# PI and PD type Iterative Learning Control Laws for Application in Wind Farms

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# Outline

# Co-workers

- Weronika Nowicka — PhD thesis: Iterative Learning Control for Load Management in Wind Turbines with Smart Rotor Blades, University of Southampton, June 2020.
- Owen Tutty — Professor of Fluid Mechanics, School of Engineering, University of Southampton.
- Bing Chu — Associate Professor, School of Electronics and Computer Science, University of Southampton.

# ILC Basics

- Applicable to systems that repeat the same finite duration task over and over again.
- Each repetition is known as a trial (or iteration or pass) and its duration is known as the trial length.
- Notation for discrete variables: $h_i(p)$, $0 \leq p \leq \alpha - 1$.
- $h$ – vector or scalar valued variable under consideration, $i \geq 0$ — **trial number**, $\alpha < \infty$ — **number of samples along the trial**.

# ILC Basics

- Let $r(p)$ be the specified **reference trajectory**.
- Then the **error on trial** $i$ is

$$e_i(p) = r(p) - y_i(p),\ 0 \leq p \leq \alpha - 1, i \geq 0$$

- Error convergence from trial-to-trial $(i)$ is a fundamental consideration in ILC design.
- Performance along the trials is also a critical consideration.

# ILC Basics

- **ILC Design Problem**
- Construct a control input sequence $\{u_i\}_i$ such that
- $$\lim_{i\to\infty} ||e_i|| = 0 \;\&\; \lim_{i\to\infty} ||u_i - u_\infty|| = 0$$
- $u_\infty$ is termed the **learned control**.
- $||\cdot||$ – an appropriate norm.
- **Basic ILC Design Philosophy:** use **previous trial data to update the control signal for the next trial and thereby improve performance from trial-to-trial.**

# ILC Basics

- Typical ILC control law: control input on trial $i+1$ is that used on the previous trial plus a 'correction' based on previous trial data, i.e.,

$$u_{i+1}(p) = u_i(p) + \Delta(e_i(p))$$

- $\Delta(e_i(p))$ is the correction term.
- **Key issue:** how to design $\Delta(e_i(p))$?
- **Phase-Lead ILC Law**

$$u_{i+1}(p) = u_i(p)+\beta e_i(p+1) = u_i(p)+\beta(r(p+1)-y_i(p+1)) \tag{1}$$

# ILC Design

- 'Phase-Lead' refers to the shift in $p$ — can be implemented as the term concerned is generated on the previous trial.
- **PD Type ILC law**:

$$u_{i+1}(p) = u_i(p) + k_p e_{i+1}(p+1) + k_d[e_i(p+1) - e_i(p)] \quad (2)$$

- Sometimes referred to as a 'non-causal' ILC law due to the $p+1$ index in these two laws.
- Many other versions exist.

# ILC Design

- **Fact:** If there is no non-causal term in an ILC law then an equivalent feedback control loop exists.
- Two general approaches to design – one is based on assembling the values of a variable along the trial into a column vector. **Known as lifting ILC design** in the literature.
- **Second method – treat ILC as a** 2**D system**, i.e., information propagation from trial-to-trial ($i$) and along the trials ($p$).
- One starting point for the early literature: Douglas A Bristow and Maria Tharayil and Andrew G. Alleyne (2006). A survey of iterative learning control. IEEE Control Systems Magazine 26(3), 96–114.

# Progress So Far

- Very significant progress for systems described by deterministic linear time-invariant dynamics, including robust designs.
- A very high level of at least experimental validation.
- New applications continue to emerge — including outside engineering.
- Personal view — applications are now in the driving seat.

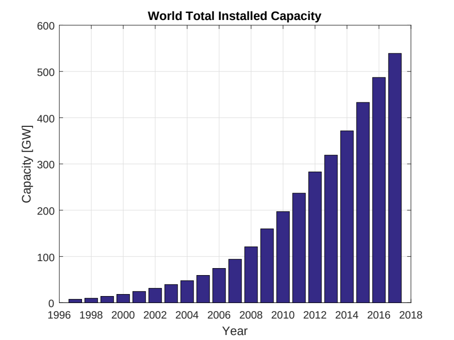
# Progress So Far

- Stochastic linear dynamics — some progress, e.g.,
- Repetitive Process based Stochastic Iterative Learning Control Design for Linear Dynamics, Pavel V. Pakshin, Julia Emelianova, Eric Rogers and Krzysztof Galkowski, 2020, Systems and Control Letters, (137), Article 104625.
- Nonlinear systems — (too) many papers on error convergence proofs but some results emerging on design, e.g.,
- Passivity based Stabilization of Repetitive Processes and Iterative Learning Control Design, Pavel Pakshin, Julia Emelianova, Mikhail Emelianov, Krzysztof Galkowski, Eric Rogers 2018, Systems and Control Letters, (122), 101–108.

# (Some) New Areas

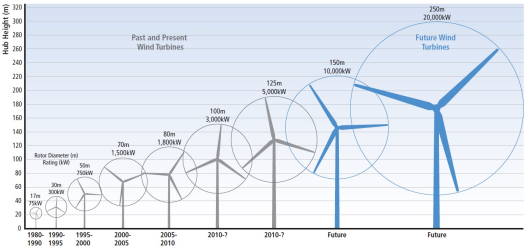
- Distributed Parameter Systems – some work on semi-group approaches and also on constructing a finite-dimensional approximate model for design, e.g.,
- Iterative Learning Control for a Class of Multivariable Distributed Systems With Experimental Validation, Slawek Mandra, Krzysztof Galkowski, Andreas Rauth, Harald Aschemann, Eric Rogers, 2020, IEEE Transactions on Control Systems Technology, Regular paper, DOI 10.1109/TCST.2020.2982612.
- Healthcare — such as robotic-assisted stroke rehabilitation.
- Networked systems.

# Wind Turbine Control




- Blade sizes are also increasing.

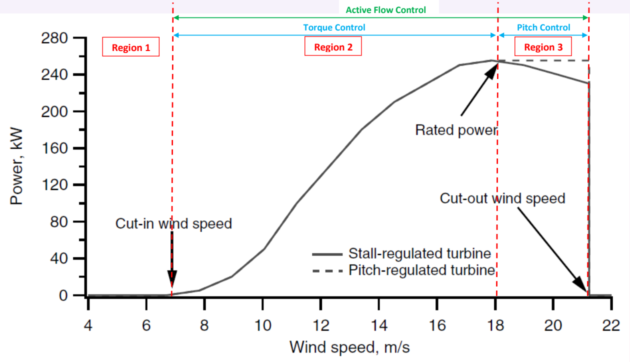
# Wind Turbine Control



# Wind Turbine Control

- Bigger blades imply more energy capture.
- Wind turbine control plays a very important role as it enables a better energy capture together with **alleviation of mechanical and aerodynamical loads and aim for lower maintenance costs.**
- Wind turbine control objectives include improving power production in its safe operating region (below rated wind speed) and preventing the unsafe operation in high wind speeds (above rated speed) by limiting the rotor speed and torque.

# Wind Turbine Control



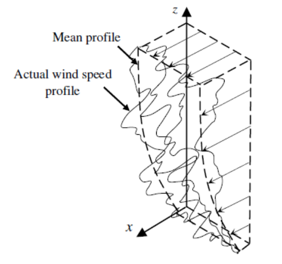
# Wind Turbine Control

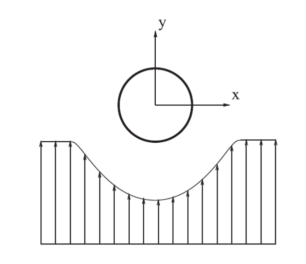
- Wind turbine blades are subject to fluctuating aerodynamic forces involving stochastic and deterministic disturbances.
- The stochastic disturbances occur because of the variable nature of the wind.
- Deterministic forces include the effects of yaw misalignment, stator-rotor interaction and atmospheric boundary layer.
- The load disturbances caused by effects such as wind shear, tower shadow or yaw motion are cyclic as they arise due to the rotation of the rotor.

# Wind Turbine Control

- Wind shear (wind gradient), is a difference in wind speed or direction over a short distance in the atmosphere.
- Precisely, the mean speed increases with height. Moreover, the actual wind speed varies in time and direction at different locations due to turbulence.
- Hence, the **flow past the blade contains a periodic component which becomes even larger as these effects increase.**

# Wind Turbine Control

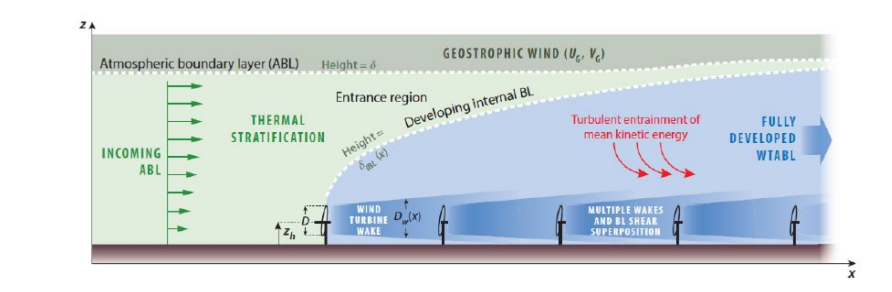



- Left: wind speed profile, right: tower shadow.
- Tower shadow effect is the alteration in uniform flow of wind due to the presence of the tower. For an upwind turbine, when the blade is directly in front of the tower, it experiences minimum wind.

# Wind Turbine Control

- These problems are compounded in Wind Farms

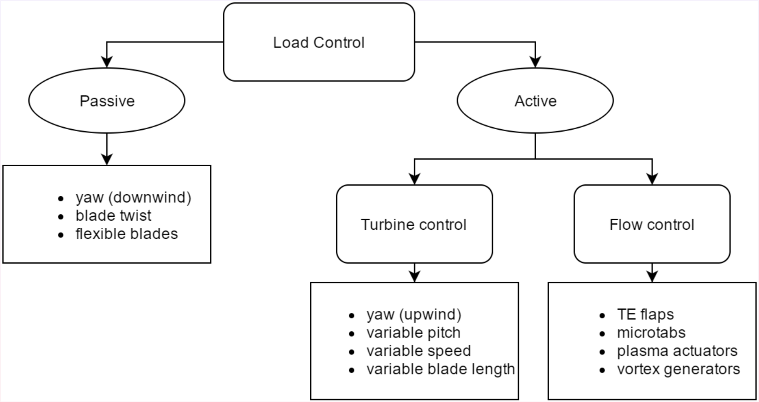



- Various flow phenomena in wind farms.

# Aerodynamic Load Control

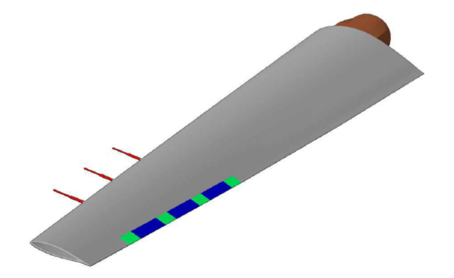
- Aerodynamic load control for wind turbines is directly linked to modification of the lift force on the blades, by e.g.,
  - varying the rotor speed,
  - varying the blade pitch angle,
  - varying the blade length,
  - modifying the blade section aerodynamics – **considered in this research**.
- The modern approach includes more **flexible structures on the blades coupled with control algorithms** — and incorporates devices such as **trailing-edge flaps or microtabs which are called 'smart rotors'.** (Also enables fast actuation).

# Aerodynamic Load Control



# Active Flow Control (AFC)

- AFC devices are placed along the span of the rotor blade (e.g. on the trailing-edge) and act by modifying the local flow and therefore the lift.
- A blade with trailing-edge flaps (blue) and Pitot tubes (red) is shown in this figure.



# AFC Benefits

- AFC devices would react quickly and reduce oscillatory high frequency loads and:
- Increase the blade lift at low wind speeds and therefore allowing an earlier cut-in.
- Enabling the blade to operate on higher lift curve.
- Aerodynamic performance improvement and noise reduction.
- Countering tower shadow every revolution (downwind turbines).

# Flow Model

- A Computational Fluid Dynamics (CFD) panel code is used to simulate the flow past an airfoil.
- The flow over a $2D$ airfoil is simulated and the boundary conditions at the body are satisfied using the panel method.
- The flow is assumed to be inviscid (i.e., zero viscosity (zero resistance to deformation at a given rate)) and extreme cases when separation is provoked are not considered.
- The motion of the **vortices, i.e., flow revolving around an axis** is found by solving the Euler equations (a numerical solution can be found using any time-stepping method, e.g. Runge-Kutta methods).

# Flow Model

- The wake effect (the region of recirculating flow immediately behind a stationary or moving flow) is simulated by releasing vortices from the trailing edge at each time step.
- The lift is calculated from the pressure distribution using the unsteady Bernoulli equation.
- The AFC devices are modelled in a generic manner by altering the strength of the new vortex generated at the trailing edge at each time step.

# Flow Model

- The governing equation for a $2D$ inviscid incompressible fluid is

$$\frac{D\omega}{Dt} = \frac{\partial \omega}{\partial t} + v_x \frac{\partial \omega}{\partial x} + v_y \frac{\partial \omega}{\partial y} = 0 \tag{3}$$

- $D/Dt = \partial/\partial t + v_x \partial/\partial x + v_y \partial/\partial y$ denotes the material derivative
- $\omega = \partial v_y/\partial x - \partial v_x/\partial y$ denotes the vorticity.
- The lift is the output variable and its calculation is based on the fact that the surface of the airfoil is a streamline with the velocity tangential to the surface and the normal velocity equal to zero

# Modeling Smart Devices

- The smart devices are modelled by modifying the circulation generated on the trailing edge.
- In the controlled case, at every time step a new vortex generated from the trailing edge will have a strength

  $$\Gamma_c = u \tag{4}$$

  where $u$ denotes the control input.
- Altering the circulation on the trailing edge modifies the lift and represents devices such as flaps or microtabs which also act by generating vortices or changing the flow on the trailing edge. This is a **generic approach to modeling smart rotors.**

# Model Free ILC Results

- The flow past an airfoil is assumed to be periodic with the velocity equal to

$$V_{0x}(k) = 1 + A\,sin(\frac{2\pi k\Delta t}{T}) \tag{5}$$

where $A$ denotes the amplitude of the oscillation and $T$ denotes the period of turbine's rotation.

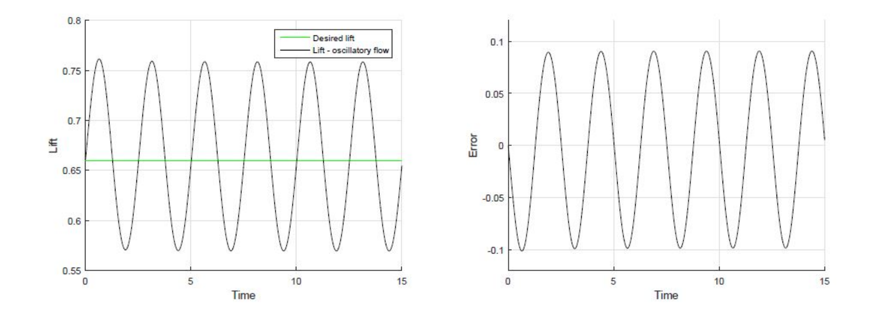
- The discrete version of the signals is used with $k = 0, 1, ..., \alpha - 1$ denoting the step within a cycle and $\alpha = T/\Delta t$ denoting the number of steps in one cycle, where $\Delta t$ is the time step.

# Model Free ILC Results

- The lift obtained for such flow will be periodic and the control objective can be defined as rejecting periodic disturbances by keeping the lift constant.
- This can be achieved by altering the lift on the rotor blades such that the error between the lift and the desired (constant) value for the lift is minimal.
- The error at step $k$ is given by

$$e(k) = L_{ref}(k) - L(k) \tag{6}$$

# Model Free ILC Results




- Lift (left) and error (right) for oscillatory flow with no control.

# Model Free ILC Results

- Two norms are used to measure the performance:
- 2-norm

$$\mathcal{L}_2 = \sqrt{\frac{1}{\alpha} \cdot \sum_{k=1}^{\alpha} (e(k))^2} \tag{7}$$

- (a measure of the error averaged over a trial).
- $\infty$-norm

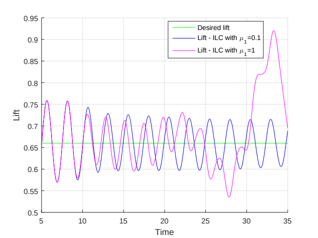
$$\mathcal{L}_\infty = max|e(k)| \tag{8}$$

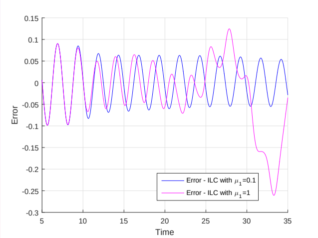
- (a measure of the maximum error).

# Phase-lead ILC

- To reduce the lift fluctuations, consider the phase-lead ILC law

$$u_i(k) = u_{i-1}(k) + \mu_1 \Delta t e_{i-1}(k+\delta) \tag{9}$$




- Lift (left) and error (right) obtained for the system with the ILC controller of Eq. (9).

# Model Free ILC Results

- For $\mu_1 = 0.1$, the 2-norm $\mathcal{L}_2 = 4.2 \times 10^{-2}$ is obtained after 10 trials compared to $\mathcal{L}_2 = 6.7 \times 10^{-2}$ for the no control case.
- The $\infty$ norm is $\mathcal{L}_\infty = 6.7 \times 10^{-2}$ and $\mathcal{L}_\infty = 9.8 \times 10^{-2}$, respectively.
- Other permutations produced no better results (or worse).

# Feedback plus ILC

- Control law

$$u_i(k_t) = u_i(k) + u(k_t) \tag{10}$$

where: $k_t = i\alpha + k$ is the total number of steps, $u_i(k)$ is the ILC update

- $u(k_t)$ and is the proportional controller update given by

$$u(k_t) = \mu_0 \Delta t e(k_t - 1) \tag{11}$$

where $\mu_0$ is the P controller gain.

# Feedback plus ILC

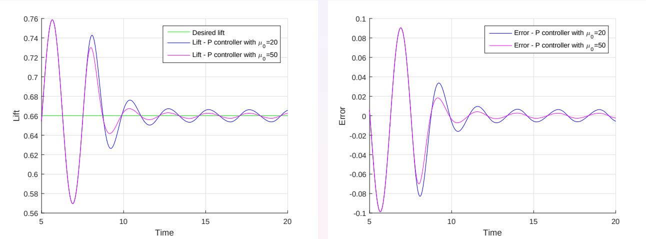



Figure: Lift (left) and error (right) obtained for the system with the ILC controller of Eq. (10)

# Feedback plus ILC

- Better performance — after 5 trials the error is significantly reduced for the choices of $\mu_0 = 20$ and $\mu_0 = 50$
- Over 90% reduction in the $\infty$-norm.
- Further increasing the gain is not possible.
- This last controller is better — as the next figure demonstrates.
- **Note:** actuator dynamics not considered.

# Comparison

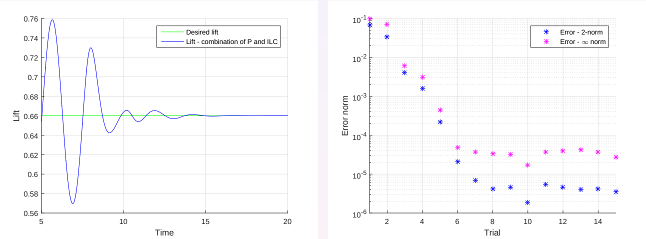



Figure: Lift (left) and error norm (right) obtained for the system controlled by the combination of P and ILC given by Eq. (10)

# Gain Varying ILC law

- $$u_i(k) = u_{i-1}(k) + \mu_1(i)\Delta t e_{i-1}(k+\delta) \qquad (12)$$

  where $\mu_1(i)$ is the function of the trial number.
- Generally gives better results, but more trials needed.
- The results so far are without disturbances.
- Disturbances can be introduced by adding vortices upstream — the next figure shows the results for the case of three added vortices.

# Disturbance Rejection

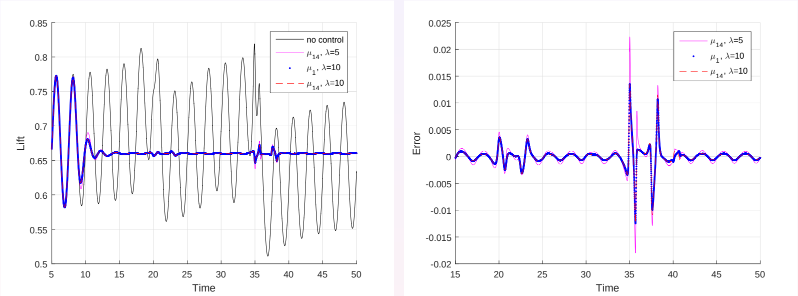



Figure: Robustness test 3 for non-deterministic flow: lift (left) and error (right)

# Conclusions/Further Work

- Progress on model-free ILC design – establishes basic feasibility.
- Development of tuning rules.
- A next step is model-based ILC design – work underway using Proper Orthogonal Decompositions (PODs) for model construction coupled with Norm Optimal ILC.
- Investigation and comparison of various actuators and their locations.
- Comparison with Repetitive Control designs.

# Conclusions/Further Work


- W. Nowicka, "Iterative Learning Control for Load Reduction in Wind Turbines with Smart Rotor Blades", a poster presented at American Control Conference, Boston 2016.
- W. Nowicka, B. Chu, O. Tutty, E. Rogers, "Load Reduction in Wind Turbines with Smart Rotors Using Trial Varying Iterative Learning Control Law", Proceedings of the American Control Conference, pp. 1377–1382, Seattle 2017.
- W. Nowicka, B. Chu, O. Tutty, E. Rogers, "Wind Turbine Aerodynamic Load Fluctuation Reduction Using Model Based Iterative Learning Control", Proceedings of the American Control Conference, pp. 6384–6389, Milwaukee 2018.