

# Konstantinos Spiliotopoulos

## Engineering Portfolio

Electro-Mechanical Systems | Control | Embedded Systems | AI

*Mechanical Engineer focused on the modeling, control, and implementation of electro-mechanical systems. Experience includes real-time embedded control, motor drives, physics-informed machine learning, and AI-based decision layers for energy systems.*

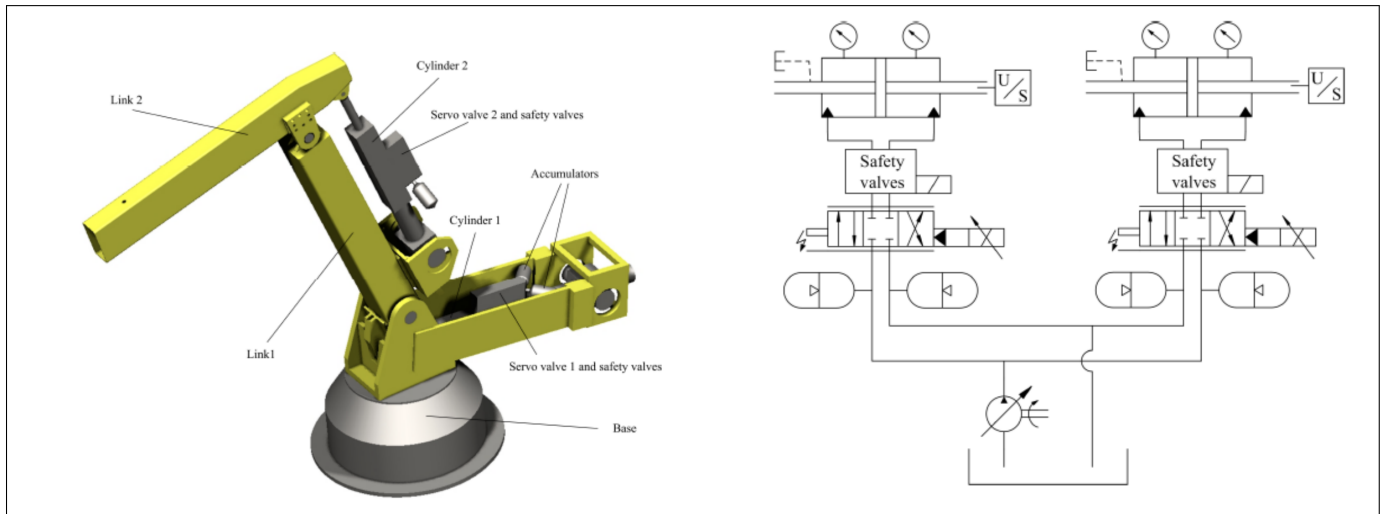
### Selected Projects

- Model-Based Control of a Hydraulic Robot Arm
- PMSM Field-Oriented Control with SVPWM on STM32
- Physics-Informed Modeling with Lagrangian Neural Networks
- AI-Based Regenerative Braking Control for Electric Vehicles
- Embedded Analog Control using ADC, PWM, and UART

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## Model-Based Control of a Hydraulic Robot Arm

*Objective: Design and validate model-based controllers capable of accurate trajectory tracking for a hydraulically actuated robot under real physical constraints.*



### Technical Contribution

- Developed a coupled mechanical–hydraulic dynamic model and linearized it around a physically meaningful operating point for control design.
- Designed and tuned P/PI/lead position controllers with polynomial trajectory generation to balance tracking accuracy and actuator limitations.
- Validated performance in simulation and on the laboratory robot, introducing feedforward and filtering to address hydraulic delays and coupling.

### Results

- Accurate tracking of square and circular trajectories with stable closed-loop behavior.
- Feedforward + filtering significantly reduced tracking error and improved responsiveness.

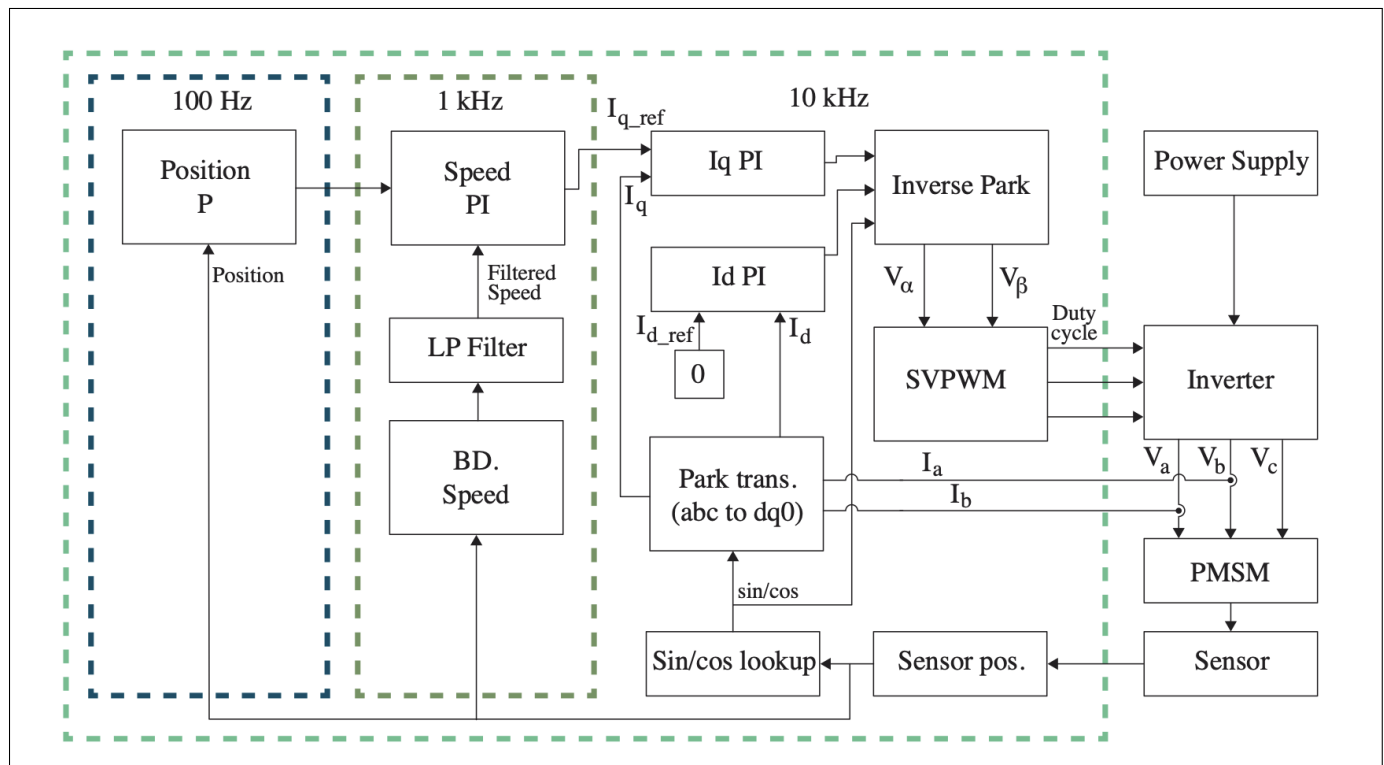
### Key Engineering Insights

- The choice of model structure and linearization point has a larger impact on real-system performance than controller order.
- Why feedforward compensation can matter more than increasing controller complexity.

Simulation	Mean error [mm]	Max error [mm]
P1	48.34	101.50
P1 - FFF	9.14	24.10
P2 - FFF - PF	5.05	11.12
PI1	38.87	78.60
PI1 - FFF	5.54	17.58
PI2 - FFF - PF	3.49	7.86
PI-Lead1	28.97	57.64
PI-Lead1 - FFF	4.25	12.95
PI-Lead2 - FFF - PF	4.26	9.21

# Permanent Magnet Synchronous Motor Field-Oriented Control with Space Vector Pulse Width Modulation (SVPWM) on STM32

*Objective: Implement a real-time motor control solution on embedded hardware, replacing a basic drive with a high-performance field-oriented control strategy.*



## Technical Contribution

- Implemented FOC with SVPWM on an STM32-based motor drive platform with synchronized ADC sampling and multi-rate control loops.
- Built cascaded current, speed, and position loops using encoder feedback, respecting real-time execution constraints.
- Tuned controllers and optimized implementation to ensure deterministic timing and stable operation.

## Results

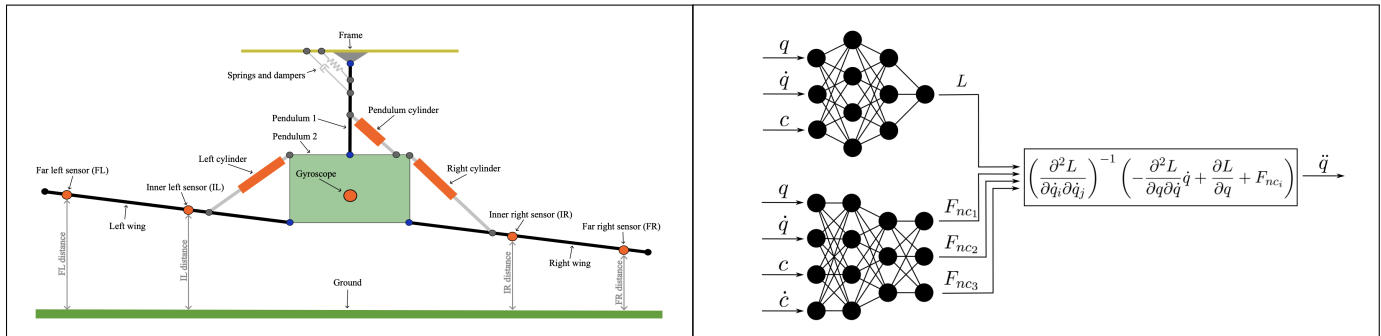
- Stable current regulation and smooth low-speed operation with reliable embedded execution.
- Demonstrated improved controllability compared to the replaced DC motor setup.
- Low-speed stability

## Key Engineering Insights

- Practical timing constraints of ADC–PWM synchronization and their impact on current control.
- How sensing quality and filtering influence torque ripple and speed stability.

# Physics-Informed Modeling with Lagrangian Neural Networks

*Objective: Learn physically consistent system dynamics from data by embedding neural networks directly into Euler–Lagrange formulations.*



## Technical Contribution

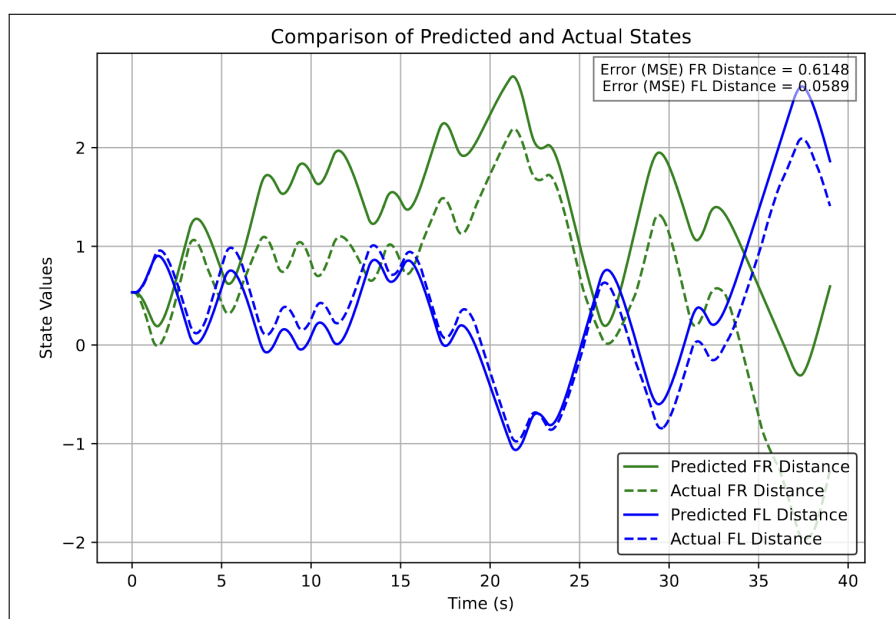
- Implemented a Generalized Lagrangian Neural Network (GLNN) framework in which neural networks parameterize the Lagrangian and non-conservative forces within Euler–Lagrange dynamics.
- Designed the training pipeline in JAX using automatic differentiation, state normalization, and rollout-based evaluation.
- Evaluated generalization under varying excitation profiles and state/input selections to assess robustness.

## Results

- Learned physically consistent dynamics with accurate short-horizon predictions on unseen trajectories.
- Adding dissipation modeling improved stability and realism compared to energy-only learning.

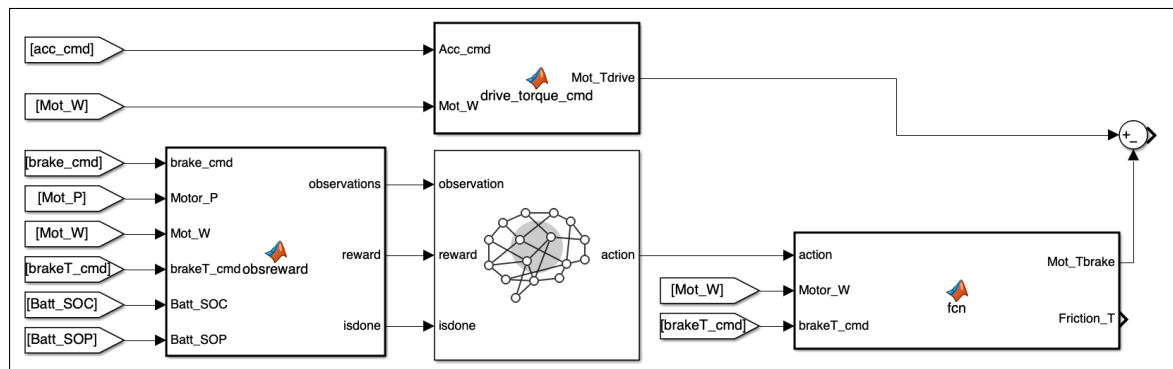
## Key Engineering Insights

- Physical structure improves generalization and stability compared to black-box models, especially under limited excitation.
- Key practical sensitivities: normalization, rollout error accumulation, and state design.



# AI-Based Regenerative Braking Control using Reinforcement Learning (RL)

*Objective: Maximize regenerative energy recovery during braking while respecting physical, safety, and battery power constraints.*



## Technical Contribution

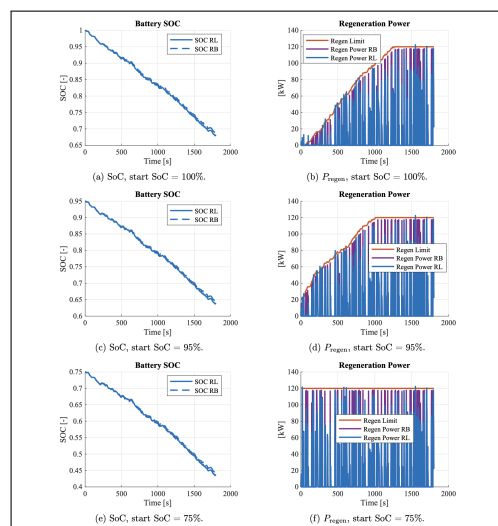
- Formulated the torque split between regenerative and friction braking as a continuous RL problem to handle nonlinear efficiency and battery power constraints.
- Built a Simulink EV braking environment including motor efficiency maps and State-of-Power limits.
- Trained a Deep Deterministic Policy Gradient (DDPG) agent with reward shaping and benchmarked performance against a rule-based strategy.

## Results

- Increased regenerative energy recovery while meeting braking demand and respecting SoP limits.
- Produced clear RL vs baseline comparisons using energy and SoC evolution metrics.

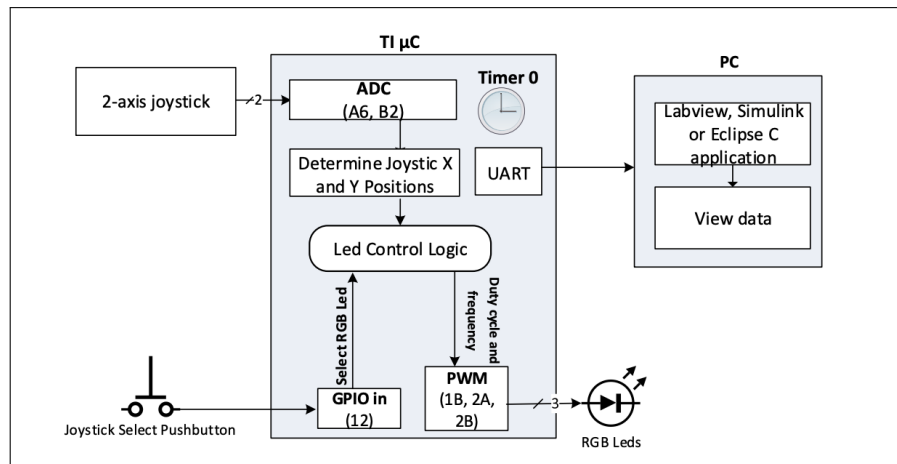
## Key Engineering Insights

- How reward design and constraint handling determine stability and usefulness of learned policies.
- RL is most effective as a decision layer on top of a physics-based model, rather than as a replacement for system dynamics.



## Analog Joystick Control of RGB LEDs (ADC, PWM, UART)

*Objective: Design a structured embedded application integrating analog sensing, real-time control, and communication using standard microcontroller peripherals.*



### Technical Contribution

- Designed a structured embedded software architecture separating sensing, control, and communication tasks.
- Implemented LED channel selection via interrupt-driven pushbutton logic.
- Transmitted joystick and PWM data to a PC via UART at 10 Hz for monitoring.

### Results

- Real-time analog control of LED intensity (0–100%) and blinking frequency (10 Hz–1 kHz).
- Stable peripheral integration with periodic communication and interrupt-driven selection.

### Key Engineering Insights

- How to structure interrupt-driven embedded code with mixed-rate tasks (fast sampling vs slow comms).
- Practical scaling, timing, and stability issues when mapping analog inputs to control outputs.