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Performance Evaluation of EHA System using Weight Aggregation Strategy in MOPSO-PID

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ABSTRACT

In this paper, an improved Particle Swarm Optimization (PSO) that combines the Proportional-Integral-Derivative (PID) controller for positioning control in Electro-Hydraulic Actuator (EHA) system is proposed. Conventionally, PSO with single objective function is designed to determine the optimal parameters of the controller. However, PSO with single objective function might not solve the problem effectively. Hence, a Multi-Objective PSO (MOPSO) is proposed in this work. Two objective functions will be used in the optimization task, which includes mean error and overshoot percentage. The most popular method in MOPSO is Linear Weight Summation (LWS). This paper focuses on investigating the effect of different weight factors combination between mean error and overshoot. Time domain analysis such as overshoot percentage, steady-state error, and mean error will be used to analyse the positioning performance of the EHA system. The results showed that the EHA system performed better by using the best combination of weight factors between mean error and overshoot.

Keywords:
Electro-Hydraulic Actuator System, Multi-Objective Particle Swarm Optimization, Linear Weight Summation

1. Introduction

Electro-Hydraulic Actuator (EHA) system is widely used in industry due to fast response, high precision and the small size-to-power ratio [1]. However, the EHA system is known as a highly non-linear system. This is mainly due to the effect of the dynamic performance, the dead zone and leakage, and the flow-pressure relationship of the servo/proportional valve [2]. Technically, the EHA system is often harnessed in the system, which requires high-performance control with high precision and heavy load [3].

Several control approaches have been proposed for controlling the EHA system. However, the Proportional-Integral-Derivative (PID) controller is still the main choice for the industry. Unlike other controllers, PID has a simple structure, fast design process and robust performance in a wide range of operating conditions [4]. In the past study, a self-tuning fuzzy PID controller has been proposed in

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Zheng *et al.,* [5] for a volume control the electro-hydraulic press. It was proven that the controller showed the great ability to restrict the disturbance and increase the ability of the volume control EHA system. Another PID controller that implemented in hose-compensation strategy and valve-compensation strategy was designed for position tracking control of hose-connected electro-hydraulic lifting system in Hou *et al.,* [6]. The results showed that both strategies worked effectively with PID controller and showed a significant improvement in tracking accuracy.

However, it is difficult to tune the PID controller for obtaining the desired controller's parameters. Traditional tuning techniques such as trial-and-error is able to achieve the optimal parameters in a very short period. However, the difference is not obvious and the desired performance is not guaranteed. Another tuning method is Ziegler-Nichols, which is one of the popular and simple methods. Unfortunately, this method is shown to be aggressive, and it will lead to large overshoot and oscillatory response [4].

Many researchers began to use the meta-heuristic optimization algorithm to find the most appropriate PID controller's parameters. Two most common optimization strategies are a genetic algorithm (GA) and particle swarm optimization (PSO). Nevertheless, PSO is simpler and its operation is much convenient as compared to GA. As compared to GA, PSO tends to converge faster in searching for the best solution [7]. In this paper, an improved PSO called Multi-Objective Particle Swarm Optimization (MOPSO) is developed for controlling the positioning of the EHA system.

The rest of the paper is organized as follow: Section II will briefly introduce the EHA system modeling, followed by the proposed optimization approach in Section III. Section IV will discuss the implementation of the simulation and the results. Finally, conclusion and future recommendation are outlined in Section V.

2. EHA System Modeling

Figure 1 shows the physical model of the electro-hydraulic actuator (EHA) system utilized in this paper. The main objective in this paper is to generate the input current to adjust the position of the hydraulic cylinder to push the mass (M) which also attached to spring and damper to the desired position. The hydraulic oil will flow through the pipeline from the servo valve and the hydraulic cylinder. The piston in the hydraulic cylinder is then pushed by the hydraulic oil to move the mass to the desired position.

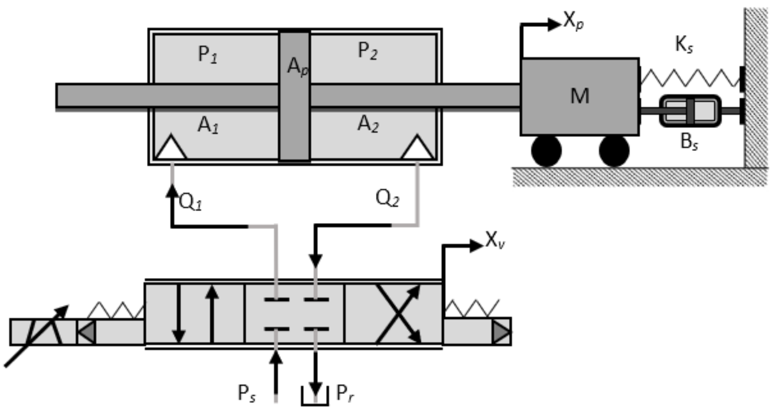

Fig. 1. Schematic diagram of the EHA system

The established mathematical modeling of the EHA system by Kalyoncu and Haydim [8] is used in this paper. Since mathematical modeling is not the main topic in this paper, it will not discuss in detail in this paper. For details dynamic equations, please refer to Kalyoncu and Haydim [8].

The final total force produced from hydraulic actuator can be obtained in Eq. (1) which had included all the dynamic's equation of moving mass, damper, and spring.

$$F_p = A_p(P_1 - P_2) = M_p \frac{d^2 x_p}{dt^2} + B_s \frac{dx_p}{dt} + K_s x_p + F_f \tag{1}$$

In this simulation study, some of the parameters might vary from Kalyoncu and Haydim [8]. The EHA system parameters used in this paper have been tabulated in Table 1.

Table 1
EHA system parameters

Symbol	Description	Value
I_{sat}	Torque motor saturation current	0.02 A
L_c	Servo-valve coil inductance	0.59 H
R_c	Servo-valve coil resistance	100 Ω
β	Hydraulic fluid bulk modulus	$1.4\text{x}10^9$ N/m^2
ω_n	Servo-valve natural frequency	543 rad/s
ξ	Servo-valve damping ratio	0.48
P_r	Return pressure	0 Pa
P_s	Pump pressure	$2.1\text{x}10^7$ Pa
K	Servo-valve gain	$2.38\text{x}10^{-5}$ m$^{5/2}$/kg$^{1/2}$
M_p	Total mass	9 kg
X_s	Total actuator displacement	0.1 m
B_s	Damping coefficient	2000 Ns/m
A_p	Piston area	$645\text{x}10^{-6}$ m^2
K_s	Spring stiffness	10 Nm

3. Proposed Optimization Approach
3.1 Proportional-Integral-Derivative Controller

PID controller is the most popular controller in the industry. Figure 2 illustrates the PID controller structure. The top path is called the proportional path, the output of the proportional path is the multiplication of the error (*e*) and the proportional gain, K_P. The second path is the integral path. The output of this path is the multiplication of the integral of the error (*e*) and the integral gain, K_I. Note that the integral of the error is the area under the curve of the graph of error (*e*) versus time. Finally, the third path is the derivative path. The error (*e*) is first differentiated to get the rate of change of the error and then multiplied it with derivative gain, K_D. All the output of these three paths is then added together using a summing block to become a total PID controller action and produce a control signal (*u*) to a plant or system.

The overall PID control function can be expressed mathematically as in Eq. (2).

$$u(t) = K_P * e(t) + K_I * \int_0^t e(t)dt + K_D * \frac{de(t)}{dt} \tag{2}$$

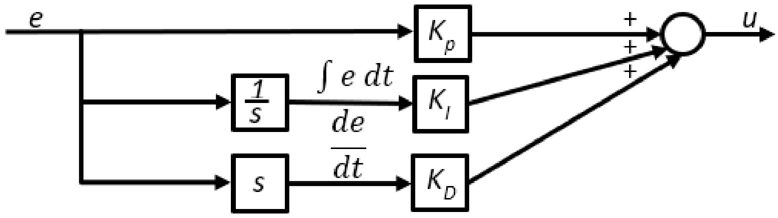

Fig. 1. PID controller structure

The PID controller parameters K_P, K_I, *and* K_D are chosen to satisfy the prescribed performance criteria regarding the mean error and the overshoot in the optimization process. Two desired objective functions are designed as shown in Eqs. (3) and (4).

$$mean\_error = mean(error) \tag{3}$$

$$overshoot = \left(\frac{\max(output) - input}{input}\right) \times 100\% \tag{4}$$

3.2 Particle Swarm Optimization (PSO)

Conventional PSO is an optimization method introduced by Kennedy and Eberhart in 1995 [9]. It was motivated by the social behavior of organisms such as bird flocking and fish schooling to find the food. In PSO, the particles population is called swarm and its potential solutions are called particles. The particles flying around in a multidimensional problem space [10].

First, the initial position of a particle is initialized using Eq. (5). Each potential solution of the optimization problem is represented by a single particle.

$$x^i = x_{\min} + (x_{\max} - x_{\min}) \times rand \tag{5}$$

where x^i is the position of the particle at *i* order, x_{min} and x_{max} are the minimum and maximum values in the search space, *rand* is randomly generated number between 0 and 1. Then the best position achieved by each particle based on its own experience will set as local best, P_{BEST} and the best position achieved by a group of particles in the entire swarm will be set as global best, G_{BEST}.

The position and velocity of each particle will change with time (iteration). The new position, x^{i+1} and new velocity, v^{i+1} of each particle in every iteration are updated using Eqs. (6) and (7).

$$x^{i+1} = x^i + v^{i+1} \tag{6}$$

$$v^{i+1} = \omega v^i + c_1 r_1 (P_{BEST}{}^i - x^i) + c_2 r_2 (G_{BEST} - x^i) \tag{7}$$

where w is the linearly decreasing inertia weight, v^i is the current velocity of the particle, r_1, r_2 are the random numbers that uniformly distributed in the interval 0 to 1, c_1 and c_2 are acceleration constants.

In order to improve the accuracy and efficiency, a linearly decreasing inertia weight from w_{max} to w_{min} as shown in Eq. (8) is applied.

$$w = w_{\max} - (\frac{(w_{\max} - w_{\min})}{i}) \times \max iter \tag{8}$$

where w_{max} and w_{min} are the boundaries on inertia weight, *maxiter* is the maximum iteration number.

3.3 Multi-Objective Particle Swarm Optimization (MOPSO)

The conventional PSO was devised only to solve for single-objective problems [11]. Multi-objective Particle Swarm Optimization (MOSPO) is an improved version of conventional PSO to handle multi-objective problems which mean to optimize more than one objective function throughout the whole optimization. Two objective functions in Eqs. (3) and (4) will be optimized using the proposed MOPSO in this paper.

Among the available MOPSO methods [4], [7], [12-17], linear weight summation (LWS) approach or another named weight aggregation (WA) strategy is the simplest and most popular method. This method converts a multi-objective problem into a single fitness equation using specific or selected weight factors (*alpha,* α and beta, β) as in Eq. (9).

$$Fitness = (\alpha \times mean\_error) + (\beta \times overshoot) \tag{9}$$

where α and β are two weight factors and $\alpha + \beta = 1$. Higher weight value means higher priority is placed on the respective objective function. Mean error and overshoot values in Eq. (9) are normalized values of the result obtained from Eqs. (3) and (4).

In order to obtain the optimum value of α and β, different combinations of α and β are tested and the output performance is shown in the next section. Table 2 shows the different combinations of weight values used in this paper.

Table 2
Different combinations of weight values

Case \ Combinations	Weight Values α	β
1	0.1	0.9
2	0.2	0.8
3	0.3	0.7
4	0.4	0.6
5	0.5	0.5
6	0.6	0.4
7	0.7	0.3
8	0.8	0.2
9	0.9	0.1

Case 1 to case 4 shows that more weight on β, which means that more priority is put on overshoot. Case 5 shows equally weight factor for both α and β, and this means that mean error and overshoot are equally important and is taken into consideration equally during our simulation. Case 6 to case 9 show more weight on α, and this indicates that more priority is put on a mean error in our optimization throughout the whole simulation.

4. Implementation, Results and Discussion

All the simulations are conducted using Intel (R) Core (TM) i7-4790 Processor, 16.0 GB RAM, 3.60 GHz, Microsoft Windows 7 and MATLAB version 2016b. The EHA system model with nonlinear equations in Kalyoncu and Haydim [8] is designed via Simulink as shown in Figure 3.

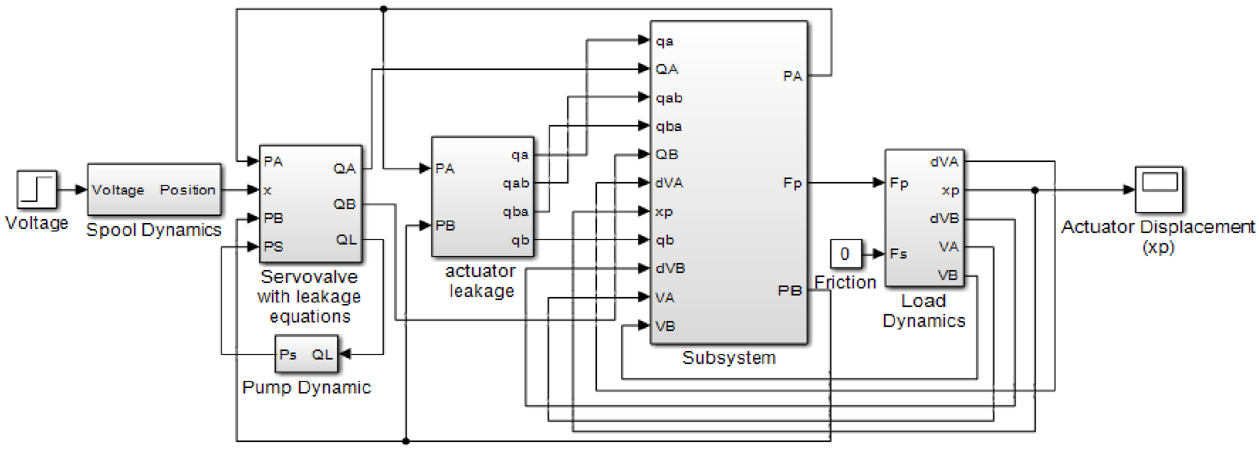

Fig. 2. The structure of the EHA system model

A complete control structure that includes the EHA system model and a PID controller is illustrated in Figure 4. An input voltage corresponding to position input (reference step input) is transmitted to the PID controller optimized using MOPSO technique. The input current is generated in proportion to the error between voltage output and the voltage input to fed into the EHA system. Time-domain specifications such as mean error, overshoot percentage, and steady-state error will be analyzed.

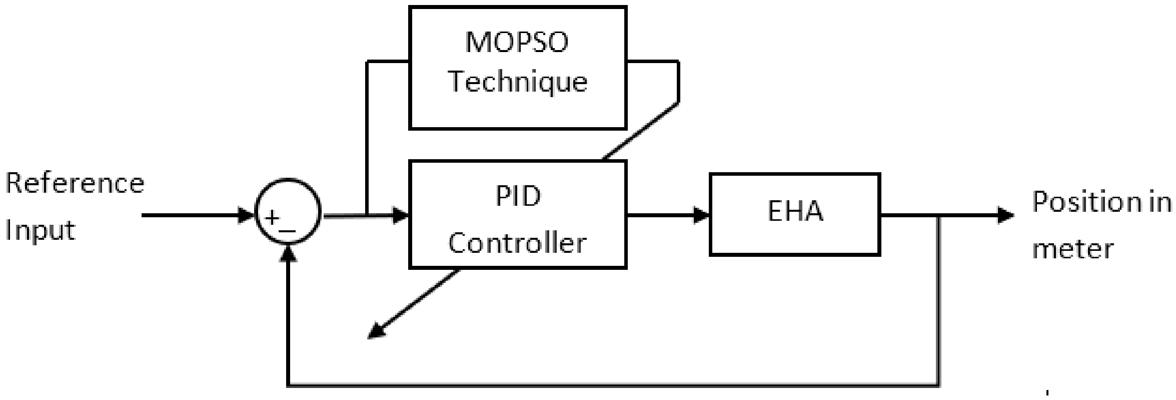

Fig. 4. The control structure of EHA system model and PID controller

The parameters setting of MOPSO is shown in Table 3. Each case in Table 2 runs for 5 times, and the average value is used for performance measurement.

The parameters of PID controller K_P, K_I, *and* K_D for each case is shown in Table 4. In each case, the parameters of the controller are the average values obtained from 5 runs.

After obtaining the controller parameters using the proposed MOSPO, the controller parameters recorded in Table 4 are then used in the PID controller and the EHA system (shown in Figure 5) is simulated again.

Table 3
Optimization parameters

Symbol	Description	Value
c_1	Cognitive component	2.0
c_2	Social component	2.0
N	Number of populations	30
dim	Dimension	3
$maxiter$	Number of iterations in each optimization	50
x_{min}	Minimum values in search space boundary	0
x_{max}	Maximum value in search space boundary	30
w_{max}	Initial weight value	0.9
w_{min}	Final weight value	0.4

Table 4
Controller parameters for each case

Case	Controller Parameters		
	K_P	K_I	K_D
1	29.1899	0.0383	0.0340
2	29.8985	0.0311	0.1789
3	29.7331	0.0250	0.4219
4	29.9736	0.8924	0.1623
5	29.9542	0.0091	0.2654
6	29.6628	0.0082	0.0090
7	29.6211	0.1035	0.0338
8	29.6781	0.0017	0.4333
9	29.8833	0.6325	0.4028

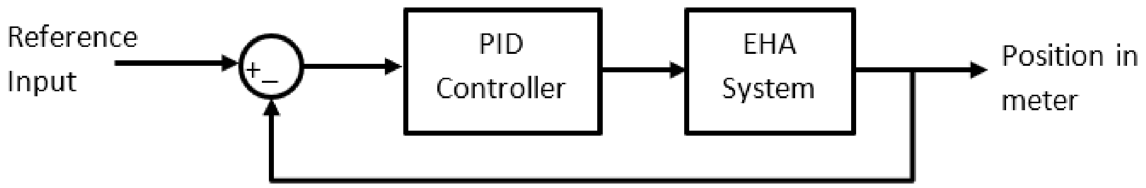

Fig. 5. The block diagram of the EHA system with a PID controller

The output performances of the EHA system are illustrated in Figure 6 and Figure 7. Figure 6 illustrates the steady state error while Figure 7 shows the overshoot of the EHA system. The simulation time is 10 seconds. A 0.03 m of displacement act as the step reference input signal is fed into the EHA system at step time equal to 3 seconds to evaluate the position tracking performance. The sampling time used in the simulation in this paper is 0.001 second.

The time-domain specifications such as mean error, overshoot percentage, and steady-state error are analyzed and recorded. Table 5 shows the output performance for each case of the combination of weight values using the PID controller parameters in Table 4.

From Table 5, mean errors for all the cases do not show much difference. The mean error for case 1 to case 9 are in between 0.635×10^{-3} m and 0.908×10^{-3} m, which are only below 1 millimeter. For the overshoot percentage, case 2 showed the highest overshoot percentage, which is 1.7057% while case 7 showed the lowest overshoot percentage, which is 0.0362%. Apart from that, case 7 showed a result of 1.081×10^{-5} m in steady-state error, which is the lowest among all the cases shown in Table 5.

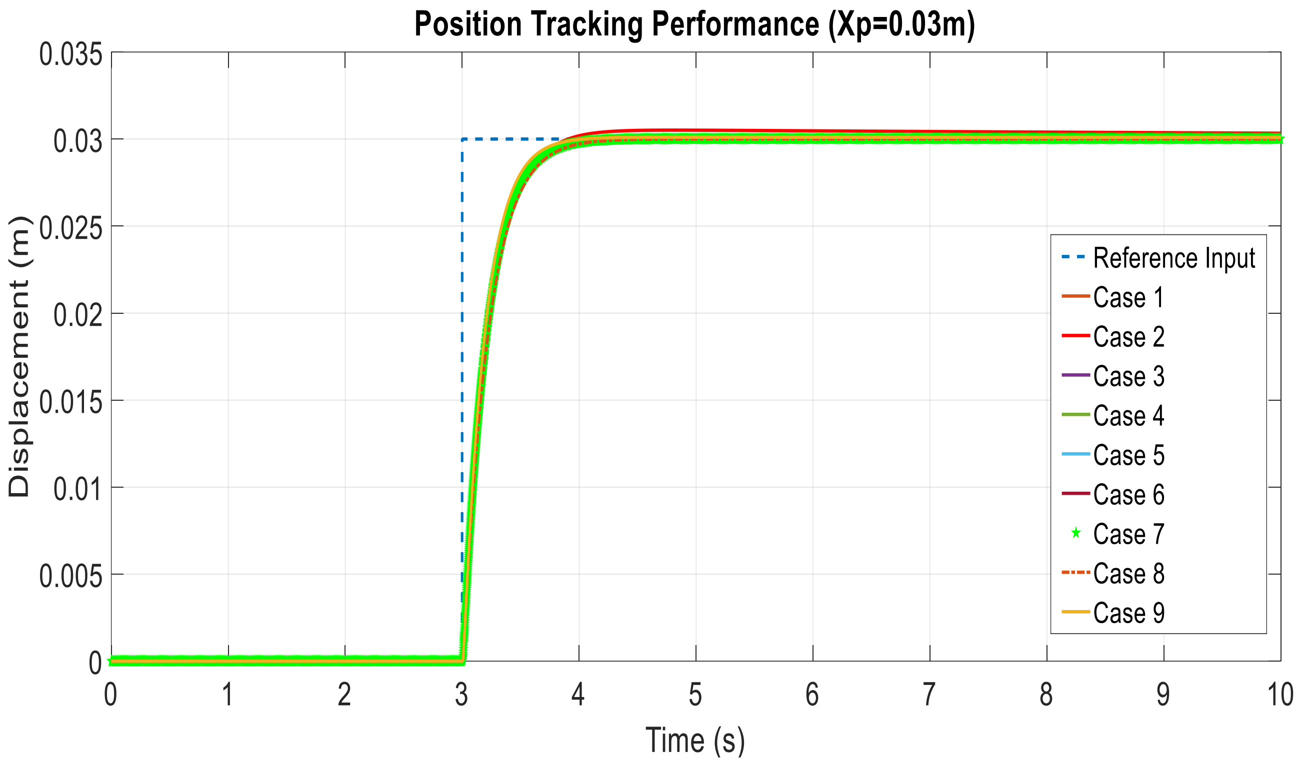

Fig. 6. The steady-state error of the EHA system

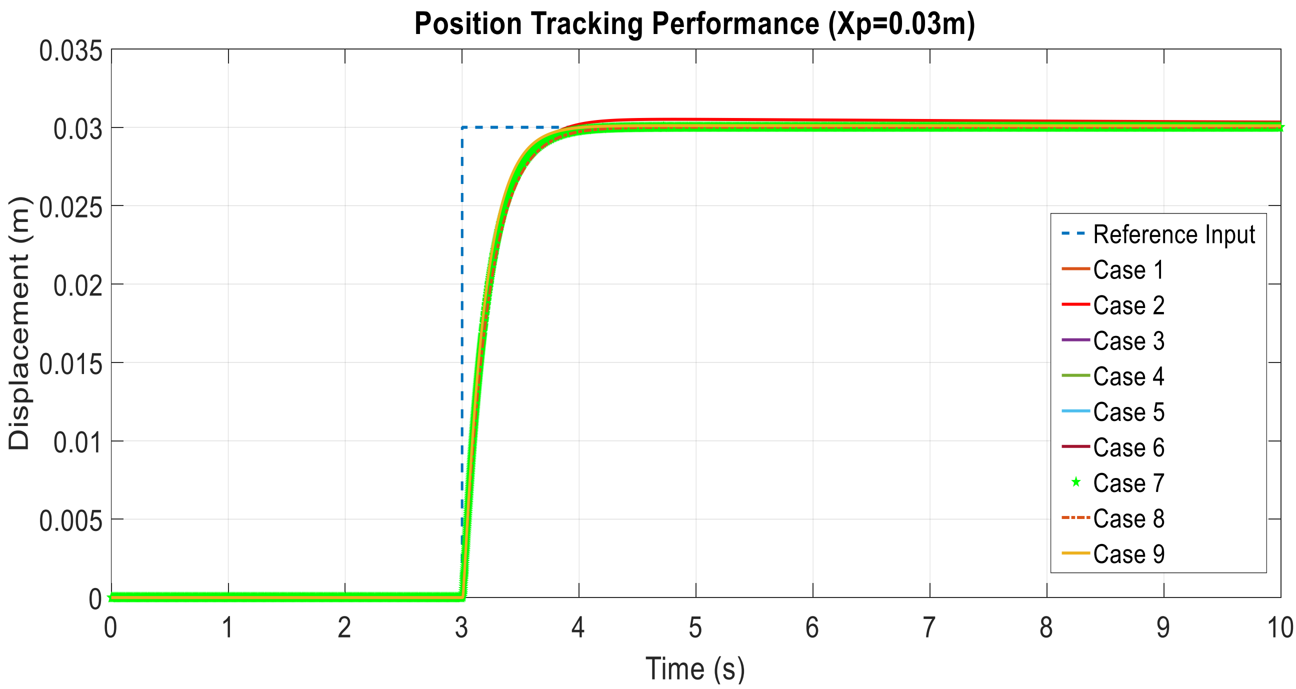

Fig. 7. The overshoot of the EHA system

Among all the case with different combinations of weight factors in MOPSO, case 7 with the weight factors of 0.7 on a mean error and 0.3 on overshoot is found to be the best combination. Simulation results showed that under this combination, the EHA system obtained the least overshoot percentage and steady-state error. Therefore, it can be concluded that the mean error is more important or having a higher priority in selecting the optimal PID controller parameters.

Table 5
The output performance of the EHA system

Case	Output Performance Mean Error (m)	Overshoot Percentage (%)	Steady-state Error (m)
1	0.645×10^{-3}	0.2360	6.712×10^{-5}
2	0.908×10^{-3}	1.7057	33.573×10^{-5}
3	0.659×10^{-3}	0.1837	5.307×10^{-5}
4	0.674×10^{-3}	0.2121	6.096×10^{-5}
5	0.666×10^{-3}	0.3017	8.460×10^{-5}
6	0.678×10^{-3}	0.5275	13.853×10^{-5}
7	0.639×10^{-3}	0.0362	1.081×10^{-5}
8	0.678×10^{-3}	0.0383	1.143×10^{-5}
9	0.635×10^{-3}	0.3540	9.709×10^{-5}

5. Conclusions

This paper presents the design of an optimal PID controller for positioning control in EHA system. In addition, the nonlinear dynamic equations of the EHA system has been derived and explained. In this paper, MOPSO based on linear weight summation has been used to find optimal PID controller gains. Time domain analysis has been examined. Simulation results have shown that the EHA system performed better by using the best combination of weight factors (mean error and overshoot is 0.7:0.3).

In the future, different types of controllers will be considered. More advanced optimization techniques such as cuckoo search, bat algorithm, firefly algorithm, and grey wolf optimizer will be used to optimize the controller parameters.

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