Modeling and Control of Electro-Hydraulic Actuator

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Abstract. Modeling and position control of an Electro-Hydraulic Actuator (EHA) system is investigated in this paper. Linear ARX EHA system model is identified by taking the experimental data using system identification toolbox in the MATLAB/Simulink. From the identified models the best fit ARX 331 model is used to design a controller using fuzzy logic and Particle swarm optimization (PSO) methods. In the self-tuning Fuzzy PID controller, the controller parameters K_P, K_I, and K_D are tuned by the fuzzy controller depending on the two inputs: error and derivatives of the error. In the PSO optimized PID controller, the sum of the time-weighted absolute error objective function is minimized and optimized controller parameters are tuned using PSO algorithms. The results are simulated in the MATLAB/Simulink and compared among conventional Ziegler-Nichols (Z-N), Fuzzy, and PSO PIDs. The results indicate that the self-tuning fuzzy PID and PSO optimized PID give better performance than the Z-N PID controller and the PSO-optimized PID controller demonstrates superior performance in terms of percentage overshoot and speed of response with 5% overshoot, 0.02 s rise time and 0.15 s settling time.

Keywords: System identification · Electro-Hydraulic Actuator · Fuzzy self-tuning PID · PSO optimized PID

1 Introduction

Electro-Hydraulic Actuators (EHA) due to high power, fast and smooth response characteristics and good positioning capability are becoming famous in many applications like manufacturing systems, mining, automotive, robotics, flight simulation, ships and marine engineering etc. [1]. However, the nonlinear nature of such actuators characterizes a great challenge in designing the best possible controller for EHA [2, 3]. Difficulties in identifying an accurate model of inherently nonlinear to its equivalent linear model, and time-varying dynamics make controller design more complicated and challenging [4, 5]. A number of studies have been conducted to minimize the impact of nonlinearity and uncertainty in the model [6–9]. Many researchers have also used

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advanced control strategies to improve the system performance mainly in tracking control and motion controllability [7–13]. In the literatures, various Fuzzy controller structures have been proposed and extensively studied [1, 2, 4–6].

Proper modeling of a given system is a decisive step before designing any control strategy. There are number of approaches that can be used to identify the model of a given system. To get the required model, two main approaches are used. The first principle based on physical and chemical laws and system identification based on input-output data [14, 15]. Physical modeling using fundamental physical laws require high level of understanding about EHA system to derive the mathematical model. In such models, it is hard to capture and insight unmodeled dynamics and uncertainties in the model. Unlike first principle method, system identification approaches able to insight and capture unmodeled dynamics and uncertainties [10, 11, 13, 15, 16].

2 Model Estimation

The most costly procedure in system identification is obtaining experimental data. Data are raw input for identification. Here, model estimation is investigated using experimental input-output data on Matlab/Simulink system identification tool box. The EHA system used in paper is single rod hydraulic cylinder driven by a direct servo valve with 40-L/min flow rate at 70 bars. The dimension of the hydraulic cylinder is 63/30/300 mm. Piston position is measured by using a 300 mm draw wire sensor with an input-output data recorder. The input to the system is the sum of sinusoidal voltage as seen in (1), which ranges from −5 V to 5 V, is used to generate an output displacement of EHA.

$$Sum\,of\,sine\,input\ =\ 2sin2t_sk + sin6t_sk + 2sin0.3t_sk \tag{1}$$

The input and output signals are shown in Fig. 1.

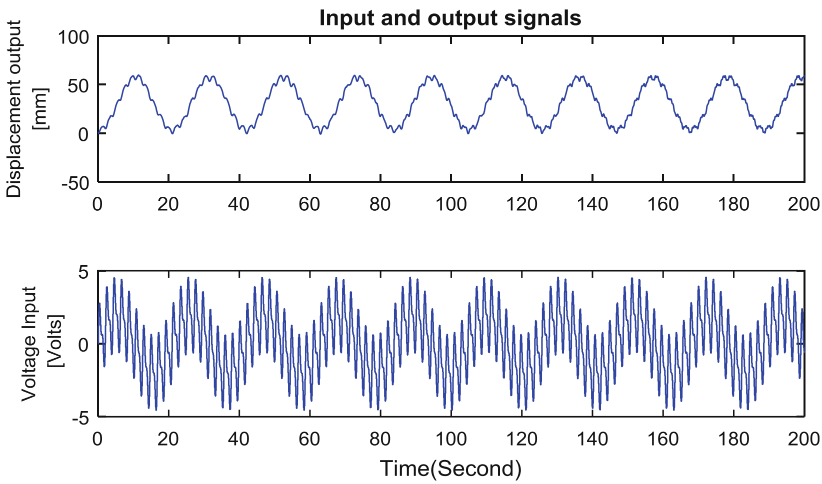

Fig. 1. Electrohydraulic model training and validation

Number of data generated for training and validation are 4000 with sampling time 50 ms. In order to estimate and validate the model, the data have been divided into two parts. The first sample (1 to 200) and the second sample (2001 to 4000) data have been used to estimate and validate the model.

One of the objectives of this paper is to find a linear EHA model with adequate accuracy to design a controller that will drive the output in the desired manner. Taking this into considerations, linear discrete-time ARX model structure is selected. As displayed in Table 1, second-order and third-order ARX models are estimated with best fit more than 85%. From the results, the ARX331 model has better performance with 92.35% percentage model fit, 0.258×10^{-4} final prediction error (FPE) and 0.2565×10^{-4} mean square error (MSE). The model validation for result of ARX331 using validation data is illustrated in Fig. 2.

The selected ARX 331 model used to design controller is represented as:

$$A(z)y(t) = B(z)u(t) + e(t). \tag{2}$$

Where $A(z) = 1 - 0.9458z^{-1} - 0.3192z^{-2} + 0.2652z^{-3}$ and $B(z) = 0.23z^{-1} - 0.1753z^{-2} - 0.3144z^{-3}$. Assuming zero initial conditions, the transfer function can be represented as shown in (3).

$$\frac{Y(z)}{U(z)} = \frac{0.23z^{-1} - 0.1753z^{-2} - 0.3144z^{-3}}{1 - 0.9458z^{-1} - 0.3192z^{-2} + 0.2652z^{-3}} \tag{3}$$

Table 1. ARX model representation with best fit criteria

S. No.	Model structure	Best fit (%)	FPE $\times 10^{-4}$	MSE $\times 10^{-4}$	ARX model
1	ARX211	87.54	0.2902	0.2967	$A(z) = 1 - 0.798z - 1 + 0.3985z^{-2}$, $B(z) = 0.2438z^{-1}$
2	Arx331	92.35	0.258	0.2565	$A(z) = 1 - 0.9458z^{-1} - 0.3192z^{-2} + 0.2652$, $B(z) = 0.23z^{-1} - 0.1753z^{-2} + 0.3144z^{-3}$
3	Arx321	92.13	0.2616	0.2603	$A(z) = 1 - 0.925z^{-1} + 0.4978z^{-2} - 0.2923z^{-3}$ $B(z) = -0.03458z^{-1} + 0.364Z^{-2}$
4	Arx332	88.5	0.2576	0.2566	$A(z) = 1 - 0.95419z^{-1} + 0.455z^{-2} - 0.336z^{-3}$, $B(z) = 0.4714z^{-2} - 0.3379z^{-1} + 0.2366z^{-4}$

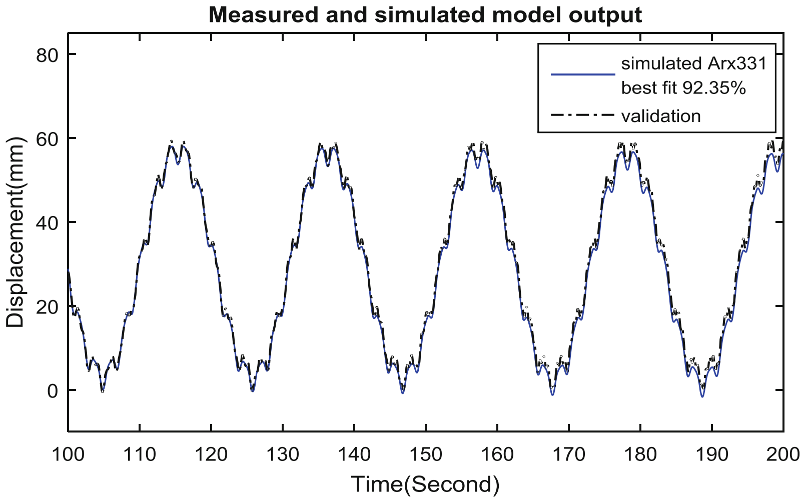

Fig. 2. Model validation curve (ARX331)

3 Self-tuning Fuzzy PID Controller

In this section of the paper, development of a self-tuning fuzzy PID controller for controlling the position variation of EHA is presented. In classical tuning methods, PID controller cannot give satisfactory response for system with nonlinearity and unpredictable parameters variations [2, 3]. Hence, the self-tuning controller, which is a combination of a classical PID and a fuzzy controller, is proposed. The general discrete PID structure shown in (4) is modified and used in combination with Fuzzy logic controller.

$$PID = K_P\left(1 + \frac{T_S}{\tau_I(z-1)} + \frac{\tau_D(z-1)}{T_s z}\right) \tag{4}$$

where K_P is proportional gain, τ_I, and τ_D are integral and derivative time constants respectively and T_s is sampling time.

The proposed structure of the self-tuning fuzzy PID controller shown in Fig. 3 has two inputs to the fuzzy logic inference engine; the feedback error *e(t)* and the derivative of error *de(t)/dt*. The PID parameters are tuned by using fuzzy inference. This provides a nonlinear mapping from the error and derivative of error to parameters (K'_P, K'_I, K'_D). The rules are designed to tune the controller parameters to get the required response characteristics of the EHA. The fuzzy reasoning of fuzzy sets of output is gained by aggregation operation of fuzzy sets inputs and the designed fuzzy rules. The aggregation and defuzzification methods are used respectively max-min and centroid method.

Before developing self-tuning Fuzzy PID controller, the performance measure and the ranges of controller parameter boundaries are defined. In this controller design, rise time less than 5 s, settling time less than 10 s, percentage overshoot less than 15% are taken as the performance measure.

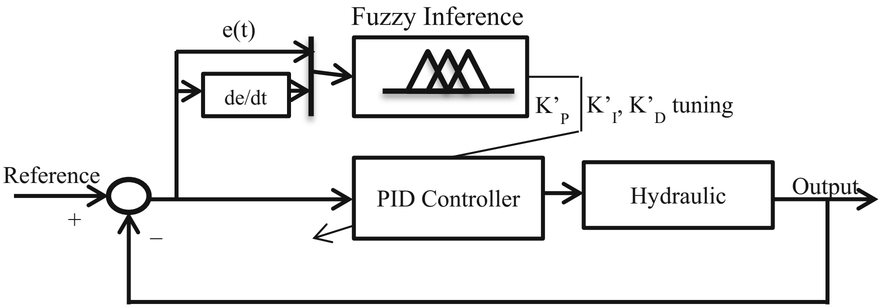

Fig. 3. Structure of self-tuning fuzzy PID Controller [1]

The upper and lower boundaries of gain values of Fuzzy PID parameters are determined simulating Z-N PID parameters ranges from stability limit with large time constants to that of near instability. This results in the ranges of each parameters, i.e., $K_P \in [1, 10]$; $K_I \in [0, 1]$; $K_D \in [0, 0.5]$. Hence, the output parameters from fuzzy tuner can be calibrated over the interval [0, 1] and, therefore, the designed discrete-PID controller has the form as shown in (5).

$$\mathrm{PID} = (9K'_P + 1) + \frac{K'_I}{(z-1)} + 0.5K'_D \frac{(z-1)}{z} \tag{5}$$

Thus, the PID controller parameters have a relation $K_p = 9K'_P + 1$, $K_I = K'_I$ and $K_D = 0.5K'_D$.

The universe discourse of the fuzzy membership function designed for the error, change of error and the outputs are Gaussian. The input membership functions for error and change of error is designed within the range [−0.1, 0.3] and [−0.1, 0.1] respectively. The output parameters K'_P, K'_I and K'_D with Gaussian membership function within the range [1, 10], [0, 1], and [0, 0.5] are taken. The linguistic values of the error and change of error are designed with 5 linguistic terms for each input: negative big (NB), negative small (NM), zero (Z), positive small (PS), and positive big (PB). For the output 5 linguistic terms small(S), medium small (MS), Medium (M), medium big (MB), and big(B) are designed. Since there are five linguistic variables that have been set, thus, 25 fuzzy rules are applied in the system. Centroid method of defuzzification is used to get the definite values that are sent to PID controller.

4 Particle Swarm Optimization (PSO) PID

In PSO-PID control design process, the objective is to minimize the objective function defined as Sum of time weighted absolute error, which determines the performance of criteria in terms of rise time, percentage overshoot and settling time. In this PSO optimized PID controller design, the objective function is modified as seen in (6)

$$f(k) = \sum\nolimits_{k=1}^{N} |e(k)| * k \tag{6}$$

Figure 4 illustrates the implementation structure of PSO optimized PID controller. The optimal values of the controller parameters (K'_P, K'_I, and K'_D) are selected using PSO algorithm based on sum of time weight absolute error performance index.

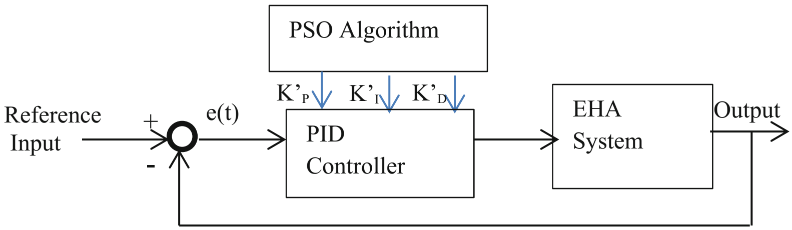

Fig. 4. PSO optimized PID control structure

For implementing the PSO algorithm the following parameters are chosen. The population number be 50, maximum iteration 100, variable size 3, damping weighting inertial maximum 0.99 to minimum 0.75, personal and social cognitive coefficients are 2. By taking Z-N PID simulation as reference, the lower and upper bounds of the PID parameters are defined within the stability ranges. The lower and the upper bounds K'_P, K'_I and K'_D are chosen from 1 to 5, 0 to 0.2 and 0 to 0.05 respectively. Then the PID controller structure has the form:

$$PID = (1 * K'_P + 3) + \frac{(K'_I + 0.019)}{(z-1)} + (K'_D + 0.01)\frac{(z-1)}{z} \tag{7}$$

5 Results and Discussion

5.1 Self-tuning Fuzzy PID

The results are simulated in the MATLAB/Simulink simulation environment. Square wave and step input test signals have been used to show the tacking and transient performance of the Fuzzy PID controller respectively. The results are illustrated in Figs. 5 and 6.

Figure 5 shows the performance of the self-tuning fuzzy PID controller with respect to step reference input signal. It achieves better response characteristics as compared to the defined design criterion with fast rise time of 0.05 s and settling time of 0.2 s. As can be seen from Fig. 5, the response demonstrates good tracking performance for the square wave test signal. However the response of the proposed system looks satisfied, it needs to develop by including disturbance and any others nonlinearity and uncertainties in the design with various frequencies in reference input signals.

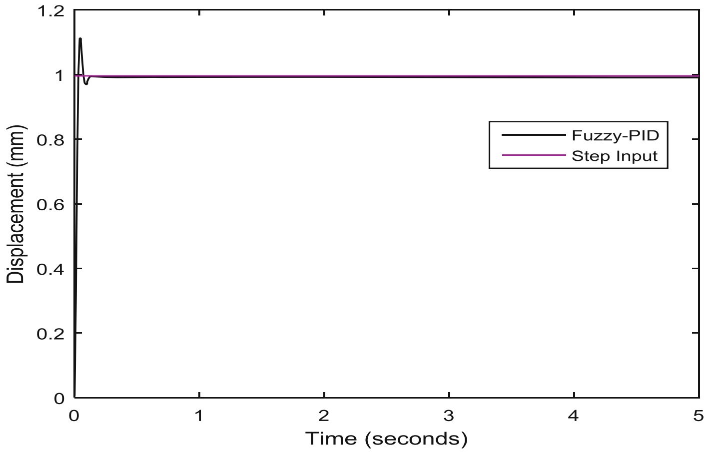

Fig. 5. Output signal of self tuning – fuzzy PID with step input

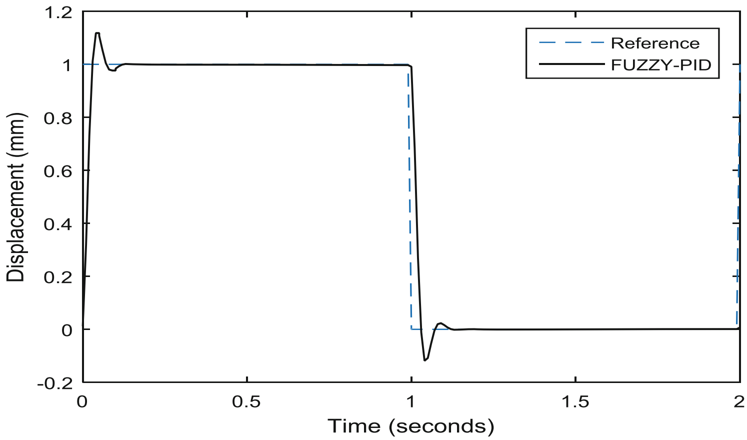

Fig. 6. Output signal of fuzzy PID with square input

5.2 PSO Optimized PID

The PSO PID algorithm is implemented in the MATLAB assuming the size of the swarm to be 50, maximum iterations 100, damping weighting inertial 0.99 max to 0.75 min, personal and social cognitive coefficients 2. The lower and the upper bounds of K'_P, K'_I and K'_D from 0.5 to 1, 0 to 0.2 and 0 to 0.05 respectively are taken. The simulation result shows that after 100 iterations the best cost that is the minimum of performance measure sum of time-weighted absolute error is 1.2752×10^{-09} with coefficient positions of K'_P, K'_I and K'_D at 0.0115, 0.0011, and 0.0642 respectively.

Figures 7 and 8 demonstrate the response of PSO-optimized PID controller with step input and square reference input. The step response shows the PSO optimized PID control has better performance with 6% overshoot, 2 ms rise time and 17 ms settling

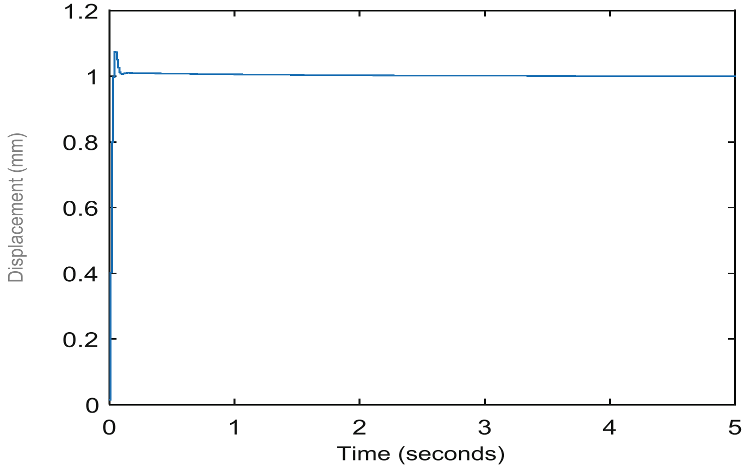

Fig. 7. Step response of PSO-PID system

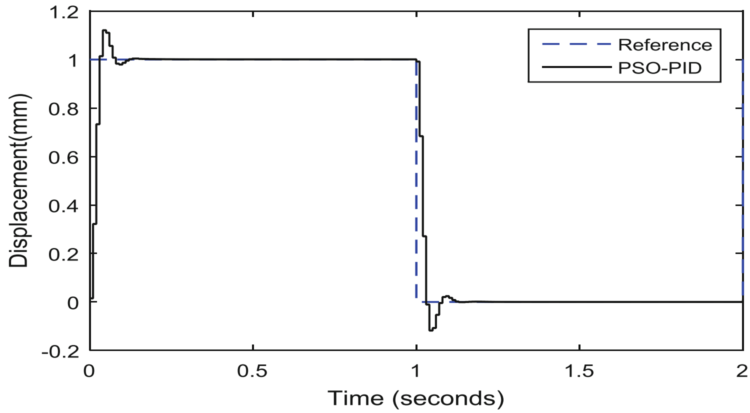

Fig. 8. Response of PSO-Optimized PID with square wave input

time with respect to the design performance criteria. From Fig. 8 it can be observed that the PSO-PID controller can track the square wave reference input with fast response and less overshoot.

5.3 Comparison of the Results

Figure 9 and Table 2 show a comparison of the step response performances of the proposed controllers with respect to the conventional Z-N PID. It can be observed that as compared to Z-NPID controller, self-tuning fuzzy PID and PSO optimized PID have better performance in terms of speed of response. However, less overshoot the classical Z-N PID demonstrates very slow response as compared to the two proposed controllers with rise time of 7 s and settling time of 30 s.

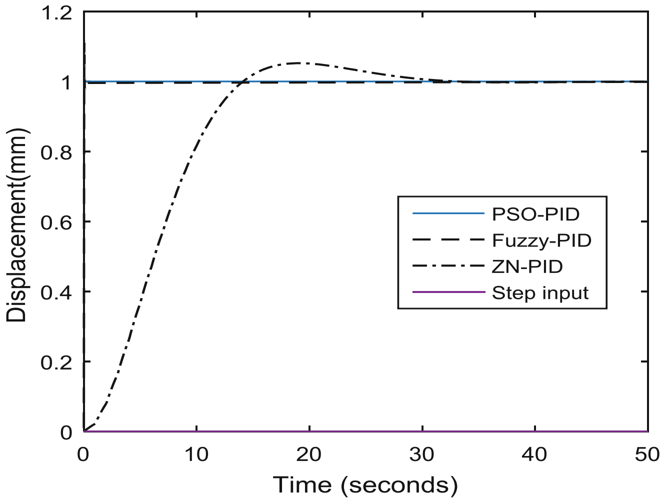

Fig. 9. PSO–PID, FUZZY–PID, and Z-N PID step response

Table 2. Step response of characteristics of Z-N-PID, Fuzzy-PID, PSO-PID

	K_P	K_I	K_D	Percentage-Overshoot	Rise time (sec.)	Settling time (sec.)
Z-NPID	1.72	0.5	0.772	6	7	30
FUZZY PID	3.855	0.311	0.1559	11.6	0.05	0.20
PSO-PID	1.55	0.1171	0.0957	5	0.02	0.15

6 Conclusion

System Identification technique has been used to get the linear model of the EHA system. Three low order ARX models are estimated and ARX331 with best fit of 92.35% is used for controller design. Self-tuning fuzzy and PSO optimized PID controllers are proposed to tune the value of K_P, K_I, and K_D of the PID controller. The responses self-tuning fuzzy PID controller and PSO optimized PID controller show that the performance of the EHA system is improved and satisfied as compare to the Z-N PID controller and the defined designed criteria. From the results, it can be observed that PSO-optimized PID controller demonstrates superior performance in terms of percentage overshot and speed of response with 5% overshoot, 0.02 s rise time and 0.15 s settling time.

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