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Progressive Certification Process Based on Living Systems Architecture Using Learning Capable Controllers

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To expedite and facilitate the certification process of a new aircraft against different climatic conditions, a new methodology has been proposed that makes use of combined advantages of both neural networks and fuzzy logic. The idea is to devise a learning capable control system that helps to decrease the number of flight tests to a minimum and, therefore, decrease the cost of the flight-test program for initial certification of an aircraft. In this approach, the certifying authorities test the learning capability of the aircraft in some preselected climatic conditions. During service life the aircraft extends its knowledge base with some suitable data collected during each flight; until it reaches a certain level of maturity, as it is the case with a living system. Moreover, with some management techniques, aircraft of the same type can share data with one another. To show the different capabilities of this approach, three autolanding controllers in the presence of different strong wind patterns have been studied, namely, a classical proportional–integral–derivative (PID), a hybrid neuro-PID, and finally an adaptive network-based fuzzy inference system-PID. It is shown that intelligent architectures are suitable tools to fulfill the proposed idea because of their learning capabilities, robustness and generalization properties.

Nomenclature

A, B, C	=	system matrices
E	=	error function
g	=	gravity, 9.81 m/s^2
h	=	altitude, ft
h_{0f}	=	flare initiation altitude, ft
h_{0g}	=	glide initiation altitude, ft
K_*	=	controller's gain
M_*	=	pitching stability derivatives
q	=	pitch rate, deg/s
U_0	=	normal speed, 235 ft/s
u	=	longitudinal body-axis velocity, ft/s
u_g	=	longitudinal wind velocity, ft/s
w	=	vertical body-axis velocity, ft/s
w_g	=	vertical wind velocity, ft/s
X_*	=	forward stability derivatives
x	=	horizontal position of aircraft, ft
Z_*	=	upward stability derivatives
α	=	angle of attack, deg
α_s	=	stall angle of attack, deg
γ_0	=	flight-path angle, -3 deg
δ_e	=	elevator angle setting, deg
δ_T	=	throttle setting, deg
θ	=	pitch angle, deg
θ_p	=	controller threshold
μ	=	membership function
ω_*	=	controller's gain

Subscripts

C	=	desired amount of parameter
e	=	elevator setting
G	=	gust (wind shear)
T	=	throttle setting
TD	=	touchdown

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I. Introduction

THE certification process is always a critical and costly part of the aircraft development process, especially for some heavy-weight aircraft such as the A-380 or B-747. The size and nature of these types of heavy-weight transports demand a meticulous type of certification program, during which the manufacturer demonstrates different capabilities of the aircraft under the supervision of certifying authorities. Once successful, this process leads to a document known as the Certificate of Airworthiness (C of A). Depending on the complexity of the aircraft and its mission capabilities, the process might take a considerable amount of time and resources. One the other hand, looking at the history of flight and associated progress in human knowledge toward designing better aircraft together with extensive and wide variety of requirements, one might conclude that humans have acted as an interface to collect the experience of flight and to convert it to some design guides and/or requirements for the next generation or version of flying machines. This process, although effective, has been very lengthy in time and is why very few new types of aircraft have been developed in the last two decades compared to the previous ones. This is mainly due to the vast amount of resources required for the test and certification process. However, the recent advances in computer technology, networking, and control techniques have created a good opportunity to decrease the role of human engineer as an interface in the certification process and to increase the role of the control system as intelligent machines with the capability of learning. As is known, a living system has number of unique features, among which is learning capability.[1] This characteristic allows a living system to enhance and readjust its control capability as its gain experience during its operational life. This paper attempts to show that such a feature is achievable through proper design of an intelligent control system.

Also note that some of the flight-test requirements, including those related to climatic conditions, such as flying quality in the presence of turbulence or icing conditions, are not always available, and this might very well lead to some complexities in the certification process. Also there is no guarantee that whatever the aircraft might experience during its service life will be similar to the test conditions of the certification process. For example, on 24 June 1975 at John F. Kennedy (JFK) Airport, a Boeing-727 (B-727) with valid C of

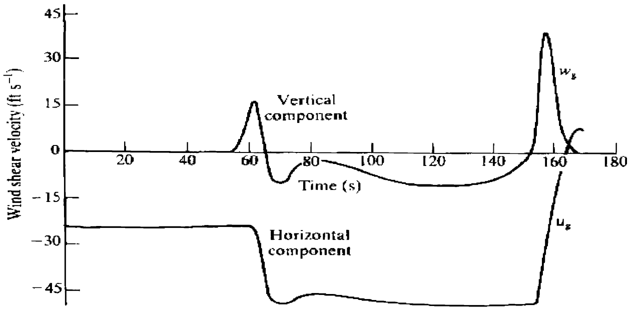

Fig. 1 JFK Airport downburst.[2]

A had a hard landing due to a strong downburst gust (Fig. 1) that resulted in 112 casualties out of 124 passengers. Obviously, a B-727 had never been tested for such a condition; nevertheless, it had to fly through it. Strong downbursts such as the one shown in Fig. 1 are responsible for number of hard landings and crashes each year.[2] This is mainly because, from a practical point of view, the certification process must be limited to a certain period of time and overall accepted level of safety. The current practice is structured in such a way that start of service life is allowed once the C of A is issued. However, as mentioned earlier, this process might not guarantee the safety of new-generation or special aircraft, such as the A-380 in worldwide climatic conditions. To alleviate this problem, the authors propose a progressive learning-based certification process (PLBCP), during which the certifying authority would test 1) a minimum and more relaxed requirement to issue an initial C of A, 2) the capability of the aircraft flight control system (AFCS) to learn from its previous flights, and 3) the ability of operator to share the knowledge of each aircraft with other aircraft of the same type, worldwide.

Obviously, for such an approach, one must deal with two different issues. The first issue, together with its required line of research, is the meticulous selection of the so-called relaxed requirements. This issue demands a through evaluation of the current requirements, as well as public and industry accepted level of safety. The second issue should deal with the AFCS. One must design an AFCS that adequately demonstrates a good learning capability instead of a rigid architecture. The purpose of this paper is to deal with the second issue and to compare different approaches to design a typical AFCS to prepare the necessary ground and support for the idea of PLBCP. This process, once deployed, should reduce the time period of certificating process by decreasing the number of required flight tests as well as eliminating the tests related to the severe climatic conditions for new aircraft types. Note that in the current practice the aircraft at most is tested against its designed capabilities. However, in the new approach, the aircraft is designed in such a way that it can go slightly beyond its existing capabilities with time, similar to a human being or other living systems. Obviously, this process must be carefully supervised after each flight. In the new procedure, in fact, the safety of aircraft is increased for severe conditions by the means of its learning capabilities. For practical reasons, only a learning flight control system for the landing phase of a jet aircraft in the presence of atmospheric turbulences is discussed here. The same approach, however, could be expanded for learning capability in other flight conditions.

The approach could be summarized in the following steps:

1) The first step is to collect some appropriate data of the known severe conditions; this sort of data could also be collected by flight computer of all aircraft in service and or suitable mathematical functions, which is more suitable for academic purposes.

2) The second step is to select a suitable mean to train the so-called intelligent controller. In this work, a previously well-designed proportional–integral–derivative (PID) controller has been used for this purpose. Note that the PID itself had a good performance in some severe climatic conditions.

The main focus of this work is comparison of learning capability of different controllers for the landing flight phase during severe climatic conditions.

Research has been conducted on the design of automatic controller for different classes of aircraft, especially heavy jet transports. For example, in Ref. 3, an automatic landing system (ALS) based on a human skill model is described. 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. 4, an adaptive controller based on a model reference adaptive system (MRAS) methodology has been designed for a flight vehicle similar to current case that enables it to track a predetermined flight-path trajectory in the presence of strong wind shears. The authors found that, although the adaptive controller could cope with very strong wind patterns theoretically, it is impossible to implement the adaptive control for such cases because of the high number of sharp fluctuations in the control signal.

In Ref. 5, a linear quadratic Gaussian with loop transfer recovery 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 a linearized inverse dynamic model.

All of these works suffer from the condition that they cannot guarantee sufficient generality for the landing flight phase. Landing as a terminal condition could vary considerably, due to its vicinity to the ground, the presence of unknown wind and gust patterns in different seasons, and, finally, the obstacles surrounding an airport. Therefore, it is desirable to develop a control system that can handle different climatic conditions based on limited tests. As mentioned earlier, an intelligent control system with learning capabilities could be a solution. PID controllers have good capabilities to control the aircraft throughout the landing phase of a flight. However, these types of controllers need precise information about system dynamics. Nevertheless, approximations in system dynamics, as well as its output parameters, are inevitable. Moreover, they must be designed for two different phases of glide and flare, which results in switching between glide and flare phases. The following steps are discussed in this work.

1) In the first step, a PID controller is discussed for a known trajectory, with the dynamic of the aircraft linearized in the vertical plane.

2) In the second step, a hybrid neuro-PID controller is discussed to handle the aircraft in a known strong wind pattern. In this controller, the inner loop is a PID-based and the outer loop is a neural-based controller.

3) In the last step, a hybrid adaptive network-based fuzzy interference system-(ANFIS-) PID controller is proposed with learning capability. 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 other controllers.

Obviously, the PID controller is deigned 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 and fuzzy-based controllers.

II. Landing Phase

During complex maneuvers, such as landing and takeoff, the dynamics of the aircraft are 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 touchdown with regard to Ref. 8. The following characteristics are usually observed, during landing phase of a flight (Fig. 2).

1) A suitable altitude should be selected for the aircraft autopilot to start the glide mode or glide mode initiation, normally around 500-ft above ground level (AGL).

2) At a height of about 15 m (45-ft) AGL, the flare maneuver is started, which results in the aircraft nose being lifted, reducing the vertical speed of the aircraft and allowing the main gear to touch the

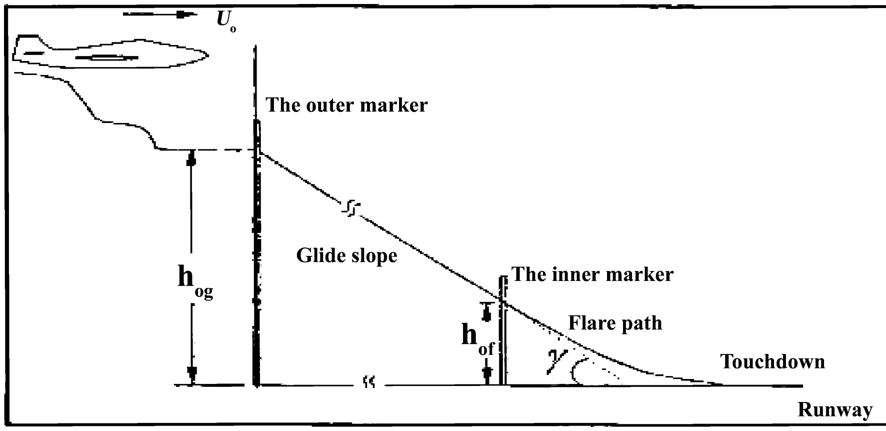

Fig. 2 Typical trajectory in landing phase.

ground first 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.

5) 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 γ). The autopilot also attempts to prevent any changes in aircraft vertical and horizontal speeds, that is, during glide mode the sink rate is constant.

6) As the flare mode starts, the autopilot starts to nose up the aircraft by changing the glide angle to prepare the aircraft for a smooth touchdown. The trajectory of the 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 ft/s. A longitudinal control surface, such as elevator, in addition to the throttle is the usual control during these modes.

Based on design performance outlined in Refs. 9 and 10 and to evaluate the controllers' performance, we consider two level of performance known as level 1 and level 2. In level 1, the controllers should satisfy the following conditions in any gust:

$$|\dot{h}| \leq 17 \text{ ft/s}, \qquad |\alpha| \leq 7 \text{ deg}$$

In level 2, the necessary conditions are as follows:

$$|\dot{h}| \leq 20 \text{ ft/s}, \qquad |\alpha| \leq 10 \text{ deg}$$

It is normally desired that the controllers achieve level 1 performance; however, level 2 is also acceptable.

III. Aircraft Equations of Motion and Turbulence Model

For simplicity in the design process, equations of motion in the vertical plane, known as longitudinal dynamics, have been used in this work. The procedure, however, could easily be extended to complete six-degree-of-freedom equations of motion. These equations[8] are

$$\dot{u} = X_u(u - u_g) + X_w(w - w_g) + X_q q - g(\pi/180)\cos(\gamma_0)\theta + X_e\delta_e + X_T\delta_T \tag{1}$$

$$\dot{w} = Z_u(u - u_g) + Z_w(w - w_g) + [Z_q - (\pi/180)U_0]q + g(\pi/180)\sin(\gamma_0)\theta + Z_e\delta_e + Z_T\delta_T \tag{2}$$

$$\dot{q} = M_u(u - u_g) + M_w(w - w_g) + M_q q + M_e\delta_e + M_T\delta_T \tag{3}$$

$$\dot{\theta} = q \tag{4}$$

$$\dot{x} = u\cos\theta + w\sin\theta \tag{5}$$

$$\dot{h} = u\sin\theta - w\cos\theta \tag{6}$$

The initial conditions are assumed to be

$$u(0) = w(0) = q(0) = \theta(0) = 0 \tag{7}$$

$$h(0) = 500 \text{ ft}, \qquad x(0) = h(0)/\tan\gamma_0 \tag{8}$$

$$\dot{x}(0) = U_0 \tag{9}$$

Disturbance components shown by u_g and w_g consist of two parts: the first part is constant velocity u_{gc} and 0 and the second part is turbulence u_{g1} and w_g. It is further assumed that the constant velocity component only exists in the horizontal direction, where u_0 is the wind speed at altitude 510 ft and its typical value is 20 ft/s,

$$u_{gc} = \begin{cases} -u_0(1 + \ln(h/510)/\ln 51), & h \geq 10 \\ 0, & h < 10 \end{cases} \tag{10}$$

Turbulence is represented by[2]

$$u_g = u_{g1} + u_{gc} \tag{11}$$

$$w_g = \sigma_w\sqrt{a_w}\left(a_w w_{g_1} + \sqrt{3}w_{g_2}\right) \tag{12}$$

$$\dot{u}_{g_1} = 0.2|u_{g_c}|\sqrt{2a_u}N_1 - a_u u_{g_1} \tag{13}$$

$$\dot{w}_{g_1} = w_{g_2} \tag{14}$$

$$\dot{w}_{g_2} = N_2 - a_w^2 w_{g_1} - 2a_w w_{g_2} \tag{15}$$

where

$$a_u = \begin{cases} U_0\big/\left(100\sqrt[3]{h}\right), & h > 230 \\ U_0/600, & h \leq 230 \end{cases} \tag{16}$$

$$a_w = U_0/h \tag{17}$$

$$\sigma_w = \begin{cases} 0.2|u_{gc}|, & h > 500 \\ 0.2|u_{gc}|(0.5 + 0.00098h), & h \leq 500 \end{cases} \tag{18}$$

N_1 and N_2 are the Gaussian random noises with mean zero and different variances that could be used to generate wind patterns with different velocities and intensities.

IV. PID Controller Design

As already mentioned, a conventional PID controller, a hybrid neuro-PID, and an ANFIS-PID controller are designed to show the effectiveness of a hybrid system. To design a PID controller to train the neuro-PID controller, longitudinal controls are selected to be the throttle and elevator. The throttle is used in such a way that the aircraft speed during landing phase remains constant.[2] Thus,

$$\delta_T = K_T(u_c - u) + K_T\omega_T \int_0^t (u_c - u)\,\mathrm{d}t \tag{19}$$

For the current study, $u_c = 0$ (command forward velocity to the controller), $k_T = 3$, and $\omega_T = 0.1$. Furthermore, the function of the elevator is to control the pitch angle, thus,

$$\delta_e = K_\theta(\theta_c - \theta) - K_q\, q \tag{20}$$

It is customary to assume that θ_c (the desired pitch angle) is a function of error in h and $\dot{h}$, so that

$$\theta_c = k_h(h_c - h) + k_h\omega_h \int_0^t (h_c - h)\,\mathrm{d}t + k_{\dot{h}}(\dot{h}_c - \dot{h}) + \theta_p \tag{21}$$

where

$$k_h = 0.3, \qquad \omega_h = 0.1, \qquad k_{\dot{h}} = 0.3$$

During the glide mode,

$$K_\theta = 3, \qquad k_q = 3, \qquad \theta_p = 0$$

During the flare mode,

$$K_\theta = 12, \qquad k_q = 6.0, \qquad \theta_p = 0.0698$$

The PID controller gains are estimated by applying the linear matrix inequality (LMI) method, which is normally used to design PID controllers for multi-input/multi-output systems. This method guarantees the stability of the designed system.[11] However, to achieve the desired performance, one needs to optimize the gains through a trial and error process.

Here h_c and $\dot{h}_c$ for each mode are obtained from their trajectories in the glide and flare modes. In the glide mode, the aircraft normally moves along a constant slope path characterized by

$$\tan\gamma_0 = h_c/x \Rightarrow h_c = x\,\tan\gamma_0 \tag{22}$$

At the flare mode, the controller is expected to smoothly decrease current value of $\dot{h}$ to a desired value of -1.5 ft/s; therefore,

$$h_c = [h_0/(\dot{h}_0 - \dot{h}_{\mathrm{TD}})]\left(\dot{h}_0 e^{-(x-x_0)\tau} - \dot{h}_{\mathrm{TD}}\right) \tag{23}$$

where

$$\dot{h}_{\mathrm{TD}} = \dot{h}(\tau) = -1.5 \text{ ft/s} \tag{24}$$

$$\tau = \frac{-h_0\dot{x}(t_0)}{\dot{h}_0 - \dot{h}_T} \tag{25}$$

Results of different simulations conducted by the authors show that better trajectories could be achieved if the throttle setting, once selected, is treated as a constant. A block diagram of the PID controller is shown in Fig. 3.

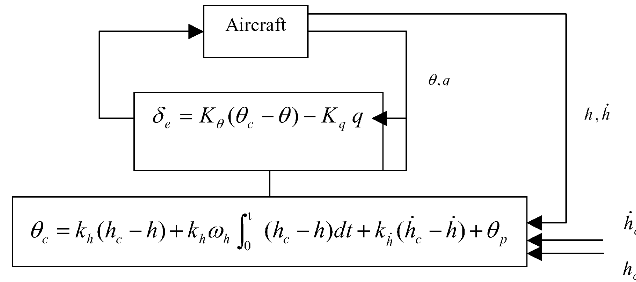

Fig. 3 PID controller block diagram.

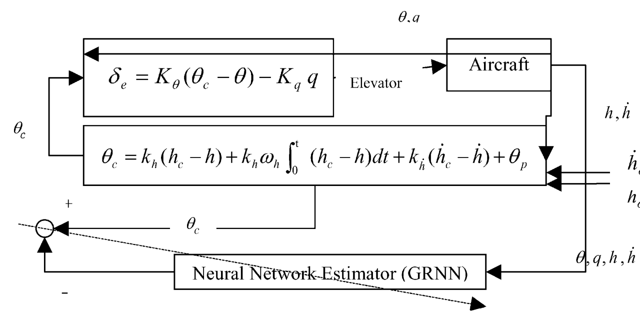

Fig. 4 Neuro-PID controller block diagram (with training procedure).

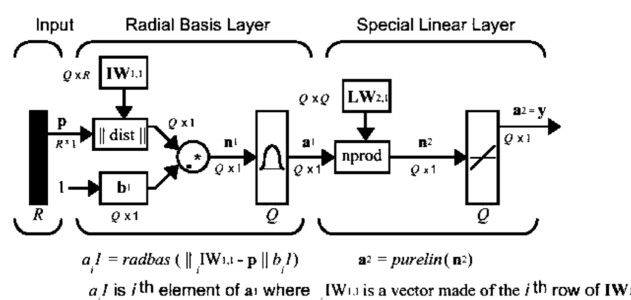

Fig. 5 Structure of GRNN.[13]

V. Hybrid Neuro-PID Controller

In Ref. 12, the authors developed a neuro-based controller for the same case; it was found that a controller that is based only on the neural networks technique does not have good performance in very strong wind patterns. In fact, it could not fulfill all requirements for levels 1 and 2 performance. Thus, to achieve better performance in the presence of strong turbulences, a hybrid neuro-PID controller has been proposed. In the new controller (Fig. 4), the inner loop that provides stability of the system is designed with the aid of classical methods such as root locus. That is, based on the equation for elevator setting [Eq. (20)], one could tune K_θ and K_q. The outer loop θ_c is estimated by a suitable type of neural network named general regression neural networks (GRNN). A generalized regression neural network is often used for function approximation. The architecture for the GRNN is shown in Fig. 5, where it has a radial basis layer and a special linear layer.[13]

VI. Hybrid ANFIS-PID Controller Design

In the final step, in a procedure similar to the neuro-PID controller, a hybrid ANFIS-PID controller has been designed. In this controller, the outer loop is fuzzy based, using a mixed type of adaptive networks and fuzzy systems, ANFIS. ANFIS acts similarly to a fuzzy system; however, it is structurally similar to an adaptive network (perceptron neural networks). When the Sugeno-type fuzzy system, in which x and y are input parameters and f is the output of the system, is followed, there are two rules:

1) If $\boldsymbol{x}$ is $\boldsymbol{A}_1$ and $\boldsymbol{y}$ is $\boldsymbol{B}_1$, then $\boldsymbol{f}_1 = \boldsymbol{P}_1\boldsymbol{x} + \boldsymbol{Q}_1\boldsymbol{y} + \boldsymbol{r}_1$.
2) If $\boldsymbol{x}$ is $\boldsymbol{A}_2$ and $\boldsymbol{y}$ is $\boldsymbol{B}_2$, then $\boldsymbol{f}_2 = \boldsymbol{P}_2\boldsymbol{x} + \boldsymbol{Q}_2\boldsymbol{y} + \boldsymbol{r}_2$.

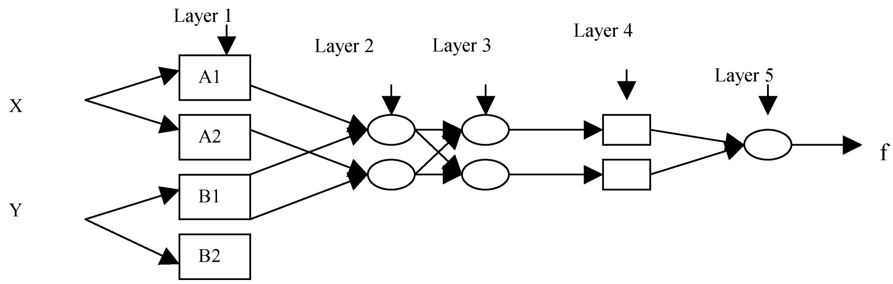

Fig. 6 ANFIS equivalent of Sugeno-type fuzzy system.[14]

Also

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{26}$$

An equivalent ANFIS system for the preceding fuzzy system is shown in Fig. 6 (Ref. 14). Layer 1 is the membership layer in which the membership degree of $\boldsymbol{x}$ relative to $\boldsymbol{A}_i$ computes the output of layer 1 as follows:

$$O_i' = \mu_{A_i}(x) \tag{27}$$

where μ is membership function of $\boldsymbol{A}_i$. In layer 2, input signals are multiplied by

$$w_i = \mu_{A_i}(x)\,\mu_{B_i}(y) \tag{28}$$

Equation (28) expresses the firing strength of each fuzzy rule. The output of each node in layer 3 is given by Eq. (29), which is called normalized firing strength,

$$\bar{w} = w_i/(w_1 + w_2) \tag{29}$$

Each node in layer 4 is a square node with the following node function:

$$O_2^4 = \bar{w}_i f_t - \bar{w}_z(P_z x + Q_z y + r_z) \tag{30}$$

Parameters $\{\boldsymbol{P}_i, \boldsymbol{Q}_i, \boldsymbol{r}_i\}$ and membership functions parameters are defined by a training process, which is usually based on steepest descent method or least-square error method. Again, the inner loop is designed by the classic PID tuning method; however, the outer loop is based on ANFIS. To train the ANFIS network, two error parameters are defined as follows:

$$E_h = h_c - h, \qquad E_{\dot{h}} = \dot{h}_c - \dot{h} \tag{31}$$

These two parameters, E_h and $E_{\dot{h}}$, are inputs to the ANFIS network and the output of ANFIS is θ_c. That is, the ANFIS network uses the two error values E_h and $E_{\dot{h}}$ to estimate the desired pitch angle θ_c. Each input, E_h and $E_{\dot{h}}$, has three bell-shaped membership functions. 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[15]:

1) If E_h is low and $E_{\dot{h}}$ is low, then θ_c is very low.
2) If E_h is low and $E_{\dot{h}}$ is medium then θ_c is very low.
3) If E_h is low and $E_{\dot{h}}$ is high then θ_c is low.
4) If E_h is medium and $E_{\dot{h}}$ is low then θ_c is low–medium.
5) If E_h is medium and $E_{\dot{h}}$ is medium then θ_c is medium.
6) If E_h is medium and $E_{\dot{h}}$ is high then θ_c is high–medium.
7) If E_h is high and $E_{\dot{h}}$ is low then θ_c is high.
8) If E_h is high and $E_{\dot{h}}$ is medium then θ_c is very-high.
9) If E_h is high and $E_{\dot{h}}$ is high then θ_c is very-very-high.

The block diagram of this controller is shown in Fig. 7.

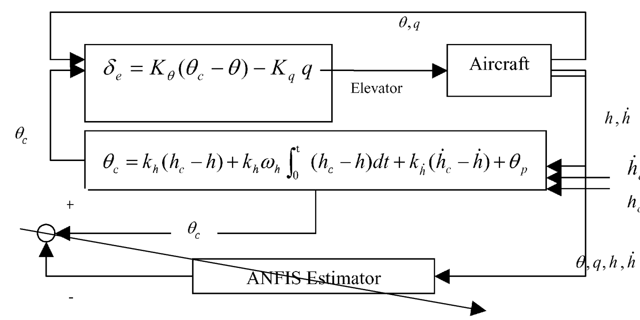

Fig. 7 ANFIS-PID controller block diagram (with training procedure).

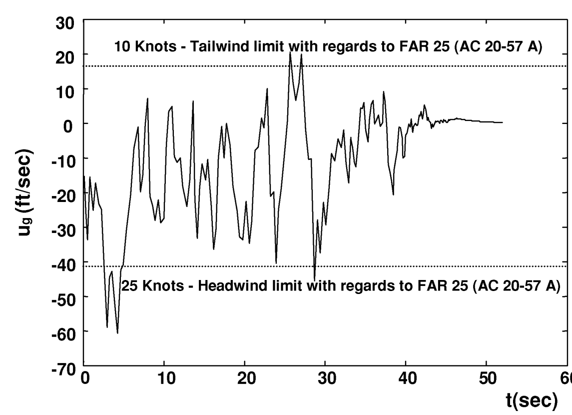

Fig. 8 Strong wind pattern, variation of u_g with h, where $N = 100$.

VII. Case Studies and Simulation Results

To train the networks, the M files and Neural Networks Toolbox[13] software of MATLAB® have been used, and to simulate the system, Simulink Toolbox[16] software of MATLAB has been used. Also suitable links between the M-files and Simulink environment have been provided. The initial conditions used for simulation results are given by Eqs. (7–9).

According to Federal Aviation Regulation FAR-25,[17] environmental conditions considered in the determination of dispersion limits are headwinds up to 25 kn (42.23 ft/s) and tailwinds up to 10 kn (16.9 ft/s). 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 Federal Aviation Administration for landing conditions. Figures 8–11 show the horizontal and vertical components of strong and very strong winds applied to the controllers.

The profile of strong wind used in this work is shown in Figs. 8 and 9 and is comparable to the JFK Airport gust of Fig. 1. Simulation results for applying strong wind are shown in Figs. 12–20. Figures 12–14 show both the followed and command trajectories for all three controllers and that the range of error is acceptable. The sink rate variations for the controllers are shown in Figs. 15–17. As can be seen, all of them satisfy the necessary conditions for the

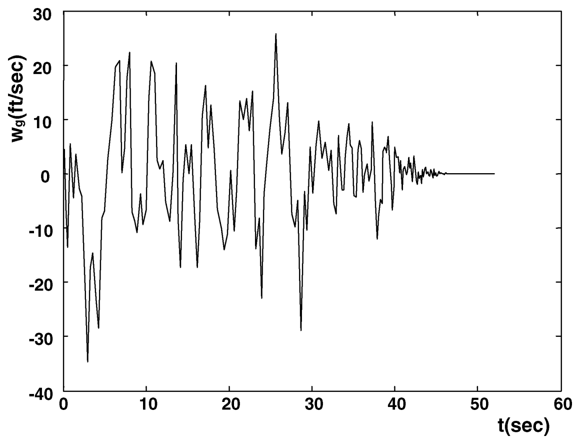

Fig. 9 Strong wind pattern, variation of w_g with h, where $N = 100$.

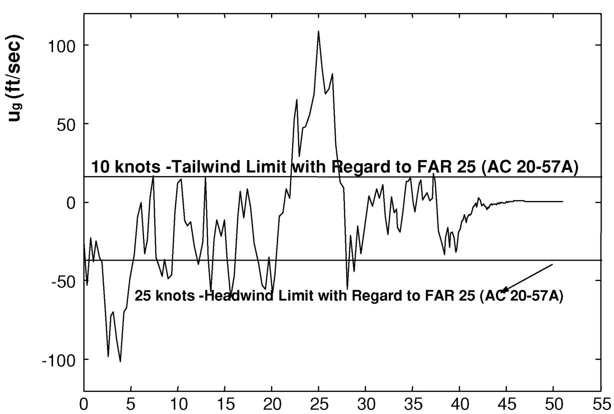

Fig. 10 Very strong wind pattern, variation of $u_g = 30$ ft/s with h, where $N = 300$.

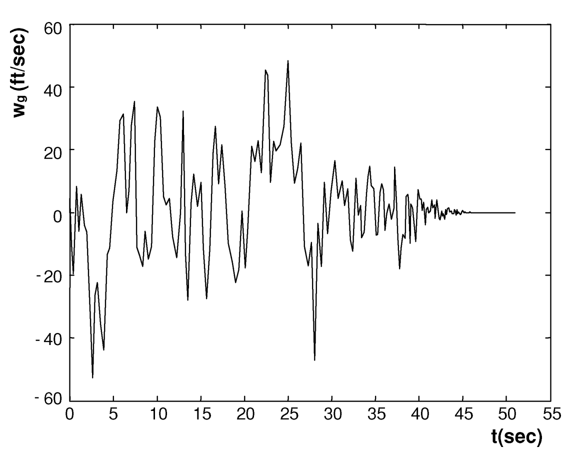

Fig. 11 Very strong wind pattern, variation of w_g with h, where $N = 250$.

so-called level 2. However, the controller based on ANFIS satisfies conditions for level 1.

Variations of angles of attack during the landing phase of all designed controllers are shown in Figs. 18–20. With regard to angle of attack limitations (stall angle α_s), they are all within the acceptable range. Consequently, all of the controllers, PID, neuro-PID, and ANFIS-PID, have good capabilities to guide the aircraft throughout the landing phase in the presence of the selected strong wind.

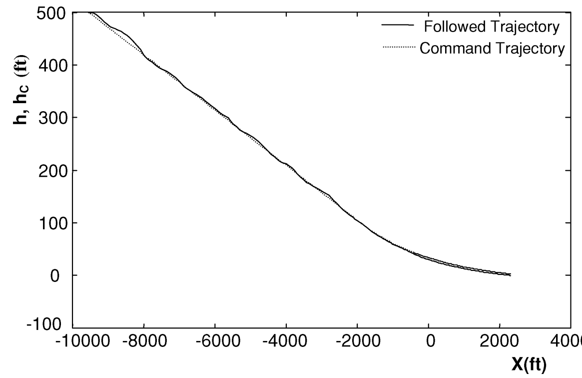

Fig. 12 Trajectory for PID controller with strong wind.

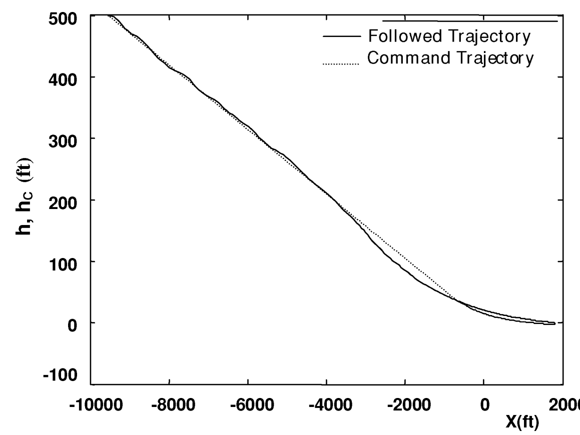

Fig. 13 Trajectory for neuro-PID controller with strong wind.

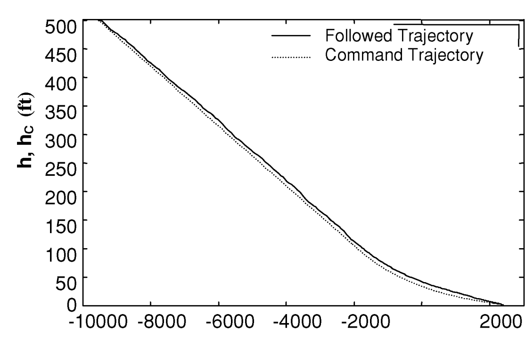

Fig. 14 Trajectory for ANFIS-PID controller with strong wind.

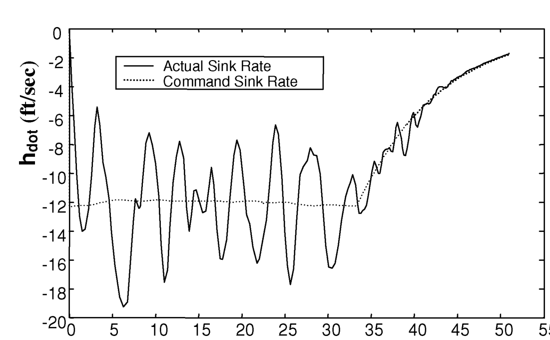

Fig. 15 Sink rate variations for PID controller with strong wind.

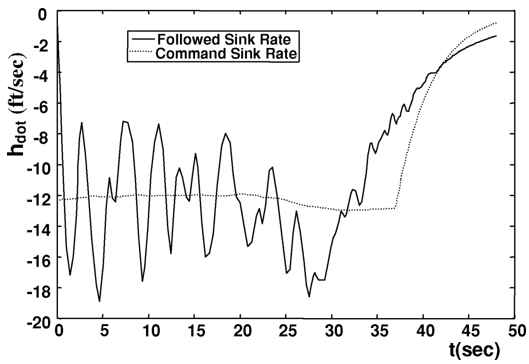

Fig. 16 Sink rate variations for neuro-PID controller with strong wind.

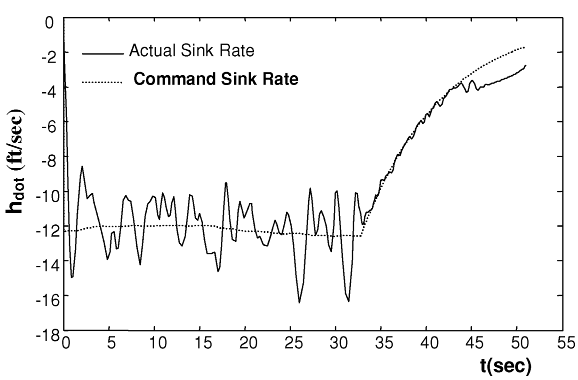

Fig. 17 Sink rate variations for ANFIS-PID controller with strong wind.

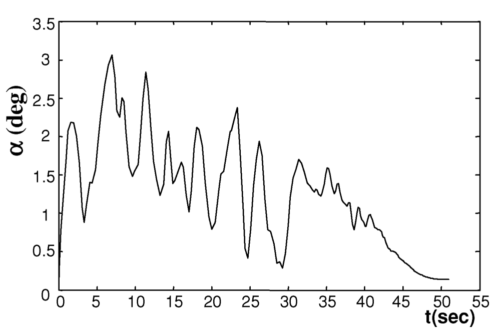

Fig. 18 Angle-of-attack variations for PID controller with strong wind.

Horizontal and vertical components of very strong wind are shown in Figs. 10 and 11 and could be considered stronger than that of the JFK Airport downburst. Figures 21–29 show simulation results for this case. Followed and command trajectories for the controllers in the presence of very strong wind are shown in Figs. 21–23. Figure 21 shows that the classic controller follows the commanded trajectory in a desirable manner; however, Fig. 22 shows that the neuro-PID controller has a relatively better performance and Fig. 23 shows that the ANFIS controller has the best performance.

Desired and actual sink rates for the controllers are shown in Figs. 24–26. Actual sink rates resulting from classic controller (Fig. 24) exceeds −20 ft/s and does not satisfy the desired conditions. The sink rate of the aircraft with hybrid neuro-PID controller (Fig. 25) in presence of the very strong wind does not exceed the −20 ft/s limitation and satisfies the necessary conditions for level 2 performance. Figure 26 shows that the actual sink rate with ANFIS-PID controller in the presence of very strong wind stays below 17 ft/s and so satisfies the necessary conditions for level 1 performance. Angle-of-attack variations for all of the controllers are shown in Figs. 27–29. Angle of attack of the aircraft in presence of very strong wind, while applying the PID and neuro-PID controllers (Figs. 27 and 28) will not exceed the stall angle limitation; however, the ANFIS-PID controller has a relatively better performance (Fig. 29). Table 1 summarizes these results. Discussion on their complexity and implementation for all of controllers may be found in Ref. 12; the results indicate that all of the described controllers are implementable.

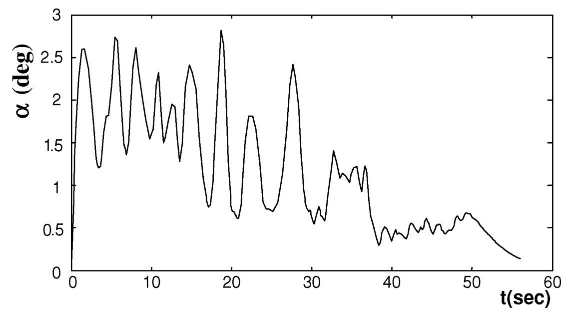

Fig. 19 Angle-of-attack variations for neuro-PID controller with strong wind.

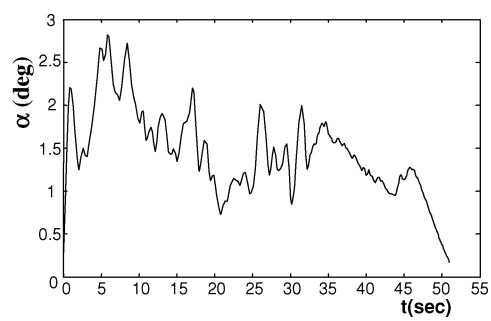

Fig. 20 Angle-of-attack variations for ANFIS-PID controller with strong wind.

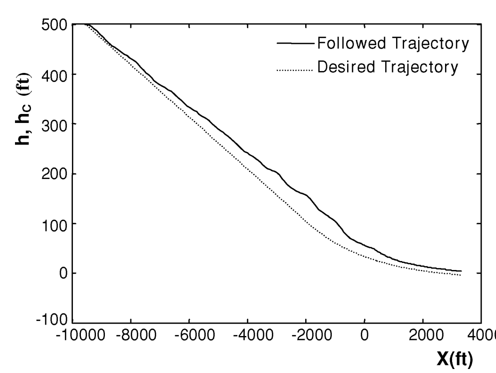

Fig. 21 Trajectory for PID controller with very strong wind.

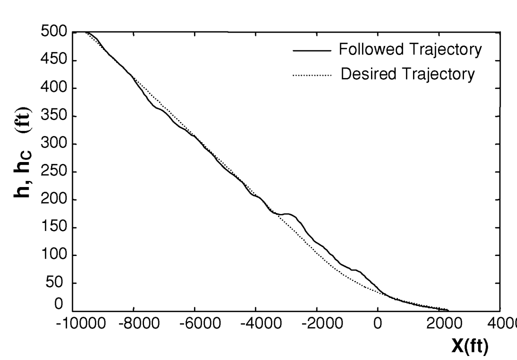

Fig. 22 Trajectory for neuro-PID controller with very strong wind.

Table 1 Performance comparison of the controllers

	Controller		
Wind pattern	PID	Neuro-PID	ANFIS-PID
Strong wind	Level 2	Level 2	Level 1
Very strong wind	Unacceptable	Level 2	Level 1
Learning capability	Not applicable	Possible	Good

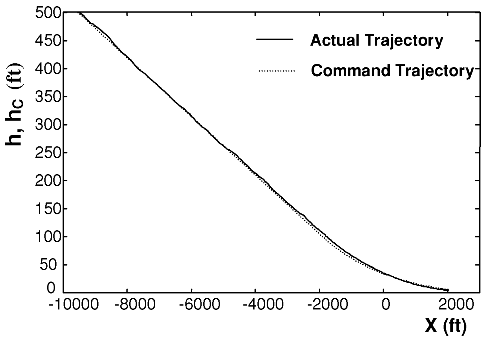

Fig. 23 Trajectory for ANFIS-PID controller with very strong wind.

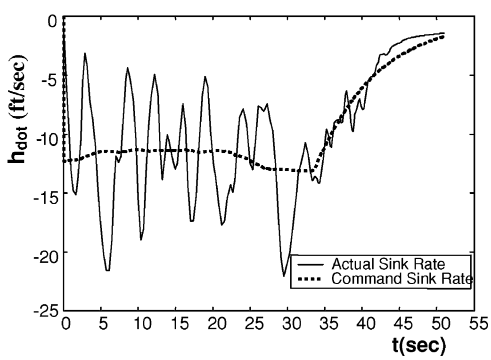

Fig. 24 Sink rate variations for PID controller with very strong wind.

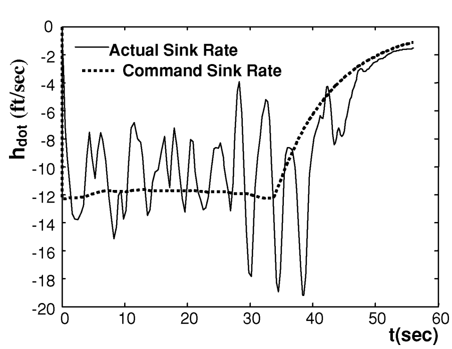

Fig. 25 Sink rate variations for neuro-PID controller with very strong wind.

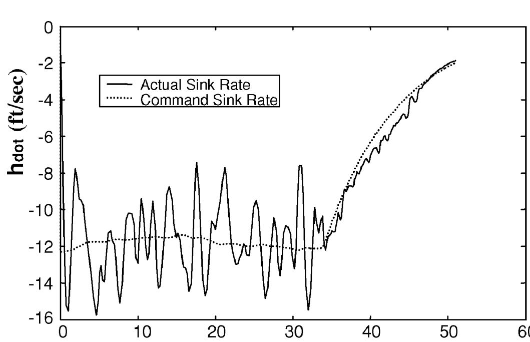

Fig. 26 Sink rate variations for ANFIS-PID controller with very strong wind.

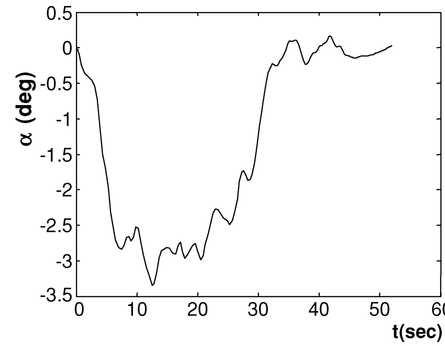

Fig. 27 Angle-of-attack variations for PID controller with very strong wind.

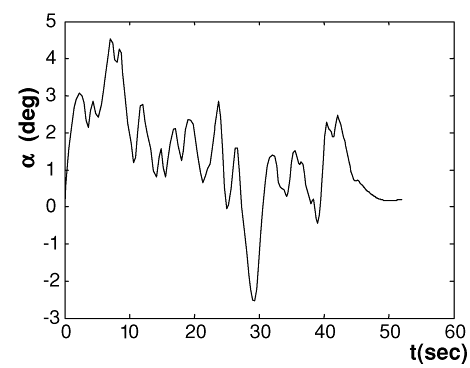

Fig. 28 Angle-of-attack variations for neuro-PID controller with very strong wind.

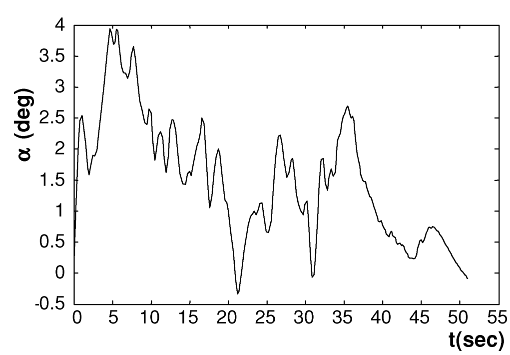

Fig. 29 Angle-of-attack variations for ANFIS-PID controller with very strong wind.

VIII. Conclusions

To provide support for the idea of the PLBCP, three different types of controllers have been compared based on similar dynamics in landing under severe climatic conditions. The results show that both hybrid neuro-PID and ANFIS-PID controllers have the required learning capability. Note that both controllers can have acceptable responses under very strong wind conditions while being trained for strong wind. Therefore, one might conclude that during the certification process it is sufficient to test the aircraft for certain available turbulence and let the learning capability of the controller take care of other stronger turbulences that the aircraft might encounter during its service life. At the first glance, this idea might not be consistent with the current practice adopted by the certifying authorities. However, similar to the nature of the human being, as well as organizations based on human expertise, that their level of performance increases in time as their experiences increase, one should exploit all available means to accumulate the experience of flight inside the knowledge base of the aircraft control system, as is the case with a human pilot. In this approach, as aircraft flying hours increases, the controller collects more data for the process of calculating proper commands. Nevertheless, the complexity of the new learning controllers remains a concern, as well as the minimum number of tests to enter the service life. Also note that in the new approach an aircraft starts its service life as soon as it passes some relaxed flight tests together with the proof that its AFCS has the sufficient learning capabilities to start its service life. Obviously, the aircraft operator receives necessary instructions regarding the learning sequence of the aircraft in such a way that its safety is not jeopardized. For example, if an aircraft with an intelligent controller is trained for turbulences with an average velocity of 25.0 ft/s, it can very well handle turbulences up to an average velocity of 40.0 ft/s. As soon as it encounters turbulences with such characteristics in service life, it is in fact trained with that of 40.0 ft/s. Once its knowledge based is modified under supervision, we can allow the aircraft to encounter turbulences for average velocity of 50.0 ft/s, as was shown in the case studies. The example intends to show that each step of learning must be carefully supervised. In mathematical terms, one might say that the amount of extrapolation must be selected make sure that learning is taking place in a gradual and predictable manner.

Considering the number of aircraft of the same type flying different routes, one can easily conclude that the degree of safety could be increased by allowing information to be shared among aircraft of the same type, as human being share information. Note that the necessary means for such an activity is already available through satellite-communication-based systems.

Overall, mixed neuro-Classic or fuzzy-classic controllers with the capability to estimate the system parameters demonstrate better performance in comparison with other controllers that are based only on classic or neural networks methods. Therefore, with the help of intelligent methods one could design different modes of a flight control computer, including autolanding controllers, that have learning capability while increasing the safety of flight with a better speed.

Note that in the new approach the role of certifying authorities should also change, and instead of numerous expensive test setups, the necessary infrastructure to test the learning capability and intelligence of the AFCS must be put into action.

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