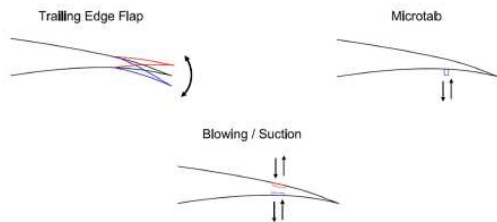


**Abstract for 10<sup>th</sup> UK Conference on Wind Engineering (Professor Tutty, Professor Rogers, Dr Sandberg, Mark Blackwell), 1<sup>st</sup> April 2012**

Currently there is significant research into the inclusion of smart devices in wind turbine rotor blades, with the aim, in conjunction with collective and individual pitch control, of improving the aerodynamic effectiveness and hence energy production.

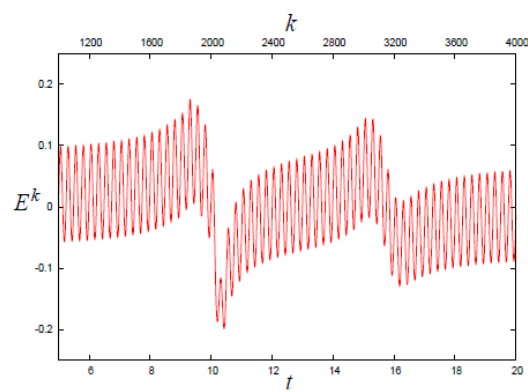
Smart aerodynamic devices, for example trailing edge flaps, microtabs and active vortex generators (see figure left), can be embedded into the blade structure and actively and independently controlled to meet set objectives. This type of control offers the potential to benefit turbine efficiency and reliability, thus increasing blade life and ultimately reducing the cost of energy.



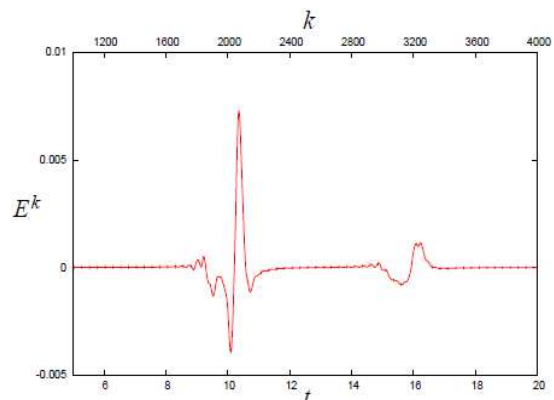
The main objective is to reduce fatigue loads, although mitigating the effects of extreme loads is also of interest. The aerodynamic loads on a wind turbine blade have periodic and non-periodic components, and the nature of these strongly suggests the application of iterative learning control. Wind turbines operate in the atmospheric boundary layer where there is a non-uniform mean velocity profile, and a regular variation in wind speed past the blade throughout a cycle, even in reasonably steady, non-gusting, conditions. Thus the flow past the blade will contain an oscillatory component. This will be more pronounced towards the tip of the blade, where the speed differential will be greatest. Further, in a wind farm, a turbine may be downstream of others, which can also add an oscillatory component to the flow. Unsteady flow conditions (relative to the blade) will cause cyclic loads on the blade, in particular in the lift, which will in turn affect the performance of the turbine. Deterministic disturbances such as repetitive oscillations tend to be easier to mitigate against as their period and magnitude can be relatively easily estimated from other turbine data, (eg. Rotor speed).

This work first presents a simple but realistic computational fluid dynamics model (vortex panel method) to represent flow past a 2D airfoil, and uses this to undertake a detailed investigation into the level of control possible by combining iterative learning control with classical control action with emphasis on how performance can be effectively measured. The vortex model captures linear and non-linear effects in the form of a fluctuating freestream velocity and streamwise vortices passing the blade. The actuator is modelled by allowing a jump in the tangential velocity at the trailing edge rather than applying the Kutta condition. The time series below show some initial results for a specific airflow configuration with 2 vortices (where  $E_k$  = the error between the target lift and the actual lift,  $k$  = time step):

This work first presents a simple but realistic computational fluid dynamics model (vortex panel method) to represent flow past a 2D airfoil, and uses this to undertake a detailed investigation into the level of control possible by combining iterative learning control with classical control action with emphasis on how performance can be effectively measured. The vortex model captures linear and non-linear effects in the form of a fluctuating freestream velocity and streamwise vortices passing the blade. The actuator is modelled by allowing a jump in the tangential velocity at the trailing edge rather than applying the Kutta condition. The time series below show some initial results for a specific airflow configuration with 2 vortices (where  $E_k$  = the error between the target lift and the actual lift,  $k$  = time step):



*Time series of lift error with no control*



*Time series of lift error with control*

Results so far have used the direct lift from the vortex panel method as a control input. For this paper, work is focusing on using pressure sensor arrays to estimate the lift and using this lift estimate as the control input.