

Ph.D. DISSERTATION DEFENSE

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Date:	Thursday, October 22 nd , 2026
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Title:	Dynamics-Informed Reinforcement Learning for Adaptive Control of Nonlinear Dynamical Systems
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ABSTRACT

Many engineering systems, including robotic systems and ocean wave energy devices, exhibit nonlinear dynamics that make reliable control challenging. These nonlinearities can cause small changes in operating conditions, system parameters, or initial states to produce substantially different responses, including transitions between distinct stable behaviors. Conventional control methods may require accurate mathematical models or repeated adjustments to accommodate these changes. This dissertation investigates how reinforcement learning (RL), combined with physical understanding, can enable such systems to learn effective control strategies across a range of operating conditions.

The research begins with a nonlinear oscillator that exhibits multiple stable responses, demonstrating how a learning-based controller can guide the system from one response to another. It then develops a dynamics-informed, time-aware RL framework for an inverted pendulum mounted on a moving cart. The controller learns to swing the pendulum upright, recover from disturbances, and maintain balance. By randomizing the control interval during training and explicitly including its duration in the observations, the policy learns to account for how long each control force acts on the system. This time awareness enables the same trained policy to control a broader range of physical configurations without retraining or explicitly observing all system parameters.

The research further examines how traditional model-based control can guide RL to sustain periodic oscillations. These ideas are extended to an ocean wave energy converter, where RL develops control strategies for generating energy under different irregular sea states, including those whose dominant excitation frequencies do not match the device's natural frequency. The learned controller adjusts the power take-off mechanism to improve energy capture across these conditions, while accounting for both extracted energy and energy supplied by the controller to evaluate net generation.

Overall, this dissertation demonstrates the potential of combining physical understanding with reinforcement learning to control nonlinear responses, transfer learned policies across system configurations, and support wave energy generation over a broader range of sea states. The resulting approaches have applications in renewable energy, intelligent machines, and autonomous technologies.