Disturbance and Performance-Weighted Economic Iterative Learning Control with Applications to Airborne Wind Energy Systems

Introduction: While wind energy capacity has tripled in the past decade[1], the installation of towered wind energy systems in remote and deep-water offshore locations, as well as the ability to harness wind resources above 100m, is severely limited by tower and foundation constraints.[2] Airborne wind energy (AWE) systems solve this problem by replacing the conventional tower with tethers and a lifting body (usually a kite or wing). Two approaches to AWE systems have been adopted: (i) ground-based generators, where the lifting body is cyclically spooled in and out and power is generated on the ground[3], and (ii) airborne generators, in which the generator is a turbine attached to the lifting body.[2][4] Both technologies possess the potential for vastly increased energy generation through the execution of ***cyclic*** crosswind flight, which results in apparent wind speeds that can far exceed the true wind speed on a high lift/drag lifting body.[2] However, the successful implementation of crosswind flight requires a robust control framework for optimizing the crosswind flight path in the presence of disturbances.

AWE systems executing crosswind flight are one of many control systems that execute ***repetitive (cyclic) motion***, under a ***varying environmental profile***, in order to ***maximize an economic metric*** (average net power output for AWE systems). Iterative Learning Control (ILC) presents a foundation for addressing this problem, allowing the controller to draw from previous iterations to inform decisions at the present iteration. However, traditional ILC techniques focus on ***tracking a prescribed path/trajectory*** in the ***absence*** of an external disturbance that can vary from iteration to iteration, rather than ***optimizing the path itself*** to maximize an economic metric in the ***presence*** of an iteration-varying disturbance. **The proposed research will, for the first time ever, fuse techniques from library-based flexible ILC[5] and optimal control to arrive at a disturbance and performance-weighted ILC (DPW-ILC) framework that**:

- Bases its learning on an economic performance index, rather than setpoint tracking, **and**
- Biases its learning to emphasize previous iterations whose conditions match the present.

Research Plan: The proposed research will focus on a DPW-ILC formulation (Fig. 1), applied to an AWE system executing crosswind flight. This control formulation involves two critical features that occur in the iteration domain, the designs of which will encompass key components of the proposed graduate research:

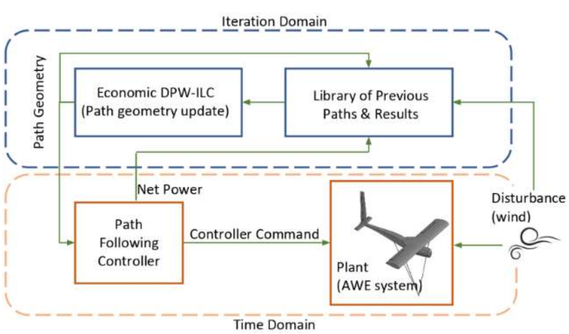

Figure 1. Block diagram of the proposed DPW-ILC control scheme, as applied to an AWE system.

1. Maintaining and managing a library of previous iterations and results: DPW-ILC is predicated upon maintaining a library of relevant previous iterations' selected path geometries, corresponding performance (iteration-averaged power output for the AWE application), and associated measured disturbance (wind speed in the AWE application). As iterations progress, a critical task will involve managing the library size, maintaining those library entries that maximize a statistical measure of information for future ILC updates.

2. Economic DPW-ILC update: The DPW-ILC framework must identify those previous iterations that are ***most relevant*** to the present iteration in terms of having similar disturbance values (wind speed in the AWE application) and favorable performance (iteration-averaged power output in the AWE application). Quantification of a relevance index, which will be informed by related work in higher-order tracking ILC[7][8], will be a significant element in the creation of the DPW-ILC update.

Formal stability and convergence analysis will be performed on the resulting DPW-ILC approaches. In particular, the following general questions will be posed:

- Defining ***regret*** as the difference between the realized and optimal performance, how does long-term ***expected regret*** depend on the statistical properties of the external disturbance (e.g., variance, temporal length scale)?
- How do the aforementioned regret bounds depend on the library size?

These convergence analysis questions also lead to metrics against which designs can be evaluated (for example, a low regret bound that is robust to the library size is highly desirable).

The DPW-ILC approaches will also be experimentally validated on a unique lab-scale, water channel-based platform. In particular, the authors of [8] designed a water channel-based setup for closed-loop flight testing of tethered systems, and [2] verified dynamic scaling between lab scale and full scale conditions. This existing platform, which has to-date been used to characterize AWE designs under constant flow profiles, will be extended to characterize real-world wind profiles, which will be dynamically scaled to the water channel level. Specifically, wind data from a Cape Henlopen, DE wind profiler will be scaled down to the water channel level to create low-frequency, iteration-to-iteration variations for initial validation of DPW-ILC algorithms. After the successful performance of this first round of experiments, high frequency, intra-iteration variation will be applied using wake generation devices upstream of the AWE model.

Intellectual Merit: The DPW-ILC framework pioneered in this research will be the first to fuse economic ILC with library-based higher-order ILC, creating an entirely new avenue of research within the ILC community. Furthermore, the research will result in the first dynamically scaled experimental validation of AWE flight control strategies on a lab-scale platform, under realistic (and also dynamically scaled) wind profiles.

Broader Impacts: The creation of robust, optimized control systems for AWE systems will render wind energy a viable alternative to diesel fuels[4] in remote, off-grid locations and a long-term solution for deep-water offshore locations. Furthermore, the control methodologies created through this research will be applicable to other engineered systems that execute ***repetitive (cyclic) motion***, under a ***varying environmental profile***, to ***maximize an economic metric***. Examples include active exoskeletons, pick-and-place robotic systems operating under variable plant conditions, and even traditional wind turbines.

[1] AWEA. https://www.awea.org/wind-101/basics-of-wind-energy/wind-facts-at-a-glance. [2] Cobb, M. et. al., "Lab-Scale Experimental Characterization and Dynamic Scaling Assessment for Closed-Loop Crosswind Flight of Airborne Wind Energy Systems" *ASME J. Dyn. Sys.,* '17. [3] Fagiano, L. et. al.,"High-Altitude Wind Power Generation," *IEEE T. Egy. Convers.*, Vol. 25, No. 1, '10. [4] Altaeros, Inc., http://www.altaeros.com/.
[5] Hoelzle, D. et. al., "Flexible iterative learning control using a library based interpolation scheme," *51st IEEE CDC.* [6] DiMarco, C., et. al., "Disturbance & Performance-weighted Iterative Learning Control with Application to Modulated Tool Path-based Manufacturing," *ASME DSCC '16.* [7] Cobb, M., et al, "Iterative Learning-Based Waypoint Optimization for Repetitive Path Planning, with Application to Airborne Wind Energy Systems," *56th IEEE CDC*. [8] Deodhar, N. et. al., "Laboratory-Scale Flight Characterization of a Multitethered Aerstat for Wind Energy Generation," *AIAA Jnl., Vol. 55, No. 6, 2017.*