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EVALUATING A DDPG REINFORCEMENT LEARNING AGENT ON A BALL-AND-PLATE SYSTEM: A COMPARATIVE STUDY OF INTELLIGENT CONTROL APPROACHES

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Abstract
This research investigates the performance of a novel deep reinforcement learning (DRL) agent in comparison with traditional intelligent control approaches for manipulating the tilt angles of ball-and-plate system. This study highlights the strengths and weaknesses of each technique through extensive experimentation and analysis of step response and trajectory tracking metrics while trailing a circular path. While the DRL agent demonstrates rapid responsiveness, it exhibits inferior trajectory tracking accuracy compared to the other methods, namely, Proportional-Integral-Derivative (PID), Model Predictive Control (MPC), Sliding Mode Control (SMC), and Linear Quadratic Regulator (LQR). These findings emphasize the importance of balancing speed and precision in control system design. Traditional methods like PID, MPC, and SMC showcase robust performance in achieving precise trajectory tracking with minimal error and overshoot, underscoring their suitability for practical applications. This comparative analysis contributes valuable insights for researchers and practitioners in control engineering, guiding the development of suitable control strategies for dynamic systems. Future research can consider hybrid control strategies that combine the strengths of traditional methods with reinforcement learning to achieve optimal tuning of the reinforcement learning agent for superior performance.

1.0 INTRODUCTION
The Ball-and-Plate system is a benchmark control system in the field of control engineering, offering a dynamic and challenging environment for testing and developing control algorithms [1], [2]. Characterized by its simplicity yet rich dynamics, this system has been extensively studied over the years, serving as a playground for exploring various control methodologies [3]. This system, consisting of a tiltable plate upon which a ball can move freely, presents inherent nonlinearities, coupled dynamics, and uncertainties making it an ideal testbed for evaluating the efficacy of intelligent control methodologies [4].

Over the years, researchers have explored myriad intelligent control approaches to tackle this problem, aiming to achieve robust and efficient performance. Early studies primarily focused on conventional control techniques such as Proportional-Integral-Derivative control [5], [6], [7], [8]. These methods laid the foundation for further research by demonstrating basic control principles and establishing performance benchmarks against which more advanced techniques could be compared.

With the advent of intelligent control paradigms, the focus shifted towards incorporating machine learning and artificial intelligence (AI) algorithms for addressing the ball and plate problem [9], [10]. One prominent approach involved the utilization of neural networks for describing the system dynamics while designing adaptive control schemes [11]. These studies showcased the potential of neural network-based controllers in achieving superior tracking accuracy as well as disturbance rejection compared to traditional methods. However, challenges related to network training, generalization, and computational complexity remained significant hurdles in practical implementations.

Presently, the field of intelligent control for the ball and plate problem continues to evolve rapidly, fueled by advancements in computational techniques, machine learning, and optimization algorithms. Future research directions may include the exploration of reinforcement learning-based approaches [12], [13], decentralized control strategies and real-time implementation considerations[14] . By building upon the rich legacy of previous studies and leveraging the latest developments in control theory and AI, researchers aim to develop robust, efficient, and scalable solutions for addressing the challenges posed by the ball and plate system in various practical applications.

Looking ahead, recent advancements in the field have seen a shift towards hybrid intelligent control approaches that combine multiple techniques to leverage their respective strengths. Hybrid control schemes, integrating elements of fuzzy logic, neural networks, and evolutionary algorithms, have demonstrated remarkable performance improvements in terms of stability, tracking accuracy, and disturbance rejection. By synergistically combining different intelligent control paradigms, researchers aim to further enhance the suitability of this system for application in areas such as robotics, automation, and motion control.

This paper evaluates PID, MPC, SMC, LQR controllers along with a DRL agent applied to the ball-and-plate problem. By examining and evaluating the effectiveness of these techniques, this study aims to provide insights into the strengths, weaknesses, and applicability of each approach in tackling the challenges posed by the ball-and-plate system.

Through rigorous experimentation and performance evaluation, this research endeavors to shed light on the relative merits of different intelligent control strategies, offering valuable guidance for researchers and practitioners in selecting the most suit able approach for their specific application requirements. Ultimately, the findings of this study contribute to advancing the state-of-the-art in intelligent control methodologies for complex dynamic systems, paving the way for improved performance and reliability in various real-world applications.

The contribution of the paper lies in its comprehensive comparative analysis of various intelligent control approaches for the ball and plate problem. By systematically evaluating and contrasting different methodologies, including classical control techniques, neural network-based control, and hybrid intelligent control schemes, the paper provides valuable insights into the strengths and limitations of each approach. This comparative study facilitates a deeper understanding of the underlying principles and mechanisms governing the control of the ball and plate system, thereby guiding researchers and practitioners in selecting the most suitable control strategy for specific application requirements.

The rest of this paper is structured as follows: In section 2, the mathematical model of the Ball-and-Plate system is given. Section 3 gives the design and integration of the various controllers while section 4 presents a comparison on the results obtained. Finally, in section 5, a conclusion and recommendation for future works is given.

2.0 MATHEMATICAL MODELLING

The mathematical description of the Ball-and-Plate system can be obtained by decomposing the system along the x and y axis into two sub-components according to [15]. This decomposition is illustrated in Figure 1.

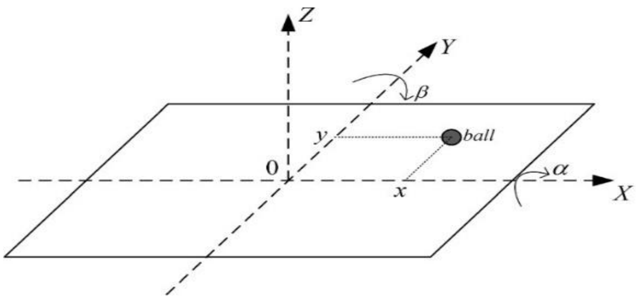

Figure 1: A pictorial illustration of a Ball-and-Plate system

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The mathematical equation representing the system's dynamics can be formulated using the Euler-Lagrange equation given in equation (1).

$$Q_i = \frac{d}{dt}\left[\frac{\partial E}{\partial \dot{q}_i}\right] - \frac{\partial E}{\partial q_i} + \frac{\partial P}{\partial q_i} \quad (1)$$

This equation describes the dynamics of a system by relating the system's energy E, to its generalized coordinates q_i their rates of change $\dot{q}_i$ and the generalized forces Q_i acting on the system. Accordingly, [16] derived the nonlinear dynamic equations governing the ball positioning along the x and y axis as follows:

$$x; \left(m_b + \frac{I_b}{r_b^2}\right)\ddot{x_b} - m_b(x_b\dot{\alpha}^2 + y_b\dot{\alpha}\dot{\beta}) + m_b g sin\alpha = 0 \quad (2)$$

$$y; \left(m_b + \frac{I_b}{r_b^2}\right)\ddot{y_b} - m_b(y_b\dot{\beta}^2 + y_b\dot{\alpha}\dot{\beta}) + m_b g sin\beta = 0 \quad (3)$$

These equations can be linearized around an operating point by making assumptions about the operation of the system according to [16].

For this study, equation (3) is neglected due to the symmetrical nature of the system and the following linear differential equation can be obtained according to [21].

$$\frac{7}{5}\ddot{x_b} + g \times \alpha = 0 \quad (4)$$

A transfer function representing the plate's inclination angle to the ball position can now be obtained by taking a Laplace transformation of equation (4). This results in the classical system representation given in equation (5).

$$\frac{x_b(s)}{\alpha(s)} = \frac{y_b(s)}{\beta(s)} = -\frac{5g}{7s^2} \quad (5)$$

The following first-order transfer function given in equation (6) can be used a reliable and approximate representation of the workings of a servo motor [16].

$$G_m(s) = \frac{k_m}{T_m(s)+1} \quad (6)$$

When Km = −0.6864 and Tm = 0.187, the resulting plant system model according to [13], [16]can be represented as shown in equation (7).

$$G_p(s) = -\frac{0.6854}{0.187s+1} \times -\frac{5g}{7s^2} = \frac{4.803}{0.187s^3+s^2} \quad (7)$$

Consequently, the state space model of the system can be derived from this transfer function as denoted in equations (8) and (9):

$$\dot{x} = Ax + Bu \quad (8)$$

$$y = Cx + Du \quad (9)$$

The A, B, C and D matrices are obtained as shown in equation (10), (11), (12) and (13).

$$A = \begin{pmatrix} -5.3476 & 0 & 0 \\ 1.0000 & 0 & 0 \\ 0 & 1.0000 & 0 \end{pmatrix} \quad (10)$$

$$B = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad (11)$$

$$C = (0 \quad 0 \quad 25.6845) \quad (12)$$

$$D = 0 \quad (13)$$

3.0 CONTROLLER DESIGN

In this section a Deep Deterministic Policy Gradient (DDPG) agent for controlling the ball positioning on the plate is proposed. This novel method is compared with four traditional control methods based on the transient and steady state responses of the overall system when excited by a step input signal. Additionally, the trajectory tracking performance of the various controllers will be analyzed based mean absolute errors when trailing a circular path.

The simulations and analysis were conducted in MATLAB on a Dell Laptop with RAM size of 16 GB. The agent was trained for 1666 episodes and the training time was 5997 seconds.

3.1 Deep Reinforcement Learning

Reinforcement learning (RL) provides a robust framework for training agents to make decisions in dynamic environments through iterative interaction. When applied to control systems such as the ball and plate system, RL enables agents to learn optimal actions by maximizing cumulative rewards [17] Deep Deterministic Policy Gradient (DDPG), an off-policy actor-critic algorithm, is particularly adept at handling continuous action spaces. In the context of the ball and plate system, DDPG utilizes neural networks to approximate both the actor (policy) and critic (value function) [18]. Mathematically, DDPG updates the actor parameters θ^π and critic parameters θ^Q by minimizing the loss functions given in equation (14) and (15):

$$L(Q^\pi) = -E\left[Q\left(s, \pi(s; \theta^\pi)\right)\right] \quad (14)$$

$$L(\theta^Q) = E[(Q(s, a; \theta^Q) - y)^2] \quad (15)$$

Where, y is the cumulative long-term reward expressed in equation (16):

$$y = R_i + \gamma Q^{t+1}(S_i^{t+1}, \mu^{t+1}(S_i^{t+1}/\theta_\mu)/\theta_Q) \quad (16)$$

By iteratively refining these parameters through experience, DDPG learns complex control policies directly from high-dimensional observations, effectively stabilizing the ball on the plate despite environmental uncertainties and disturbances, thus showcasing the efficacy of RL in real-world control scenarios [19]. A block diagram illustrating the DDPG controller integrated with the Ball-and-Plate system is shown in Figure 2 while the rewards generated after

1666 training episodes is shown in Figure 3. The states are defined as shown in equation (17):

$$s = \left(e(z), e(z) \times \frac{KT_s}{z-1}, e(z) \times \frac{K(z-1)}{T_s z}\right) \quad (17)$$

The reward signal evaluates the agent's performance continually using equation (18):

$$R_i = -(u(t)^2 + e(t)^2 + 10[OR(T_1, T_2)]) + 10 \quad (18)$$

Where, T_1 and T_2 denotes stopping conditions the current episode and e(t) represents error signal.

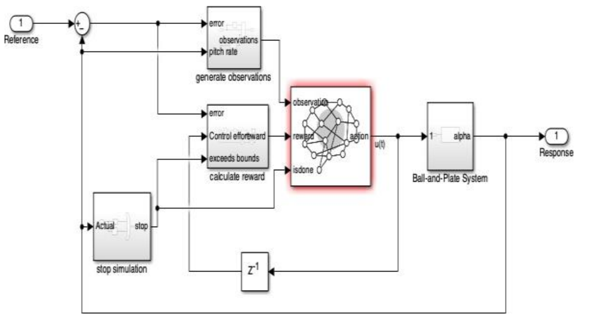


Figure 2: Closed-loop system of the DDPG controller integrated with the Ball-and-Plate system

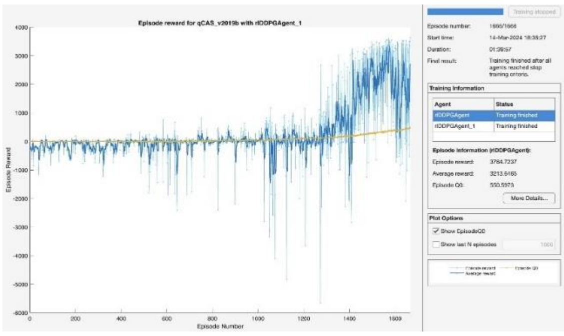
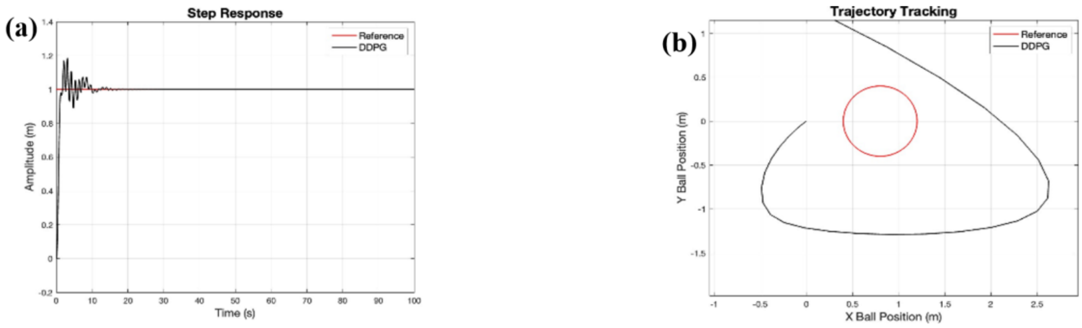


Figure 3: Rewards generated after training the DDPG agent for 1666 episodes

The step response and trajectory tracking performance of the proposed controller is shown in Figure 4(a) and 4(b) respectively.

The quantitative performance of the system can also be obtained as: t_r = 0.0102 seconds, t_s = 7.8975 seconds, M_p = 18.6290%, and MAE = 0.0158. Additionally, the trajectory tracking error is obtained as MAE = 7.0924e + 03.



4(a): Step response plot

4(b): Trajectory tracking plot

Figure 4: Step response and trajectory tracking of the DDPG controller when integrated with the Ball-and-Plate system

3.2 Proportional Integral Derivative Control

Proportional Integral Derivative (PID) controllers have widespread usage in various engineering applications, including robotics and automation systems. The PID controller operates by continuously calculating an error signal, which is the difference between a desired setpoint and the measured process variable. The controller then adjusts the system's output based on three components: proportional, integral, and derivative terms in accordance with equation (19).

$$u(t) = K_p \times e(t) + K_i \int_0^\infty e(t) + K_d \frac{d}{dt} e(t) \quad (19)$$

The proportional term contributes to the output proportionally to the current error magnitude, aiming to minimize steady-state error. The integral term integrates the error over time, addressing any accumulated error and eliminating steady-state offsets. Meanwhile, the derivative term considers the rate of change of the error signal, providing damping to prevent overshoot and improve system stability. The layout of the PID controller connected to the Ball-and-Plate system is given in Figure 5.

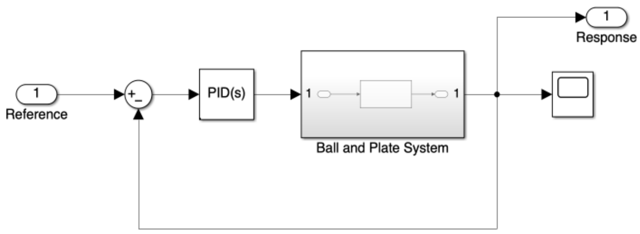
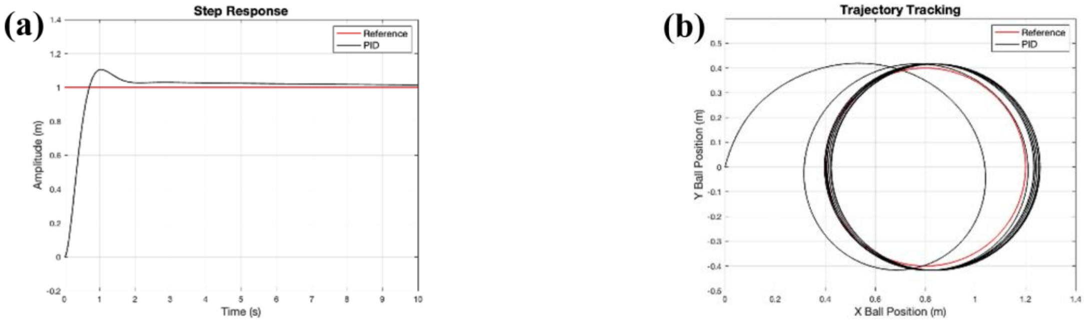


Figure 5: PID controller integrated with the Ball-and-Plate System

The PID controller for stabilizing the ball positioning was tuned using the transfer function method of MATLAB's inbuilt PID tuner with a response time of

0.7290 seconds and transient behavior of 0.600 seconds. The proportional, integral and derivative gains were obtained as follows: K_p = 0.071913824221689, K_i = 0.00135667138094145, and K_d = 0.6413967703623824. The step response of the overall system integrated with the PID controller is given in Figure 6(a) while the circular trajectory tracking performance is demonstrated in Figure 6(b).



6(a) Step response plot **6(b)** Trajectory tracking plot

Figure 6: Performance of the PID controller when integrated with the Ball-and-Plate system illustrated by step response and trajectory tracking plots

The quantitative performance of the system can also be obtained as: t_r = 0.4812 seconds, t_s = 1.7612 seconds, M_p = 8.9739%, and *MAE* = 0.4262. Additionally, the trajectory tracking error is obtained as *MAE* = 0.1149

3.3 Model Predictive Control

Model Predictive Control (MPC) is a control method that uses a dynamic model to predict future system behavior and determine optimal control actions over a defined time horizon. Unlike traditional controllers that compute feedback based on current states, MPC considers future states and system dynamics, enabling it to handle constraints and anticipate future disturbances [28]. The MPC algorithm formulates an optimization problem where the objective is typically to minimize a cost function (J_{mpc}), which incorporates control objectives such as setpoint tracking, disturbance rejection, and constraint satisfaction.

$$J_{mpc} = \sum_{i=1}^{p} \left(r_{k+j} - y^{c-}_{k+j}\right)^2 + w \sum_{i=1}^{m-1} \Delta u^2_{k+1} \quad (20)$$

Given that:

$$r_{k+j} - y^{c-}_{k+j} = r_{k+j} - \sum_{i-1}^{n-1} S_i \Delta u_{k-i+j} + S_n \Delta u_{k-n+j} + d_{k+j} - \sum_{i=1}^{j} S_i \Delta u_{k-i+j} \quad (21)$$

Where r_{k+j} is the reference signal and the y^{c-}_{k+j} is the manipulated signal, the variable w accounts for the weights and u_{k+1} describes the control input for a time step k. The variables $S_i \ldots S_n$ accounts for the model coefficients. By solving this optimization problem iteratively at each time step, MPC generates control signals that steer the system towards optimal performance while satisfying constraints.

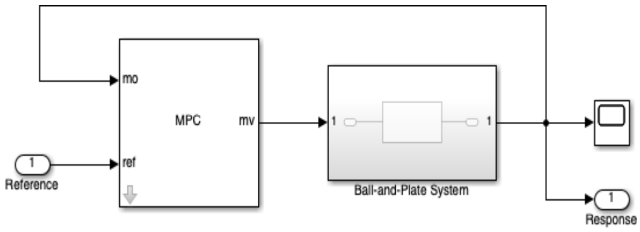
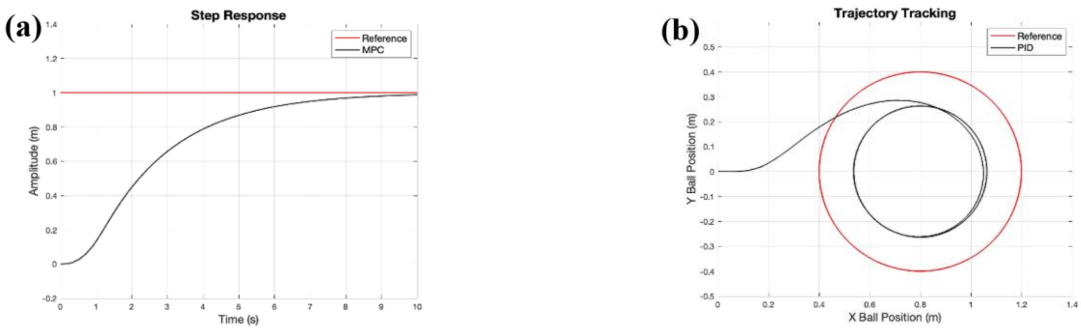


Figure 7: MPC controller integrated with the Ball-and-Plate System



8(a) Step response plot **8(b)** Trajectory tracking plot

Figure 8: Performance of the MPC controller when integrated with the Ball-and-Plate system illustrated by step response and trajectory tracking plots

In the context of the Ball-and-Plate problem, MPC could provide robust and adaptive control by continuously predicting the ball's trajectory and optimizing control actions to maintain stability and achieve desired performance objectives despite uncertainties and external disturbances. The overall layout the MPC controller integrated to the Ball-and-Plate system is shown in Figure 7 while the step response trajectory tracking plots are given in Figures 8(a) and 8(b) respectively.

The quantitative performance of the system can also be obtained as: t_r = 0.8485 seconds, t_s = 0.9867 seconds, M_p = 0.0000%, and MAE = 0.3675. Additionally, the trajectory tracking error is obtained as MAE = 0.5845.

3.4 Sliding Model Control

A Sliding Mode Controller (SMC) is a robust control technique renowned for its ability to ensure system stability and performance in the presence of uncertainties and disturbances. At the core of SMC is the concept of a sliding surface, a hyperplane in the state space along which the system dynamics are constrained to evolve. The controller's objective is to drive the system states onto this sliding surface and keep them there. Once on the sliding surface, the system dynamics are governed by a simple and robust control law designed to maintain the system's motion along this surface, effectively decoupling the system from uncertainties and disturbances. The sliding surface s is typically designed as the error between the desired state x_d and the actual state x.

$$s = x_d - x \tag{22}$$

The control law is often discontinuous and designed to drive the system trajectory onto the sliding surface. A common choice for the control law is:

$$u = -k sign(s) \tag{23}$$

The distinctive feature of SMC lies in its ability to achieve robustness against parameter variations and external disturbances by enforcing a sliding motion, making it particularly suitable for systems with nonlinear dynamics and uncertainties.

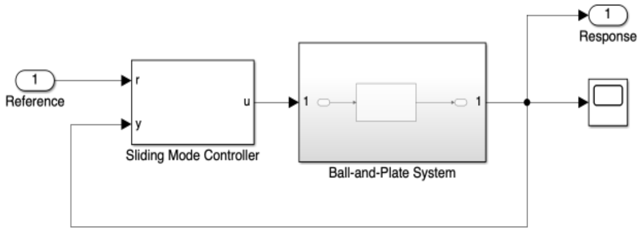
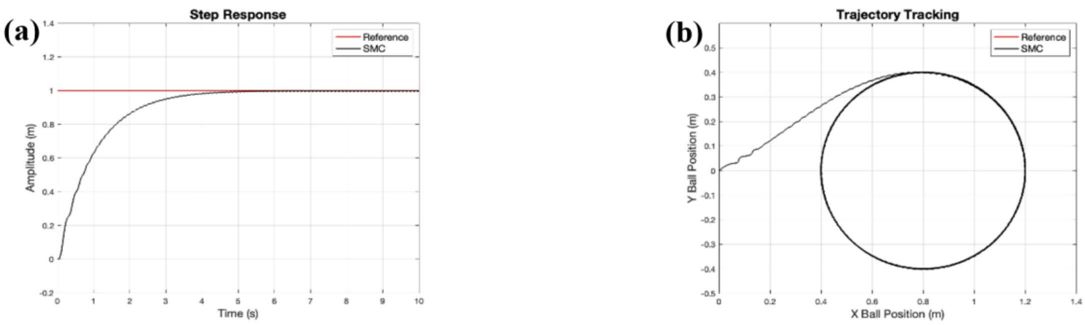


Figure 9: SMC controller integrated with the Ball-and-Plate System

In the context of the Ball-and-Plate problem, a Sliding Mode Controller could offer precise and robust control, ensuring that the ball's position on the plate remains stable and resilient to disturbances, even in the presence of uncertainties in the system dynamics or external forces acting on the ball. The overall layout the SMC controller integrated to the Ball-and-Plate system is shown in Figure 9 while the step response trajectory tracking plots are given in Figures 10(a) and 10(b) respectively.



10(a) Step response plot

10(b) Trajectory tracking plot

Figure 10: Performance of the SMC controller when integrated with the Ball-and-Plate system illustrated by step response and trajectory tracking plots

The quantitative performance of the system can also be obtained as: t_r = 0.3701 seconds, t_s = 0.9997 seconds, M_p = 0.0000, and MAE = 0.1024. Additionally, the trajectory tracking error is obtained as MAE = 0.0061.

3.5 Linear Quadratic Regulator

Linear Quadratic Regulator (LQR) control is a method used to design controllers for linear systems, aiming to minimize a quadratic cost function representing the system's performance and control effort. It operates by computing a control law that minimizes the expected value of the cost function J over a finite time horizon, considering both the current state and future state predictions. The LQR controller leverages a state feedback approach, where the control input is a linear function of the state variables.

$$J = \int_0^\infty (x^T Qx + u^T Ru)dt \quad (24)$$

We chose Q, R matrices as follows:

$$Q = \begin{pmatrix} 0.3 & 0 & 0 \\ 0 & 0 & 0.21 \\ 0 & 0 & 0.1 \end{pmatrix} \quad (25)$$

$$R = 0.00015 \quad (26)$$

By solving the associated Riccati equation, the LQR algorithm determines the optimal feedback gain matrix that minimizes the cost function, thus enabling precise and efficient control.

$$K = (40.8079 \quad 61.2896 \quad 25.6850) \quad (27)$$

LQR is particularly effective for systems with known dynamics and noise characteristics, providing optimal control solutions that balance between tracking desired setpoints and minimizing control effort.

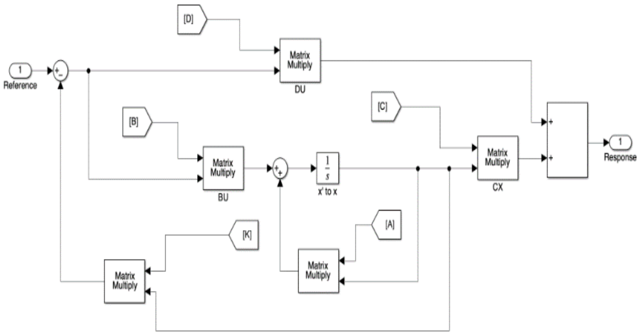
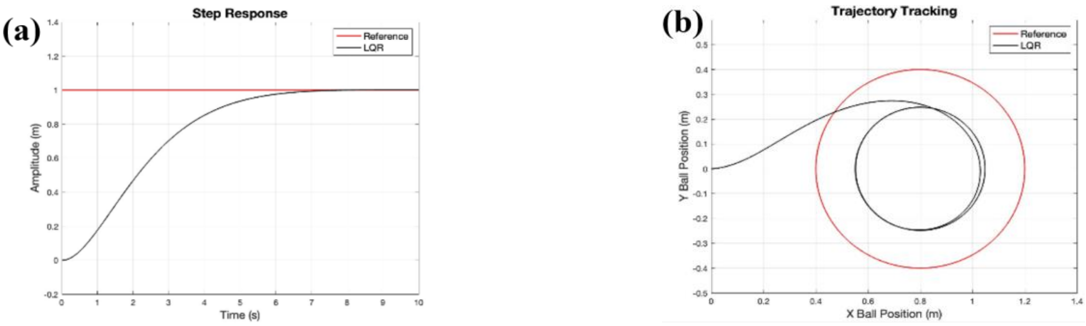


Figure 11: LQR controller integrated with the Ball-and-Plate System

In applications such as the Ball-and-Plate problem, where the dynamics can be approximated as linear and uncertainties are relatively low, an LQR controller could offer stable and accurate control to maintain the ball's position on the plate while minimizing deviations from the desired trajectory. The overall layout the LQR controller integrated to the Ball-and-Plate system is shown in Figure 11, while the step response trajectory tracking plots are given in Figures 12(a) and 12(b) respectively.



12(a) Step response plot **12(b)** Trajectory tracking plot

Figure 12: Performance of the LQR controller when integrated with the Ball-and-Plate system illustrated by step response and trajectory tracking plots

The quantitative performance of the system can also be obtained as: t_r = 0.0017 seconds, t_s = 1.0000 seconds, M_p = 0.0000%, and *MAE* = 0.0310. Additionally, the trajectory tracking error is obtained as *MAE* = 0.5140.

4.0 RESULT ANALYSIS

Table 1 presents a comparative analysis of various intelligent control approaches for addressing the Ball-and-Plate problem, focusing on both step response and trajectory tracking performance metrics.

Table 1: Comparison of the 5 control methods investigated on the Ball-and-Plate System

	Step Response				Trajectory Tracking
Techniques	**t_r (s)**	**t_s (s)**	**MAE**	**M_p(%)**	**MAE**
DDPG	0.0102	7.8975	0.0158	18.6290	7.0924e+03
PID	0.4812	1.7612	0.4262	8.9739	0.1149
MPC	0.8485	0.9867	0.3675	0.0000	0.5845
SMC	0.3701	0.9997	0.1024	0.0000	0.0061
LQR	0.0017	1.0000	0.0310	0.0000	0.5140

The DDPG technique exhibits a remarkably fast rise time (t_r) of 0.0102 seconds, although with a longer settling time (t_s) of 7.8975 seconds and a relatively higher peakovershoot (M_p) of 18.6290%. In terms of trajectory tracking, DDPG demonstratesa significa-ntly higher mean absolute error (MAE) of 7.0924e+03 compared to other techniques. This result suggests that while DDPG shows promise in terms of rapid response, it may require further refinement to improve trajectory tracking accuracy to the other traditional control methods like PID, MPC, SMC and LQR. It is also important to note that the training time of this DDPG agent was 5997 seconds which implies that this method is significantly slower than the other methods.

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Conversely, the other methods present distinctive performance characteristics. PID exhibits moderate rise time and settling time with comparatively low overshoot and trajectory tracking error. MPC displays a longer rise time but achieves the lowest settling time and overshoot, resulting in precise trajectory tracking. SMC demonstrates a fast rise time and settling time with very low overshoot and trajectory tracking error, indicating robust performance. LQR achieves an extremely fast rise time but with higher trajectory tracking error compared to MPC and SMC. These results provide insights into the comparative effectiveness of intelligent control methods on a classical control system.

5.0 CONCLUSION

In conclusion, this research provides a comprehensive evaluation of intelligent control approaches for the ball-and-plate system, focusing on both step response and trajectory tracking metrics. The comparative analysis highlights the strengths and weak- nesses of each technique, shedding light on their applicability and performance in real-world scenarios. Notably, while DDPG exhibits impressive responsiveness with a rapid rise time, it falls short in trajectory tracking accuracy compared to traditional control methods like PID, MPC, SMC and LQR. These findings underscore the importance of balancing speed and precision in control system design, particularly in dynamic environments where accurate trajectory tracking is crucial.

Moreover, the study underscores the potential of traditional control methods, such as PID, MPC, and SMC, in achieving precise trajectory tracking with minimal over- shoot and error. Their robust performance across various metrics highlights their suit- ability for practical applications where stability and accuracy are paramount. Further-more, the research contributes to the ongoing discourse on the integration of reinforcement learning techniques like DDPG into control systems, emphasizing the need for further refinement to improve trajectory tracking capabilities. Overall, this comparative study offers insights into the relative merits of different intelligent control approaches and guiding future developments toward more efficient and effective control strategies for complex systems like the ball-and-plate setup.

Future research can consider hybrid control strategies that combine the strengths of traditional methods with reinforcement learning could be investigated to achieve tuning of the reinforcement learning agent.

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