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Dynamic Inversion with Neural Network For Aircraft Attitude Control

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***Abstract*—Classical dynamic inversion has been applied for the most types of aircrafts. It is a feedback linearization designed method and it is employed to linearize the dynamic behaviour that is separated into slow and fast dynamics. However, classical dynamic inversion controllers need an accurate dynamic model in order to satisfy the objective desired command and it has been shown previously that it is a sensitive to the unknown uncertainties. In this study, we combine the Radial Basis Function neural network for controller with dynamic inversion through the outer loop to obtain the desired dynamics that can improve the system robust stability. In addition, with different training parameters, the same network structure is used for the system model identification in order to obtain the sensitivity function. This function is necessary to support the neural network in the outer loop through the training algorithm so that the input command tracking can be achieved. Finally simulation results for the aircraft attitude control motion were presented to assure the robustness of this design approach when the input time delay is considered.**

***Keywords*—Dynamic Inversion, Aircraft Control, Neural Network, Nonlinear Control, System Identification.**

I. INTRODUCTION

In real flight of aircraft, the control engineer has to work to deliver a control law that performs well over the complete flight envelope trajectory defined by altitude, speed and aircraft configuration. Based on the classical control design techniques, the linear control laws have to be designed at different specific operating points in the complete flight trajectory. However, this design issue usually results a complex control laws and massive values of controller gains called gain scheduling. Gain scheduling has proven to be a successful approach to controlling aircraft over a large range of operating conditions. Many approaches schedule the parameters of a linear controller based on measured variables such as Mach number, angle-of-attack, or dynamic pressure. This can be accomplished by linear interpolation between pre-computed controllers. Methods such as Linear Parameter Varying Control allow continuous dependence of the control law on the scheduling parameters [1, 2]. An alternative design method has been introduced by dynamic inversion. Historically, the dynamic inversion was first developed in the aerospace engineering field [3], [4]. The main drawback of the classical dynamic inversion is its sensitivity to the unknown uncertainties, and to achieve a high nominal performance, an accurate model for the considered system dynamics is required. Researchers are interested to overcome of these problems by supporting the traditional dynamic inversion with H_∞ controller in order to improve its robustness when the effect of uncertainties is considered [5], [6] and [7]. The neural network design for system control and identification has been presented in [8]. This design challenge attracted the attention of many researchers. Where, they are related to use of adaptive Neural Nets to add robustness to the nonlinear dynamic inversion control law [9, 10, 11]. In this paper, the artificial neural network using Radial Basis Function [RBF] is applied in order to improve the robustness of the classical dynamic inversion. This can be done by incorporating this network with dynamic inversion through the outer loop in order to cancel the slow dynamics and to obtain the input desired command. And further to achieve the command tracking by the neural network in the outer loop, the same type of this network with different training parameters is used for system model identification. This is to provide the system model information (input/output aircraft model variations) into the outer loop neural network via the generated sensitivity function. In the inner loop, the fast desired command is obtained by using of classical proportional controller. As a result, the system dynamics are cancelled by the inversion of the elevator deflection. Lastly, the comparison with classical dynamic inversion using Proportional Derivative controller (PD) is carried out to demonstrate the capability of this design approach to sustain the attitude stability of the aircraft, when the uncertainty due to transportation lag with time delay in the input command of the attitude dynamics is considered.

The organization of this paper is as follows. In the next section, the aircraft simplified longitudinal model is written. The dynamic inversion with RBF neural network model is included in section III. Simulation results are shown in section IV and finally section V presents the conclusion.

II. AIRCRAFT DYNAMIC MODEL

In order to describe the attitude motion of the aircraft, the equilibrium aircraft body stability axes $x_b y_b z_b$ are shown in Fig. 1. Which shows an aircraft with the conventional right handed (forward, starboard and down) set of body fixed axes illustrated. The angles of attack and sideslip are defined by performing a plane rotation about the body y_b-axis, followed by a plane rotation about the new z_b- axis such that the final x-axis is aligned directly into the relative wind x- axes.

Let the information for the coefficient matrices of the linear states in longitudinal motion are given by the following state space model [13] and [14]:

$$E\dot{\boldsymbol{x}} = A\boldsymbol{x} + B\boldsymbol{u} \quad (1)$$

With state vectors $\boldsymbol{x^T} = [\ \alpha \quad q]$, u= δ_e

Where $\propto$ denotes to angle of attack [deg] and q;is the pitch rate [deg/sec] and δ_e is the elevator deflection [deg]. If we consider only α and q equations and control deflections due to an elevator actuator, then the following state model is obtained: [14]

$$\begin{bmatrix} V_T - Z_{\dot{\alpha}} & 0 \\ -M_{\dot{\alpha}} & 1 \end{bmatrix} \begin{bmatrix} \dot{\alpha} \\ \dot{q} \end{bmatrix} = \begin{bmatrix} Z_\alpha & V_T + Z_q \\ M_\alpha & M_q \end{bmatrix} \begin{bmatrix} \alpha \\ q \end{bmatrix} + \begin{bmatrix} Z_{\delta e} \\ M_{\delta e} \end{bmatrix} \delta_e \quad (2)$$

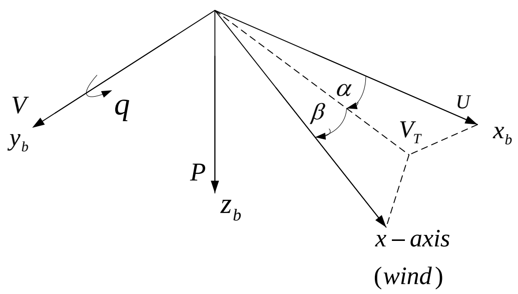

Fig. 1 Definition of the aircraft axes and angles

Where V_T denotes to the true airspeed [meter/sec] which is obtained from the following expression:

$$V_T = \sqrt{U^2 + V^2 + P^2} \quad (3)$$

And the velocities U, V and P [meter/sec] in x_b, y_b and z_b respectively are evaluated as follows.

$$U = V_T cos(\propto) cos(\beta) \quad (4)$$

$$V = V_T sin(\beta) \quad (5)$$

$$P = V_T sin(\propto)\ cos(\beta) \quad (6)$$

The angle of attack $\propto$ and sideslip angle β are calculated from the following two relations:

$$tan(\alpha) = {}^{P}/_{U} \quad (7)$$

$$sin(\beta) = {}^{V}/_{V_T} \quad (8)$$

It should be noted that, due to a small sideslip angle β in the longitudinal motion, the velocities in three body axis are assumed to be

$$U = V_T\ , P = 0\ , V = 0$$

And the longitudinal dimensional stability derivatives $Z_{\dot{\propto}}$, $M_{\dot{\propto}}$, $Z_\propto$, $M_\propto$, Z_q, M_q, Z_{δ_e} and M_{δ_e} are given as a function of the following dimensionless aerodynamic derivatives:

$$Z_{\dot{\propto}} = -(QSc/(2mV_T))C_{L\dot{\propto}} \quad (9)$$

$$M_{\dot{\alpha}} = \left(QSc^2/\left(2J_yV_T\right)\right)C_{m_{\dot{\propto}}} \quad (10)$$

$$Z_\propto = -(QS/m)(C_D + C_{L\propto}) \quad (11)$$

$$M_\propto = \left(QSc/J_y\right)C_{m_\propto} \quad (12)$$

$$Z_q = -(QSc/(2mV_T))C_{L_q} \quad (13)$$

$$M_q = \left(QSc^2/\left(2V_TJ_y\right)\right)C_{m_q} \quad (14)$$

$$Z_{\delta_e} = -(QS/m)C_{L\delta e} \quad (15)$$

$$M_{\delta_e} = \left(QSc/J_y\right)C_{m_{\delta e}} \quad (16)$$

Where ($Q = 0.5\rho V_T^2$) denotes to the free stream dynamic pressure (Pascals), ρ; air density $[kg.meter^{-3}]$, S; wing reference area $[meter^2]$, c; wing mean geometric chord $(meter)$, m; mass (kg) and J_y represents the moment of ineria in y axis ($kg.meter^2$) . The aerodynamic lift derivatives $C_{L\dot{\propto}}$, , $C_{L\propto}$, C_{L_q}, $C_{L_{\delta e}}$ and moment derivatives $C_{m_{\dot{\propto}}}$, $C_{m_\propto}$, C_{m_q} and $C_{m_{\delta e}}$ due to angle of attack derivative, angle of attack, pitch rate and elevator deflection respectively are dimensionless parameters. And C_D represent the dimensionless drag derivative coefficient. .

And because $Z_{\dot{\alpha}}$ and $M_{\dot{\alpha}}$ are normally small and V_T is greater than zero during time of flight manoeuvring, so the E matrix is always nonsingular. As a result, the following two linear longitudinal equations are extracted from the state model given in (2) to get

$$\dot{\alpha} = L_\alpha \alpha + L_q q + L_{\delta_e}\delta_e \quad (17)$$

$$\dot{q} = M_\propto \propto + M_q q + M_{\delta_e}\delta_e \quad (18)$$

Where

$$L_\propto = Z_\propto / V_T \quad , \quad L_q = \left(V_T + Z_q\right)/V_T \quad , \quad L_{\delta_e} = Z_{\delta_e}/V_T$$

III. DYNAMIC INVERSION WITH RBF NEURAL MODEL

As known previously, the dynamic inversion is one of the nonlinear control design approaches based on the concepts of the feedback linearization technique. It is used to synthesize flight controllers whereby the set of existing undesirable dynamics are discarded out and replaced by a selected desired one. In this study, the desired dynamics are generated through the outer loop by using of PD or RBF neural network controllers and then they are subtracted from the attitude aircraft slow dynamics, in order to obtain the pitch rate command q_c for the inner loop command. As a result, the input desired command $\dot{q}_d$ is obtained to eliminate the fast dynamics by using of estimated elevator deflection $\hat{\delta}_e$through the subtraction loop shown in Fig.2.

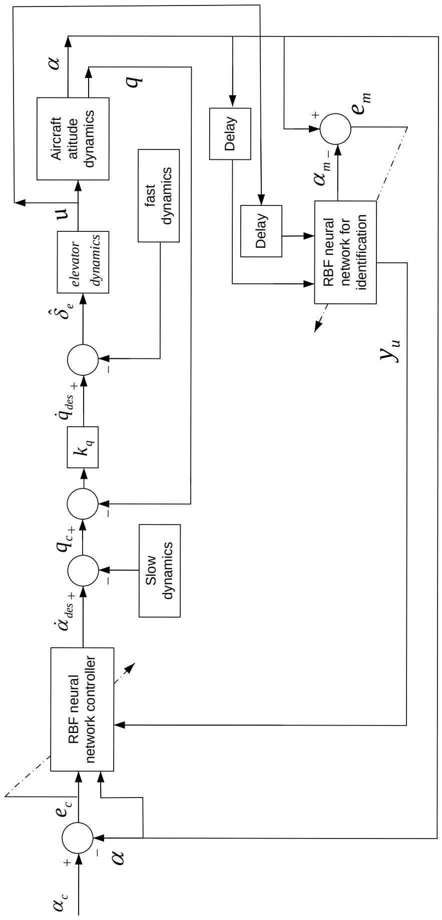

Fig. 2 Attitude control autopilot using dynamic inversion with RBF neural network

A. Outer Loop Control

In this loop, the desired slow dynamics $\dot{\alpha}_{des}$ is obtained by using of RBF neural network controller for the purpose of slow dynamics cancellation existed in (17). It should be noted that, due to weak effect of the elevator deflection δ_e in case of slow dynamic motion, then it is neglected and only its effect appears in the inner loop to carry out the inversion process as will be seen in (30).

The desired dynamics in this loop is obtained from the following nonlinear relation:

$$\dot{\alpha}_{des} = u_{RBF}(\propto, e_c(t), y_u) \quad (19)$$

The pitch rate command q_c for the inner loop is obtained by subtracting the desired loop dynamics $\dot{\alpha}_{des}$ from the slow dynamics in (17) by the following manner:

$$q_c = (\dot{\alpha}_{des} - L_\alpha \alpha)/L_q \quad (20)$$

The u_{RBF} is the control signal obtained from the output of RBF neural controller shown in Fig. 3. In this figure, the input vector R is given by

$$\boldsymbol{R} = [\propto \quad e_c(t) \quad y_u]^T \quad (21)$$

And output $y_o = \dot{\alpha}_{des}$

The sensitivity function is given by the following relation:

$$y_u = sgn\left(\frac{(\propto_m(t) - \propto_m(t-1))}{(u(t) - u(t-1))}\right) \quad (22)$$

This function is obtained from the RBF neural network for aircraft attitude model identification as shown in Fig. 2. And the construction of this network is similar to that one used for controller in Fig. 3 with

$$\boldsymbol{R} = \left[\propto (t-1) \quad \hat{\delta}_e(t-1)\right]^T \quad (23)$$

And with output $y_o = \ \propto_m$

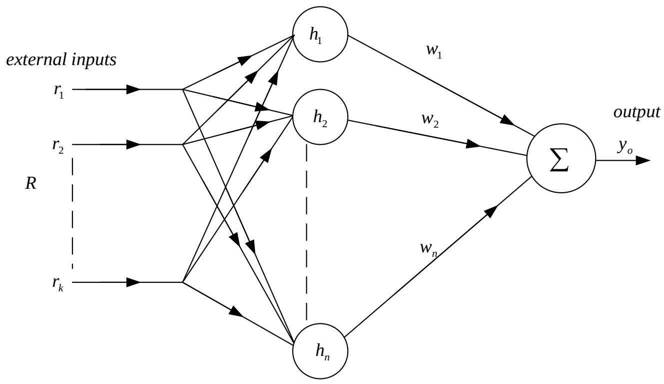

Fig. 3 RBF neural network structure

The RBF network for both controller and identification has four number of neurons ($n = 4$) and the static Gaussian RBF is considered as the nonlinearity for the hidden layer processing neuron elements which is given by [12]

$$h_j = e^{\left(-\|\boldsymbol{R}-\boldsymbol{C}_j\|^2/2b_j^2\right)} \quad j = 1,2 \ldots\ldots n \quad (24)$$

Where $\boldsymbol{C}$ denotes to the vector of centre values of the RBF neural network. And b is the width of the RBF which stands for the standard deviation of the Gaussian.
The weight vector for the network is given by

$$\boldsymbol{W} = [w_1, w_2, \ldots\ldots w_n]^T \quad (25)$$

And the output y_o is obtained as follows.

$$y_o = w_1 h_1 + w_2 h_2 + \cdots \dots\dots\dots\dots . w_n h_n \quad (26)$$

The parameters of the weighting function in (25) and Gaussian function in (24) are trained based on the Backpropagation algorithm written below. Where, the same model in [12] is used with a small modification obtained by inserting the sensitivity function y_u in this training algorithm, in order to add information about the system model into the RBF neural network controller located in the dynamic inversion outer loop.

1) Weight parameters:

$$w_j(k) = w_j(k-1) + \eta \boldsymbol{e}(k) y_u h_j + \xi\big((w_j(k-1) - w_j(k-2)\big) \quad (27)$$

2) Width parameters:

$$b_j(k) = b_j(k-1) + \eta \boldsymbol{e}(k) y_u w_j h_j \left(\frac{\|\boldsymbol{R} - \boldsymbol{C}_j\|^2}{b_j^3}\right) + \xi\big((b_j(k-1) - b_j(k-2)\big) \quad (28)$$

3) Centre parameters:

$$c_{ji}(k) = c_{ji}(k-1) + \eta e(k) y_u w_j \left(\frac{r_i - c_{ji}}{b_j^2}\right) + \xi\big((c_{ji}(k-1) - c_{ji}(k-2)\big) \quad (29)$$

Where η and ξ are respectively the learning rate and momentum parameters. And the error $e(k)$ represents the errors $e_c(k)$ and $e_m(k)$ which are obtained by the way shown in Fig. 2.

B. Inner Loop Control

As mentioned before, the fast dynamics of the simplified aircraft attitude model given in (18) can be discarded by subtracting them from the fast desired command $\dot{q}_{des}$ in the manner shown by Fig. 2. Finally, the dynamic inversion process is done via the elevator actuator deflection as follows.

$$\hat{\delta}_e = \left(M_{\delta_e}\right)^{-1}\left[k_q(q_c - q) - \left(M_\propto \propto + M_q q\right)\right] \quad (30)$$

Where k_q represents the proportional controller gain constant.

IV. SIMULATION RESULTS

The computer simulation results are obtained here by simulating the designed control system shown in Fig. 2 in a Matlab/Simulink environment, and the effectiveness of the considered design technique has been tested with a campaign of numerical simulation. Furthermore, again the same block diagram is simulated when the desired outer loop dynamics are obtained by using of PD controller instead of RBF neural network. Where, the continuous conventional PD controller is described by the following differential equation: [15]

$$\dot{\propto}_{des} = k_p e_c(t) + k_d(de_c(t)/dt) \quad (31)$$

To carry out the linear simulation, the flight condition for the equilibrium condition of the aircraft at Mach number 0.9 and height of 6096 (*meter)* is chosen as a case study. TABLE I. Shows the values of the longitudinal stability derivatives of the simplified model of the aircraft at this point condition [16].

TABLE I

AIRCRAFT SIMULATION DATA

Aerodynamic parameters	Values
$L_\propto$	$-1.6187\ sec^{-1}$
L_q	$0.997\ sec^{-1}$
L_{δ_e}	$-0.16625\ sec^{-1}$
$M_\propto$	$2.9618\ sec^{-2}$
M_q	$-0.7704\ sec^{-1}$
M_{δ_e}	$-22.5382\ sec^{-2}$

Where, in this scenario, the first order elevator transfer function model with time constant *0.01 sec* is considered. And the designed controller parameters for dynamic inversion with RBF neural network and classical PD controllers are shown by TABLE. II.

TABLE II

CONTROL DESIGN PARAMETERS

Design Method	**Outer Loop**	**Inner Loop**
Dynamic Inversion with PD	$k_d = 2$ $k_p = 50$	$k_q = 15$
Dynamic inversion with RBF	***RBF for controller*** W=$[6.91\ \ 0.76\ \ 8.20\ \ -2.9859]^T$ $b = [8.70\ 8.55\ \ 1.75\ 7.96\ ]^T$ $c = \begin{bmatrix} -2.66 & -9.97 \\ -4.48 & 7.86 \\ 4.67 & -0.93 \\ -5.46 & 1.56 \end{bmatrix}$ $\eta = 0.45$, $\xi = 0.01$ ***RBF for identification*** W=$[-3.68\ \ 9.88\ \ 8.20\ \ 9.29]^T$ $b = [3.32\ \ 4.52\ \ -3.31\ \ -0.45\ ]^T$ $c = \begin{bmatrix} -4.35 & -5.56 \\ 4.36 & -5.92 \\ 5.56 & 2.48 \\ -8.37 & 4.50 \end{bmatrix}$ $\eta = 0.6$, $\xi = 0.08$	$k_q = 14$

For the objective analysis of this study, the following two conditions are considered

A. Nominal Condition

To test the control system performance in this case, the closed loop for system shown in Fig. 2 is simulated to get the angle of attack step response as shown in Fig. 4. In this simulation results, the effect of disturbances or uncertainties is not considered. And it is clear that, in comparing to the classical dynamic inversion, a smaller steady state error response is obtained when the dynamic inversion with RBF is used. However, the slower response of RBF dynamic inversion is due to a slow dynamic training of the Backpropagation algorithm.

Fig. 5 shows the relation trajectories of the actual plant and identified model outputs. It is observed that, the RBF neural network for identification is successful to track the system response. Consequently, the sensitivity function y_u is obtained as shown in Fig. 6. This function is necessary here for the convergence of RBF neural network training parameters in the outer loop according to equations (27) to (29).

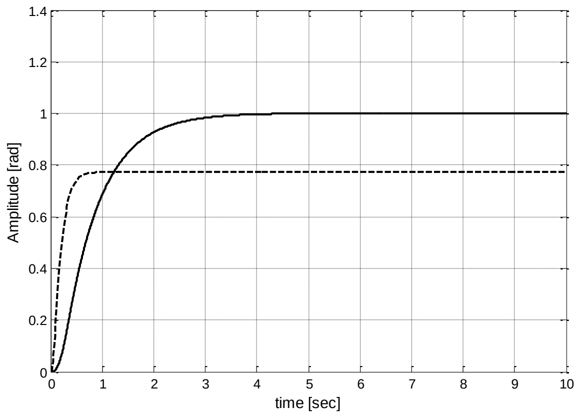

Fig. 4 Angle of attack response in nominal case [solid]: Dynamic inversion with RBF. [dashed]: Classical dynamic inversion

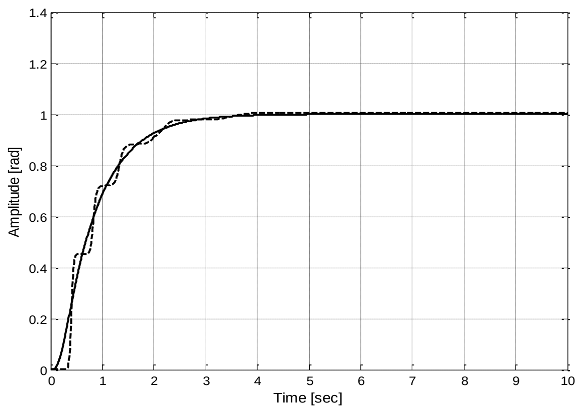

Fig. 5 Angle of attack response in nominal case [solid]: Actual response – [dashed]: Identified response

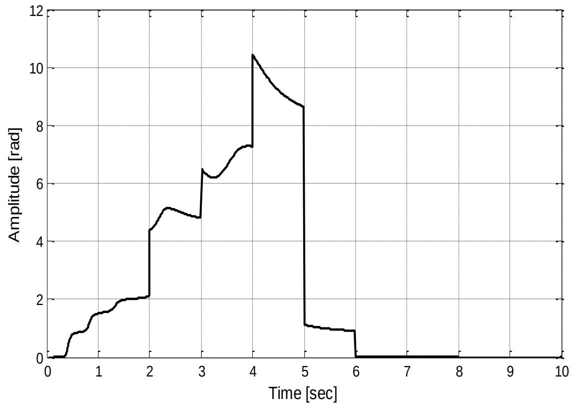

Fig. 6 Sensitivity function in nominal case

B. Influence of Time Delay

Time delay is one of the serious uncertainties which cause degradation in the system performance and sometimes cause instability of the system dynamics. In this study analysis, we certain by simulation results that, the instability due to this uncertainty can be overcome in case of attitude aircraft stabilization using dynamic inversion with RBF neural network as shown in Fig. 7, while the system become unstable in case of other design method. This condition is tested with time delay *(T=0.075 sec)* at the input of the aircraft simplified model. Where, the time delay dynamics is described by the following exponential transport lag function.

$$G_D(s) = e^{-Ts} \tag{32}$$

Similarly, under this uncertain condition, the response behaviour for both the actual and identified system outputs is obtained as shown in Fig. 8. It is seen that the RBF for identification is succussed to track the actual output of the angle of attack response. This successful identification process again will provide information about the variations of the plant input u to model output α_m into the RBF controller via the sensitivity function y_u shown in Fig. 9.

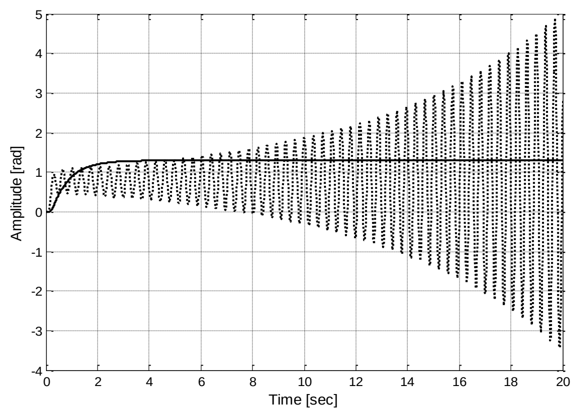

Fig. 7 Angle of attack response with input time delay. [solid]: Dynamic inversion with RBF. [dashed]: Classical dynamic inversion

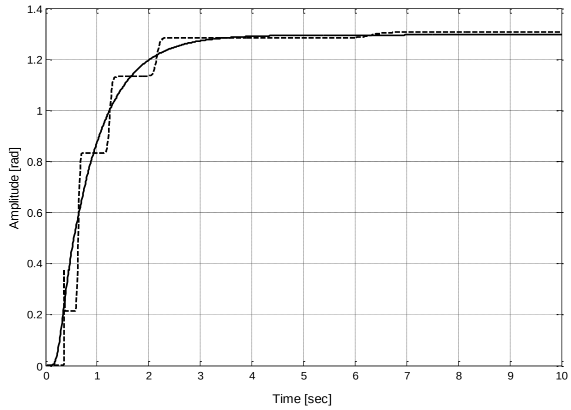

Fig. 8 Angle of attack response with input time delay [solid]: Actual response [dashed]: Identified response

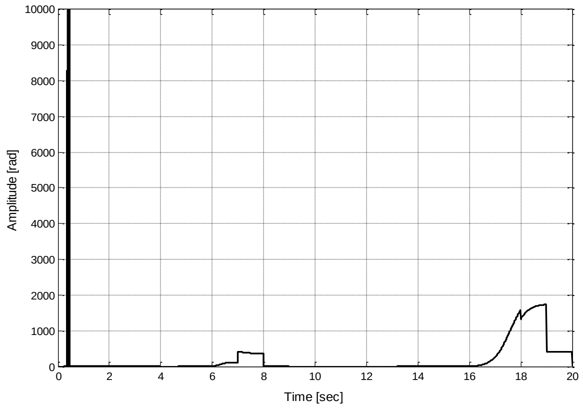

Fig.9 Sensitivity function with input time delay

V. CONCLUSION

The flight dynamic inversion with Radial Basis Function neural network is designed. This design cooperation has been done via the outer loop of the classical dynamic inversion to satisfy the desired loop dynamics. The sensitivity function which shows the variations of the system input/output is obtained from the learning process of the Radial Basis Function network for identification through the feedback loop. It is concluded that, using this design technique, the robustness of the dynamic inversion to the unstructured model uncertainties such as input time delay can be improved. As a result, the drawback of the classical dynamic inversion due to requirement of a system accurate dynamic model is overcome. In addition, the neural network for identification is successful to add the system information into the neural network for controller so that the system stability and command angle of attack response can be satisfied. Moreover, the capability of the considered design approach is superior to the classical dynamic inversion using PD controller to keep the system stability under the influence of uncertainty.

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