



James Reed

PhD Candidate
North Carolina State University
Department of Mechanical and Aerospace
Engineering
Control and Optimization for Renewables
and Energy Efficiency (CORE) Laboratory

1840 Entrepreneur Dr.
Campus Box 7910
Raleigh, North Carolina, 27695-7910
United States

jcreed2@ncsu.edu
www.mae.ncsu.edu/corelab



Iterative Learning-Based Kite Path Optimization for Maximum Energy Harvesting

James Reed¹, Maxwell Wu², Kira Barton², Chris Vermillion¹

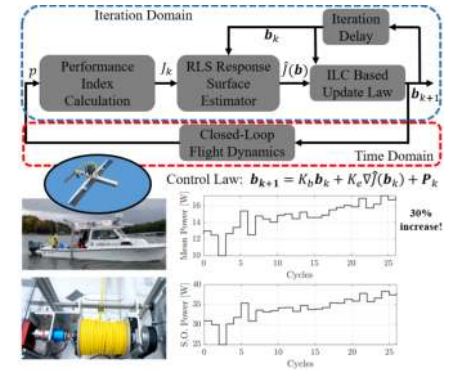
¹North Carolina State University

²University of Michigan

In this work, we have adapted and validated an iterative learning-based basis parameter optimization that optimizes the parameters of a flight path or orientation trajectory for an *airborne wind energy* or *marine hydrokinetic kite system*. This algorithm, first seen in [1] and further developed in [2], was adapted to accommodate parameters that describe target roll and yaw trajectories.

The algorithm consists of two steps that take place after each spool-out/spool-in (“pumping”) cycle of the kite. In the first step, a meta-model is updated using a recursive least squares estimate to characterize an economic performance index as a function of a set of basis parameters (\mathbf{b}_k) that describe either a spatial path or orientation (roll and yaw) trajectory. The second part is an iterative learning update, which uses information from past cycles to update basis parameters at future cycles using a gradient ascent formulation with an added perturbation (\mathbf{P}_k) to push the controller out of local maxima.

While this algorithm can be applied to either airborne or underwater kites, it was experimentally validated on a 1/12th scale experimental prototype underwater kite system towed behind a test vessel in Lake Norman, North Carolina. On top of the iterative learning update, a state machine was used for transitioning from figure-8 cross-current flight when spooling tether out to wings-level flight on spool-in. Furthermore, lower-level controllers were used to track setpoints generated based on the parameters updated by the iterative learning algorithm. Using our experimental system and algorithm, we were able to increase cycle-averaged power by 30 percent, relative to an initial baseline controller.



System diagram, control law, experimental apparatus, and results for an iterative learning-based optimization applied to a kite system. **Diagram:** \mathbf{b}_k are the basis parameters, p are the plant variables, J_k is the performance metric, and $\hat{J}(\mathbf{b})$ is the estimated response surface. **Control law:** K_b and K_g are controller gains and $\nabla \hat{J}(\mathbf{b}_k)$ is the estimated gradient of the response surface. **Results:** Cycle- and spool-out-averaged power are greatly increased.

References:

- [1] M. Cobb, K. Barton, H. Fathy, and C. Vermillion, “Iterative learning-based waypoint optimization for repetitive path planning, with application to airborne wind energy systems,” in 2017 IEEE 56th Annual Conference on Decision and Control (CDC), Dec 2017, pp. 2698–2704.
- [2] M. Cobb, J. Reed, J. Daniels, A. Siddiqui, M. Wu, H. Fathy, K. Barton, and C. Vermillion, “Iterative learning-based path optimization with application to marine hydrokinetic energy systems,” IEEE Transactions on Control Systems Technology, 2021.