IE415: Control of Autonomous Systems

Tuning PID Controllers Using TD3 Reinforcement Learning for Nonlinear Systems

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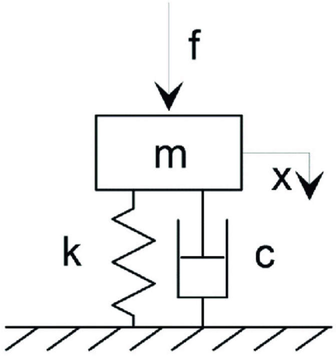
I. System Modeling (Equations and Dynamics)

The system used for this project is a **mass-spring-damper system**, which models real-world dynamic systems such as car suspensions. The dynamics are governed by the second-order differential equation:

$$mx'' + cx' + kx = F$$



Where:

- m: Mass (kg).
- c: Damping coefficient (N·s/m).
- k: Spring constant (N/m).
- F: External force applied to the system.

In this project:

- The **state variables** are the position (x) and velocity (x').
- The **control objective** is to stabilize the system with minimal overshoot and fast settling time by tuning the PID parameters (KP, KI, KD).

II. Control Strategies

PID Control:

- Proportional, Integral, and Derivative (PID) controllers are widely used for their simplicity and robustness.
- The controller computes the control input based on:

$$u(t) = K_P e(t) + K_I \int e(t)\, dt + K_D \frac{de(t)}{dt}$$

  Where e(t) is the error between the desired setpoint and the actual position.

- However, tuning PID controllers manually for nonlinear systems is challenging, as they struggle with dynamic changes and system nonlinearities.

Reinforcement Learning with TD3:

- **TD3 (Twin Delayed Deep Deterministic Policy Gradient)** is an advanced RL algorithm designed to overcome limitations in earlier methods like DDPG.
- The **RL agent** learns to dynamically optimize PID parameters (KP, KI, KD) by interacting with the system.
- Key TD3 Features:
  - **Clip Double Q-Learning**: Reduces overestimation bias by using two Q-networks.
  - **Target Policy Smoothing**: Adds noise to actions to improve stability.
  - **Delayed Policy Updates**: Ensures more stable learning by updating the policy less frequently.

In this project:

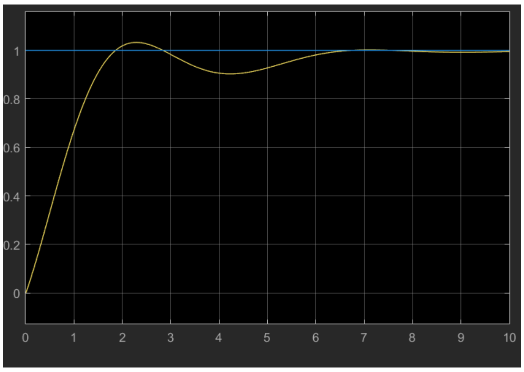
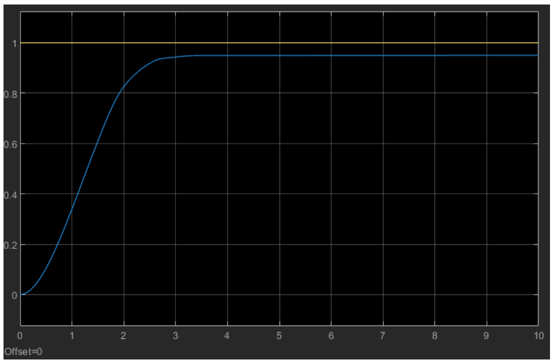
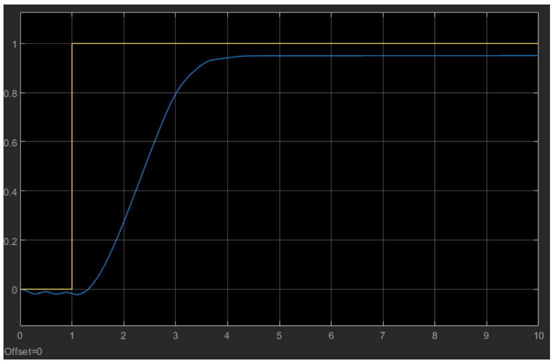
- The RL agent interacts with the mass-spring-damper system through a **Simulink model**.
- The agent receives feedback from the **Observation Block** (PID parameters) and adjusts the control force based on the **Reward Block**, which penalizes overshoot and weak control while rewarding stability.

III. Results Comparison

- **Conventional PID Tuning**:
  - The system shows stability but with significant overshoot and slower settling times.
  - This highlights the limitations of static tuning methods in handling nonlinearities.
- **RL-Tuned PID (TD3)**:
  - The agent, trained over 500 episodes, demonstrates significant improvement:
    - Reduced overshoot.
    - Faster settling time.
    - Smooth transitions with minimal oscillations.
  - Consistent performance is observed under both constant and step input scenarios.

Visual Examples:

- In comparison simulations:

Grid	Conventional PID causes oscillations and slower responses	RL-Tuned PID achieves stability faster and avoids oscillations entirely
Graph		 

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IV. References

1. **"Tuning of PID Controllers Using Reinforcement Learning for Nonlinear Systems Control" -** Gheorghe Bujgoi and Dorin Sendrescu
2. **Simscape Model From Matlab's Community File Exchange -** [LINK]
3. **MATLAB and Simulink documentation**
4. **Reinforcement Learning Onramp**