DISTURBANCE ESTIMATION FOR THE HYDRAULIC DRIVE SYSTEM BASED ON THE STATE OBSERVER AND NEURAL NETWORK

Chu Duc Chinh*, Le Tran Thang, Nguyen Van Vu

Academy of Military Science and Technology, Hanoi, Vietnam

*Corresponding author: ducchinhcpx@gmail.com

(Received: June 02, 2023; Revised: August 01, 2023; Accepted: August 10, 2023)

Abstract - The hydraulic servo drive system has the ability to operate stably with high reliability in conditions of continuous operation and large capacity. Aside from these advantages, the system always has nonlinear and uncertain factors that affect and reduce the quality of the controller. These factors include the affected disturbances and the uncertainty of the system model. This paper proposes a method to identify the sum of nonlinear effects and disturbances for the hydraulic drive system, which uses the axial piston pump, based on the application of the Radial Basic Functions neural network (RBF) and state observer model. The simulation results show that the total disturbances and nonlinear effects can be accurately estimated in real time through the weight updating rule.

Key words - Disturbance estimation; parallel model; RBF neural network; state observer

1. Introduction

Hydraulic drive systems have been widely applied to many systems in civil and other dedicated applications because of their high reliability under continuous operating conditions and large working capacity. This study examines a hydraulic servo drive system using the axial piston pump and motor normally installed for the inertial stabilization platform on dedicated mobility vehicles. The axial piston pump has the advantages of compact size and the ability to precisely regulate flow through the tilt angle adjustment of the inclined disc structure in the pump. In addition, due to their sealed design and less wear and tear than other pumps, piston pumps are widely used in high-pressure hydraulic systems. However, there are always nonlinear factors or noise that can affect the stability of the control process ([1] to [4]), such as oil leakage, load change, compressibility of the oil, elasticity of the pipelines, temperature, viscosity, etc. Traditional control methods like PID are difficult to achieve the desired quality [5], [6]. Therefore, to improve the quality of the controller, it is necessary to identify the state changes and disturbances that affect the system. There are many proposed disturbance compensation solutions ([7] to [13]), but they are only applied to systems which do not require high accuracy and fast response. Studies [14] and [15] also proposed solutions for estimating nonlinear disturbances using observers to improve the quality of the control system. In which [14] uses the design of a variable neural adaptive robust observer for the state, [15] uses the NDO observer combined with the SMC algorithm. However, in [14], due to the characteristics of the neural adaptive observer, the system has a low convergence rate and a large error during the initial time. In [15], the NDO observer could minimize "chattering" effect on control activities but also cause the tracking precision of the system to degrade.

In the scope of this paper, the authors propose a method that combines an external state observer (ESO) with a radial neural network (RBF) based on the parallel model to estimate the state of the system and disturbances. With the fast response advantage of the RBF network, disturbances can be approximated with high accuracy in real time using the online weight update rule.

2. Mathematical model of the system

In systems that use hydraulic actuators with cylinders and pistons, the oil flow always varies with the displacements of the pistons in the cylinders. That variation depends not only on the number but also on the moving characteristics of the pistons. For an axial piston hydraulic pump or motor, the stroke of the pistons of the pump is adjusted using a swashplate. In which the angle α of the swashplate relative to the piston axis is adjusted by the servo-valve mechanism (Figure 1). The servo-valve works as an electro-hydraulic converter that converts the input electrical control signal into the pump flow, resulting in a change in hydraulic motor speed and then the actuator position.

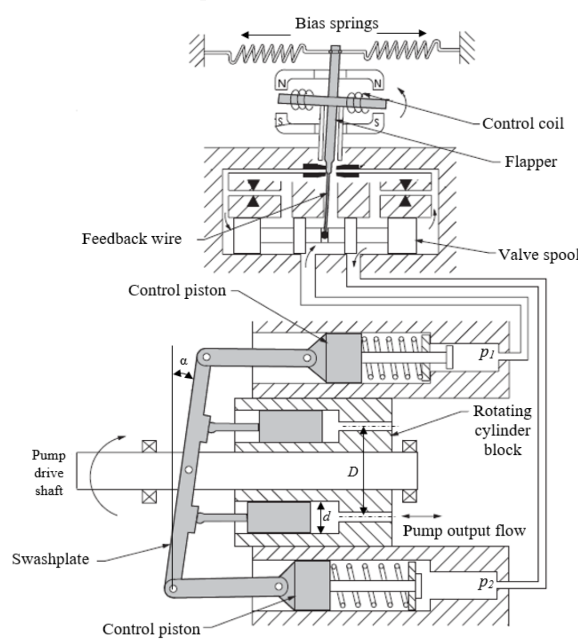

***Figure 1**. Servo valve-controlled axial piston hydraulic pump*

The volume flow rate is obtained by:

$$q = \frac{\pi d^2}{4} \cdot D \cdot i \cdot n \cdot \tan(\alpha) \cdot 10^3 \text{ (l/min)}, \quad (1)$$

Where, d is the piston diameter (m); D is the diameter of the piston circle in rotating cylinder block (m); i is the number of pistons; n is the rotation rate of the pump shaft (rpm); and α is the angle of the swashplate.

Swashplate angle α is adjusted by electromagnetic force using a magnetic coil, so $\tan(\alpha) \approx K_p \cdot u(t)$, where K_p is the gain factor of the magnetic coil and $u(t)$ is the control input signal.

Assuming that the rotation speed of the drive shaft is constant, one has the force balance equation of control pistons with load:

$$m_p \ddot{y} + d_p \dot{y} + k_s y + F = A_P p$$
$$\Rightarrow \ddot{y} = \frac{1}{m_p}\left(-d_p \dot{y} - k_s y - F + A_P p\right), \quad (2)$$

where: y - displacement of actuator; m_p - total weight of loads; d_p - viscous damping of pistons and loads; k_s - spring constant; A_P - effective area of cylinders; p - total load pressure; F - total force applied to pistons.

Assume that the total load pressure p depends on the control signal $u(t)$ in following nonlinear relationship:

$$p = f_N(\cdot)\cdot u(t), \quad (3)$$

Replace (3) to (2), one gets:

$$\ddot{y} = \frac{1}{m_p}\left(-d_p \dot{y} - k_s y - F + A_P \cdot f_N(\cdot)\cdot u(t)\right), \quad (4)$$

Define the state variables: $x_1 = y,\ x_2 = \dot{y}$;

Assume that the system has been affected by external disturbance $d(t)$.

Define the nonlinear functions: $F_N(x,u) = \ddot{y} + d(t)$.

The state space model of the system can be represented by following expressions:

$$\begin{cases} \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}}_{A} \cdot \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ 1 \end{bmatrix}}_{B} F_N(x,u) \\ y(t) = \underbrace{\begin{bmatrix} 1 & 0 \end{bmatrix}}_{C} \cdot \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} \end{cases} \quad (5)$$

The system of equations (5) can be written in the following short form:

$$\begin{cases} \dot{x} = Ax + B \cdot F_N(x,u) \\ y(t) = C \cdot x \end{cases} \quad (6)$$

3. Design the disturbance estimator based on state observer and RBF neural network

In the extended state observer (ESO), a gain matrix $L = \begin{bmatrix} l_1 & l_2 \end{bmatrix}^T$, and an adjustment function $v(t)$ were added to make the error prediction process converge. The system of equations of the ESO can be expressed as:

$$\begin{cases} \dot{\hat{x}} = A\hat{x} + B \cdot [\hat{F}_N(x,u) + v(t)] + L(y - \hat{y}) \\ \hat{y}(t) = C \cdot x \end{cases} \quad (7)$$

where $\hat{x}$ and $\hat{y}$ are respectively estimated values of x, y and $v(t) = \lambda\,\mathrm{sign}(y - \hat{y})$.

Define $e_i = x_i - \hat{x}_i,\ i = 1,2.$ as the state estimation errors and $e = [e_1, e_2]^T$, from (6) and (7), lead to:

$$\dot{e} = K \cdot e + B[\tilde{F}_N(x,u) + v(t)] \quad (8)$$

where $\tilde{F}_N(x,u) = F_N(x,u) - \hat{F}_N(x,u)$ are estimation errors of $F_N(x,u)$ and $K = A - LC$.

The gain matrix L is chosen so that K is a Hurwitz matrix and $\lim_{t\to\infty} e(t) = 0$ with fast enough convergence rate without destabilizing the system.

Based on the dynamic equations that describe the system model (6) and the expression of the ESO (7), structure of the system with the state and disturbance observer using an RBF neural network can be built, as shown in Figure 2.

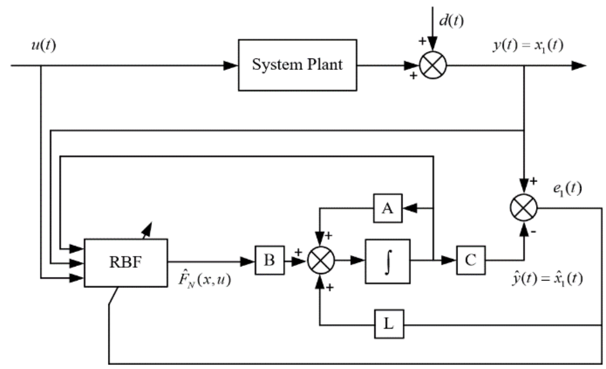

Figure 2. *Structure of the estimation system*

Since $F_N(x,u)$ satisfy the conditions of the Stone-Weierstrass theorem, we can use an RBF neural network to estimate it with the desired precision. Function $F_N(x,u)$ is estimated using the RBF neural network with the following expressions:

$$F_N(x,u) = \sum_{i=1}^{m} w_i^* \varphi_i(x) + \varepsilon = W^* \psi^T(x) + \varepsilon, \quad (9)$$

Where, ε is the estimation errors which satisfy $|\varepsilon| \le \varepsilon_M$; ε_M is the desired limitation value of the estimation errors; $W^* = [w_1^*, w_2^*, ..., w_m^*]$, are the “ideal weights” of neural network used in order to estimate $F_N(x,u)$; and $\psi(x) = [\varphi_1 ... \varphi_m]$ are activation functions that are chosen by using Gaussian functions (10):

$$\varphi_i = \exp\left(\frac{-\|x - c_i\|^2}{2\sigma_i^2}\right), i = 1...\mathrm{m} \quad (10)$$

Estimated value $\hat{F}_N(x,u)$ is fed to the ESO as inputs to enhance the accuracy of the system state estimating process, thus improving the quality of the control loop. Figure 3 represents the structure of the RBF neural network used to estimate the function $F_N(x,u)$, and m is the number of nodes in the hidden layer.

Estimated value $\hat{F}_N(x,u)$ is calculated by the following expression:

$$\hat{F}_N(x,u) = \hat{W}\psi^T(x), \tag{11}$$

where $\hat{W}$ is the weight matrix of the RBF network. Let $\tilde{W}$ be the estimation error:

$$\tilde{W} = \hat{W} - W^*. \tag{12}$$

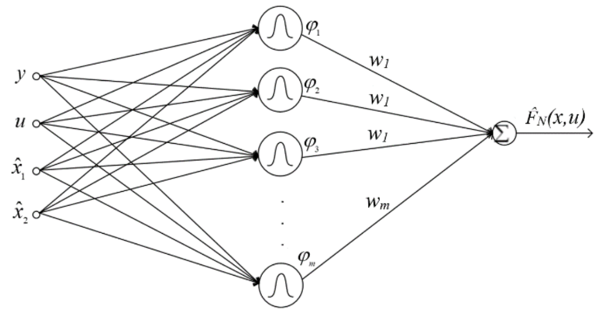

Figure 3. *Structure of the RBF neural network used to estimate $F_N(x,u)$ function*

Obviously, when $\tilde{W} \to 0$, or $\hat{W} \to W^*$, function $F_N(x,u)$ could be estimated with error value $\tilde{F}_N(x,u)$ smaller than given ε_M.

The cost function of RBF network is:

$$J = \frac{1}{2}e_1^2 = \frac{1}{2}(y - \hat{y})^2 \tag{13}$$

From (8), it follows that

$$\begin{cases} e = -K^{-1} \cdot B \cdot (\tilde{W} \cdot \psi^T) + \zeta \\ e_1 = C \cdot e \end{cases} \tag{14}$$

The weights of the neural network are updated online during the learning process without any available data set. And these weight matrices are updated according to the Gradient Descent method:

$$\hat{W}(k+1) = \hat{W}(k) + \eta \cdot \Delta W(k+1) \tag{15}$$

Where η is learning rate of the network. From (13) and (14), $\Delta W_i(k+1)$ are calculated according to:

$$\begin{aligned} \Delta W(k+1) &= \left(\frac{\partial J}{\partial W(k+1)}\right)^T = \left(\frac{\partial J}{\partial e} \cdot \frac{\partial e}{\partial W(k+1)}\right)^T \\ &= \left(-C^T C e K^{-1} B \psi^T\right)^T = -\psi B^T \left(K^{-1}\right)^T e_1^T C \end{aligned} \tag{16}$$

Thus, (15) is equivalent to:

$$\dot{\hat{W}} = \hat{W} - \eta \cdot \psi B^T \left(K^{-1}\right)^T e_1^T C. \tag{17}$$

Combine (12) and (17), it follows that

$$\dot{\tilde{W}} = \tilde{W} - \eta \cdot \psi B^T \left(K^{-1}\right)^T e_1^T C. \tag{18}$$

With these learning techniques, after every sampling period, the weights of the neural network are updated using online data instead of a pre-collected data set. This method ensures the system can operate in real-time with a fast response.

4. Stability analysis

Consider the candidate Lyapunov function:

$$V = e^T P e + tr(\tilde{W}^T \tilde{W}) \tag{19}$$

Thus, $\dot{V} = \dot{e}^T P e + e^T P \dot{e} + tr(\tilde{W}^T \dot{\tilde{W}})$, (20)

Where, P is a positive-definite symmetric matrix. Since K is a Hurwitz matrix, there exists a positive-definite matrix Q, which is defined by the formula:

$$Q = -(K^T \mathrm{P} + PK), \tag{21}$$

and $r_{\min}(Q)$ is the minimum eigenvalue of Q.

Combining (8), (18), (19), (20), and (21), the derivation of the V function is determined by the following expression:

$$\begin{aligned} \dot{V} &= \begin{bmatrix} e^T\left(K^T P + PK\right)e + 2e^T PB\left(\tilde{F}_N(x,u) + v(t)\right) \\ +tr[\tilde{W}^T(\tilde{W} - \eta \cdot \psi B^T \left(K^{-1}\right)^T e_1^T C)] \end{bmatrix} \\ &\le \begin{bmatrix} -e^T Q e + 2e^T PB\left(\tilde{F}_N(x,u) + v(t)\right) \\ +tr\left(\tilde{W}^T \tilde{W}\right) - tr\left(\tilde{W}^T \eta \psi B^T \left(K^{-1}\right)^T e_1^T C\right) \end{bmatrix} \end{aligned} \tag{22}$$

Apply the inequalities:

$2a^T b \le a^T a + b^T b$; $\|ab\| \le \|a\| \cdot \|b\|$;

$tr(a^T a) = \|a\|^2$; and $tr(a+b) \le tr(a) + tr(b)$,

it follows that

$$\begin{cases} -e^T Q e \le -r_{\min}(Q)\|e\|^2 \\ 2e^T PB\left(\tilde{F}_N(x,u) + v(t)\right) \le 2\|e\| \cdot \|PB\| \cdot \left(\varepsilon_M + v(t)\right) \\ -tr\left(\tilde{W}^T \eta \psi B^T \left(K^{-1}\right)^T e_1^T C\right) \le \\ -\frac{\eta}{4}\|\psi\|^2 - \frac{1}{4}\|\tilde{W}\|^2 - \frac{1}{4}\left\|B^T\left(K^{-1}\right)^T C^T C\right\|^2 \cdot \|e\|^2 \end{cases} \tag{23}$$

Replace the inequalities (23) to (22) and denotes matrix $Z = \frac{1}{2}B^T\left(K^{-1}\right)^T C^T C$, it follows that

$$\begin{aligned} \dot{V} &\le \begin{bmatrix} \left(-r_{\min}(Q) - \|Z\|^2\right)\|e\|^2 + 2\|e\| \cdot \|PB\|\left(\varepsilon_M + v(t)\right) \\ +\frac{3}{4}\|\tilde{W}\|^2 - \frac{\eta}{4}\|\psi\|^2 \end{bmatrix} \\ \dot{V} &\le \begin{bmatrix} \left[\left(-r_{\min}(Q) - \|Z\|^2\right)\|e\| + 2\|PB\|\left(\varepsilon_M + v(t)\right)\right]\|e\| \\ +\frac{1}{4}\left(3\|W_{Max}\|^2 - \eta\|\psi_{Max}\|^2\right) \end{bmatrix} \end{aligned} \tag{24}$$

If these following conditions

$$\begin{cases} \|e\| \ge \dfrac{2\|PB\| \cdot \left(\varepsilon_M + v(t)\right)}{r_{\min}(Q) + \|Z\|^2} \\ \eta \ge \dfrac{3\|W_{Max}\|^2}{\|\psi_{Max}\|^2} \end{cases} \tag{25}$$

are met, then $\dot{V} \le 0$, the state observer system combined with the RBF neural network is stable.

5. Simulation results

In order to illustrate the performance of the estimation algorithm, the system is simulated in the Malab-Simulink environment based on the built model.

Considering a hydraulic drive system with the following parameters:

$$m_p = 0,96\,(kg); d_p = 20\,(Ns/m); k_s = 500(N/m);$$

$$F = 10(N); A_p = \pi / 4 \times 0.5^2 (m^2);$$

In RBF neural network approximation, the parameters of c_i and σ_i must be chosen according to the scope of the input value (amplitude U_0 of signal $u(t)$).

In detail, for the input $u(t)$ signal with $U_0 = 5$, use a RBF network with a number of nodes in the hidden layer of $m = 7$ and activation functions with the following parameters:

$$\sigma_i = 5; \eta = 0.5;\ c = \begin{bmatrix} -3 & -2 & -1 & 0 & 1 & 2 & 3 \end{bmatrix}; \lambda = 4;$$

and extended state observer with parameter matrices:

$$L = \begin{bmatrix} 150 & 300 \end{bmatrix}^T;\ A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix};\ B = \begin{bmatrix} 0 \\ 1 \end{bmatrix};\ C = \begin{bmatrix} 1 & 0 \end{bmatrix}.$$

The simulation result of the estimation algorithm that estimates the nonlinear function $F_N(x,u)$ is shown as Figure 4.

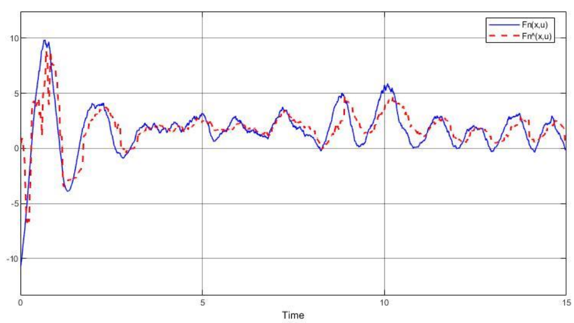

Figure 4. *Estimating the nonlinear function with $\sigma_i = 5$*

Remark 1: According to simulation results, it can be seen that, if c_i and σ_i are set in an effective range relative to input signal scope, the neural network RBF can fairly accurately estimate the total disturbances and nonlinear function with small time delay. Basically, this delay time depends on the activation functions and the number of nodes in the hidden layer of the neural network.

Conversely, if these parameter values are chosen inappropriately, the Gaussian function will not be effectively mapped, and the RBF network will be invalid.

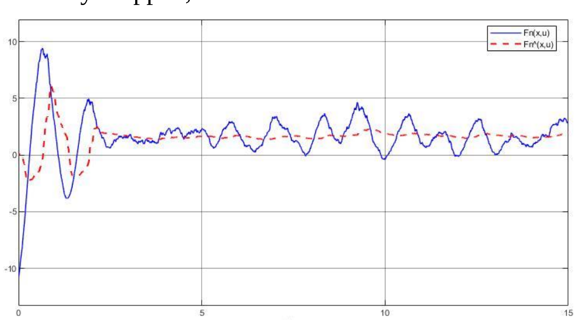

Figure 5. *Estimating the nonlinear function with $\sigma_i = 1$*

This issue is illustrated in Figure 5. In this case, activation functions with $\sigma_i = 1$ cannot cover the range of the input signal scope U_0. As a result, the function $F(x,u)$ cannot be estimated correctly.

Estimated value $\hat{F}_N(x,u)$ is then fed to the extended state observer to estimate the system states x_1, x_2. Results are shown in Figures 6 and 7.

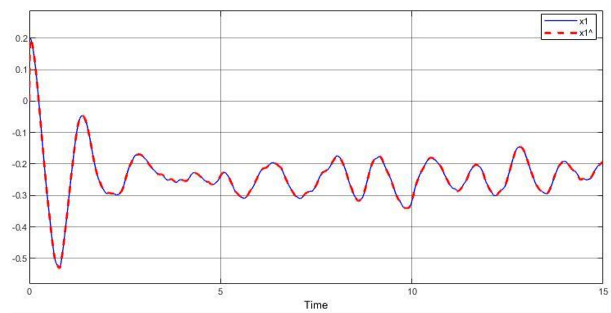

Figure 6. *Estimating the system state variable x_1*

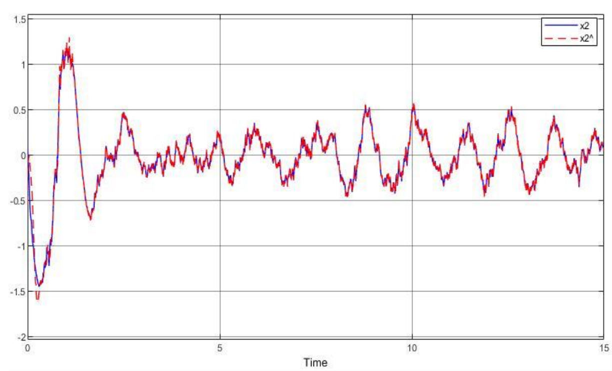

Figure 7. *Estimating the system state variable x_2*

Remark 2: After the settling time of the network training process, state estimation errors approach 0 and depend on the initial system states, convergence rate, and learning rate of the network. According to simulation results, the system, with the combination of the state observer and the RBF neural network with an online weight updating rule, could accurately estimate the affected disturbances and the states of the servo valve-controlled hydraulic system.

To evaluate the effectiveness of the proposed method to estimate the system states on the basis of combining an RBF neural network with the ESO, the article simulates the estimation algorithm in the case of using only the Luenberger state observer (as shown in Figures 8 and 9).

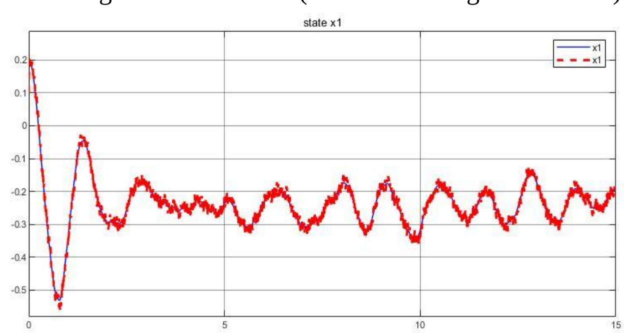

Figure 8. *Estimating x_1 without RBF neural network*

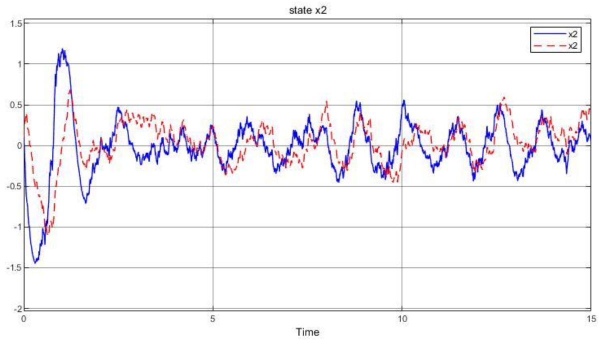

Figure 9. *Estimating x_2 without RBF neural network*

Remark 3: The system state estimation method using the state observer combined with an RBF neural network has way more accurate results than using only the Luenberger state observer. This is especially evident for the state variable x_2, which contains nonlinear and disturbance factors affecting the system.

6. Conclusion

The servo-valve-controlled hydraulic systems using axial piston pumps, like any other hydraulic systems, are always affected by disturbances and nonlinear factors. Therefore, control strategies using traditional controllers like PID make it difficult to meet the high accuracy requirement. This article presents a method to estimate the nonlinear components and external disturbances based on a parallel model that combines the RBF neural network with an extended state observer. The built model has a simple structure and the ability to estimate those factors in real time with the desired accuracy. The advantages of this estimation algorithm also have also been demonstrated by simulation results in the Matlab-Simulink environment.

In addition, the model of this disturbance estimator can be used for the development of high-quality adaptive controls for hydraulic servo drive systems.

REFERENCES

[1] K. Jin, J. Song, Y. Li, Z. Zhang, H. Zhou, and X. Chang, "Linear active disturbance rejection control for the electro-hydraulic position servo system", *Science Progress*, vol. 104, no. 1, pp. 1-30, 2021. https://doi.org/10.1177/00368504211000907

[2] M. E. M. Essa, M. A. Aboela, and M. A. M. Hassan, "Position control of hydraulic servo system using PID controller turned by some evolutionary techniques", *Journal of Vibration and Control*, vol. 22, no. 12, pp. 2946-2957, 2016. https://doi.org/10.1177/1077546314551445

[3] X. Yang, Y. Cui, Z. Yuan, and J. Hang, "RISE-based adaptive control of electro-hydraulic servo system with uncertain compensation", *Mathematical Biosciences and Engineering*, vol. 20, no. 5, pp. 9288-9304, 2023. https://doi.org/10.3934/mbe.2023407

[4] A. K. Pandey, K. Dasgupta, N. Kumar, and A. Vardhan, "Leakage analysis of Bent-axis hydro-motors: An experimental study", *Journal of the Chinese Society of Mechanical Enginners*, vol. 38, no. 1, pp. 93-98, 2017.

[5] T. Samakwong and W. Assawinchaichote, "PID controller design for electro-hydraulic servo valve system with genetic algorithm", *ISSN 1877-0509*, vol. 86, pp. 91-94, 2016. https://doi.org/10.1016/j.procs.2016.05.023

[6] Y. Guo, X. Zha, Y. Shen, Y. Wang, and G. Chen, "Research on PID position control of a hydraulic servo system based on Kalman genetic optimization", *Actuators*, vol. 11, no. 16: 162, 2022. https://doi.org/10.3390/act11060162

[7] W. Hao and J. Kan, "Application of self-tuning fuzzy proportional-integral-derivative control in hydraulic crane control system", *Advances in Mechanical Engineering*, vol. 8, no. 6, pp. 1-10, 2016. https://doi.org/10.1177/1687814016655258

[8] N. H. Cong, "Research on the application of neural networks in identification and control robot arm – a nonlinear dynamic object". *The University of Danang - Journal of Science and Technology*, vol. 5, no. 102, pp. 14-18, 2016.

[9] S. Song, J. Liu, and H. Wang "Adaptive Neural Network control for uncertain switched nonlinear systems with time delays". *IEEE Access*, vol. 6, pp. 22899-22907, 2018. https://doi.org/10.1109/ACCESS.2018.2827399

[10] J. Liu, *Radial Basis Function (RBF) neural network control for mechanical systems*, New York: Springer, 2013.

[11] Y. Ma and Y. Li, "Active disturbance compensation based robust control for speed regulation system of permanent magnet synchronous motor", *Applied Sciences*, vol. 10, no. 2, pp. 709, 2020. https://doi.org/10.3390/app10020709

[12] S. Yordanova, M. Slavov, and G. Prokopiev, "Disturbance compensation in fuzzy logic control of level in carbonisation column for soda production", *WSEAS Trans. On Systems and Control*, vol. 15, pp. 64-72, 2020. https://doi.org/10.37394/23203.2020.15.8

[13] H. Ren, S. Jiao, X. Wang, and J. Li, "Adaptive RBF neural network control method for Pneumatic position servo system", *IFAC PapersOnline*, vol. 53, no. 2, pp. 8826-8831, 2020. https://doi.org/10.1016/j.ifacol.2020.12.1394

[14] J. Lian, J. Hu and S. H. Zak, "Variable neural network adaptive robust observer for uncertain systems", *IEEE International Symposium on Intelligent Control*, pp. 1335-1340, 2011. https://doi.org/10.1109/ISIC.2011.6045403

[15] Z. Has, M. F. Rahmat, A. R. Husain, and M. N. Ahmad, "Robust precision control for a class of Electro-Hydraulic actuator based on disturbance observer", *Int. J. Precis. Eng. Manuf.*, vol. 16, pp. 1753-1760, 2015. https://doi.org/10.1007/s12541-015-0230-y