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Real-time performance enhancement of Electro Pneumatic System for position-tracking applications using Iterative Learning Controller

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Abstract: This study investigates the application of Iterative Learning Control (ILC) for the precise regulation of piston displacement in an electro-pneumatic system (EPS), a technology that has gained prominence in various industrial applications. EPS combines the advantages of electrical control and pneumatic power to offer versatile automation solutions, yet it is not without its limitations, such as nonlinearity, limited precision, energy consumption, noise, vibration, complex maintenance, and response time. Despite these drawbacks, electro-pneumatic systems remain valuable for numerous industrial applications, especially those that benefit from the simplicity, durability, and cost-effectiveness of pneumatic power. This research aims to leverage ILC to enhance control and mitigate some of these limitations, offering a more refined and efficient solution for electro-pneumatic cylinder control in practical industrial settings. Simulation and real-time experiments are carried out to test the performance of ILC. When comparing step input, sine wave, and sawtooth responses of ILC and a PID controller, it shows that ILC exhibits superior performance, particularly in crucial aspects such as minimal settling time, overshoot, and error indices as compared to the PID controller. However, the PID controller exhibits a better rise time, attributed to model uncertainties in the ILC design. These findings emphasize the effectiveness of ILC in managing unexpected nonlinearities within industrial pneumatic applications, offering an improved and more refined control solution for practical industrial settings.

Keywords: Iterative Learning Control; Electro-PneumaticSystem; PID controller; Performance Enhancement.

1. INTRODUCTION

Intelligent automation has become essential in a variety of industries in order to improve production as well as quality (Attaran, 2023). Robots and Mechatronics systems have mostly substituted humans in the execution of repetitive activities (Tortorici et al., 2023). The goal is to increase the efficacy of robot controllers. Robotic operations employ EPS, which is an integration of pneumatic and electrical technologies that use compressed air as a working medium (Zaeh et al., 2023). Most automation sectors rely on EPS due to their ease of installation, low maintenance and faster functioning. Because of their greater accuracy and precision, EPS are the most popular choice for position control systems (Mojallizadeh et al., 2023).

Tracking control has often been focused on for linear systems using feedback approaches such as Proportional-Integral-Derivative (PID) controllers. PID controllers have extensive application in a variety of industrial operations (Bai et al., 2023). But the use of PID controller makes finite-time tracking control difficult; across the complete working range, traditional controllers can no longer provide adequate and attainable control performance. An intelligent control technique that attempts to imitate essential elements of human cognition, such as learning, can solve this problem. This gave rise to the concept of ILC. The knowledge from the prior trial is used by the ILC to improve the control performance. Memory-based learning and the reset accomplish this (Ahn et al., 2007).

Robot manipulators, submersible robots, robots' path planning, cutting robots and gantry robots have all benefited from ILC (Shi et al., 2019; Bao et al., 2023; Yang et al., 2022). Rotary system control is an excellent contender for ILC applications. Switched reluctance motors, linear motors, induction motors, permanent-magnet synchronous motors, and servo actuators are examples of ILC applications in rotary systems (Fei et al., 2019; Hui et al., 2019; Cao et al., 2005; Schwarz et al., 2014). ILC is used in quality control in Agile batch production processes, Chemical reactors, Heating systems, Laser cutting, cyclic production process, Anaesthesia Process, Inverted pendulum and Injection molding to control repetitive activities in chemical processes (Lautenschlager et al., 2016; Sathiyavathi et al., 2013).ILC controls electro-mechanical valves, piezoelectric actuators, linear actuators and electro-hydraulic servo systems (Samadi et al., 2011; Jian et al., 2018; Naveen et al., 2023). ILC is also widely used in semiconductor manufacturing, Inverters, Hard disc drives, Magnetic bearings and Aerospace applications (Chen et al., 2006; Tang et al., 2019; Buelta et al., 2021).

There are significant advancements in ILC research. Attempts have been made to describe the idea behind an ILC(Moore et al., 2006) and how monotonic convergence on the ILC might be enhanced (Skach et al., 2016).

To show monotonic convergence, a number of mathematical theorems are applied, which is the convergence of monotonic sequences. ILC is used in conjunction with a proportional controller. In order to control a pneumatically operated X-Y table that responds non-linearly to changes in input. Lack of the integral and derivative methods results in a steady-state error and an inability to react quickly to sudden changes. An ILC can be connected for forward control or feedback (Chen et al., 2004). ILC compares the error and the disturbance and uses them to decrease the consequences of the disturbance (Yu et al., 2008).

ILC is used to improve the tracking performance of the system (Bristow et al., 2006). ILC has been classified as model-based and model-free design. In model-based design of ILC, learning control is designed based on previous input and error. The example for model-based design is PID-based ILC, ILC with adaptive control and data-driven type ILC (Poomani et al., 2023; Bolder et al., 2018). In the model-based design of ILC, some of the informationis explicitly used from the system. The examples for this type are inverse ILC, gradient ILC and ILC with optimization (Owens et al., 2009; Barton et al., 2011). ILC is used for repetitive operations. In ILC, input from previous the iteration is compared with the current output to generate a control signal. The process is continued until the error reaches zero. ILC simply alters the control signal in accordance with a predetermined control law, in contrast to other learning-type control techniques like the neural network and adaptive control. Other learning-type controllers look on the system's performance and adjust their control rule as necessary (Moore, 2012). ILC just relies on the past input and output and does not require any knowledge of the system's model.

Additionally, unlike other intelligent controllers, the ILC approach should be able to converge to the desired state in a few numbers of repetitions without the need for training (Hunt et al., 1992). The ILC is combined with PID to control a simplified model of a pneumatic servo system. Without reconfiguring the existing PID controller model, ILC controller is implemented. Recently, the ILC method is proposed for accurate tracking of pneumatic muscle Actuators (Qian et al., 2021; Ai et al., 2019) and controlling pneumatic valves (Rwafa et al., 2019). The model-free ILC for a pneumatic system is suggested to overcome the non-linearities from air characteristics, pressure loss, and leakage and load variations in a pneumatic system (Rwafa et al., 2022).

Following is the arrangement of the remaining portion of the paper: Section II presented the flow diagram, photography and structural outline of EPPCS. Section III presented the PID controller design and ILC controller design strategy. Section IV illustrates that tabulated and discussed the results of simulation and experiment.

2. FLOW DIAGRAM OF EPPCS

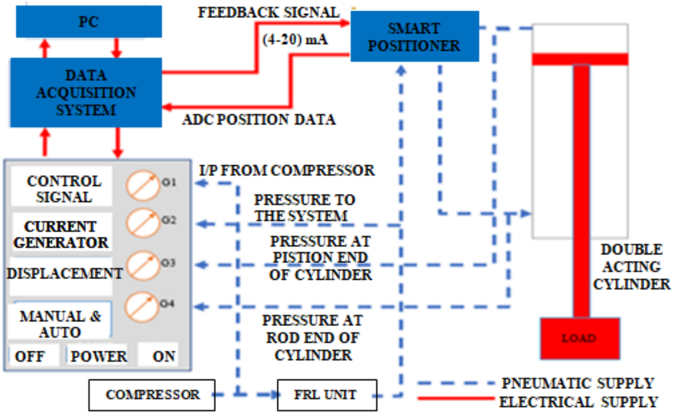

Fig.1. Flow diagram of EPPCS.

A Flow diagram of the EPPCS is shown in Fig. 1. The compressor converts electric power into pressurized air. The compressed air is passed through a filter, regulator and lubricator (FRL) unit, which ensures clean air to the system. It is fixed to regulate the pressure and sends the lubricated pressurized air to the system. Compressed air output of FRL actuates the double-acting cylinder through a smart positioner. The positioner end of cylinder is internally connected with a potentiometer which acts as a feedback element. DAQ provides serial communication between the smart positioner and personal computer (PC).

A Graphical user interface (GUI) is developed in MATLAB Simulink for real-time closed-loop position control of double-acting cylinder. The control panel consists of pressure gauges, a control signal display (4-20mA), a current generator display, the position of cylinder (mm) and switches (ON/OFF control). Pressure gauges G1, G2, G3 and G4 display the pressure from the compressor, the pressure sent to the system, the pressure at the piston end and rod end of the cylinder, respectively. The current generator displays the operating rating between (4 – 20mA). Switches are used to change the mode between manual and automatic.

2.1 Photography of EPPCS

Photography of the EPPCS is shown in Fig. 2. The MATLAB Simulink model developed in the PC (1) controls the EPPCS. Serial communication between the PC and double-acting cylinder is done through DAQ (2). It consists of an ADC converter and a DAC converter. The operating range of double-acting cylinder (5) is 0-300mm. the displacement of the cylinder sensed by the potentiometer is an analog signal. It is converted into a digital signal by the ADC. Digital signals are sent to the PC through the smart positioner (4). The digital control signal generated by closed loop control system GUI in MATLAB Simulink is converted into analog signal by the DAC and sent to the double-acting cylinder through the smart transmitter. The control Panel (3) displays signals like control signal, current, displacement and pressure at various positions. The FRL unit (6) attached to the side of control panel regulates pressure and provides clean lubricated air. Specifications of the Smart Positioner are given in Table 1.

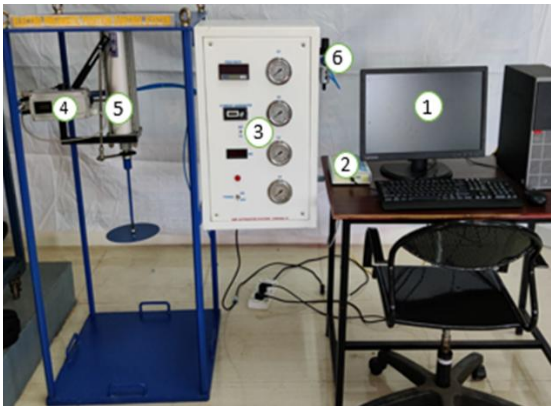

Fig. 2. Photography of EPPCS.

Table 1. Specifications of Smart Positioner.

Model	YT-3300
Input signal	4~20mA DC
Min. Current Signal	3.2mA (Standard), 3.8mA (Hart included)
SupplyPressure	0.14~0.7 MPa (1.4~7 bar)
Impedance	Max.450 @ 20mA
Stroke	0~90°
Linearity	0.5% F.S. (cable length: 5m)
Hysteresis	0.5% F.S. (cable length: 5m)
Sensitivity	0.2% F.S (cable length: 5m)
Repeatability	
Flow Capacity	70 LPM (Sup = 0.14 MPa)
Air consumption	Below 2 LPM (sup = 0.14 MPa), Below 3 LPM (sup = 0.7 MPa)
Output characteristics	Linear, Quick-Open, EQ%, User Set (16 points)
Vibration	No resonance up to 100 Hz @ 6G
Humidity	5-95% RH @ 40°C
Communication	HART Communication
Feedback Signal	4~20 mA (DC 10-30V)
Material	Aluminium Diecasting
Weight	2.0 kg

2.2 Structural Outline of EPPCS

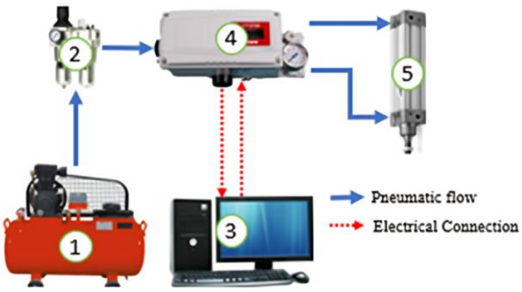

Fig. 3.StructuralOutlineof EPPCS.

The structural outline of EPPCS is shown in Fig. 3. Compressor (1) develops the pressurized air. The FRL unit (2) regulates the necessary pressure to operate the EPPCS. A personal computer (3) sends and receives the required signals between the smart positioner and the computer. Double-acting Extension and retraction of the cylinder (5) happens for a stroke length of 0 – 300mm. The connection between the cylinder and the smart transmitter is provided through a mechanical linkage. The link acts as a feedback element to achieve the required position.

3. CONTROLLER DESIGN

3.1 PID Controller

A PID controller is a three-mode controller. It is a control loop based on feedback from output, frequently utilized in industrial control systems and various applications that require continuous modulation. To find the transfer function (TF) of the EPPCS,referto "(1),"

$$\frac{X(s)}{V(s)} = \frac{K_m e^{-st_m}}{1+s\tau} = \frac{13.27}{1+8.24s} \tag{1}$$

The term X denotes output displacement of the cylinder, V denotes input voltage, Km (equal to 13.27) denotes gain of the system, t_m (assumed to be 0.824) denotes delay time of the system and τ (equal to 8.24) represents time constant of the system. The parameters of the PID controller such as Kp, T_i and T_d are calculated using the three constraints method (Murrill et al., 1967).For relation,referto "(2)," "(3)," "(4)," and the values are recorded in Table 2.

$$K_p = \frac{1.370}{K_m} \cdot \left(\frac{\tau}{T_d}\right)^{0.950} \tag{2}$$

$$T_i = \frac{\tau}{1.351} \cdot \left(\frac{t_d}{\tau}\right)^{0.738} \tag{3}$$

$$T_d = 0.365\,\tau \cdot \left(\frac{t_d}{\tau}\right)^{0.950} \tag{4}$$

Table 2. PID parameters by three constraints method.

Parameters	K_p	T_i	T_d
Values	0.92013	1.11499	0.337458

3.2 Iterative Learning Control (ILC)

ILC is a control mechanism for systems that perform repetitive tasks. Robot arm manipulators (Ai et al., 2019), chemical batch operations (Rwafa et al., 2019) and reliability testing rigs (Rwafa et al., 2022) are examples of systems that work in a repeated manner. For the system to do any of these tasks, it must repeatedly execute the same action with extreme precision. Exact tracking of a selected reference signal r(t) across a finite time span is the aim of this work. The system is able to learn from the necessary information to precisely track the reference, which increases tracking accuracy with each cycle. Repetitive finding of the proper control action, the learning process enables the repetitive identification of the appropriate control action by utilizing knowledge from previous iterations to enhance the control signal. While requirements for perfect tracking are yielded by the internal model concept, the architecture of the control algorithm still requires making many decisions to suit the desired outcome. For a simple control law,refer to (5),

$$U_{k+1} = U_k + K * e_k \tag{5}$$

where Uk represents the system's input during the kth iteration, ek denotes tracking error at the kth repetition and gain is represented as K. When the details of process dynamics are unknown, a good control algorithm is vital to ensure the closed-loop performance. K is essential for accomplishing design goals and embraces simple scalar gains to complex optimization algorithms.

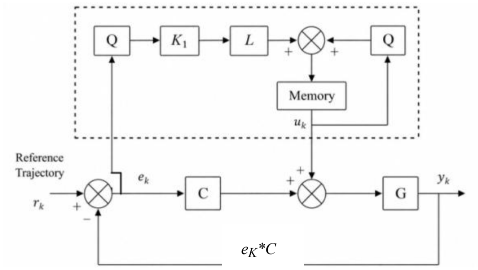

Fig. 4. Block diagram of ILC.

Fig. 4 shows the block diagram of the ILC where r denotes the reference input of the system, G is the transfer function of the system, C is the PID controller, Q is the quality filter, K_1denotes the gain of the system, L is a learning filter and Memory element is used to store the previous function control signal to improve the accuracy of the system.

$$e_{k+1} = \left[\frac{-G}{1+GC}\right] u_{k+1} \quad (6)$$

$$u_{k+1} = Q.\, u_k + QK_1.L.e_k \quad (7)$$

For error signal at the next run,refer to “(6),” “(7),”

Substituting “(7)” in equation “(6),”

$$e_{k+1} = -\frac{G}{1+GC}\,.[Q.U_k + Q.K_1.L.e_k]$$

$$= \frac{-G}{1+GC}\,.Q.U_k + Q.K_1.L * \frac{-G}{1+GC}.e_k \quad (8)$$

Substitute“(6)”in “(8),” and it becomes

$$e_{k+1} = \left[Q + \frac{-G}{1+GC} * Q.K_1.L\right] e_k \quad (9)$$

$$e_{k+1} = Q\left[1 - \frac{G}{1+GC} * K_1.L\right] e_k \quad (10)$$

$$e_{k+1} = Q[1 - K_1.L * P_s]e_k \quad (11)$$

Where process complimentary sensitivity, Ps, is given by Refer “(12),”

$$P_s = \left[\frac{G}{1+GC}\right] \quad (12)$$

Refer“(9),” “(10),” and “(11),”whichshow the error signal propagation that takes place from iteration to iteration and convergence occurs if |Q (1- K_1 L* Ps)|<1

Apparently, an appropriate option for a learning filter L is $(Ps)^{-1}$. i.e., the inverse of the complementary process sensitivity, Ps= G/(1+GC).

Interrelated responsiveness in reverse Ps^{-1} is unsteady and not appropriate for use as a filter. The zero phase error tracking controller method yields an unchanged stable discrete inverse complementary sensitivity when a discrete complementary sensitivity is introduced into it (Wang et al., 2012).

If K_l=1 and L = Ps^{-1}, e_{k+1}equals zero. There is no flexibility against model defects. The pace of convergence is decreased if 0 <K_l< 1. In this study, the learning gain with the least tracking error as the objective function is computed using an optimization method.

4. RESULTS AND DISCUSSION

Simulation and experimentation are carried out with the developed model to determine the best suitable controller for the EPPCS. Comparisons are made between PID and Iterative Learning Controllers and the results are plotted. Overshoot, settling time and rise time of the cylinder are recorded to monitor the accuracy of the controllers.

4.1 Setup Input Response

The piston has a total stroke length of 0–300 mm. Simulation and real-time step input response of the system are tested at the displacements of 25% (75 mm), 50% (150 mm) and 75% (255 mm) respectively.

The simulation and real-time responses of step input at 75mm, 150mm and 225mm are illustrated in the Figs. 5-10. Additionally, Table 3 provides a detailed summary of their performance metrics, including overshoot, rise time, and settling time.

During simulation, in the case of step input tracking, the PID controller exhibits an overshoot ranging around 15% during simulation. However, in real-time scenarios, the percentage of overshoot decreases from 136% to 13.5% as the set point increases from 75mm to 225mm. ILC exhibits 0% overshoot throughout the entire operating range in both simulation and real-time scenarios.

In the case of rise time, PID anincrease in rise time from 1.2 sec to 2.5 sec during simulation and an average of 4.5 sec rise time during real time. Meanwhile, ILC has an average rise time of 4.2 sec during simulation and 5.3 sec during the real-time observation.

PID controller has a slightly better rise time than the ILC which is the cause of model uncertainty during the system modeling. ILC settles quicker than PID in both the simulation and real time conditions. The average settling time is 4 Sec during simulation and 5.3 sec at real time irrespective tothe set point. PID settles 2-5 sec slower than the ILC at simulation and has a higher settling time in the range of 9.5 sec – 23 sec. This observation clearly highlights the remarkable ability of the ILC to effectively suppress overshoot and faster settling time during simulation and real-time scenarios.

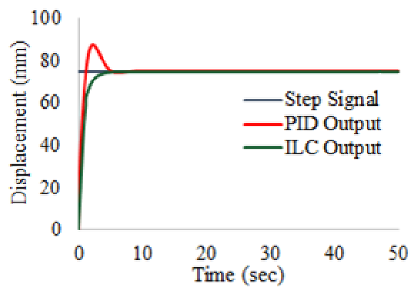

Fig. 5.Simulation response of step input at 75mm.

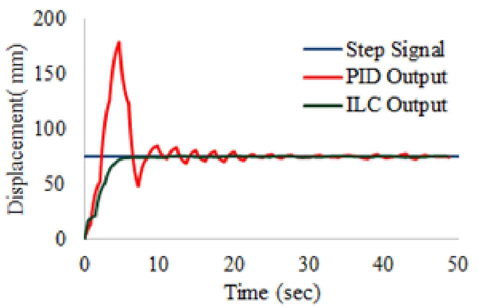

Fig. 6. Real-time response of step input at 75mm.

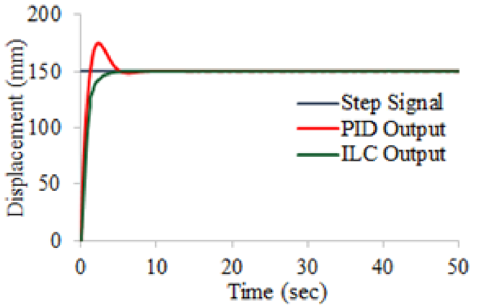

Fig. 7. Simulation response of step input at 150mm.

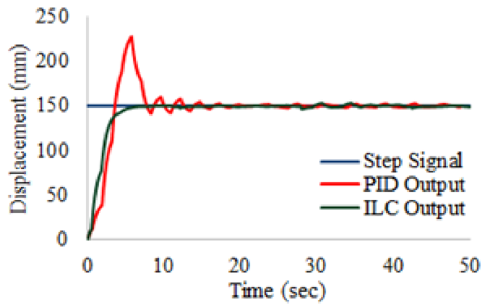

Fig. 8. Real-time response of step input at 150mm.

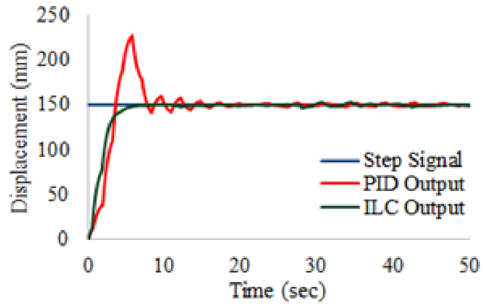

Fig. 9.Simulation response of step input at 225mm.

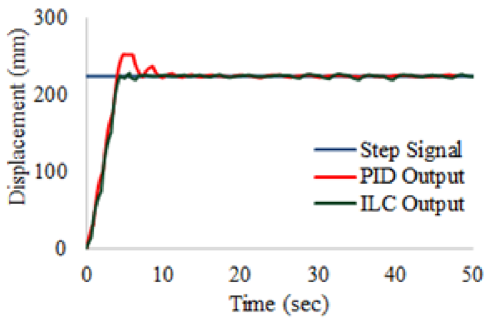

Fig. 10. Real-time response of step input at 225mm.

Table 3. Performance measures of Simulation and real time Step input response.

Set point	**Controllers**	**PID Output**		**ILC Output**	
		Simulation	**Real-time**	**Simulation**	**Real-time**
75mm	Overshoot %	14.6 %	136 %	**0%**	**0%**
	Rise time (sec)	**1.2**	**4.6**	4.2	5.5
	Setting time (sec)	9	23	**4.2**	**5.5**
150mm	Overshoot %	15.3 %	58.4%	**0%**	**0%**
	Rise time (sec)	**1.5**	**4.2**	3.5	6
	Setting time (sec)	6	18	**3.5**	**6**
225mm	Overshoot %	16 %	13.5%	**0%**	**0%**
	Rise time (sec)	**2.5**	4.5	4.5	4.5
	Setting time (sec)	6	9.5	**4.5**	**4.5**

4.2 Sine Wave Response

Following the step signal, the sine wave is simulated and recorded. First, simulation model for PID and ILC was created in MATLAB using Simulink. Various input test frequencies like 0.075 Hz, 0.02 Hz and 1 Hz with a fixed bias value of 50 and amplitude of 25 were tested for both PID and ILC models and a graph is plotted against displacement (mm) and time (sec).

The sine wave tracking simulation results are shown in Figs. 11, 13 and 15. Performance measures are tabulated in Table 4. When monitoring the sine wave response, the ILC exhibits very little overshoot; in contrast, the PID controller exhibits significant overrun during the first waveform tracking cycle. Experimental results of sine wave tracking are shown in Figs. 12, 14 and 16.

The PID controller permits the piston to reach its maximum position of 255 mm and remains there for a short while before tracking the input waveform since it is unable to regulate the overshoot as frequency increases. Even when the frequency rises, the ILC is still able to regulate the piston displacement with very little overshoot. ILC has fewer error indices, such as integral square error (ISE) and integral absolute error (IAE) than the PID controller.

At simulation, the ILC has relatively less ISE than the PID controller by 2.7%-10.7% and less IAE of 0.9-9.8% at 0.075, 0.2, and 1 Hz than the PID controller. During real-time experimentation, ILC shows a relatively lower ISE of 6.5%-14.9% and IAE of 0.6%-31% lower than the PID controller. From the results, it shows that ILC tends to perform better compared to PID's output.

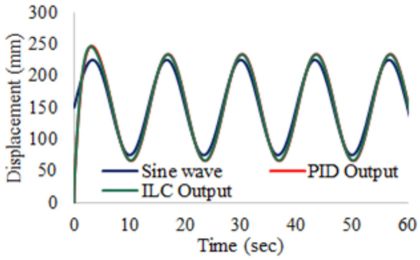

Fig. 11. Simulation response of a sine wave at 0.075 Hz.

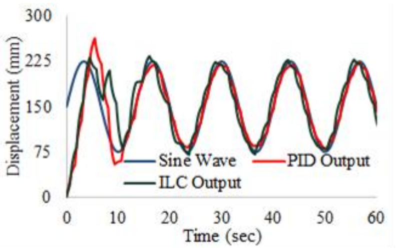

Fig. 12. Real-time response of a sine wave at 0.075 Hz.

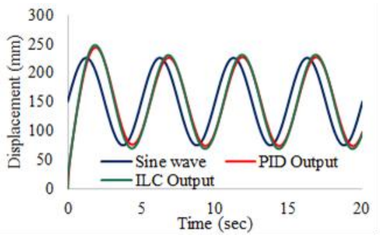

Fig. 13. Simulation response of a sine wave at 0.2 Hz.

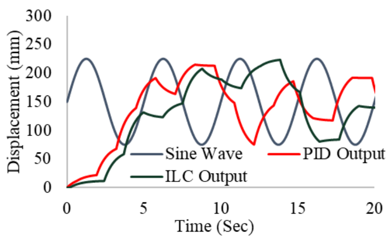

Fig. 14. Real-time response of a sine wave at 0.2 Hz.

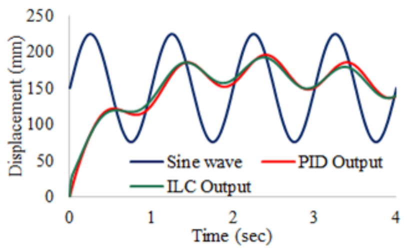

Fig. 15. Simulation response of a sine wave at 1 Hz.

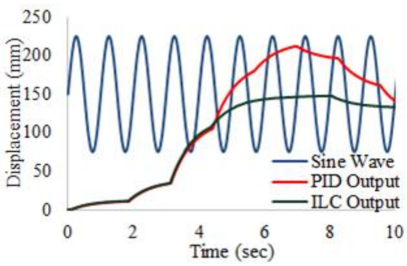

Fig. 16. Real-time response of a sine wave at 1 Hz.

Table 4. Performance measures of simulation and real-time a sine wave response.

Input frequency	Controllers	PID Output		ILC Output	
		Simulation	Real-time	Simulation	Real-time
0.075 Hz	ISE	**699740**	8349222	**624846**	7098645
	IAE	**23409**	136656	**21097**	94186
0.2 Hz	ISE	**1672521**	19919676	**1626430**	18477478
	IAE	**29526**	162589	**29236**	161491
1 Hz	ISE	**972331**	10684038	**927387**	9980981
	IAE	**10871**	85204	**10652**	82864

4.3 Sawtooth Responses

Following the sine wave response, the sawtooth response is simulated and experimented with various input test frequencies like 0.02 Hz, 0.05 Hz and 0.1 Hz was tested with both the controller and graphs are plotted against displacement (mm) and time (sec).

Figs. 17, 19, and 21 display the simulation outcomes for sawtooth responses, while Table 5 provides performance metrics. ILC exhibits more precise tracking of the sawtooth waveform than the PID controller; for the initial cycle both the controller has an overshoot, but later they tracks the waveform. Real-time results are shown in Figs. 18, 20 and 22.

As the frequency increases, the PID controller struggles to manage overshoot, leading to the piston reaching its maximum position of 255mm and remaining there for a brief period before eventually tracking the input waveform. In contrast, the ILC effectively regulates piston displacement with slight overshoot, even as the frequency increases. ILC exhibits a lower ISE and IAE compared to the PID controller.

In simulations, the ILC demonstrates a notably lower ISE, around 5.8%-6.1% less than that of the PID controller, and also achieves a reduced IAE of 0.6-4.1% at frequencies of 0.02, 0.05, and 0.1 Hz when compared to the PID controller.

Moreover, in experimental trials, the ILC consistently exhibits a lower ISE, ranging from 0.5% to 29% less, and a reduced IAE ranging from 1% to 37% less than that of the PID controller. These results underscore the superior performance of the ILC in comparison to the PID controller's output while tracking the sawtooth response.

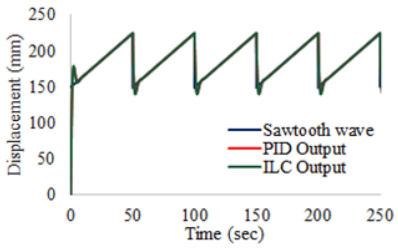

Fig. 17. Simulation response of a sawtooth wave at 0.02 Hz.

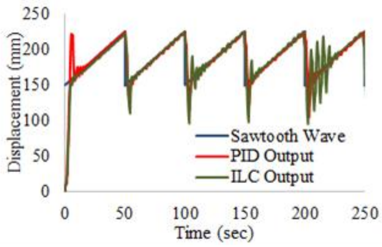

Fig. 18. Real-time response of asawtooth wave at 0.02 Hz.

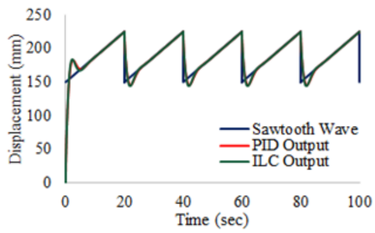

Fig. 19. Simulation response of a sawtooth wave at 0.05 Hz.

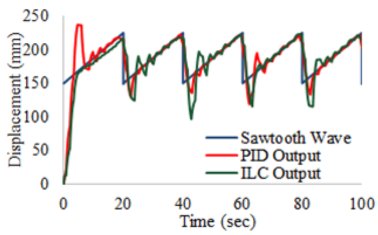

Fig. 20. Real-time response of a sawtooth wave at 0.05 Hz.

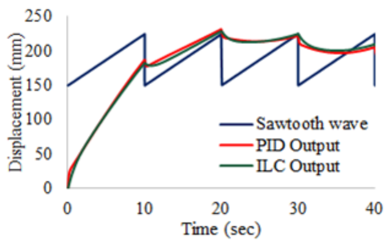

Fig. 21. Simulation response of a sawtooth wave at 0.1 Hz.

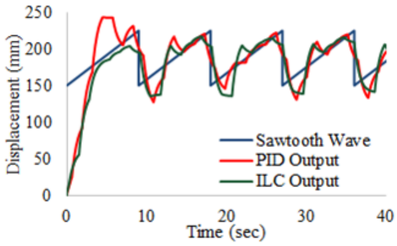

Fig. 22. Real-time response of a sawtooth wave at 0.1 Hz.

Table 5. Performance measures of simulation and real-time sawtooth response

Input frequency	Controllers	PID Output		ILC Output	
		Simulation	Real-time	Simulation	Real-time
0.02 Hz	ISE	**877413**	11674564	**824343**	8219825
	IAE	**18109**	233428	**17366**	145611
0.05 Hz	ISE	**847406**	7317509	**795376**	5237645
	IAE	**17400**	136333	**16718**	97704
0.1 Hz	ISE	**682464**	4180094	**642303**	4159399
	IAE	**8125**	79381	**8069**	78480

4.4 Nyquist Stability

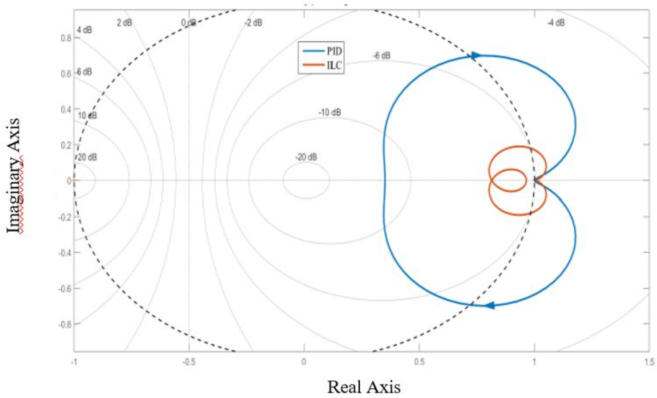

Fig. 23. Nyquist Plot.

The Nyquist stability analysis of the PID and Iterative Learning Control (ILC)-based system is illustrated in Fig. 23. The stability assessment is performed with respect to the critical point (−1+j0). From the obtained characteristics, both controllers exhibit stable behavior since their Nyquist loci do not encircle the critical point, thereby satisfying the Nyquist stability criterion. However, the PID controller shows a comparatively larger loop trajectory and operates closer to the unit circle boundary, indicating relatively lower robustness and higher sensitivity to disturbances and parameter variations. In contrast, the proposed ILC-based controller exhibits a compact and well-confined Nyquist locus near the positive real axis, demonstrating improved robustness, enhanced damping characteristics and good stability margins. The reduced loop spread of the ILC response confirms improved convergence and stable repetitive learning behavior, which contributes to better tracking accuracy and minimized steady-state error. Therefore, the Nyquist analysis validates that the proposed ILC-assisted control strategy provides enhanced closed-loop stability and robustness compared with the PID controller.

5. CONCLUSIONS

In this study, an ILC is designed and implemented to control the piston displacement of EPS. Both the simulation and experimental results of the ILC and PID controllers are compared. ILC controllers outperform PID controllers in critical areas such as settling time, overshoot and minimal error indices. This demonstrates the ILC's durability and demonstrates how the ILC technology handles nonlinear and uncertain industrial pneumatic applications. Meanwhile, PID has a better rise time which is primarily due to model uncertainties in ILC design. In the future, the proposed controller is applied in real-time industrial hydraulic applications to prove its practicality.

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