2025 11th International Conference on Control, Decision and Information Technologies
CoDIT 2025 | Split, Croatia / July 15-18, 2025 Technically co-sponsored by IEEE & IFAC

2025 11th International Conference on Control, Decision and Information Technologies (CoDIT) | 979-8-3315-0338-3/25/$31.00 ©2025 IEEE | DOI: 10.1109/CoDIT66093.2025.11321820

Neural Network Bias Compensator for Flight Control Actuators

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Abstract— **Flight control actuators are the primary equipment of the Automatic Flight Control System (AFCS) that is used to provide short and long term stabilization. Flight control actuators are electrohydraulic actuators that are directly connected to the flight control surface. The hydraulic flow in these actuators is controlled using an Electro-Hydraulic Servo Valve (EHSV) with reference electrical command. Each EHSV has a null bias command to hold the valve in the null position. The null bias command depends on valve hysteresis, temperature, hydraulic pressure, and reference acceleration command. The null bias command and its variation reduce the tracking performance of the flight control actuators. In this article, we proposed a neural network bias compensator to compensate for the EHSV null bias command and improve the tracking performance of the controller. The nonlinear Hammerstein-Wiener model of the actuator was estimated from the test data. Then, a neural network bias compensator was designed in addition to the lead controller. The performance of the neural network bias compensator is analyzed through a series of simulations that demonstrate the desired qualities.**

I. INTRODUCTION

The electro-hydraulic servo valve (EHSV) plays an important role in many areas as it provides a great power-to-weight ratio and quick response. However, controlling these servo valves is still difficult due to the nonlinear behavior and uncertainty of the parameters of EHSV [1].

The tracking accuracy of the flight control actuator is crucial for the short and long term stabilization of the helicopter. Hydraulic fluids are used in these actuators to provide or compensate for large loads. EHSV is a valve that can be electrically controlled to adjust the hydraulic flow to the actuator. These valves are the main equipment of the flight control actuator to achieve precise control of the position of hydraulic cylinders by reference command. The natural or null position of the electrohydraulic actuator is where the direction and magnitude of the hydraulic fluid are in balance. Due to the nature of EHSV, a null bias command must be applied to maintain the position at null position [2].

Classical control theory and feedback linearization are the main approaches to controlling the EHSV. The disadvantage of these control approaches is that the controller works well under nominal conditions. Since both EHSV and other hydraulic systems have uncertainties in their operation, these controllers cannot achieve high tracking performance [3].

*This work was supported by Turkish Aerospace Inc.

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Several studies have been published in the literature to alleviate the effect of parameter uncertainties and unknown nonlinearities such as sliding mode, adaptive, fuzzy logic, and neural network controller [4]–[7]. Adaptive and sliding mode controllers can cope with the parameter uncertainty of EHSV. However, adaptive controllers have little effect on nonlinear dynamics, and sliding mode controllers can produce large control signals due to the chatter problem. The fuzzy logic controller requires knowledge of the nonlinear behavior of the EHVS, and the neural network controller requires a large amount of training data.

As mentioned earlier, the null bias command is required to hold the null position of the actuator. The null bias command depends on valve hysteresis, temperature, hydraulic pressure, and reference acceleration command. It is one of the most crucial factors that make EHSV difficult to control because if the correct null bias command is not supplied to the system, the control performance will deteriorate, or the system cannot be controlled. The null bias command is the main source of the nonlinearity, and it can modeled as a dead zone of control command of the EHSV.

Several studies have demonstrated different controller methods to overcome the dead zone problem. A parallel CMAC network to PD controller is proposed in [8], a fuzzy logic dead zone compensator developed in [9], a neural network compensator implemented in [10] to overcome the dead zone of the actuators.

In this article, we proposed a neural network bias compensator to compensate for the EHSV null bias command and improve the tracking performance of the controller. The neural network dead zone compensator described in [10] is used as a reference to model the null bias command of the EHSV. Two different neural structures are built to predict the null bias command and provide adaptive compensation of nonlinearities. The neural network bias compensator is connected to the linear lead controller to control the position of the actuator. Therefore, the proposed approach improves the tracking performance of the controller and compensates for the nonlinearities caused by the null bias command using the neural network. Since the neural network structure helps in improving the linear controller, less training data is required compared to neural network controller applications.

The remaining parts of this paper are organized as follows. The nonlinear Hammerstein-Wiener model and classical controller approach are given in Section II. The proposed neural network bias compensator for EHSV is examined in detail in Section III. Simulation results of both the classical approach and the neural network bias compensator are presented in Section IV. Finally, the paper is concluded in Section V.

II. FLIGHT CONTROL ACTUATOR

A. Overview

The block diagram of the flight control actuator is shown in Fig. 1. Each flight control actuator has a hydraulic flow input, shut-off valve (SOV) input, EHSV command input, hydraulic flow output, and LVDT position output. The SOV switches the hydraulic flow of the EHSV and the EHSV controls the flow in the hydraulic cylinder. The mechanical movement of the cylinder caused by the hydraulic flow is measured by a Linear Variable Differential Transformer (LVDT).

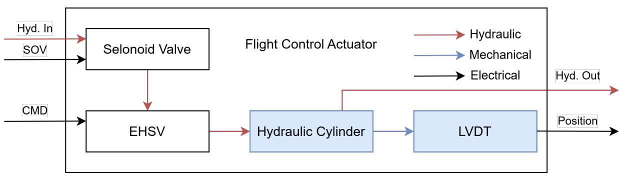

Fig. 1. Block diagram of flight control actuator

B. Actuator Model

The nonlinear model is identified from the test data to simulate the neural network bias compensator and compare the performance of the neural network. Test data were collected from classical control closed-loop test results. A nonlinear Hammerstein-Wiener model structure was used in the identification process to preserve the nonlinear properties of the system. The input of the model was the EHSV command and the corresponding LVDT position value was the model output. The system definition toolbox was used and the dead zone was selected as the input nonlinear rule. The generated Hammerstein-Wiener model agrees with the test data by approximately 90% as shown in Fig. 2. The sampling time of the test data is 0.0001 sec. The details of the generated model are as follows:

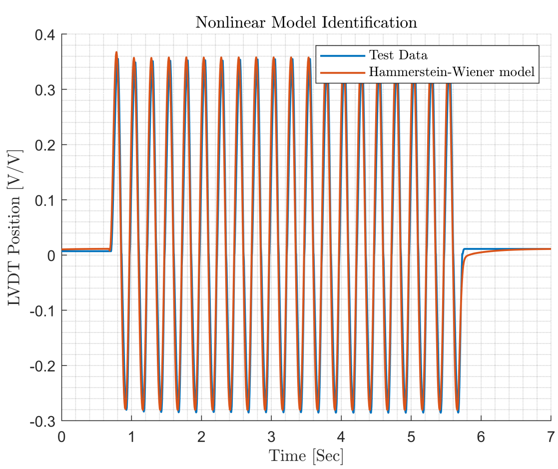

Fig. 2. Identified nonlinear model response from test data

1) Input Nonlinearity: The input nonlinearity is selected as a dead zone. The resulting input nonlinearity function is shown in (1).

$$w(t) = \begin{cases} 0, & 0.6447 \leq u(t) \leq 0.7445 \\ u(t), & otherwise \end{cases} \tag{1}$$

2) Linear Model: The generated linear model can be seen in (2).

$$G(z) = \frac{-0.9854z^{-3} + z^{-4}}{1 - 1.0104z^{-1} - 0.9678z^{-2} + 0.9782z^{-3}} \tag{2}$$

3) Output Nonlinearity: The output nonlinearity is chosen as a polynomial. The resulting output nonlinearity function is shown in (3). Here, $x(t)$ refers the linear output and $y(t)$ refers to nonlinear output.

$$y(t) = 6.4162 \times 10^{-8}x(t)^2 + 7.0066 \times 10^{-4}x(t) + 0.0115 \tag{3}$$

C. Classical Control Approach

The classical control approach to control the EHSV is to use a linear type controller such as Lead-Lag or PID and constant null bias command. As mentioned earlier, there is a command value required for the EHSV to remain in the null position. Once the EHSV reaches the desired position, this command value is also required for the EHSV to remain in that position. To overcome this situation, a bias command is added to the controller output. This prevents tracking error that may be caused by the controller. The classical control approach can be seen in Fig. 3.

However, there are some serious disadvantages to adding a fixed null bias command value to the controller output. Firstly, the null bias current is highly dependent on environmental conditions such as the temperature and pressure of the hydraulic fluid. These environmental conditions can change the value of the null bias command. Since the EHSV operates with very small electrical signals, even a small change in the null bias value can cause large position tracking errors.

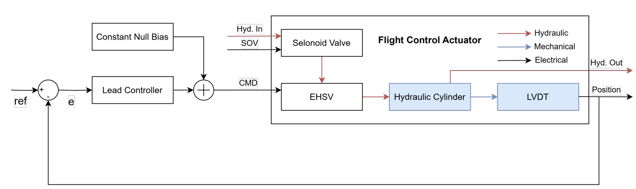

Fig. 3. Classical control approach of the flight control actuator

III. NEURAL NETWORK COMPENSATOR

The purpose of the neural network structure is to eliminate the dead zone caused by the null bias command of EHSV and achieve better tracking performance. To achieve this goal, two different neural network structures labeled NN1 and NN2 are used. NN1 and NN2 are designed as two different neural networks that work together. Each structure contains a two-layer neural network. While NN1 estimates the dead zone functions, NN2 compensates for the effects of the dead zone. Both NN1 and NN2 perform online learning.

A. Dead zone Function Model

The dead zone inverse method is one of the approaches used to design the dead zone compensator. Therefore, before constructing the neural network structure, a general dead zone function should be designed as shown in (4).

$$\tau = D(u) = \begin{cases} g(u) < 0, & u \leq d_- \\ 0, & -d_- < u < d_+ \\ h(u) > 0, & u \geq d_+ \end{cases} \tag{4}$$

The boundaries of the dead zone function may be asymmetric and the system may have nonlinear behavior outside the dead zone. Therefore, the lower and upper bounds of the function are defined by different parameters. We assume that the functions $h(u)$ and $g(u)$ are smooth invertible continuous functions. If the dead zone function is invertible and continuous, the inverse of the dead zone is given in (5).

$$D^{-1}(w) = \begin{cases} g^{-1}(w) < 0, & w < 0 \\ 0, & w = 0 \\ h{-}1(w) > 0, & w > 0 \end{cases} \tag{5}$$

The dead zone inverse function can be defined as follows.

$$D(D^{-1}(w)) = w + w_{NN}(w) \tag{6}$$

Where the term $w_{NN}(w)$ is called the modified inverse function and is used for dead zone compensation. The equation of modified inverse function $w_{NN}(w)$ is given in (7).

$$w_{NN}(w) = \begin{cases} g^{-1}(w) - w, & w < 0 \\ 0, & w = 0 \\ h^{-1}(w) - w, & w > 0 \end{cases} \tag{7}$$

B. Neural Network Structure

In this study, two neural networks, NN1 and NN2, are designed and have different purposes. NN1 estimates the dead zone function given in (4). In this application, NN1 has the 2-layer feedforward neural network architecture. V and W are the weights of the 2-layer NN1 feedforward neural network. The dead zone function is given in (8) and the estimated dead zone function can be calculated using (9).

$$\tau = D(u) = \mathbf{W}^T \tanh(\mathbf{V}^T \mathbf{u} + \mathbf{v}_0) + \epsilon(\mathbf{u}) \tag{8}$$

$$\hat{\tau} = \hat{D}(u) = \hat{\mathbf{W}}^T \tanh\left(\mathbf{V}^T \mathbf{u} + \mathbf{v}_0\right) \tag{9}$$

where the $\mathbf{v}_0$ is the bias values of NN1, the $\mathbf{u}$ is the input vector of the neural network and $\mathbf{u} = (\mathbf{w} + \hat{\mathbf{w}}_{NN})/(max(|\mathbf{w} + \mathbf{w}_{nn}|) + \epsilon)$. tanh is the hyperbolic tangent function used as the activation function in the neural network.

NN2 compensates for the dead zone function by estimating (7). NN2 has a 2-layer feedforward neural network architecture. V_i and W_i are the weights of the 2-layer NN2 feedforward neural network. The dead zone compensation function is given in (10) and the estimated dead zone compensation function can be calculated using (11).

$$w_{NN}(w) = W_i^T \tanh(V_i^T w + \mathbf{v}_{0i}) + \epsilon_i(w) \tag{10}$$

$$\hat{w}_{NN}(\mathbf{w}) = \hat{\mathbf{W}}_i^T \tanh\left(\mathbf{V}_i^T \mathbf{w} + \mathbf{v}_{0i}\right) \tag{11}$$

where the $\mathbf{v}_{0i}$ is the bias values of NN2, the $\mathbf{w}$ is the input vector of the neural network and $\mathbf{w} = \mathbf{w}/(|\mathbf{w}| + \epsilon)$. tanh is the hyperbolic tangent function used as the activation function in the neural network.

The block diagram of the neural network bias compensator with a lead controller is shown in Fig. 4. The lead controller output is defined as r. The neural network bias compensator takes the $\mathbf{w}$ (12) and $\mathbf{R}$ (13) and calculates estimated $\hat{w}_{NN}$ (11). The total EHSV command u_{cmd} is calculated using (14).

$$\mathbf{w} = [(r + \hat{w}_{NN}) \quad \dot{e}] \tag{12}$$

$$\mathbf{R} = [r \quad e] \tag{13}$$

$$u_{cmd} = r + \hat{w}_{NN}(\mathbf{w}) \tag{14}$$

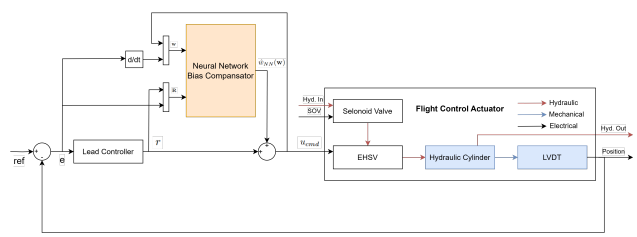

Fig. 4. Neural Network Bias Compensator with controller for flight control actuator

The tuning algorithms for updating the weights of the estimated functions for NN1 and NN2 are given in (15) and (16), respectively.

$$\dot{\hat{W}} = -\mathbf{S} \tanh\left(\mathbf{V}^T \mathbf{u} + \mathbf{v_0}\right) E - k_1 \mathbf{S} \hat{\mathbf{W}} \tag{15}$$

$$\dot{\hat{W}}_i = \mathbf{T} \tanh\left(\mathbf{V}_i^T \mathbf{w} + \mathbf{v}_{0i}\right) E - k_2 \mathbf{T} \hat{\mathbf{W}}_\mathbf{i} \tag{16}$$

where the $E = r - \hat{\tau}$. Here, the expressions $\mathbf{V}$ and $\mathbf{V}_i$ are the weights of the hidden layers of NN1 and NN2. The expressions $\mathbf{W}$ and $\mathbf{W}_i$ are the weights of the output layer of NN1 and NN2. $\mathbf{S}$ and $\mathbf{T}$ are symmetric matrices and their values are greater than zero. k_1 and k_2 are learning rates and have small scalar values.

IV. RESULTS

The performance of the neural network bias compensator is compared with the classical control approach by applying different position commands to the controller. Pulse and sine position commands are applied to examine the performance of the controller. The pulse and sine results of both the classical control approach and the neural network bias compensator are shown in Fig. 5 and 6, respectively. The neural network bias compensator has better performance than the classical control approach. The neural network compensator eliminates the steady-state error of the controller and increases the action on negative commands.

The parameters of the neural network are taken as follows. The number of hidden layer nodes of NN1 is 20, and NN2 is 24, respectively. The design parameters of neural network are selected as $\mathbf{S} = 1.5 * diag(20, 20)$, $\mathbf{T} = 7 * diag(24, 24)$, $k_1 = 0.001$ and $k_2 = 0.001$, $\mathbf{V}$ and $\mathbf{V}_i$ are initialized uniformly randomly distributed between -0.1 and 0.1. $\mathbf{v}_0$ and $\mathbf{v}_{0i}$ are initialized uniformly randomly distributed between -0.2 and 0.2. $\mathbf{W}$ is selected uniformly randomly distributed between -1 and 1. $\mathbf{W}_i$ is initialized uniformly randomly distributed between -0.1 and 0.1.

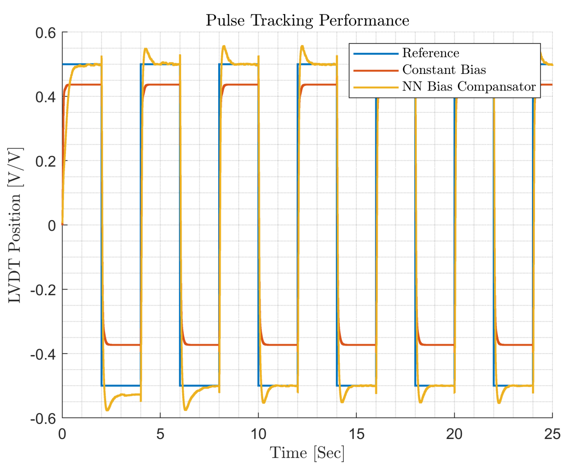

Fig. 5. Pulse tracking response of constant bias and NN bias compensator

V. CONCLUSIONS

In this article, we implemented the neural network bias compensator to compensate for the EHSV null bias command and improve the tracking performance of the controller. The nonlinear flight actuator model was estimated from the test data. The implemented neural network bias compensator was compared with the classical control approach. Simulation results showed that the neural network bias compensator both estimates null bias command and improves the tracking performance of the controller. For future work, the implemented neural network bias compensator will be applied to a real flight control actuator.

ACKNOWLEDGMENT

The authors acknowledge the support of Turkish Aerospace Industries Inc. The authors express their appreciation to Turkish Aerospace Industries Inc. for providing the opportunity to develop the neural network bias compensator for the flight controller actuator.

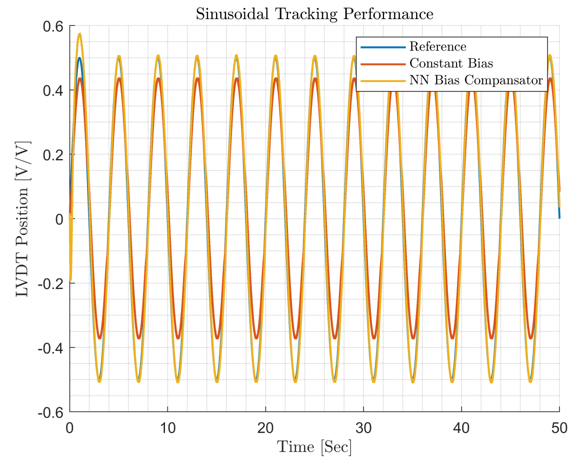

Fig. 6. Sine tracking response of constant bias and NN bias compensator

REFERENCES

[1] J. Yao and W. Deng, ”Active Disturbance Rejection Adaptive Control of Hydraulic Servo Systems,” in *IEEE Transactions on Industrial Electronics*, vol. 64, no. 10, pp. 8023-8032, Oct. 2017, doi: 10.1109/TIE.2017.2694382.

[2] Yin, Y., *Electro hydraulic control theory and its applications under extreme environment*. Butterworth-Heinemann, 2019.

[3] H. Angue Mintsa, R. Venugopal, J. -P. Kenne and C. Belleau, ”Feedback Linearization-Based Position Control of an Electrohydraulic Servo System With Supply Pressure Uncertainty,” in *IEEE Transactions on Control Systems Technology*, vol. 20, no. 4, pp. 1092-1099, July 2012, doi: 10.1109/TCST.2011.2158101.

[4] Alleyne, A., and Liu, R., ”A simplified approach to force control for electro-hydraulic systems.”, *Control Engineering Practice*, vol. 8, no. 12, pp. 1347-1356, 2000.

[5] Guan, C., and Pan, S., ”Adaptive sliding mode control of electro-hydraulic system with nonlinear unknown parameters.”, *Control Engineering Practice*, vol. 16, no. 11, pp. 1275-1284, 2008.

[6] Kalyoncu, M., and Haydim, M., ”Mathematical modelling and fuzzy logic based position control of an electrohydraulic servosystem with internal leakage.”, *Mechatronics*, vol. 19, no. 6, pp. 847-858, 2009.

[7] Kim, H. M., Park, S. H., Lee, J. M., and Kim, J. S., ”A robust control of electro hydrostatic actuator using the adaptive back-stepping scheme and fuzzy neural networks.” *International journal of precision engineering and manufacturing*, vol. 11, pp. 227-236, 2010.

[8] Lee, S. W., and Kim, J. H., ”Control of systems with deadzones using neural-network based learning controller,” *Proceedings of 1994 IEEE International Conference on Neural Networks (ICNN'94)*, Orlando, FL, USA, 1994, pp. 2535-2538 vol.4, doi: 10.1109/ICNN.1994.374619.

[9] Jang, J. O., Chung, H. T., and Jeon, G. J.. ”Saturation and deadzone compensation of systems using neural network and fuzzy logic.”, *Proceedings of the 2005, American Control Conference*, pp. 1715-1720, 2005.

[10] R. R. Selmic and F. L. Lewis, ”Deadzone compensation in motion control systems using neural networks,” in I*EEE Transactions on Automatic Control*, vol. 45, no. 4, pp. 602-613, April 2000, doi: 10.1109/9.847098.