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## DESIGN OF UAV ROBUST AUTOPILOT BASED ON ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

*This paper is devoted to the application of adaptive neuro-fuzzy inference systems to the robust control of the UAV longitudinal motion. The adaptive neore-fuzzy inference system model needs to be trained by input/output data. This data were obtained from the modeling of a "crisp" robust control system. The synthesis of this system is based on the separation theorem, which defines the structure and parameters of LQG-optimal controller, and further* $H_2/H_\infty$ *- robust optimization of this controller, based on the genetic algorithm. Such design procedure can define the rule base and parameters of fuzzyfication and defuzzyfication algorithms of the adaptive neore-fuzzy inference system controller, which ensure the robust properties of the control system. Simulation of the closed loop control system of UAV longitudinal motion with adaptive neore-fuzzy inference system controller demonstrates high efficiency of proposed design procedure.*

*Розглянуто синтез нейронечіткої багатовимірної системи управління польотом малого БПЛА за умови знаходження компромісу між якістю та робастністю цієї системи. Як робастний прототип, який використовується для навчання нейронечіткої системи, застосовується багатовимірний чіткий регулятор, синтезований за допомогою теореми розділення з наступною робастизацією отриманого рішення на основі робастної* $H_2/H_\infty$ *- оптимізації, використовуючи генетичний алгоритм. Зміни вхідних та вихідних координат чіткої системи використовуються для навчання нейронечіткої мережі, яка застосовується для алгоритму зворотного розповсюдження похибки для налаштування параметрів функцій приналежності вхідних сигналів та градієнтної оптимізації для налаштування параметрів алгоритму дефаззифікації Сугено. Наведено результати моделювання нейронечіткої системи керування поздовжнім рухом малого БПЛА, які підтверджують її ефективність.*

### Introduction

Essential parametrical uncertainty of the small UAV mathematical models is one of the most difficult problems arising in the process of the UAV control system's design. Modern robust control theory proposes very effective methods to overcome this difficulty [1−4]. These methods use the "crisp" robust control approach [1−3], as well as usage of the fuzzy logics [5].

Some previous works were devoted to the design of the robust control systems based on the combination of the "crisp" and fuzzy principles [5; 6]. In these systems internal control loop for the angular stabilization was designed on the basis of the $H_2/H_\infty$ - robust control [5; 6], meanwhile the outer loop for the altitude stabilization used fuzzy controllers. This design approach can produce systems using the simplest fuzzy controllers, because usage of the fuzzy controllers for multivariable angular, altitude and speed stabilizations requires development of large amount of inference rules and makes problem of creation the knowledge base of fuzzy controller practically unsolvable.

In order to overcome this hindrance the method based on the application of adaptive neuro-fuzzy control principles [7−9] can be applied, because creation of the inference rule base and tuning the fuzzification and defuzzification parameters are supported by proper software in MATLAB, thus facilitating design of the control system. As it is known [8−11], the adaptive neuro–fuzzy inference system (ANFIS) consists of fuzzy Takagi-Sugeno (FTS) type, which has the ability of learning. The construction of the FTS system is a complex task [7; 12], especially in the area of unmanned aerial vehicles, due to the complexity of the flight dynamic nonlinear model and to the unavailability of perfect model. Some methods, to create the FTS models were exposed in the literature, these models depend on the objectives expected from the designer. In this paper, the synthesis of the FTS model is based on the ANFIS approach [7; 9−11]. ANFIS is an adaptive neuro-fuzzy inference system, which uses the advantage of the fuzzy logic system and artificial neural networks and constructs the hybrid intelligent system [7; 9−11].

The design of this system is based on the observed input/output data produced by linear multivariable robust control system. This system is used as the generator of training input/output time histories. The synthesis of the training system consists of 2 stages. The first one uses the separation theorem [13] applied to the model of the UAV at some nominal flight conditions augmented with Dryden model of the turbulent wind [14] in order to find the linear quadratic Gaussian (LQG) controller. The second stage is based on $H_2/H_\infty$ - robust optimization [1−3] of closed loop system with LQG-controller. The paper gives out the training methodology of such adaptive networks based on ANFIS under MATLAB. Its implementation in the autopilot's control law and simulation results are given for the longitudinal channel of Aerosonde UAV [15], which is widely used for the meteorological surveillance.

**Structure of Adaptive Neuro-Fuzzy Inference System**

Adaptive neuro-fuzzy inference system was first initiated by Jang's PhD thesis supervised by Zadeh at school of Berkley of California University [7]. ANFIS approximates any linear or nonlinear function using input/output data [7]. The fuzzy inference is used to set the existing relations between these data, and the neural network applies its learning capability to adjust parameters of the fuzzy inference.
As an example, ANFIS model with two inputs, two rules and one output is depicted in the fig. 1.

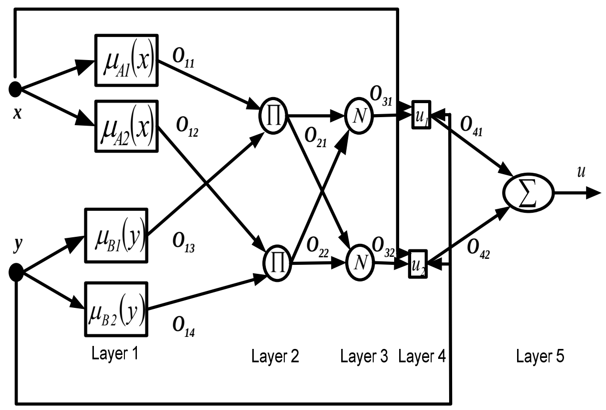



Fig. 1. ANFIS structure with 2 rules, two inputs and one output

It uses a hybrid learning, which combines two training methods: the least-squares method and the back-propagation [7; 16]. Back-propagation is applied to the learning the antecedent parameters, while the least-squares method is learning the consequent parameters.
Typical fuzzy rules in a Takagi – Sugeno model corresponding to the graph represented in fig. 1 are expressed as follows:
*IF* $x$ is $A_1$ and $y$ is $B_1$ then $u_1 = f_1(x, y)$;
*IF* $x$ is $A_2$ and $y$ is $B_2$ then $u_2 = f_2(x, y)$,

where
$\{A_1, B_1, A_2, B_2\}$ are fuzzy sets in the antecedent:
$u_i = f_i(x, y)$ , $i = 1, 2$ is a crisp function in the consequent.
The function $f_i(x, y)$ can be any function that approximates the output of the system within fuzzy region specified by the antecedent of the rule [7; 8; 16]. When $f_i(x, y)$ is a first order polynomial, we have the first order FTS fuzzy model.
The fig. 2 shows the first order FTS, where {x, y} is the input vector. $\overline{O}_{ij}$ are the normalized ratio of each firing strength to the total of all firing strengths.
The architecture shown in fig. 1, is known as a multilayer feed forward network [7]. In ANFIS, the FTS is synthesized knowing some parameters of the antecedent and the consequent, as the number and shape of the input membership function of the fuzzy sets, and parameters of the output function $f_i(x, y)$.
For the first order FTS functions $f_i(x, y)$ have the following form:
$f_i = p_i x + q_i y + r_i$, $i = 1,2$.
In the next section, the function of each layer in the fig. 1 is given, where:

$$\overline{O}_{12} = \frac{O_{21}}{O_{21} + O_{22}}$$

and

$$\overline{O}_{22} = \frac{O_{22}}{O_{21} + O_{22}}.$$

Layer 1: node $i$ has the output function
$O_{1i} = \mu_{A_i}(x)$ $\quad i = 1,2$;
$O_{1i} = \mu_{B_{i-2}}(y)$ $\quad i = 3,4$,
where $O_{1i}$ are the membership grades of $A_i$ and $B_i$. They show the degree that $x$ and $y$ belong to $A_i$ and $B_i$. The membership functions could have any shape, but most used in ANFIS [7−10] are generalized "bell-type functions", their equation is as follows [17]:

$$\mu_{A_i}(x_j) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}}$$

the parameters $\{a_i, b_i, c_i\}$ are the parameters of the antecedent, which will be tuned by the ANFIS.

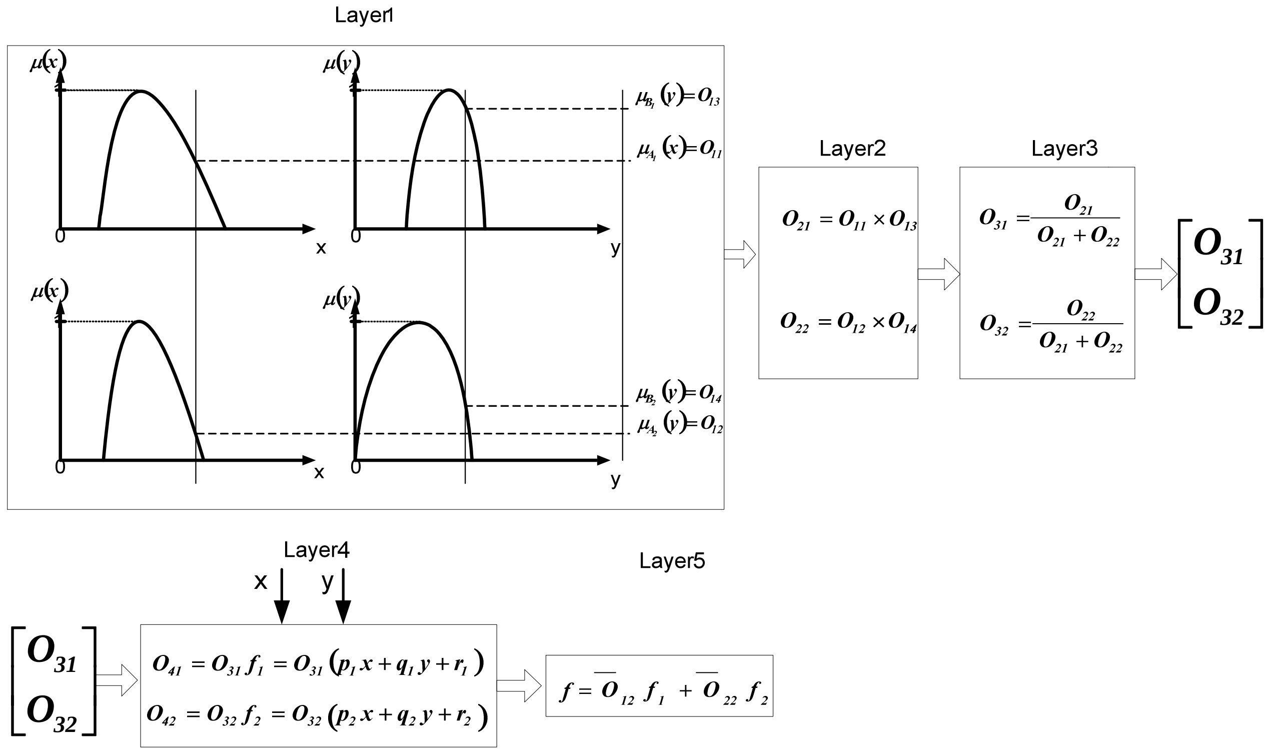



Fig. 2. First order Sugeno model

Layer 2: this layer computes the firing strength of each rule using t-norm operator

$$O_{2i} = \mu_{A_i}(x) \times \mu_{B_i}(y) \qquad i = 1,2\,, \tag{1}$$

where $\times$ stands for probabilistic product operator.

Layer 3: in this layer the normalized ratio of $i-th$ rule's firing strength to the total firing strength is computed as follows:

$$\mathrm{O}_{3i} = \frac{\mathrm{O}_{2i}}{O_{11} + \mathrm{O}_{22}} \qquad i = 1,2\,. \tag{2}$$

Layer 4: this layer computes the contribution of each rule toward the overall output, and is done using the following node function

$$\mathrm{O}_{4i} = O_{3i} f_i = \mathrm{O}_{3i}(p_i x + q_i y + r_i) \qquad i = 1,2\,, \tag{3}$$

where $\{p_i, q_i, r_i\}$ are the consequent parameters to be tuned by the ANFIS.

Layer 5: the node of this layer computes the overall output as the summation of contribution from each rule, using the following formula:

$$\begin{aligned}\mathrm{O}_{5i} &= \sum_i \mathrm{O}_{4i} = \sum_i \mathrm{O}_{3i} f_i = \sum_i \frac{\mathrm{O}_{2i} f_i}{O_{11} + \mathrm{O}_{22}} = \\ &= \frac{\mathrm{O}_{21}}{\mathrm{O}_{11} + \mathrm{O}_{22}}(p_1 x + q_1 y + r_1) + \\ &+ \frac{\mathrm{O}_{22}}{\mathrm{O}_{11} + \mathrm{O}_{22}}(p_2 x + q_2 y + r_2) = \overline{w}_1 f_1 + \overline{w}_2 f_2.\end{aligned} \tag{4}$$

## Adaptive neore-fuzzy inference system Training algorithm

In the above section, the ANFIS is represented graphically, which displays the computations steps of Takagi-Sugeno procedure. This representation is useful for control law synthesis if it is equipped with a learning algorithm. The most used learning algorithm in neural network is back-propagation [18] to learn the weight of the connecting arrows between neurons from input/output information.

In the ANFIS structure, the adjusted or synthesized parameters are the parameters of the antecedent $\{a_i, b_i, c_i\}$, which are initially given parametrically, as explained before. The parameters of the consequent are also adjusted and initially given by the structure of the Sugeno model (type 0 or type 1). As stated before, the training algorithm used for synthesis the Sugeno model is hybrid [7; 19]. The least-squares algorithm is applied for training consequent parameters, and back propagation is used to tune the antecedent parameters $\{a_i, b_i, c_i\}$ describing the generalized bell shaped membership function, width, slope, and center, respectively. The hybrid algorithm can be partitioned into the following two steps [7; 11; 19]: The first step is designated for adjustment of the output consequent FTS parameters $\{p_i, q_i, r_i\}$ by least square training algorithm. Suppose that training robust system generates the training set as the input/output data, which can be represented as vector time series $\{(x^1, y^1), \cdots, (x^K, y^K)\}$ where $x^K = (x_1^k, \cdots, x_n^k) \in R^k$ and $y^k \in R^k$. In order to approximate the control law from this given set, a fuzzy *If-Then* rules are used. Let $R_i$, $i = 1, \cdots, m$ be the $i-th$ rule of the form:

$R_i$: *If* $x_1^k$ is $A_i^1$ and … and $x_n^k$ is $A_i^n$ then

$$y = \sum_{j=1}^{n} z_i^j x_j^k + z_1^0, \qquad (5)$$

where $A_i^j$ are fuzzy membership function and $z_i^j$ are real numbers, which depend on parameters $p, q, r$.

Note that the algorithm described graphically for two rules in the last section, is generalized to $m$ rules.

Let $O^k$ be the output from the fuzzy system corresponding to the input $x^k$. The antecedent of the $i-th$ rule is defined by:

$$\mu_k^i = \prod_{j=1}^{n} A_i^j(x_j^k). \qquad (6)$$

As it is shown, the *t*-norm operator used in (6) is the probabilistic product.

Using formulas (1)–(5), the output of the system is computed as follows:

$$O^k = \frac{\sum_{i=1}^{m} \mu_i^k \left(\sum_{j=1}^{n} z_i^j x_j^k + z_i^0\right)}{\sum_{i=1}^{m} \mu_i^k} = \frac{\sum_{i=1}^{m} \left(\prod_{j=1}^{n} A_i^j(x_j^k)\right)\left(\sum_{j=1}^{n} z_i^j x_j^k + z_i^0\right)}{\sum_{i=1}^{m} \prod_{j=1}^{n} A_i^j(x_j^k)}$$

define the error for the $k-th$ training pattern as:

$$E^k(Z) = \frac{1}{2}\left(O^k(Z) - y^k\right)^2, \qquad (7)$$

where

$O^k(Z)$ is the computed output from the fuzzy system corresponding to the input pattern $x^k$;

$y^k$ is the desired output, $k = 1, \cdots, K$ depending on vector $Z$.

Using the least squares estimate, we can gain the optimal solution by minimizing the summation of the error given in (7), using gradient descent optimization procedure over variable vector Z:

$$\frac{\partial E^k(Z)}{\partial Z} = 0, \quad Z_{opt} = \arg \min_{p \in R^{k \times 1}} E^k(Z). \qquad (8)$$

The second step is to train the antecedent parameters using the back-propagation (BP). Basing on the consequence parameters obtained in the first step, we can compute the error. The BP algorithm of the forward fee network is used to propagate the error backward, from output layer to input layer. The parameters $a_i, b_i, c_i$ of the membership functions are updated using the gradient descent [8; 9]. Then, the shape of the input membership function will change.

## Adaptive neuro-fuzzy inference system Training system

To train the Sugeno model some training data should be presented to the input and output. Consequently, the ANFIS can interpolate between inputs/output data to generate the control law. The best source of acquiring the training data is naturally coming, from the trial of the actual UAV in fly; however, this method is very difficult and seems to be not realistic. Therefore, the training data used in this paper are obtained from the simulation of the training system.

It is well known, that the Sugeno model can be viewed as special case in gain scheduling or state feedback [7; 8], where the gains depends on the input membership function. For this reason, a stochastic state feedback, based on robust multivariable LQG technique, seems an appropriate choice to generate the training data for the ANFIS algorithm, especially in the area of UAV flight control, due to the exposition of the UAV to many disturbances.

The robust multivariable LQG technique used in this paper is based on $H_2/H_\infty$ - robust optimization, well studied in [1-3]. The first stage of this method is to design an LQG regulator baser on the separation theorem, which consist on the Kalman filter and linear quadratic regulator (LQR). In the second stage the “robustization” of the control law using genetic algorithms (GAs) is adopted. The fitness function used in GAs optimization is composed from $H_2$ - norm of the sensitivity function, to estimate the performances of the closed loop system, and $H_\infty$- norm of the complementary sensitivity function, which is used to estimate the robustness of the closed loop. This method is used to find the trade-off between the performance and the robustness of the control system. The fig. 3 gives the scheme used to robustify the LQG controller using genetic algorithms.

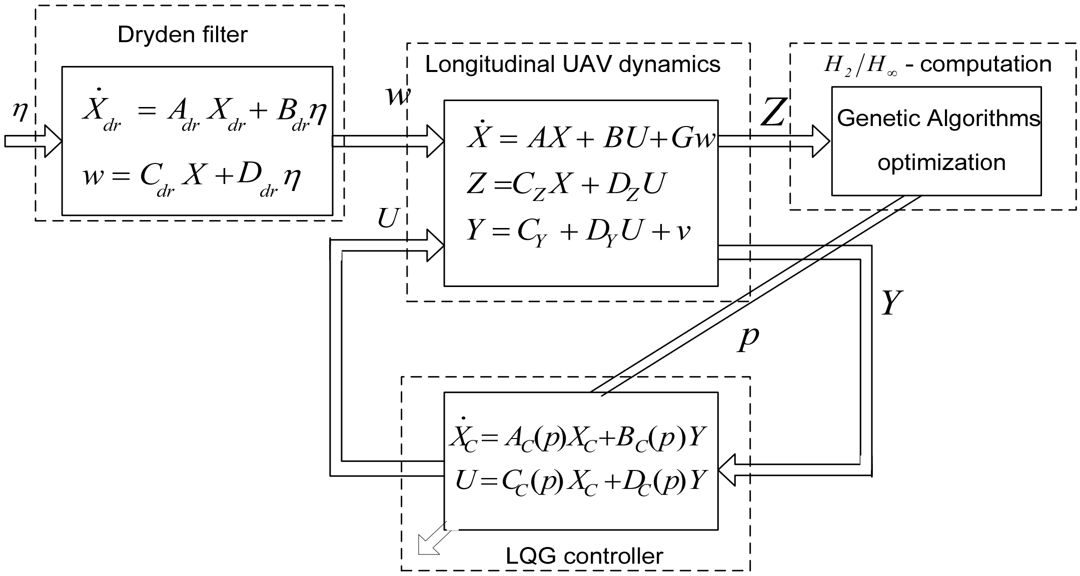



Fig. 3. Closed loop system (p is a vector of adjustable parameters of controller)

The model used in this study is the longitudinal dynamic of the Aerosonde UAV [19]. Notice that the nonlinear model is trimmed at several operating conditions, resulting in the nominal model and disturbed models. The state space models $N$ - operating condition are described by the quintuple of matrices $[A_i, B_i, C_i, D_i, G_i]$,

where:

$A_i \in R^{n\times n}$,

$B_i \in R^{n\times q}$,

$C_i \in R^{p\times n}$,

$D_i \in R^{p\times q}$,

$G_i \in R^{n\times l}$,

where the index $i$ represents the $i-th$ operating condition. The state space representation is given as follows:

$$\begin{aligned} \dot{X} &= A_i X + B_i U + G_i w; \\ Y &= C_i X + D_i U + v. \end{aligned} \tag{9}$$

The vector $w$ represents the process disturbances, and here it is given by the wind turbulence described by the outputs of the Dryden filter [6], $v$ is the white noise of measurement the separation theorem is applied to the extended model formed by the UAV model and the Dryden forming filter. Let the quadruple of matrices $[A_{dr}, B_{dr}, C_{dr}, D_{dr}]$ represents the state space model of the forming filter, where $A_{dr} \in R^{r\times r}, B_{dr} \in R^{r\times 2}, C_{dr} \in R^{l\times r}, D_{dr} \in R^{l\times r}$.

The extended state space model of the overall system is described in the following way:

$$\left[\begin{array}{c|c} \mathbf{A}_{ex} & \mathbf{B}_{ex} \\ \hline \mathbf{C}_{ex} & \mathbf{D}_{ex} \end{array}\right] = \left[\begin{array}{cc|cc} \mathbf{A}_{nom} & G_{nom}C_{dr} & B_{nom} & G_{nom}B_{dr} \\ 0_{r\times n} & \mathbf{A}_{dr} & 0_{r\times q} & B_{dr} \\ \hline C_{nom} & 0_{p\times r} & D_{nom} & 0_{p\times 2} \end{array}\right]. \tag{10}$$

The subscript $nom$ stands for nominal.

After forming the extended model (10), the separation theorem [13], which state, as it is well known, that optimal stochastic observer using Kalman filter to restore the full states vector of (9), an optimal deterministic controller based on the LQR can be applied to the restored states. The optimal Kalman filter is designed to restore the nominal state vector and defined as:

$$\dot{\tilde{X}} = A_{ex}\tilde{X}_{ex} + B_{ex}U + L\left(Y - C_{ex}\tilde{X}_{ex} - D_{ex}U\right);$$

$$\begin{bmatrix} \tilde{Y} \\ \tilde{X} \end{bmatrix} = \begin{bmatrix} C_{ex} \\ I \end{bmatrix}\tilde{X}_{ex} + \begin{bmatrix} D_{ex} \\ 0 \end{bmatrix}U,$$

where

L is the Kalman gain matrix given by the following expression:

$L = PC_{ex}^T R_N^{-1}$,

where $P$ is the unique positive-definite solution to the following Algebraic Riccati Equation (ARE):

$$A_{ex}P + PA_{ex}^T + B_{ex}Q_N B_{ex}^T - PC_{ex}^T R_N^{-1} C_{ex} P = 0,$$

$Q_N$ and $R_N$ are the covariance matrices associated with the measurement and process noises respectively.

The state feedback $K$ is given in the following expression:

$$K = R^{-1} B_{ex}^T S,$$

where $S$ is the unique positive definite matrix of *(ARE)* associated with the optimal feedback problem:

$$A_{ex}^T S + S A_{ex} - S B_{ex} R^{-1} B_{ex}^T S + Q = 0$$

and the optimal control law minimizing the performance index, is as follows:

$$U = -K\widetilde{X}_{ex}.$$

The connection of the Kalman filter and the optimal regulator leads to the following state space model of the closed loop system:

$$\begin{bmatrix} X \\ \widetilde{X} \end{bmatrix} = \begin{bmatrix} A_{ex} & -B_{ex}K \\ LC_{ex} & A_{ex} - LC_{ex} - B_{ex}K \end{bmatrix} \begin{bmatrix} X \\ \widetilde{X} \end{bmatrix},$$

where $\widetilde{X}$ is the restored state vector.

The $H_2/H_\infty$ - robust optimization consists of minimization of certain cost function computed for different models; nominal and perturbed controlled by the same controller designed above. The terms of the fitness function are computed using $H_2$ - norm of the sensitivity function, to measure the performances of the closed loop system, and $H_\infty$ - norm of the complementary sensitivity function. These norms are function of the Kalman gain matrix $L$ and the LQR gain matrix $K$, since they are computed to closed loop system including the controller. The performance index is found as follows:

$$J(L,K) = \lambda_{dn}\|H_{UZ}\|_2^{dn} + \lambda_{sn}\|H_{UZ}\|_2^{sn} + \lambda_{\infty n}\|T_{wZ}\|_\infty^{n} + \\ + \sum_{k=1}^{N-1}\lambda_{dpk}\left(\|H_{UZ}\|_2^{dpk}\right) + \sum_{k=1}^{N-1}\lambda_{spk}\left(\|H_{UZ}\|_2^{spk}\right) + \\ + \sum_{k=1}^{N-1}\lambda_{\infty pk}\left(\|T_{wZ}\|_\infty^{pk}\right),$$

where $\|H_{UZ}\|_2^{dn}$ defines the $H_2$ – norm of the nominal model in deterministic case;

$\sum_{k=1}^{N-1}\|H_{UZ}\|_2^{dpk}$ stands for summation of the $H_2$ – norms of $(N-1)$ perturbed models;

$\|T_{wZ}\|_\infty^{n}$ is the $H_\infty$ – norm and gives the estimation of the robustness of the nominal controlled plant, $\sum_{k=1}^{N-1}\|T_{wZ}\|_\infty^{pk}$ computes the summation of the $H_\infty$ –norm for all $(N-1)$ parametrically disturbed plants. $\|H_{UZ}\|_2^{sn}$ defines the performances of the nominal stochastic model, the same summation of the $H_2$ – norm being defined for all perturbed models with the expression $\sum_{k=1}^{N-1}\|H_{UZ}\|_2^{spk}$.

The LaGrange factors $\lambda_{dn}$, $\lambda_{sn}$, $\lambda_{dpk}$, $\lambda_{spk}$, $\lambda_{\infty n}$, $\lambda_{\infty pk}$ weight the contribution of each term in the cost function. After optimization the designed control law is able to control a wide range of operating conditions.

Once this control law is deigned it can be used to train the ANFIS. During the simulation process of the robust control system, described before, we can write down the system inputs, the system outputs, the values of the state variable and the output of the optimal controller, and use these data as training data for the ANFIS.

The ANFIS used in this paper is based on first-order Sugeno model and, therefore allow only a single output. The longitudinal dynamic of the Aerosonde UAV has two control variables $[\delta_e, \delta_{th}]$, elevator deflection and throttle setting. This requires the design of two independent fuzzy controllers, one for each control variable.

The state space models are calculated by imposing the uncertainty for the true airspeed, which is given by the following expression

$$V = \sqrt{u^2 + v^2 + w^2},$$

where $v$ defines the lateral velocity component.

For the sake of simplicity and without loss of generality two models $(N = 2)$ are defined, the nominal model is taken at $V_n = 30$ m/s and one perturbed model $V_p = 35$ m/s . The following matrices give the respective states models:

$$A_n = \begin{bmatrix} -0.293 & 0.38 & -0.55 & -9.78 & 0 & 0.01 \\ -0.55 & -5.36 & 30 & -0.18 & 0 & 0 \\ 0.33 & -5.63 & -6.19 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0.01 & -1 & 0 & 30 & 0 & 0 \\ 41.53 & 0.78 & 0 & 0 & -0.63 & -3.85 \end{bmatrix};$$

$$B_n = \begin{bmatrix} -0.3 & 0 \\ -3.7 & 0 \\ -50 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 2664 \end{bmatrix};$$

$$A_p = \begin{bmatrix} -0.35 & 0.28 & -0.05 & -9.82 & 0 & 0.01 \\ -0.55 & -6.25 & 35 & -0.01 & 0 & 0 \\ 0.28 & -6.43 & -7.21 & 0 & 0 & -0.01 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 35 & 0 & 0 \\ 48.5 & 0.08 & 0 & 0 & -0.78 & -4.43 \end{bmatrix};$$

$$B_p = \begin{bmatrix} -0.5 & 0 \\ -5 & 0 \\ -68.2 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 3040.3 \end{bmatrix}.$$

In series the models of actuators are connected to the model of the UAV and are approximated by the first order model given in the following:

$$\left[\begin{array}{c|c} A_{act} & B_{act} \\ \hline C_{act} & D_{act} \end{array}\right] = \left[\begin{array}{c|c} -1/\tau_{\delta act} & 1/\tau_{\delta act} \\ \hline 1 & 0 \end{array}\right],$$

where $\tau_{\delta act} = 0.25$ s stands for the time constant of the actuator and the subscript $\delta act$ can be either for elevator or throttle.

In this case study only four states are measured: $\overline{X} = [u \quad q \quad \theta \quad h]$,

so the observation matrix is given as follows: $C = \left[ [1 \;\; 0_{3\times1}]^T \quad 0_{4\times1} \quad [0_{1\times4} \;\; I_{3\times3} \;\; 0_{3\times1}]^T \right]$, where $I$ represents the unity matrix with appropriate dimension. According to [14], the Dryden filter has two inputs: horizontal and vertical wind gests, the outputs are the longitudinal turbulent speed $u_g$, vertical turbulent speed $w_g$ and turbulent pitch rate $q_g$. State space of the Dryden filter is defined by the following matrices:

$$A_{dr} = \begin{bmatrix} -1/\lambda_u & 0 & 0 \\ 0 & -1/\lambda_w & 0 \\ 0 & -K_q/\lambda_q^2 & -1/\lambda_q \end{bmatrix};$$

$$B_{dr} = \begin{bmatrix} K_u/\lambda_u & 0 \\ 0 & K_w/\lambda_w \\ 0 & 0 \end{bmatrix};$$

$$C_{dr} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & K_q/\lambda_q & 1 \end{bmatrix},$$

where the subscript $w$ corresponds to vertical components and $u$ for the longitudinal. In our case the Aerosonde flies at an altitude of 200 m, and in moderate turbulence. The parameters appearing in the state space of Dryden filter are given in the following:

$K_u = \sigma_u \sqrt{(2L_u/\pi V)}$; $\lambda_u = L_u/V$;

$K_w = 2.2$; $\lambda_w = 0.6$;

$K_q = 1/V$; $\lambda_q = 4b/\pi V$,

where $b$ is the wing span for the Aerosonde $b = 2.9m$ $L_u$ is the horizontal turbulence scale lengths;

$\sigma_u$ is turbulence intensities.

The same parameters are defined for different models with different true airspeed $V$.

The ANFIS model has 4 training inputs for each pair $(x, y)$, the vector

$x = [eu \quad eq \quad e\theta \quad eh]$,

where $eu$ is the velocity error between the reference and the velocity output of the UAV plus the sensor noises; $eq$;

$e\theta$ are the pitch rate and angle, respectively, contaminated by sensor noises and $eh$ is the altitude error between the reference signal and the altitude output.

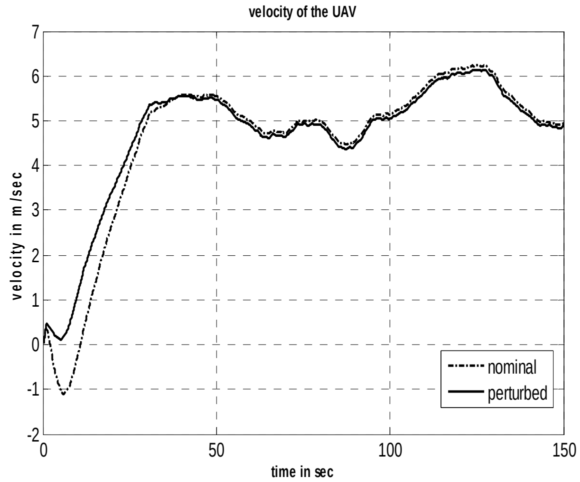
The outputs of the fuzzy controllers are elevator $\delta_e$ and throttle $\delta_{th}$.

The simulation results are shown in the fig. 4.

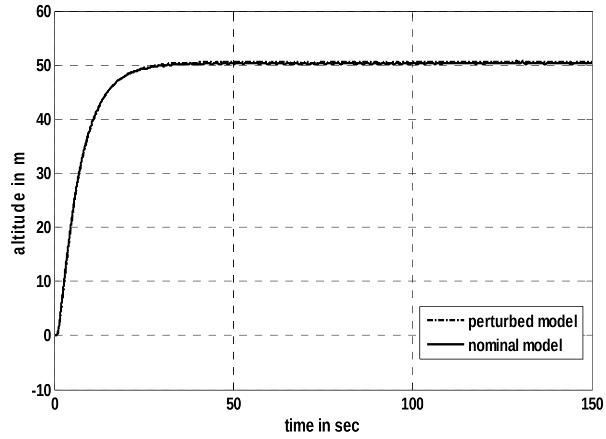
## Conclusion

The simulations results prove the efficiency of the control law designed using Adaptive Neuro-Fuzzy Inference system. As it can be seen from the figures all flight requirement are respected for the nominal as well as for the perturbed model. All ranges of the angles variations for the Aerosonde are satisfied, altitude is stabilized at the reference signal (50 m), as well as the velocity (5 m/s), as it is shown in the first and second figures, respectively.

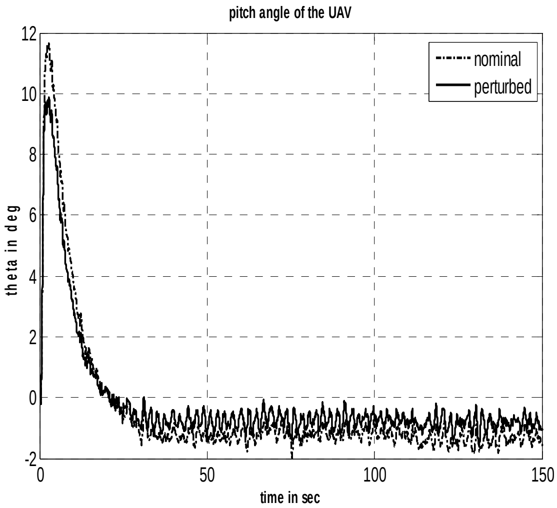
One can also conclude that the autopilot designed using ANFIS holds the property of the robustness.



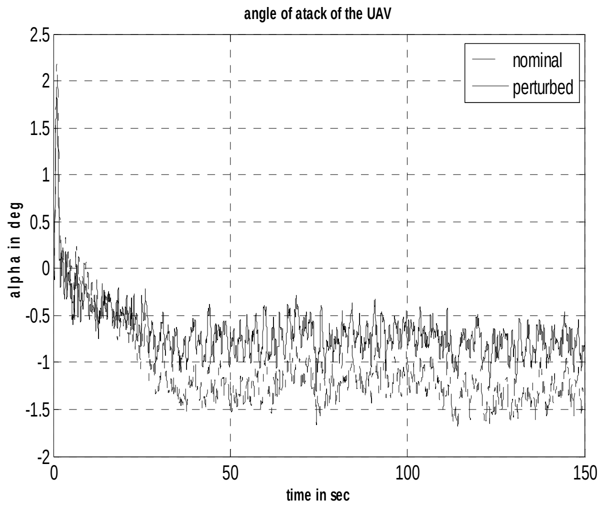

*a*



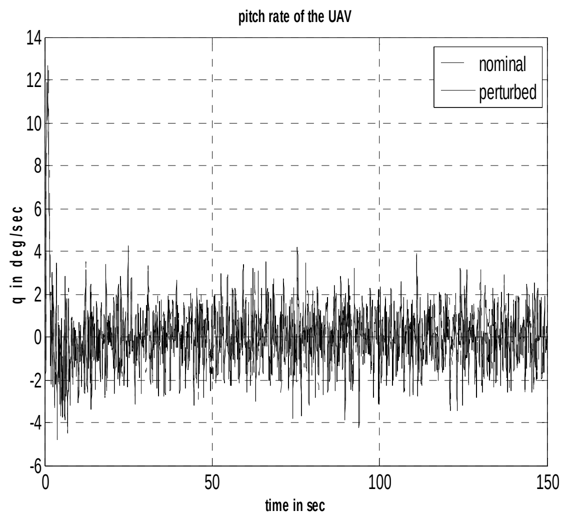

*b*




*c*




*d*




*e*

Fig. 4. ANFIS simulation results:
*a* is velocity of the UAV nominal and perturbed model in m/sec;
*b* is altitude of the UAV nominal and perturbed model in m;
*c* is pitch angle of the UAV nominal and perturbed model in deg;
*d* is pitch rate of the UAV nominal and perturbed model in deg/sec;
*e* is angle of attack of the UAV nominal and perturbed model in deg

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