The neuro controller also doesn’t satisfy the limitations in this case (Fig. 21). Sink rate of the aircraft with hybrid neuro-PID controller (Fig. 22) in presence of Very Strong wind doesn’t exceed -20 fps limitation and satisfies the necessary conditions for level 2 of performance and Fig. 23 shows that the actual sink rate with Anfis-PID controller in presence of Very Strong wind doesn’t exceed 17 fps and then satisfies the necessary conditions for Level 1 of performance. Angle of Attack variations for the controllers have not been shown here. But, variations of angle of attack with neuro controller were not acceptable at all. Angle of attack of the aircraft in presence of Very Strong wind, with applying the PID and neuro-PID controllers, didn’t exceed the stall angle limitation, during the landing phase of flight, but Anfis-PID controller has a relative better performance. The aforementioned results have been showed briefly in Table 1:

<table>
<thead>
<tr>
<th>Controller</th>
<th>PID Controller</th>
<th>Neuro Controller</th>
<th>Neuro-PID Controller</th>
<th>Anfis-PID Controller</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong Wind</td>
<td>Level 2</td>
<td>Level 2</td>
<td>Level 2</td>
<td>Level 1</td>
</tr>
<tr>
<td>Very Strong Wind</td>
<td>Unacceptable</td>
<td>Unacceptable</td>
<td>Level 2</td>
<td>Level 1</td>
</tr>
</tbody>
</table>
10 Discussion and Conclusion

Four different types of controllers (Classic, Neuro, Neuro-PID and Anfis-PID) have been designed and simulated. To evaluate performance of the controllers, two different wind patterns have been introduced, named Strong and Very Strong winds. Also, 2 level of performance have been considered named Level 1 and Level 2. Strong wind is weaker than the JFK Downburst and Very Strong wind is stronger than it. Results show that performance of controllers in presence of Strong wind satisfy necessary conditions for Level 2(acceptable), and only Anfis–PID controller satisfies Level 1(desired) of performance. Simulations of applying Very Strong wind, shows that only Anfis-PID controller satisfies the necessary conditions for Level 1 performance and only Neuro-PID controller satisfies the necessary conditions for Level 2 performance. So, only with applying the hybrid neuro-PID and Anfis-PID controllers we can extend the flight envelop of the aircraft. Block diagrams of the PID, neuro, neuro-PID and Anfis-PID controllers have been shown consequently in Fig. 24 to 27. As it is obvious, \( \theta, q, h \) and \( \dot{h} \) are the inputs of the controllers, so the number of required sensors for all of the controllers is equal.

On the other hand, the neuro-controller has a good ability to estimate the system parameters in a condition that had not been trained before, and it is capable to extend the performance range of the system. In other words by this technique, the flight safety envelope of the aircraft can be extended in a wide range and this make the landing system operate more safely in presence of sudden and unpredicted conditions. Moreover; it is possible to decrease the number of flight tests with this controller. In overall, a mixed Neuro-Classic or Fuzzy-classic controller has a better performance in comparison with the controllers which are based only on classic methods or only on neural networks methods.

References

10 Knots - Tailwind limit with regards to FAR 25 (AC 20-57A)
25 Knots - Headwind limit with regards to FAR 25 (AC 20-57A)

Fig. 1: JFK Airport Downburst

Fig. 2: Typical trajectory in landing

Fig. 3: Anfis equivalent of Sugno Type fuzzy

Fig. 4: Strong wind pattern, Variation of $u_g$ with $h$, $N=200$

Fig. 5: Strong wind Pattern, Variation of $w_g$ with $h$, $N=100$

Fig. 6: Very Strong wind pattern, Variation of $u_g$ with $h$, $N=300$

Fig. 7: Very Strong wind Pattern, Variation of $w_g$ with $h$, $N=250$

Fig. 8: Trajectory for PID controller with Strong wind

Fig. 9: Trajectory for Neuro controller with Strong wind

Fig. 10: Trajectory for Neuro-PID controller with Strong wind
Fig. 20: Sink rate variations for PID controller with Very Strong wind

Fig. 21: Sink rate variations for Neuro controller with Very Strong wind

Fig. 22: Sink rate variations for Neuro-PID controller with Very Strong wind

Fig. 23: Sink rate variations for Anfis-PID controller with Very Strong wind

Fig. 24: PID Controller block diagram

Fig. 25: Neuro Controller block diagram (with training procedure)

Fig. 26: Neuro-PID Controller block diagram (with training procedure)

Fig. 27: Anfis-PID Controller block diagram (with training procedure)