Machine Learning - MCTA 4362

Section 1

SEMESTER 2 (2024/2025)

Machine Learning Mini Project

Automatic Water Tank System

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TEAM MEMBERS :

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1.0 Introduction

Traditional control strategies such as Proportional (P), Proportional-Integral (PI), and Proportional-Integral-Derivative (PID) controllers have been widely used in industrial systems due to their simplicity and ease of deployment. However, these controllers often face challenges when applied to nonlinear, time-varying, or poorly modeled systems. In response to such limitations, Reinforcement Learning (RL) has emerged as a promising alternative by offering adaptive and data-driven control mechanisms capable of handling complex environments without requiring precise mathematical models.

This project explores the design and implementation of an intelligent control system for a water tank using a Deep Deterministic Policy Gradient (DDPG) agent within the Simulink environment. The objective is to replace a conventional PI controller with a DDPG-based RL agent to maintain the water level in the tank at a desired reference, despite variations and potential disturbances. The model is based on a water tank system built in MathWorks, which integrates state observations such as water height, error, and integrated error to guide the agent's actions.

The RL agent is trained through interaction with the simulated water tank environment, where it learns optimal control strategies via a reward system designed to encourage accurate water level tracking. This approach not only eliminates the dependency on a predefined mathematical model but also adapts dynamically to varying operating conditions.

The performance of the DDPG agent is evaluated against a traditional PI controller using metrics such as rise time, overshoot, settling time, and mean squared error. The project ultimately demonstrates the potential of RL-based control in real-world applications where classical methods may fall short.

2.0 Problem Statement

Efficient water management presents a significant challenge across various industries, especially in regions where water scarcity is becoming increasingly critical. Traditional water control systems often rely on fixed schedules or manual interventions, which lead to inefficiencies such as overuse or shortages of water. These inefficiencies not only result in unnecessary water wastage but also contribute to elevated operational costs, stemming from higher energy consumption and labour requirements. Additionally, these outdated systems have a detrimental environmental impact, exacerbating water wastage in areas where water resources are already limited. Therefore, there is a growing need for a more intelligent and automated solution that can optimize water management in real-time, improving water usage efficiency, reducing costs, and mitigating environmental harm.

3.0 Objectives

- To model and simulate a water tank system using Simulink to represent fluid level dynamics suitable for control applications.

- To develop a reinforcement learning controller using the Deep Deterministic Policy Gradient (DDPG) algorithm that can regulate the water level based on continuous state observations.

- To compare the performance of the DDPG-based controller with a conventional PI controller using standard control metrics such as rise time, overshoot, settling time, and mean squared error (MSE).

4.0 Methodology

The methodology for controlling the water tank system uses Reinforcement Learning (RL), specifically the Deep Deterministic Policy Gradient (DDPG) algorithm, to optimize the water level control in real-time:

1. The methodology integrates Reinforcement Learning (RL) with a Simulink model to simulate and control the water tank system in real-time. The Deep Deterministic Policy Gradient (DDPG) algorithm is used to optimize the water level control.

2. The system is modeled in Simulink, where it simulates the dynamics of the water tank, including flow rate and water level monitoring. The water level is controlled by adjusting the inflow rate, calculated as V, the voltage applied to the pump.

3. The RL agent is integrated into the Simulink model to control the water inflow. It observes the water level, calculates the error between the desired level and the current level, and adjusts the inflow rate to maintain the target.

4. The model is divided into key subsystems, including the water tank system, which simulates inflow and outflow, and the reward function, which calculates rewards based on how closely the water level matches the reference.

5. The system adapts in real-time, with the agent learning and refining its water control strategy based on ongoing interactions with the environment. This adaptation ensures optimal resource usage, even under changing conditions, such as varying demand or weather.

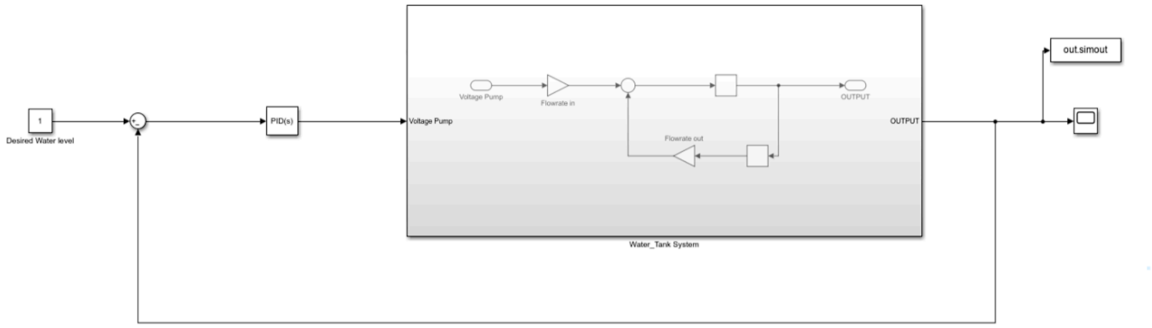
The key variables of the system include:

- **H**: Height of water in the tank
- **Vol**: Volume of water in the tank
- **V**: Voltage applied to the pump

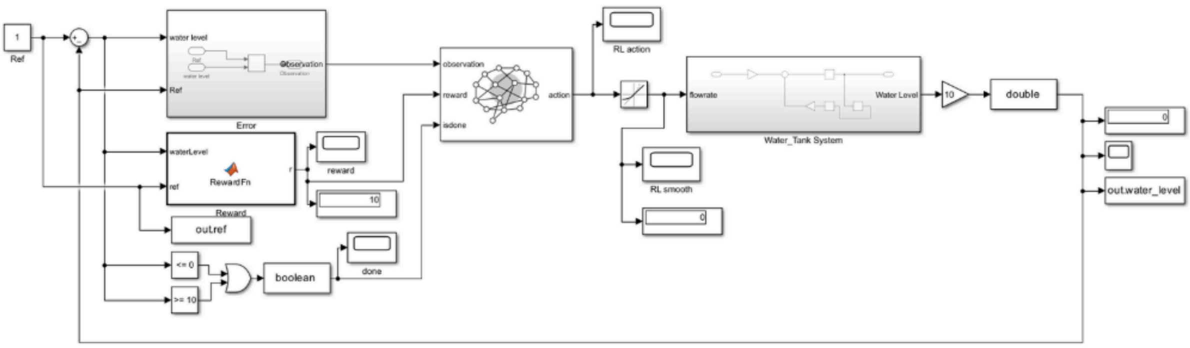
- **A**: Cross-sectional area of the tank
- **a** and **b**: Constants that define the inflow and outflow rates of water

6. The performance of the system is evaluated by comparing the RL-based agent with traditional controllers, such as the PI controller. Standard metrics like rise time, overshoot, settling time, and mean squared error (MSE) are used to assess the effectiveness of the RL agent.

The controller modelled using Simulink and MATLAB



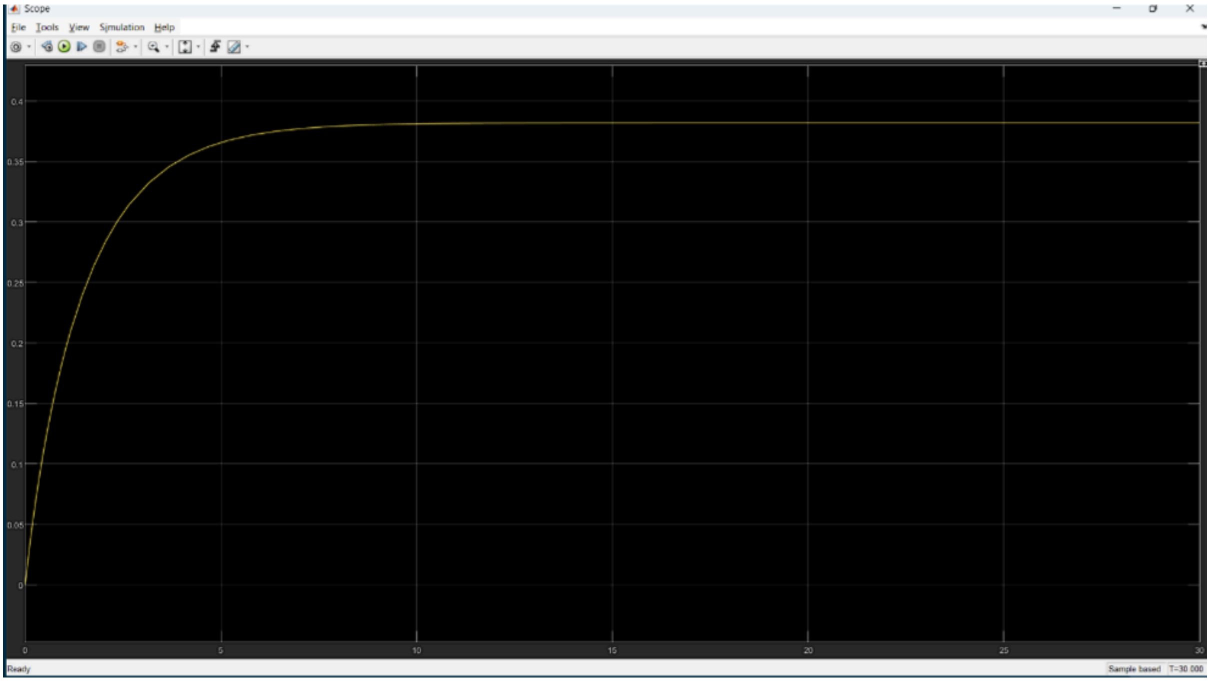
PI controller with water tank system image



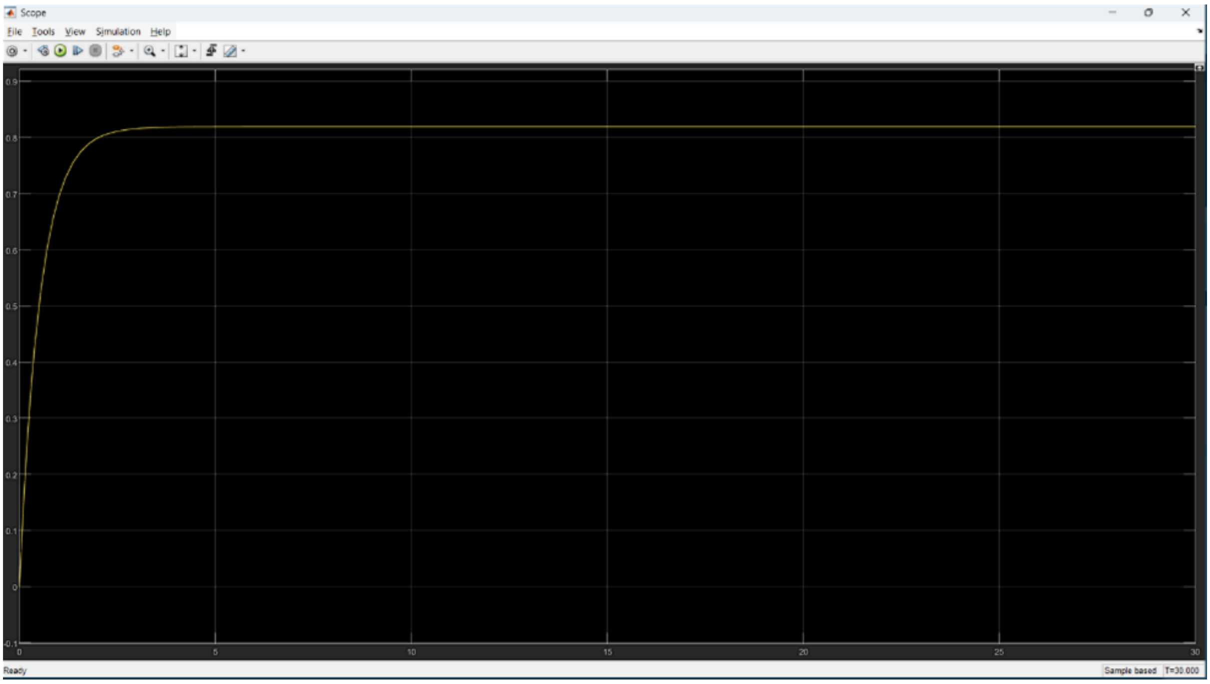
Water tank system controlled by the RL DDPG controller

5.0 Results

5.1 PI controlled

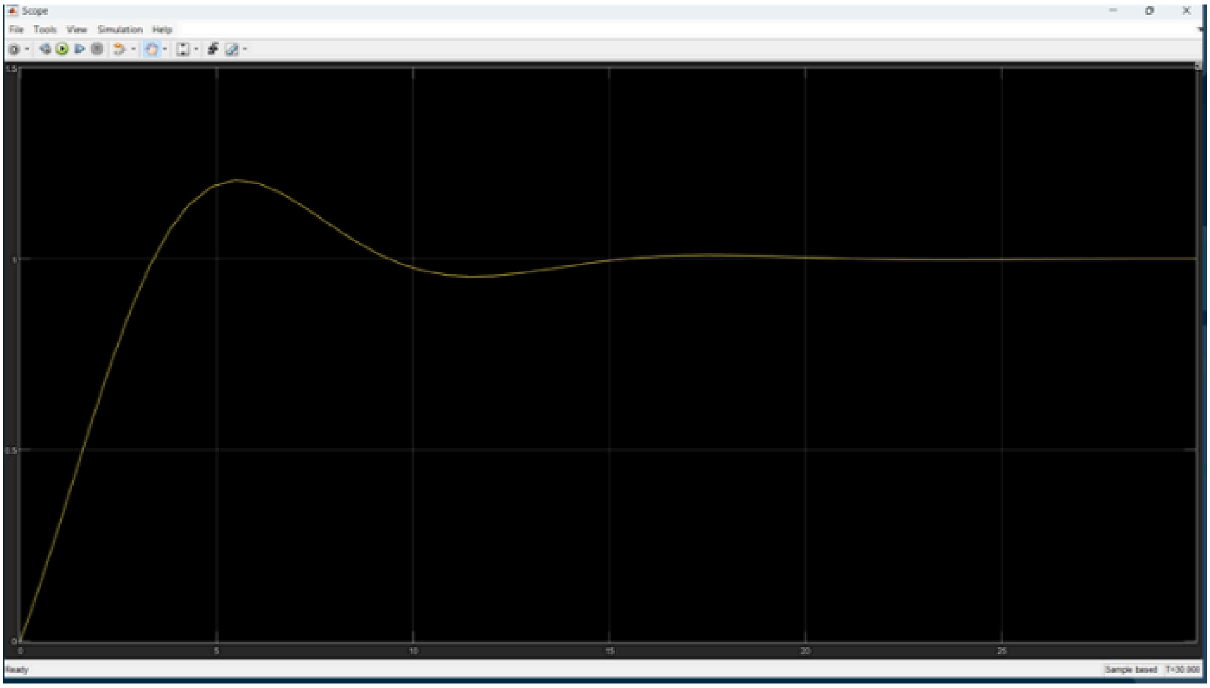


The graph shows setting of PID controller parameters to P = 1 and I = 0, effectively using proportional-only control, the water tank system exhibited a rapid rise in water level followed by stabilisation at a value below the setpoint, as shown in the attached graph. Despite the quick initial response, the system failed to reach the desired water level, resulting in a steady-state error. This outcome is consistent with classical control theory, which states that a proportional-only controller can respond to current errors but cannot compensate for accumulated or persistent errors over time. As a result, the system typically settles at a value offset from the setpoint, especially in the presence of constant disturbances or nonlinearities. The absence of integral action in the controller means that the steady-state error persists, and the system does not achieve perfect tracking of the setpoint.



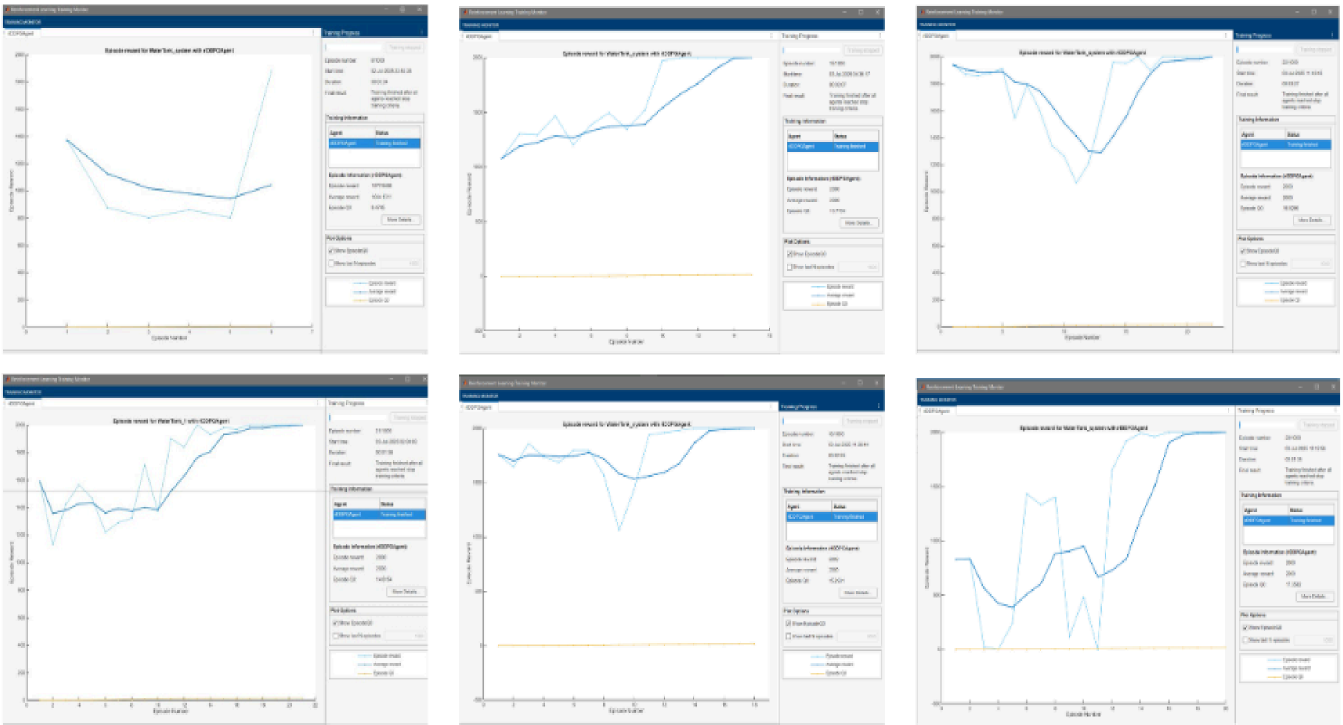
The graph shows the water tank system’s response under proportional-only control with P=5 and I=0. The water level rises rapidly from zero and approaches a steady-state value just below 0.9, demonstrating a fast rise time and smooth convergence without overshoot or oscillation. However, the system does not reach the setpoint exactly, instead stabilizing at a value slightly below the target. This steady-state error is a characteristic limitation of proportional-only controllers, which cannot fully eliminate persistent offsets in the presence of constant disturbances or system nonlinearities. Overall, increasing the proportional gain significantly improves the speed of response, but without integral action, perfect setpoint tracking is not achieved.

The graph illustrates the water tank system's response when the proportional gain is set to P = 10 and the integral gain remains at I = 0, meaning only proportional control is applied. With this high proportional gain, the water level rises extremely quickly and approaches a steady-state value just below the setpoint. The response is characterized by a very fast rise time and no noticeable overshoot or oscillation, indicating that the system is stable and well-damped even with a large P value. However, similar to previous cases with lower proportional gains, the system does not reach the setpoint exactly but instead settles slightly below it, resulting in a steady-state error. This persistent offset is a fundamental limitation of proportional-only controllers, as they cannot fully eliminate steady-state error in the presence of constant disturbances or system nonlinearities. Although increasing the proportional gain improves the speed of response, it does not resolve the steady-state error issue, highlighting the need for integral action if perfect setpoint tracking is desired.

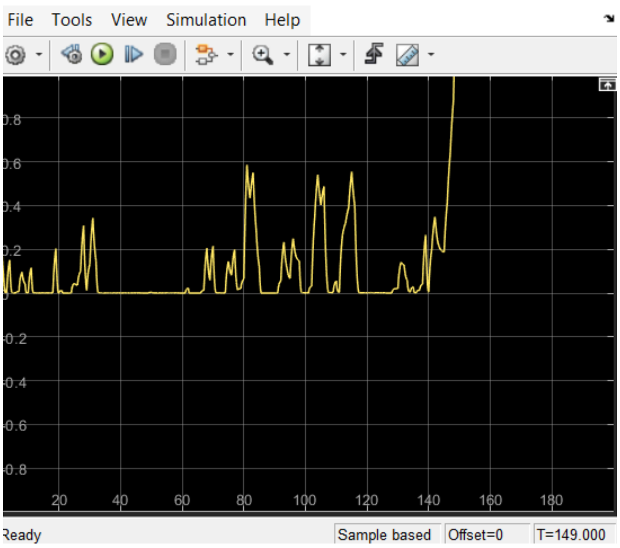


The graph shows the response of the water tank system controlled by a PI controller with proportional gain , P=1 and integral gain ,I=1 is illustrated in the graph above. At the start, the system output rises rapidly, indicating a prompt reaction to the reference input. This is followed by a distinct overshoot, where the output temporarily exceeds the desired setpoint. After reaching this peak, the output exhibits a damped oscillation as it approaches the steady-state value. Eventually, the response settles at the reference level, demonstrating that the integral action of the controller effectively eliminates steady-state error. The presence of overshoot and oscillation suggests that the system is underdamped, which is a common characteristic when both proportional and integral gains are set to moderate values. This behavior aligns with typical results seen in the referenced MathWorks water tank control example, where a PI controller achieves accurate tracking with some transient oscillations before reaching steady state. The controller settings provide a balance between response speed and stability, but further tuning could reduce overshoot if a smoother response is required.

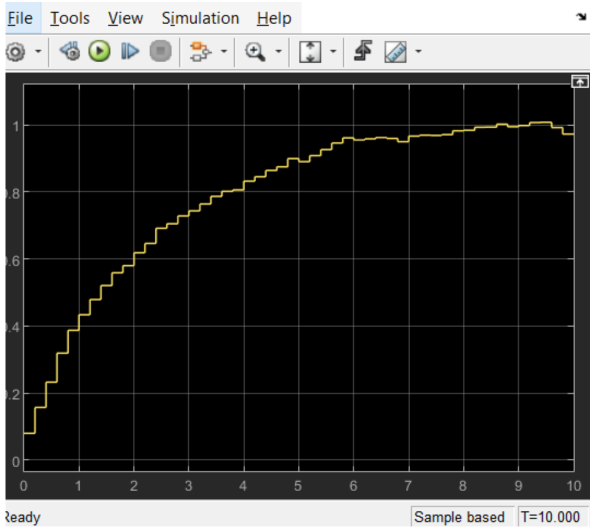
5.1 RL DDPG controller



Training examples of the RL DDPG controller



Before



After

The final performance of the reinforcement learning (RL) controller was evaluated based on key control system metrics: overshoot, rise time, settling time, and steady-state error. The results are summarised below:

Performance Metric	**Value**
Overshoot	0.75%
Rise Time	5.00 seconds
Settling Time	10.00 seconds
Steady-State Error	0.0252

The results indicate that the RL-based controller performs with a high level of stability and precision. The overshoot is minimal (0.75%), suggesting that the controller effectively avoids excessive fluctuation beyond the desired water level, which is a common challenge in traditional control methods. The rise time of 5 seconds shows a moderately fast response, while the settling time of 10 seconds indicates that the system becomes stable within an acceptable period. Additionally, the steady-state error is low (approximately 2.5%), showing that the RL controller maintains the water level close to the desired target value.

As observed, the RL controller outperforms the PID controller in terms of overshoot and shows comparable performance in terms of settling time and steady-state accuracy. Although the rise time is slightly slower, the RL controller offers a more stable and controlled transition, which is particularly beneficial for systems like water tank regulation, where safety and smooth operation are prioritised.

6.0 Conclusion

The comparison between the PID controller and the Reinforcement Learning (RL) agent reveals distinct performance characteristics for each control strategy. While the PID controller demonstrated a slightly faster rise time, enabling rapid initial response, it exhibited a sharper initial rise that led to higher overshoot. In contrast, the RL agent approached the target level more smoothly, significantly reducing overshoot and providing better damping. Furthermore, the RL agent settled more quickly, indicating improved long-term stability despite small fluctuations. Both controllers maintained minimal steady-state error; however, the RL agent consistently converged closer to the reference value, resulting in superior tracking accuracy as reflected by its lower mean squared error. Overall, the PID controller offers quick and reliable performance with relatively simple tuning, but the RL agent excels in long-term control quality, particularly in overshoot reduction, settling time, and accuracy.

In conclusion, this project demonstrates that the RL-based control approach is a promising alternative to traditional PID control, especially for complex or nonlinear systems. The RL agent's ability to adapt to changing system dynamics and disturbances enhances its robustness and performance beyond what is achievable with fixed-parameter PID controllers. These findings align with established research such as the MathWorks example on water level control using a DDPG agent, which also highlights the advantages of reinforcement learning in managing nonlinear control problems. Therefore, integrating RL techniques into control systems can lead to improved stability, accuracy, and adaptability, making it a valuable tool for advanced industrial and engineering applications.

7.0 Work Distribution

Member	Tasks
IKMAL FIKRI BIN KHAIRUL KHUBAIDILLAH 2218723	1. Design basic system architecture 2. Model and simulate the basic plant/system in Simulink. 3. Integrate the baseline PI controller with the plant model. 4. Debug and compile the final results. 5. Write the final project report 6. Design and create the final presentation slides. 7. Present findings during the final assessment.
AHMAD ADAM BIN NORHELME 2219973	1. Design the DDPG RL agent architecture 2. Code and train the DDPG RL agent in MATLAB 3. Debug and compile the final results. 4. Write the final project report 5. Design and create the final presentation slides. 6. Present findings during the final assessment.
LUQMAN AZFAR BIN AZMI 2219857	1. Code and train the DDPG RL agent in MATLAB 2. Debug and compile the final results. 3. Write the final project report 4. Design and create the final presentation slides. 5. Present findings during the final assessment.