Parameter Identification of Electro-Hydrostatic Actuator Based on Particle Swarm Optimization

Guozhe Zhou¹*, Tieshan Feng¹, Xin Lv¹ and Lihui Liu¹

¹China Academy of Launch Vehicle Technology, Beijing, 100076, China
*Corresponding author’s e-mail: zhoudguzhe12@163.com

Abstract. The Electro-hydrostatic actuator with high power/weight ratio is compact and efficient. In order to obtain an accurate linear model of the actuator, particle swarm optimization is adopted to identify the parameters of the model. A group of parameters can be seen as the position coordinates of a particle. The real frequency response data of the system is used to evaluate the quality of the particle position and a fitness function is established. The evolution equation with constraint conditions is employed. The particle swarm gradually evolves to search for the optimal solution. Finally, the identification result is presented to prove the efficacy of this method.

1. Introduction

Much of the research in hydraulic servo system focused on valve-controlled actuators which suffer from throttling losses of the servo valves. In contrast, electro-hydrostatic actuators (EHAs) that are directly driven by pumps contribute to increase energy efficiency. Consequently, it is critical to investigate the applications of servo control to EHAs.

The knowledge of the model is essential for the examination of position controller stability and the implementation of stable and accuracy servo control. Due to the difficulty for identification of four coefficients in the model, particle swarm optimization (PSO) algorithm [1] is employed. In this algorithm, massive particles are generated to search for the optimal result via iterative calculation. The particle swarm optimization algorithm is based on the behaviour of social system like bird flocking [2]. A number of particles are located in the solution space of the problem, so each particle’s position represents a solution. Then they move in the space to search the optimal solution. Each particle determines its next movement according to the best position has been found by itself and the best position has been found by the swarm. After a number of iterations, the swarm, like bird flocking looking for corn, is likely to approach the optimal solution. This method has been successfully employed in some parameters optimization problems, such as model identification of fluid dampers [3] and electric power systems [4].

The rest of this article is organized as follows. Section 2 introduces the mathematical model of EHA. Process of particle swarm optimization and coefficient identification are presented in Section 3 and Section 4. In Section 5, comparison of identification result and experimental data is shown. Conclusions are provided in Section 6.

2. Mathematical model of EHA

The schematic of the EHA control system is described in figure 1. The hydraulic cylinder is driven by a fixed displacement piston pump. Rotary speed of the pump is controlled by a permanent magnet
servomotor. A pneumatic source supply the oil tank 0.8 MPa pressure to charge the low pressure side of the loop in order to avoid cavitation.

Figure 1. Schematic of electro-hydrostatic actuator control system.

The mathematical model of EHA is derived so that the position controller stability and target impedance parameters selection can be analysed prior to implementation. The motor rotary speed $\omega_m$ regulated by the control signal $u_c$ is immune to the variable torque load by virtue of the high performance motor controller. Hence, the relationship between the motor rotary speed $\omega_m$ and the control signal $u_c$ can be simplified as an inertial element:

$$\frac{\omega_m}{u_c} = \frac{K_m}{T_m s + 1}$$ (1)

where $K_m$ is the rotary speed gain and $T_m$ is the time constant. The pump flow considering internal leakage is described as follows:

$$Q_L = \frac{D_p \omega_m}{2\pi}$$ (2)

where $Q_L$ is the load flow and $D_p$ is the pump displacement. Considering the viscous friction in the actuator, the actuator dynamics are shown by the following equation:

$$A P_L = M_L \dddot{x}_p + K_{pv} \ddot{x}_p + F_L$$ (3)

where $A$ is the piston area; $P_L$ is the load pressure; $M_L$ is the total mass of piston and load; $K_{pv}$ is the viscous friction coefficient; $F_L$ is the load force; $\dot{x}_p$ and $\dddot{x}_p$ are the piston velocity and acceleration, respectively. The load flow $Q_L$ is consumed by hydraulic compression, leakage and piston motion. The equation given in [5] describes this phenomenon as follows:

$$Q_L = \frac{V_t}{2\beta_e} \dot{P}_L + K_{pl} P_L + A \dddot{x}_p$$ (4)

where $V_t$ is the total actuator volume; $\beta_e$ is the effective bulk modulus; $K_{pl}$ is the cylinder leakage coefficient. For simplicity, the cylinder leakage is neglected in subsequent analysis. Combining equations (1) to (4) and taking the Laplace transform, the transfer function of EHA is obtained:

$$\hat{x}_p = \frac{D_p}{2\pi} \frac{AK_m K_{at} u_c - s(T_m s + 1)F_L}{M_L T_m s^4 + K_m s^3 + K_{dp} s^2 + A^2 K_{at} s}$$ (5)

where $K_{at}$, $K_{at}$ and $K_m$ are given below:
\[ \begin{align*}
K_m &= M_L + T_m K_f, \\
K_{hs} &= \frac{2\beta_v}{V_t}, \\
K_{dp} &= K_f + T_m A^2 K_{hs}
\end{align*} \] (6)

Considering a general situation that the actuator interact with a stiffness dominant environment, the relationship between the piston position, \( x_p \), and the load force, \( F_L \), is shown as follows:
\[ F_L = K_e x_p \] (7)
where \( K_e \) is the environment stiffness. Substitute equation (7) into equation (5), then the transfer function of EHA, \( G_{EHA} \), can be written as below:
\[ G_{EHA}(s) = \frac{x_p}{u_c} = \frac{A_1}{s^a + A_2 s^2 + A_3 s^3 + A_4 s} \] (8)

The coefficients, \( A_1 \) to \( A_4 \), are listed below:
\[ \begin{align*}
A_1 &= \frac{D \cdot A K_m K_{hs}}{2\pi M_L T_m} \\
A_2 &= \frac{K_{in}}{M_L T_m} \\
A_3 &= \frac{K_{dp} + T_m K_f}{M_L T_m} \\
A_4 &= \frac{A^2 K_{hs} + K_f}{M_L T_m}
\end{align*} \] (9)

From the above transfer function, EHA can be seen as a fourth-order system with four coefficients, \( A_1 \) to \( A_4 \), whose values should be determined. For identification of these coefficients, particle swarm optimization algorithm which will be described next is adopted.

3. Process of particle swarm optimization algorithm

In the algorithm, each particle, \( i \), has three \( D \)-dimensional vectors as below:
\[ \begin{align*}
\mathbf{x}_i &= [x_{i1} x_{i2} \ldots x_{id}]^T \\
\mathbf{v}_i &= [v_{i1} v_{i2} \ldots v_{id}]^T \\
\mathbf{p}_i &= [p_{i1} p_{i2} \ldots p_{id}]^T
\end{align*} \] (10-12)
where \( i \) is the particle’s index; \( D \) is the dimensionality of the solution space; \( \mathbf{x}_i \) is the \( i \)th particle’s current position which denotes a solution; \( \mathbf{v}_i \) is the velocity of the \( i \)th particle; \( \mathbf{p}_i \) is the best position that has been found by the \( i \)th particle. There is another vector for the whole swarm as follows:
\[ \mathbf{p}_g = [p_{g1} p_{g2} \ldots p_{gd}]^T \] (13)
where \( \mathbf{p}_g \) is the best position that has been found by the swarm. In each iteration, the quality of current position, \( \mathbf{x}_i \), is assessed by a fitness function. If this position is better than the previous best position, \( \mathbf{p}_i \), then the vector, \( \mathbf{p}_i \), is updated with the vector, \( \mathbf{x}_i \). When all particles’ vectors, \( \mathbf{p}_i \), are obtained, the best one is chosen to compare with the global best position, \( \mathbf{p}_g \). If the chosen position, \( \mathbf{p}_i \), is better, then update the vector, \( \mathbf{p}_g \). After that, the velocity, \( \mathbf{v}_i \), is added to the current position, \( \mathbf{x}_i \), to move the \( i \)th particle and obtain a new position for next iteration. After all of the iterations, the global best position, \( \mathbf{p}_g \), is the best solution as the final result.

On each dimension \( j \), the iterative equations of the \( i \)th particle are shown as below:
\[ x_i(k+1) = x_i(k) + v_i(k+1) \]
\[ v_i(k+1) = v_i(k) + c_1 r_{ij}(k)[p_i(k) - x_i(k)] + c_2 r_{ij}(k)[p_g(k) - x_i(k)] \]

where \( k \) is the iteration number; \( i \) is the particle’s index; \( j \) is the dimension; \( c_1 \) and \( c_2 \) are the acceleration constants both set to 0.1; \( r_{ij} \) and \( r_{ij} \) are the random coefficients from 0 to 1. In equation (15), the position \( p_i \) and \( p_g \) absorb the particle via adjusting the particle’s velocity. The acceleration constants \( c_1 \) and \( c_2 \) determine the convergence speed of the algorithm. The random coefficients \( r_{ij} \) and \( r_{ij} \) bring some disturbance to prevent the particle from falling into the local optimal area. The specific process of the algorithm is illustrated in figure 2.

**Figure 2. Particle swarm optimization flow chart.**

4. Identification of transfer function coefficients

In this work, 50 particles are generated to search for the values of four coefficients. The dimensionality of the solution space is four. The four coordinates of each particle’s position, \( x_i \), represent the values of four coefficients, \( A_1 \) to \( A_4 \), respectively. The EHA model obtained by each particle, \( G_{EHA}^i \), is written as below:

\[ G_{EHA}^i(s) = \frac{x_{i1}}{s^4 + x_{i2}s^3 + x_{i3}s^2 + x_{i4}s} \]

In order to evaluate the quality of each particle, a fitness function is constructed. The actual frequency response of EHA system is obtained first via experiments. The stiffness dominant environment is emulated by a spring of 170kN/m stiffness. A linear PI controller with proportional gain \( K_p=550\text{V/m} \) and integral gain \( K_i=100\text{V/sm} \) is employed to constitute a position loop with EHA. 24 groups of amplitude and phase data are shown in figure 3 and figure 4.

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Then the transfer function (16) is used with the same environment and controller in simulation. Then the simulated frequency response of EHA system is acquired. The errors between the simulated results and the experimental results are used to assess the fitness of particle. The fitness function, \( f \), is given below:

\[
f = \sum_{n=1}^{24} \left[ (\frac{\text{amp}_n^a - \text{amp}_n^s}{\text{amp}_n^a})^2 + \lambda (\frac{\text{phs}_n^a - \text{phs}_n^s}{\text{phs}_n^a})^2 \right]
\]  

(17)

where \( \text{amp}_n^a \) and \( \text{phs}_n^a \) are the actual amplitude and phase; \( \text{amp}_n^s \) and \( \text{phs}_n^s \) are the simulated amplitude and phase; \( \lambda \) is the weight coefficient which increases the weight of phase accuracy in the fitness function. By observing the curves of various identification results and the experimental data points, the weight coefficient is ultimately set to 10. During the identifications, the fitness value of global best position usually does not change after 100 times iteration. Therefore, the termination criteria is set as reaching the maximum iteration of 100 times.

5. Identification result
The convergence of fitness value of global best position is manifested in figure 5.
The fitness value eventually converges to 0.702 and the identified values of coefficients are listed in table 1. The frequency response of the identified system and the experimental data points are plotted in figure 6 and figure 7.

| Table 1. Identified values of coefficients. |
|------------------|------------------|------------------|------------------|
| $A_1$            | $A_2$            | $A_3$            | $A_4$            |
| 1504100          | 4286.3           | 341830           | $5.9959 \times 10^7$ |

Figure 6. Magnitude frequency response of identified system.

Figure 7. Phase frequency response of identified system.

Solid line represents response of the identified model. Experimental data are shown as circles. The identification result is well coincident with all experimental data points. This actuating system model can be used in the investigation on servo controller.

6. Conclusions
In this paper, the model of EHA was established. Using experimental frequency response of EHA, the coefficients of the model were identified using the particle swarm optimization. The optimization was proven to be very effective to find an optimal solution to fit all the experimental data.

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