Automatic tuning of multiple PID motor controllers for a self-balancing platform via machine learning

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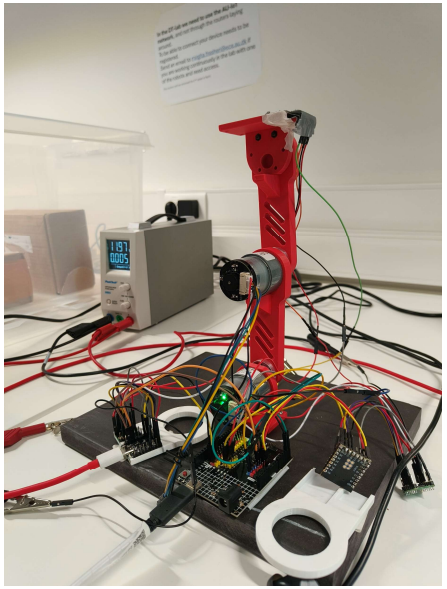
Order of Business

Presentation Focus:

- General outline of the project
- Present project nuances in formats not suitable for a written report
- Highlight topics deserving of more attention

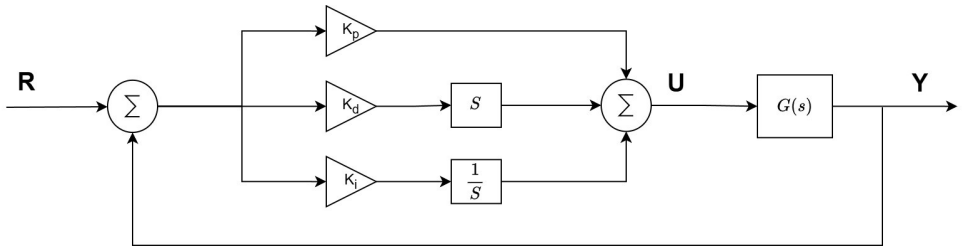
Content:

- Introduction & Problem Description
- Research Methodology & Materials
- Design & System Analysis
- Implementation & Testing
- Results
- Discussion
- Future Work



Introduction and Problem Description

- **PID controllers** remain industry standard for motor control but require manual tuning
- **Multi-motor systems** (e.g., robotic arms) suffer from interdependencies and nonlinearities
- Traditional tuning methods (e.g., Ziegler-Nichols, gain scheduling) are:
  - Time-consuming
  - Rely on accurate system models
  - Inflexible to dynamic environments
- **Challenge:** Online PID tuning for unknown or changing system dynamics
- **Goal**: Develop a learning-based approach to
  - Automatically tune **multiple PID controllers**
  - Handle disturbances and nonlinear behaviour
  - Operate without prior system modelling



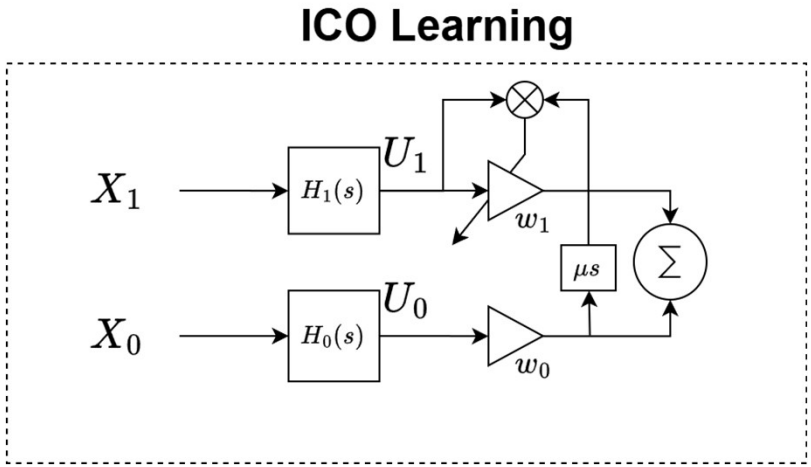
Research Methodology and Materials

Other intelligent control algorithms for auto tuning PID-gains?

- **Yes!**
- Often based on Reinforcement Learning (**RL**)
- Works by **minimizing** an error-based loss function via gradient descent
- Computationally heavy, especially if deployed with many agents or with a Deep Neural Networks **(DNN)** architecture for accurate parameter adaption

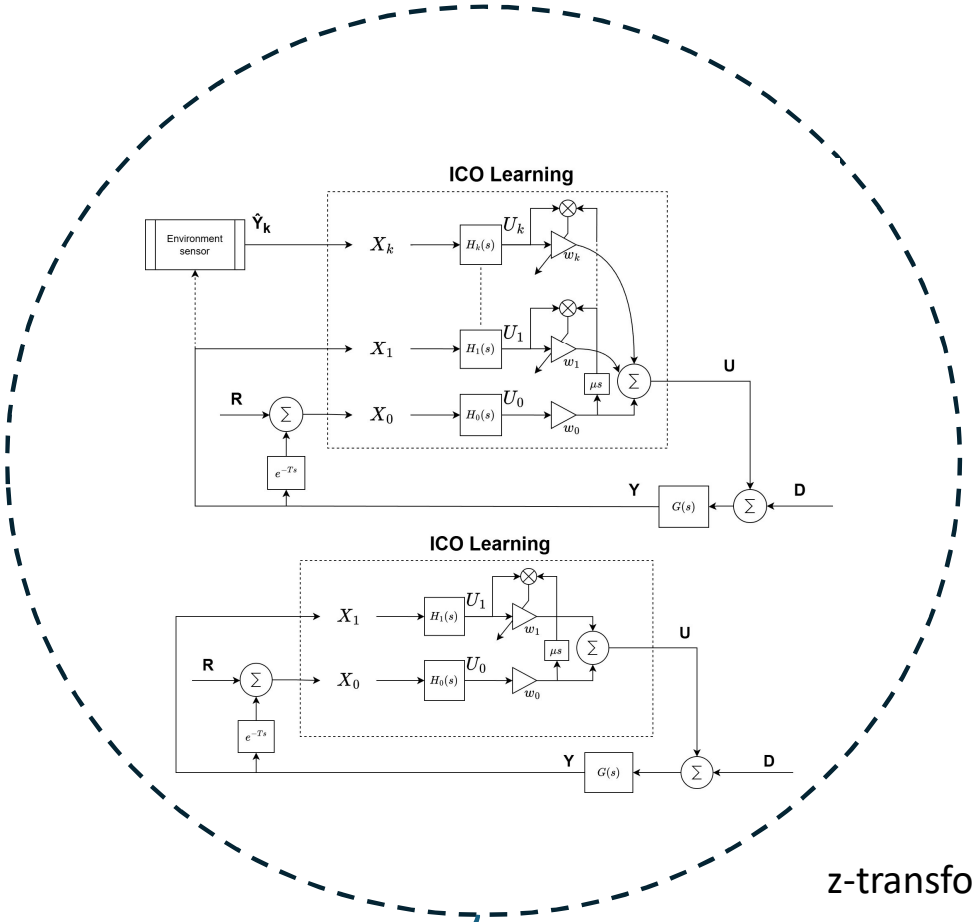
Proposed Solution: Use **Input Correlation (ICO) learning** for:

- Hebbian inspired weight adaptation
- Works by **maximizing** correlation between input signals in time
- Low computational cost
- Used before on embedded systems

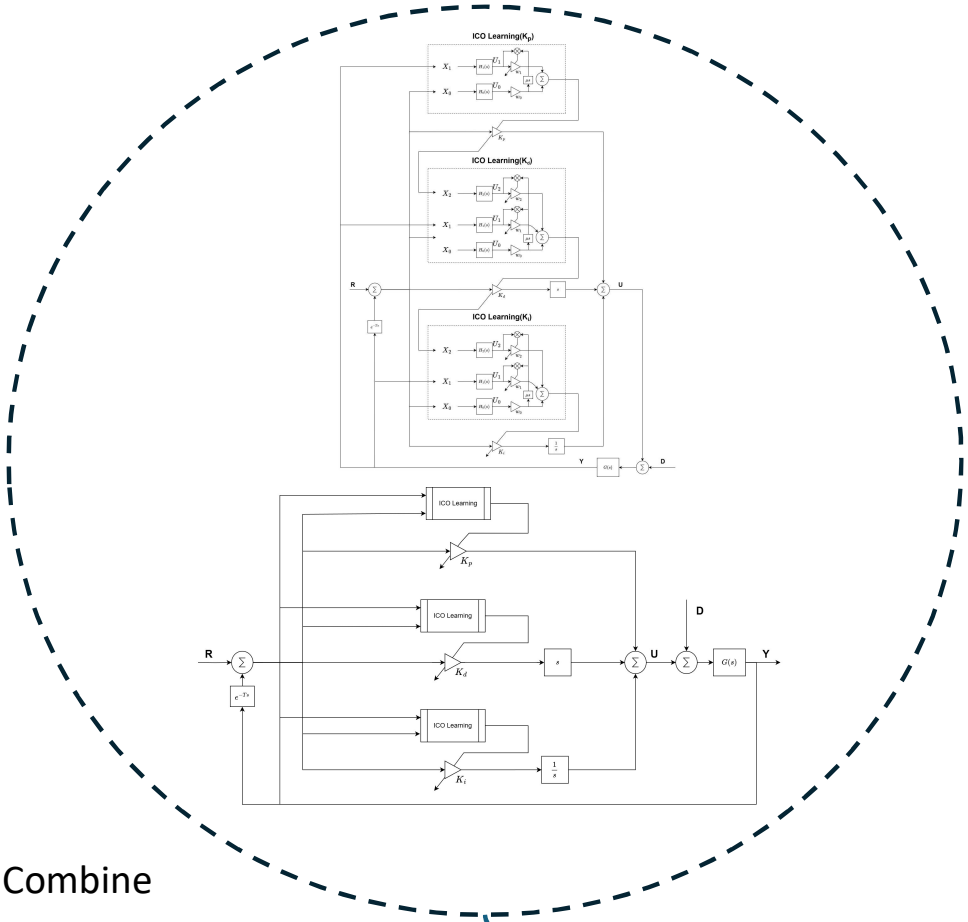


Design and System Analysis

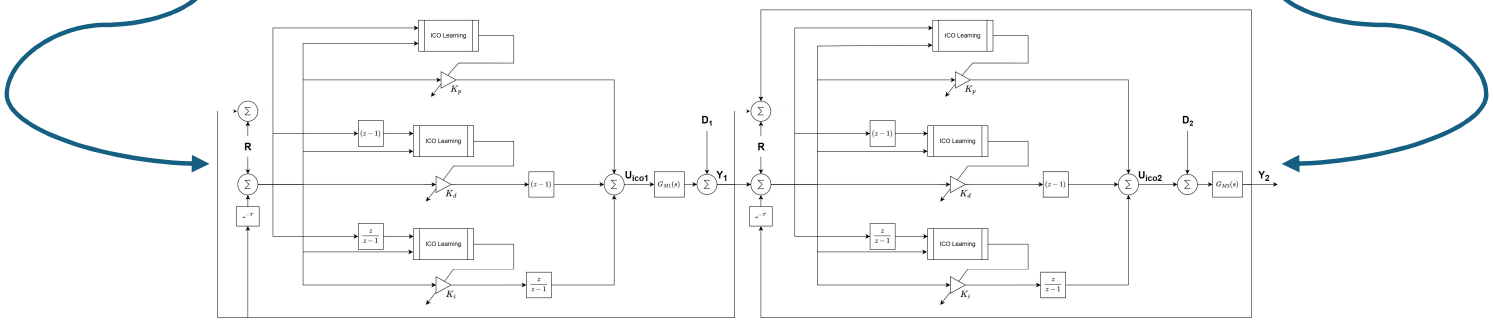
Intelligent Control View



Control Architecture View

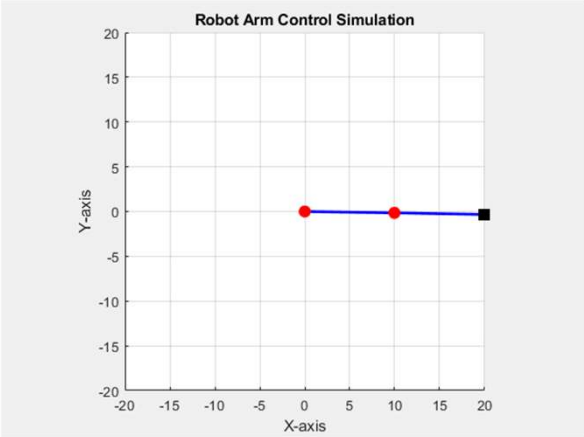


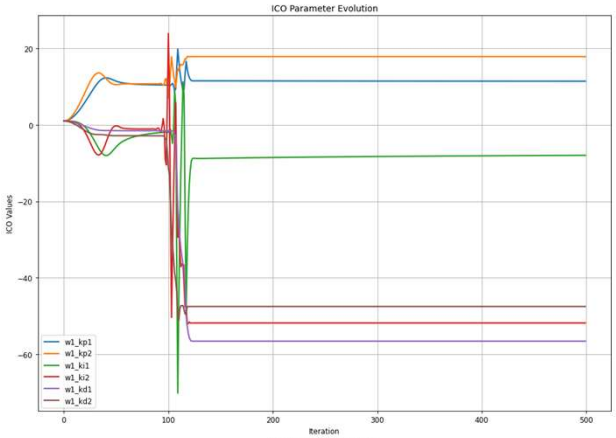
z-transform & Combine

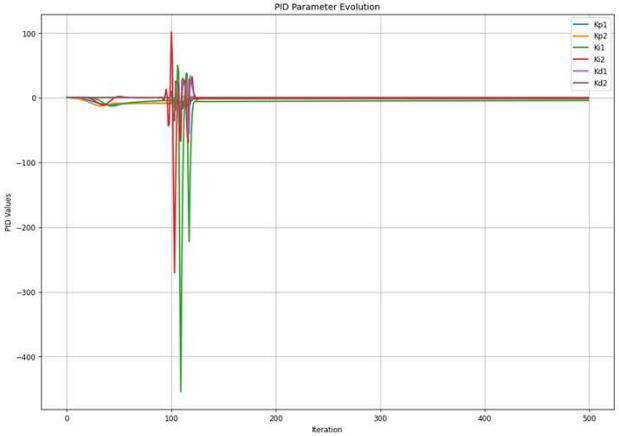


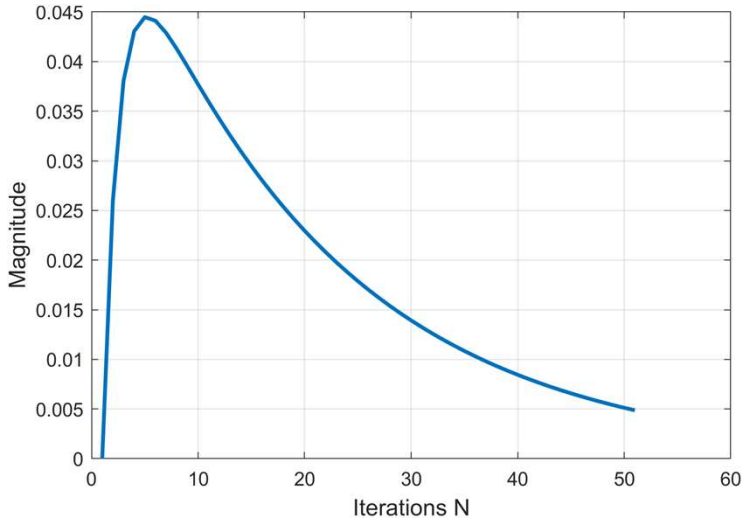
Design and System Analysis - Filtering and Stability

S1.3









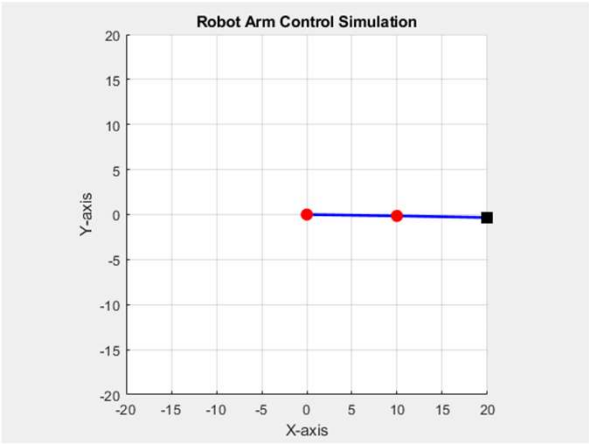
Deduce smoothening delay

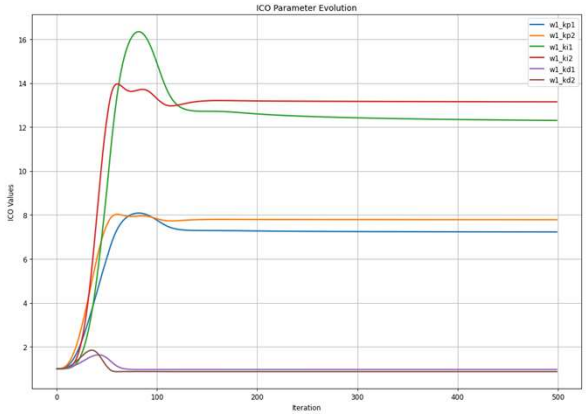
Filtering

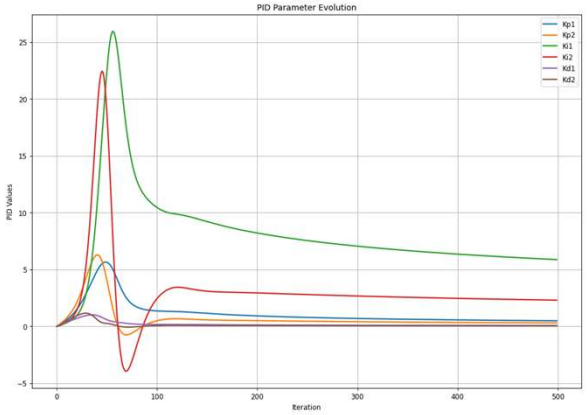
BIBO Stability in weight change response

$$\sum_{n=-\infty}^{\infty} |h[n]| < \infty$$

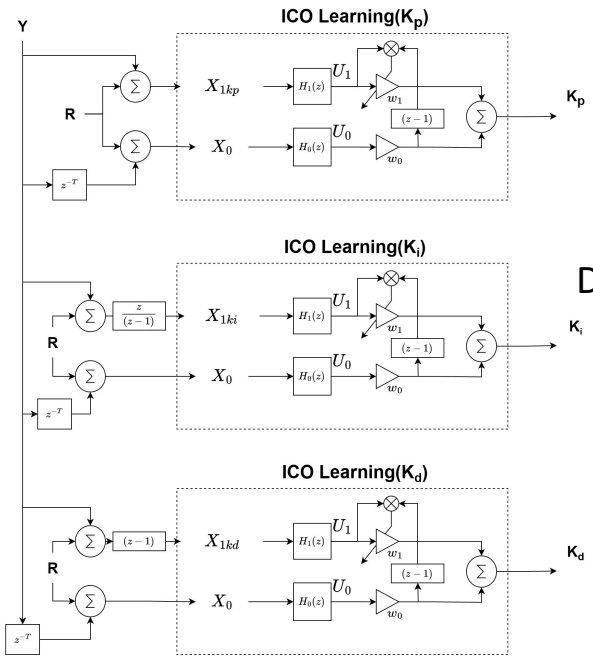
S5.3







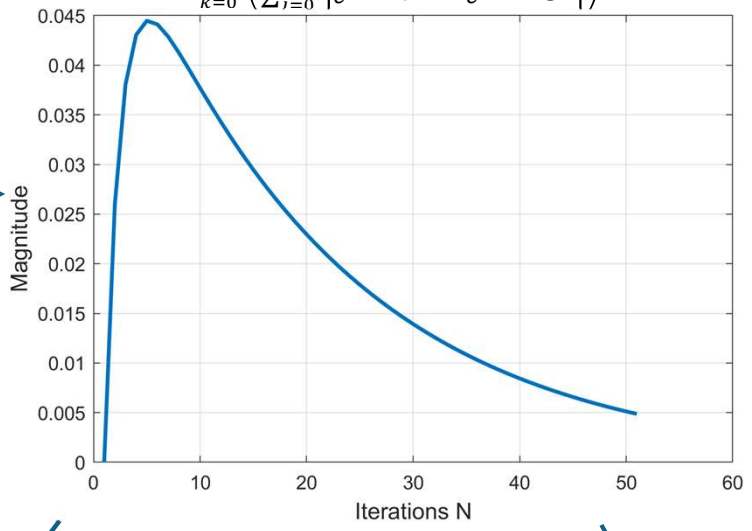
Design and System Analysis - Deduced Filter Models



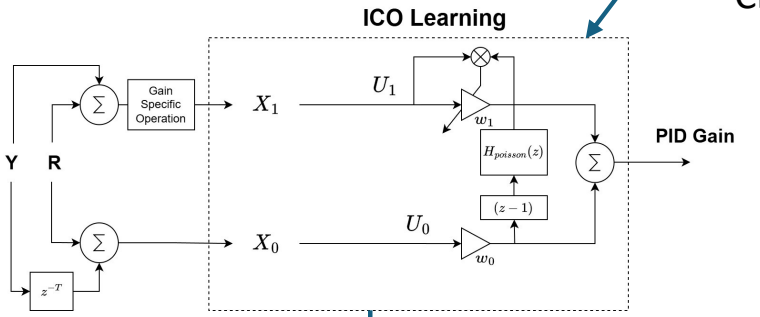
Design FIR Filter

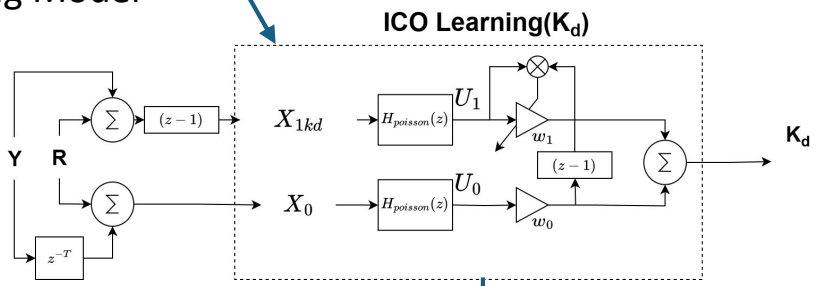
Poisson-like FIR Filter

$$y[n] = \sum_{k=0}^{N-1} \left(\frac{e^{-k/\lambda}low - e^{-k/\lambda}high}{\sum_{j=0}^{N-1} \left| e^{-j/\lambda}low - e^{-j/\lambda}high \right|} \right) x[n-k]$$



Choose Filtering Model





Update Learning Rules

$$PID\_gain = w_0 x_0[n] + w_1 x_1[n]$$

$$\Delta w_1 = \mu \left(u_1[n] \left(\sum_{k=0}^{L-1} \frac{u_0[k] - u_0[k-1]}{dt} \cdot h_{poisson} \left[\frac{(M-1)}{2} + L - 1 - k \right] \right) \right)$$

$$K_d = w_0 \left(\sum_{k=0}^{L-1} x_0[k] \cdot h_{poisson} \left[\frac{(M-1)}{2} + L - 1 - k \right] \right) + w_1 \left(\sum_{k=0}^{L-1} x_1[k] \cdot h_{poisson} \left[\frac{(M-1)}{2} + L - 1 - k \right] \right)$$

$$\Delta w_1 = \mu \left(u_1[n] \frac{u_0[n] - u_0[n-1]}{dt} \right)$$

Implementation and Testing

Pseudocode

Algorithm 2 Filtering of Derivative Dynamic in ICO Learning

Require: Initial weights w_0, w_{1_kp}, w_{1_ki}, w_{1_kd}; learning rate μ; Poisson kernel $h_{poisson}[\,]$ (or alternate LTI filter) of length L; time step dt

1: Initialize previous values: $X_0[-1] \leftarrow 0$, $error[-1] \leftarrow 0$

2: Initialize buffer: $\mathscr{B} \leftarrow \emptyset$

3: **for** each time step n **do**

4: Compute system error (for the robot arm, this is a cumulative joint angles error: $error[n] \leftarrow target - \sum_i joint\_angle_i$)

5: Compute $X_0[n] \leftarrow error[n-1]$

6: Compute integral $integral[n] \leftarrow \sum_{k=-\infty}^{n} error[n] \cdot dt$

7: Compute raw derivative: $\Delta error[n] \leftarrow \frac{(error[n] - error[n-1])}{dt}$

8: Compute $ICO\_derivative[n] \leftarrow \frac{(X_0[n] - X_0[n-1])}{dt}$

9: Append $ICO\_derivative[n]$ to buffer $\mathscr{B}$ (keep latest L elements)

10: Compute filtered derivative:

$$\hat{d}_{ICO}[n] \leftarrow \sum_{k=0}^{L-1} \mathscr{B}[k] \cdot h_{poisson}\left[\frac{(M-1)}{2} + L - 1 - k\right]$$

(implemented as convolution over buffer)

11: Update weights:

$$X_{1\_kp}[n] \leftarrow error[n]$$
$$\Delta w_{1\_kp} \leftarrow \mu \cdot X_{1\_kp}[n] \cdot \hat{d}_{ICO}[n]$$
$$w_{1\_kp} \leftarrow w_{1\_kp} + \Delta w_{1\_kp}$$

$$X_{1\_ki}[n] \leftarrow error[n] \cdot integral[n]$$
$$\Delta w_{1\_ki} \leftarrow \mu \cdot X_{1\_ki}[n] \cdot \hat{d}_{ICO}[n]$$
$$w_{1\_ki} \leftarrow w_{1\_ki} + \Delta w_{1\_ki}$$

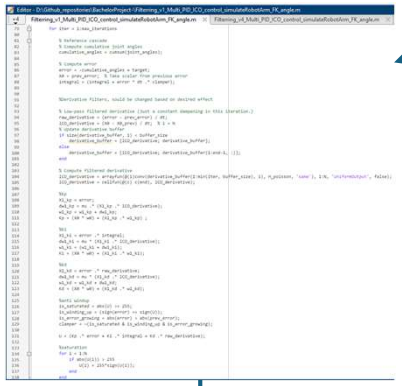
$$X_{1\_kd}[n] \leftarrow error[n] \cdot \Delta error[n]$$
$$\Delta w_{1\_kd} \leftarrow \mu \cdot X_{1\_kd}[n] \cdot \hat{d}_{ICO}[n]$$
$$w_{1\_kd} \leftarrow w_{1\_kd} + \Delta w_{1\_kd}$$

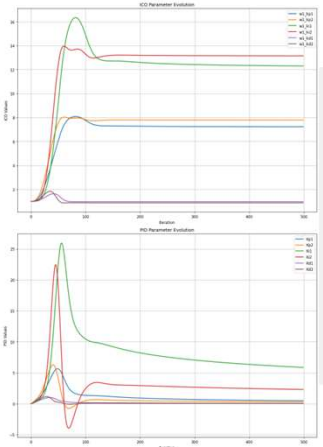
12: Compute PID-gain parameters:

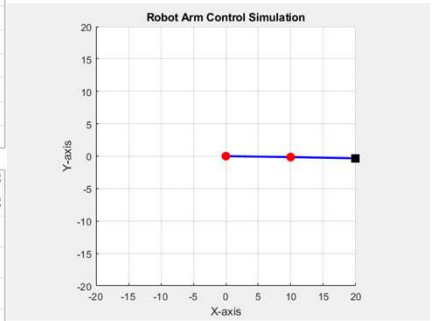
$$K_p \leftarrow w_0 \cdot X_0[n] + w_{1\_kp} \cdot X_{1\_kp}[n]$$
$$K_i \leftarrow w_0 \cdot X_0[n] + w_{1\_ki} \cdot X_{1\_ki}[n]$$
$$K_d \leftarrow w_0 \cdot X_0[n] + w_{1\_kd} \cdot X_{1\_kd}[n]$$

13: **end for**

Simulation Environment Implementation

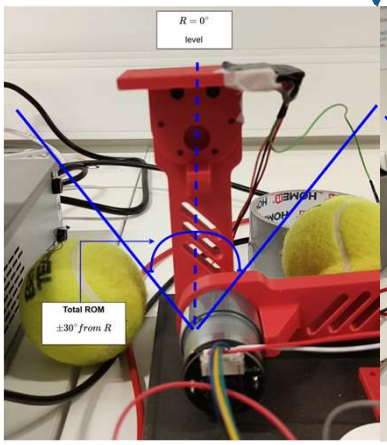


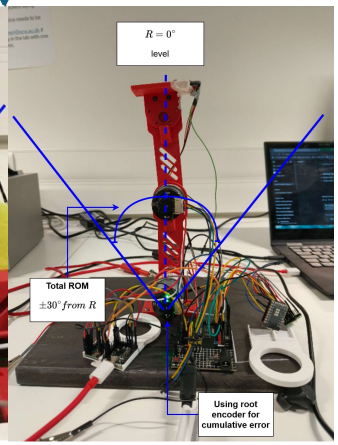




Hardware Environment Implementation

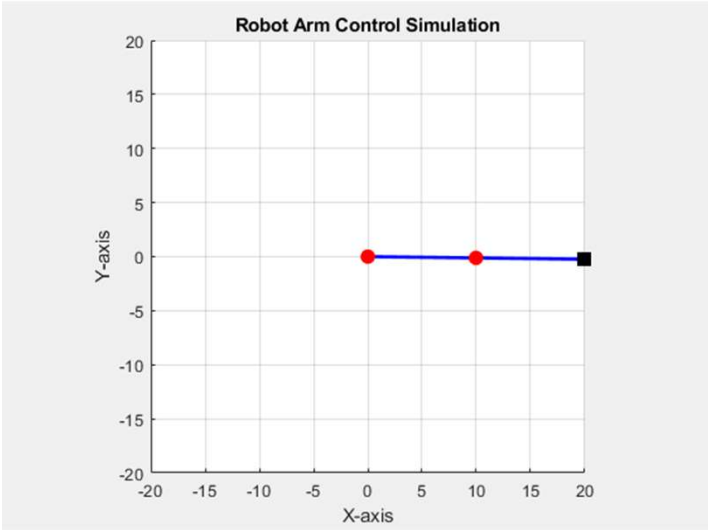
Design Test Criteria



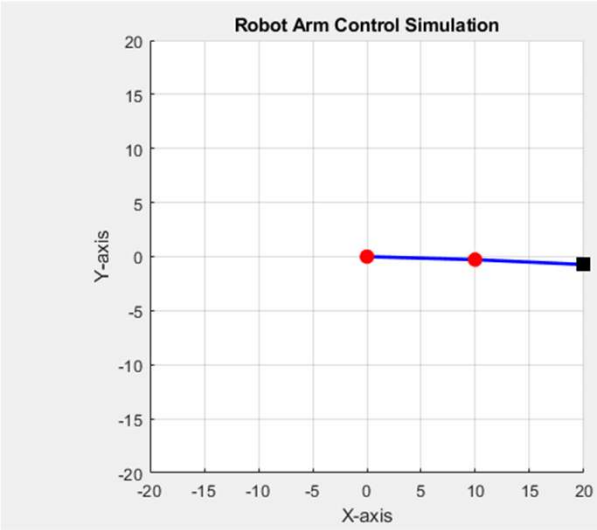


Results - Simulation

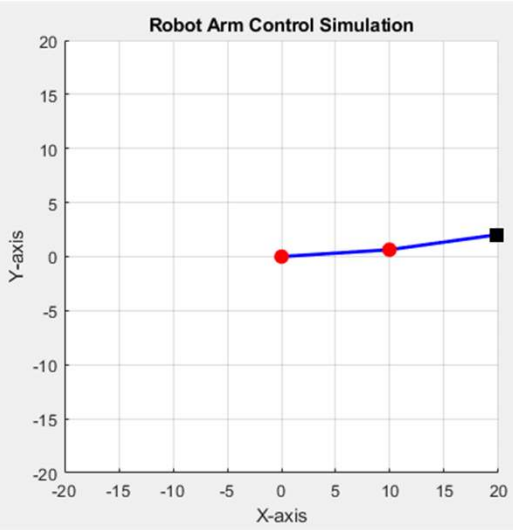
S3.3



S8.3

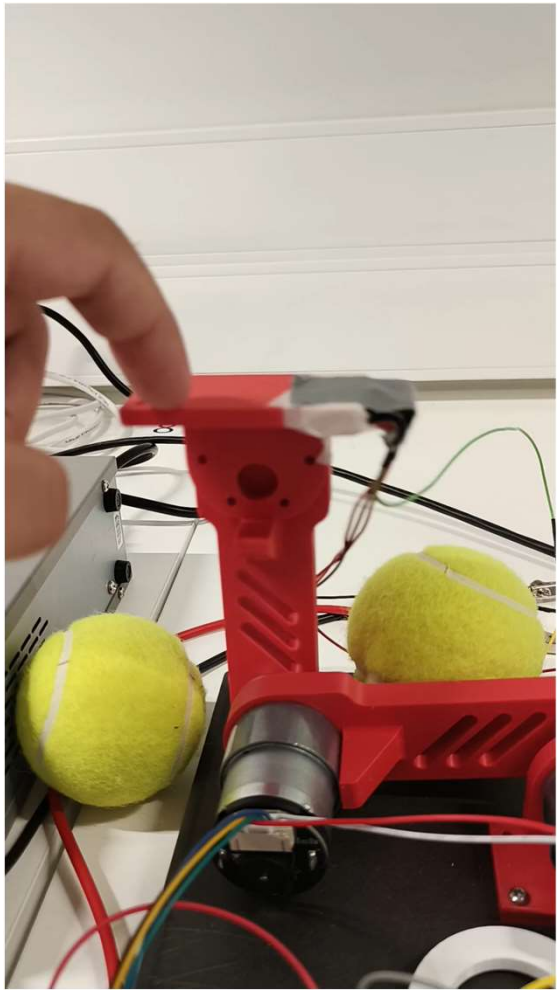


S9.3



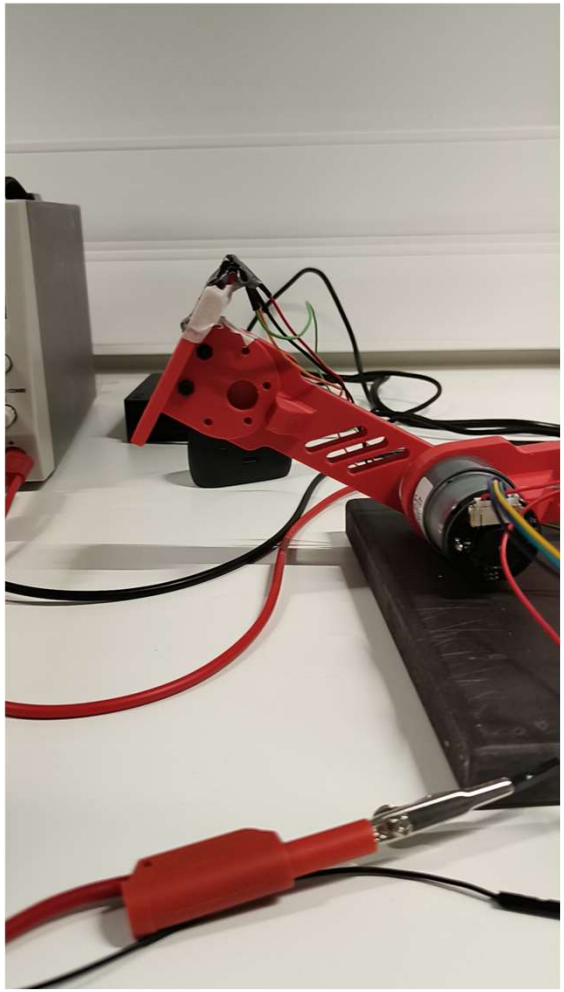
Results - Embedded System

Additional Test 1



MS.2

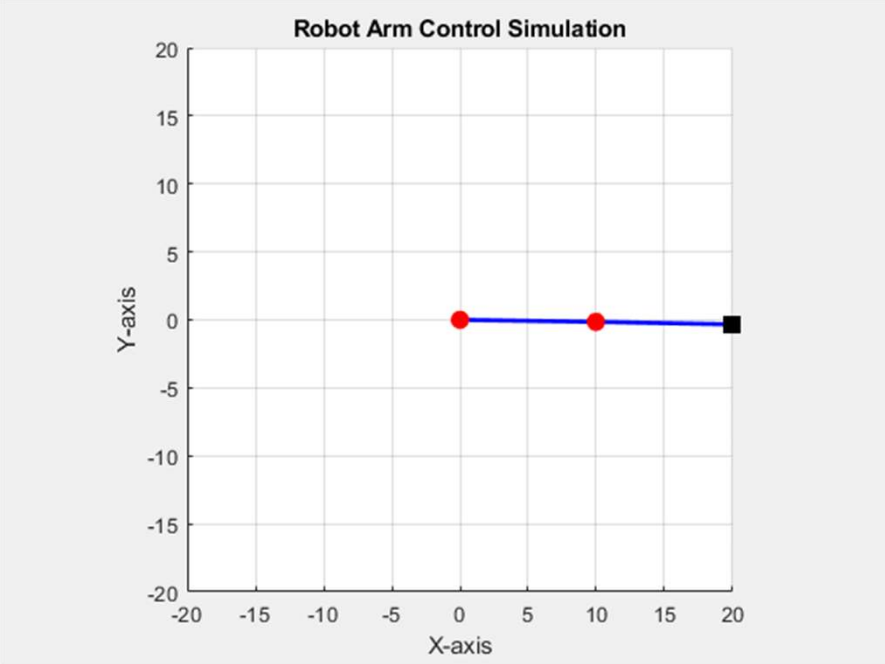
Additional Test 3

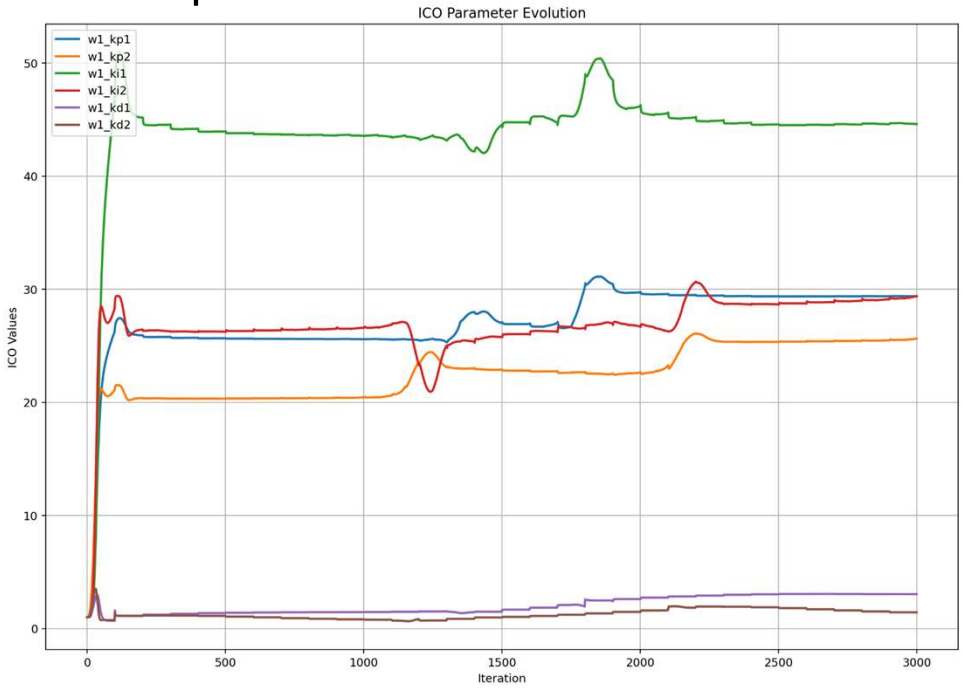


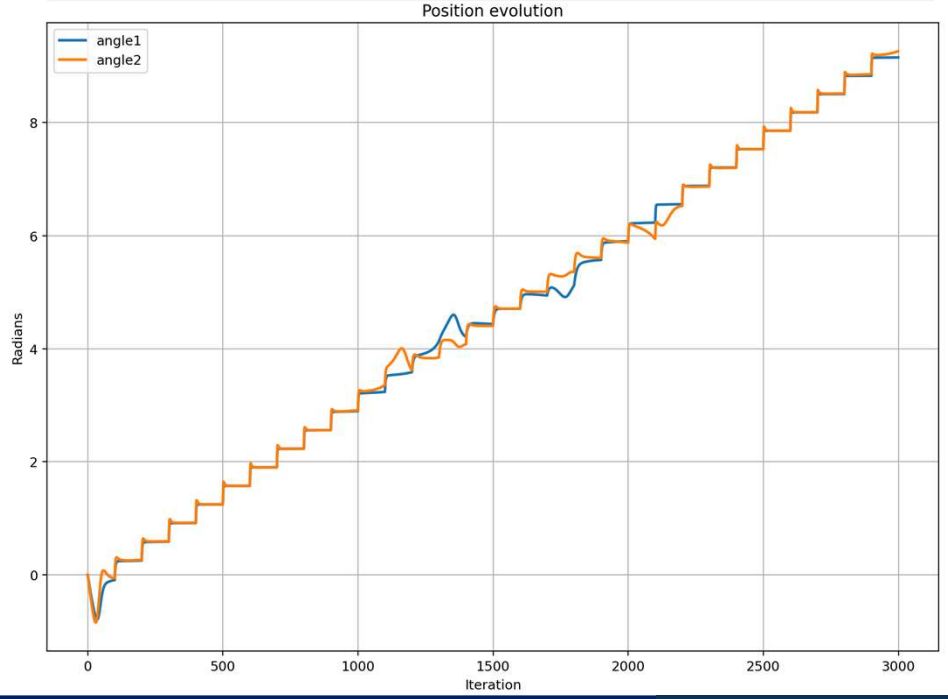
Results - An Added Insight

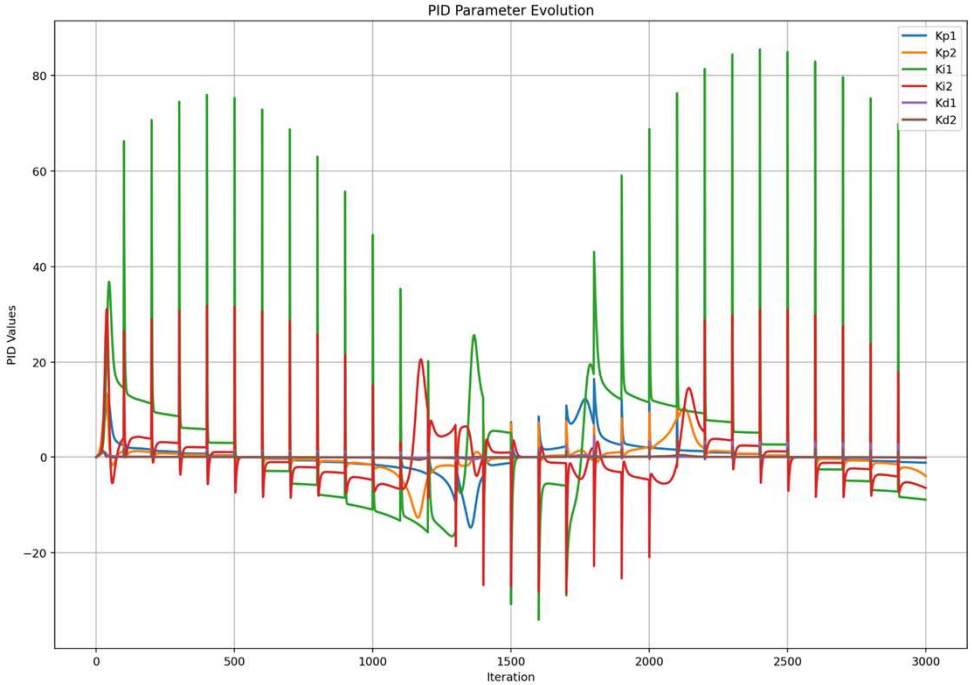
$\mu = 0.1,\ dt = 0.1\ s$

Analog Clock Example





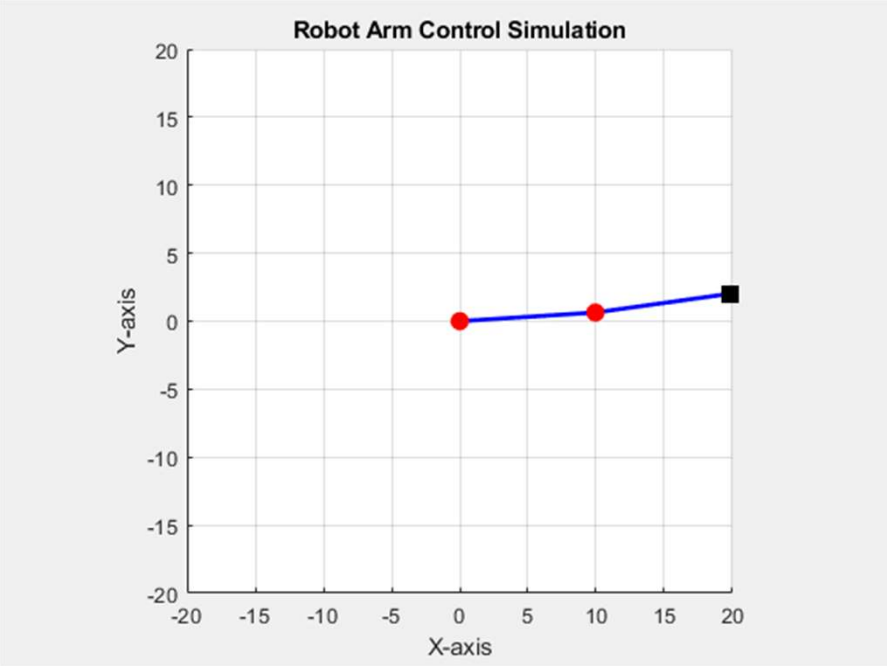


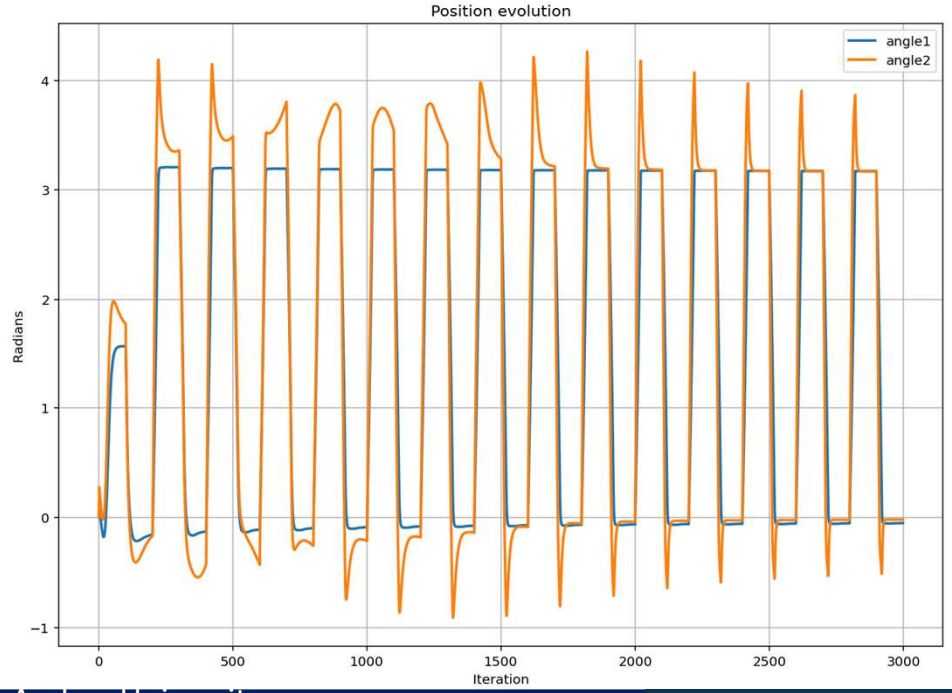


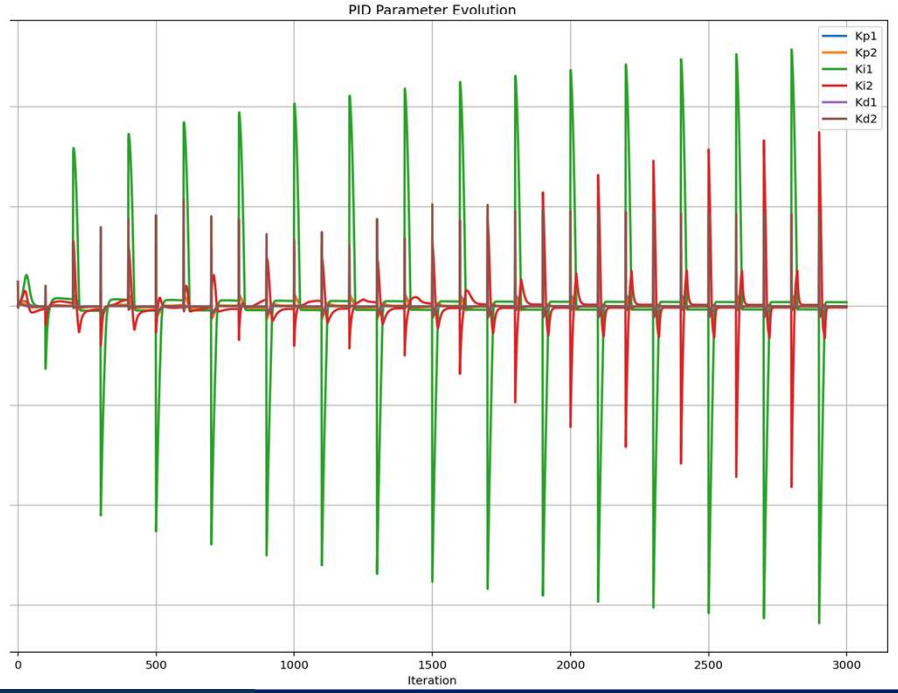
Results - An Added Insight

$\mu = 0.1,\ dt = 0.1\ s$

Metronome Example

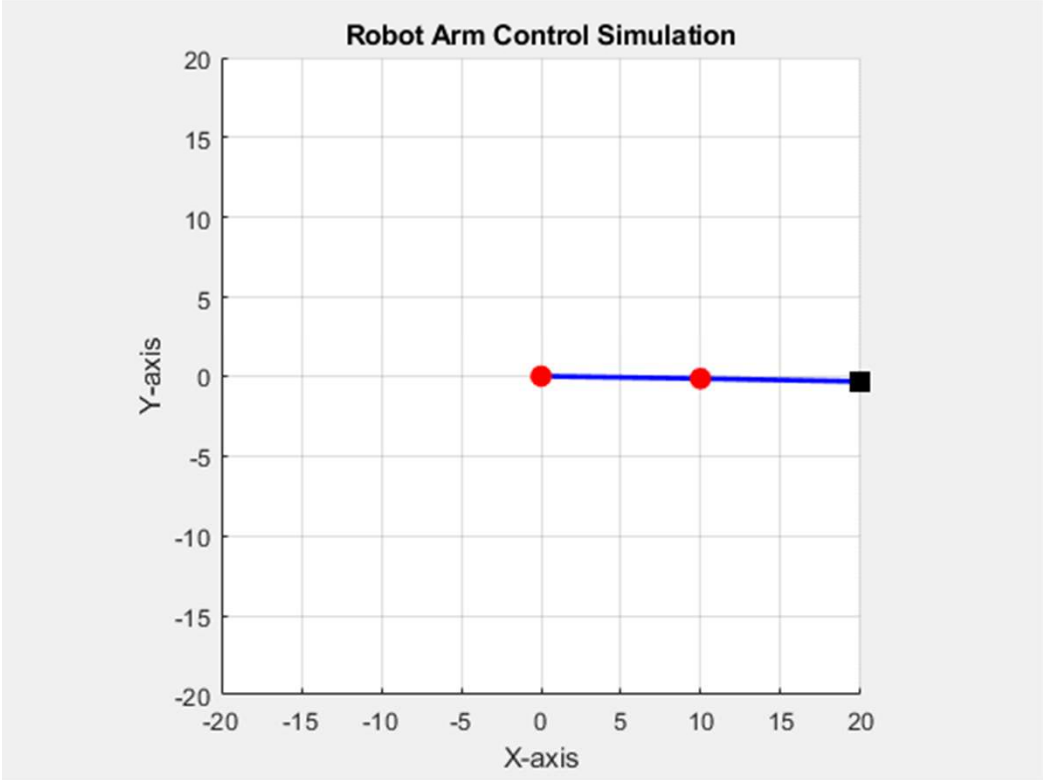


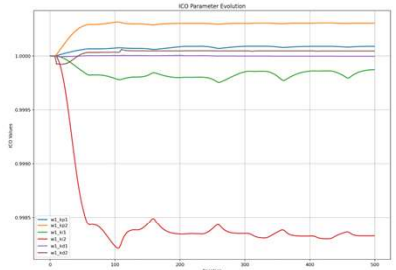


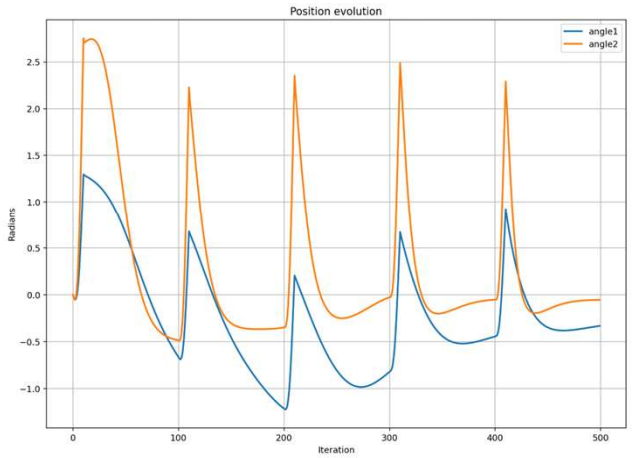


Results - An Added Insight

Untrained:

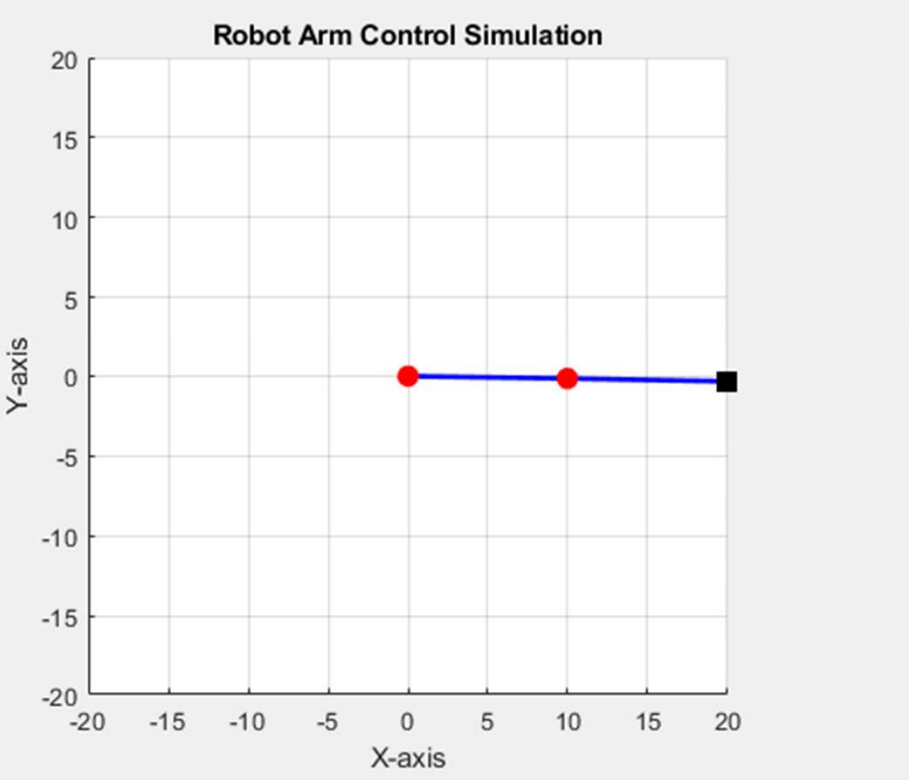


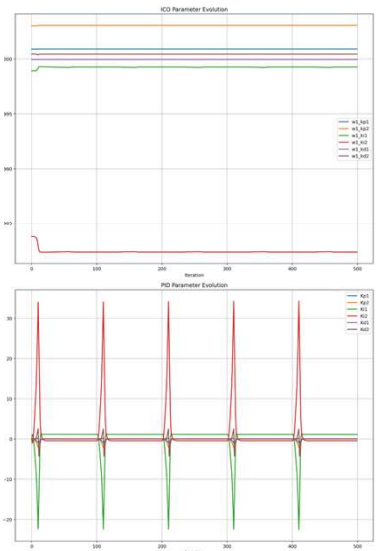


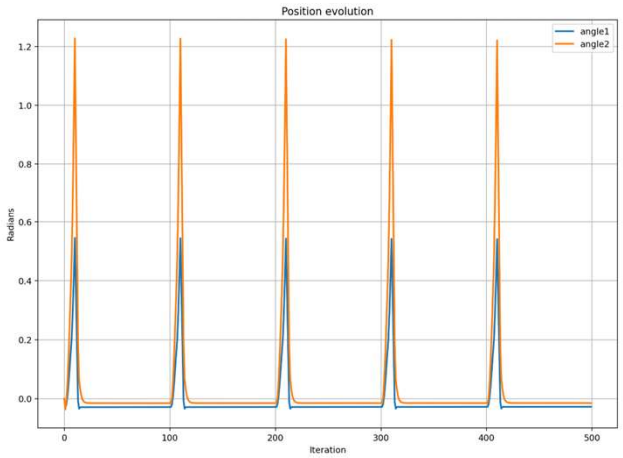


$\mu = 0.0001,\ dt = 0.1\ s$

Trained for 10000 iterations (16 min 40 s):







$\mu = 0.0001,\ dt = 0.1\ s$

Discussion

- Is ICO-PID capable of adapting PID-gain parameters?
  - Adapting to disturbances and gravitational non-linearities?
- Is filtering needed?
  - Working as intended?
- Computation cost efficient compared to other PID auto tuning algorithms?
  - Intelligent control?
- Implementation feasible?
  - Calibration sequence?
  - Necessity for offline training?

Future Work

Hardware:

- Create an embedded system capable of experiencing the full effect of the nonlinear dynamics
- Testing and deployment on multiple arms

Software:

- Develop a standard framework for saving and reapplying states from previous sessions
- Test in alternate nonlinear environments and assert feasibility

References

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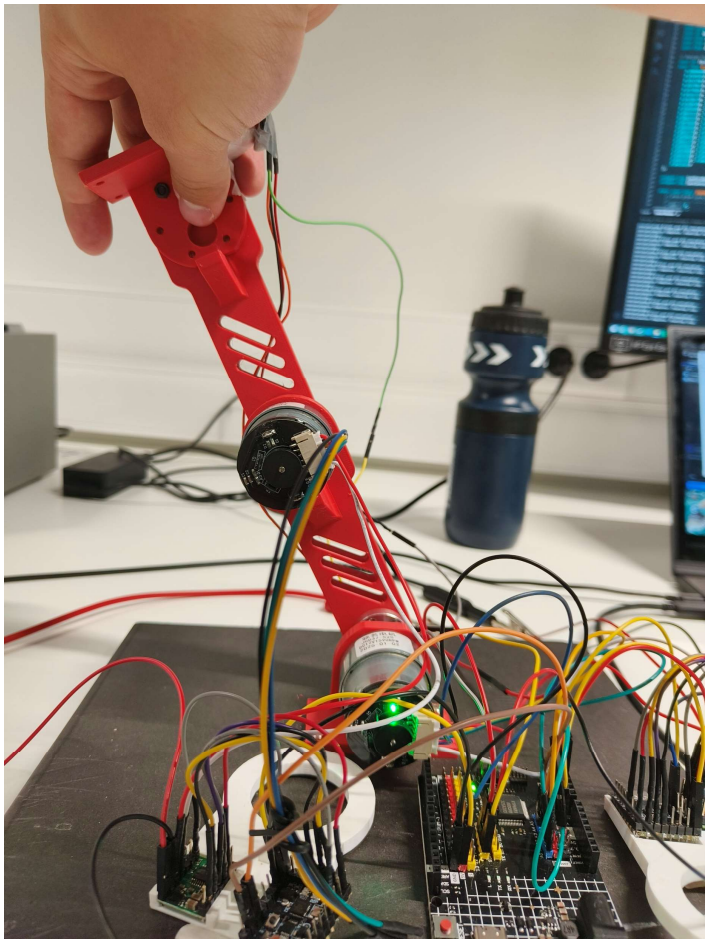
Max physically feasible angle of motor:



DS.1: