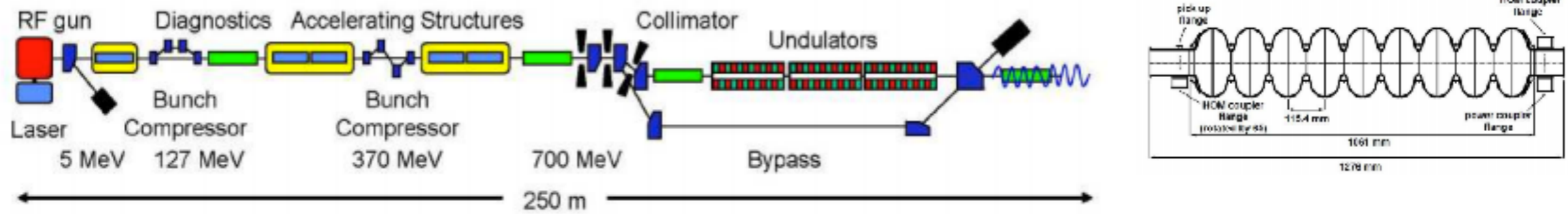


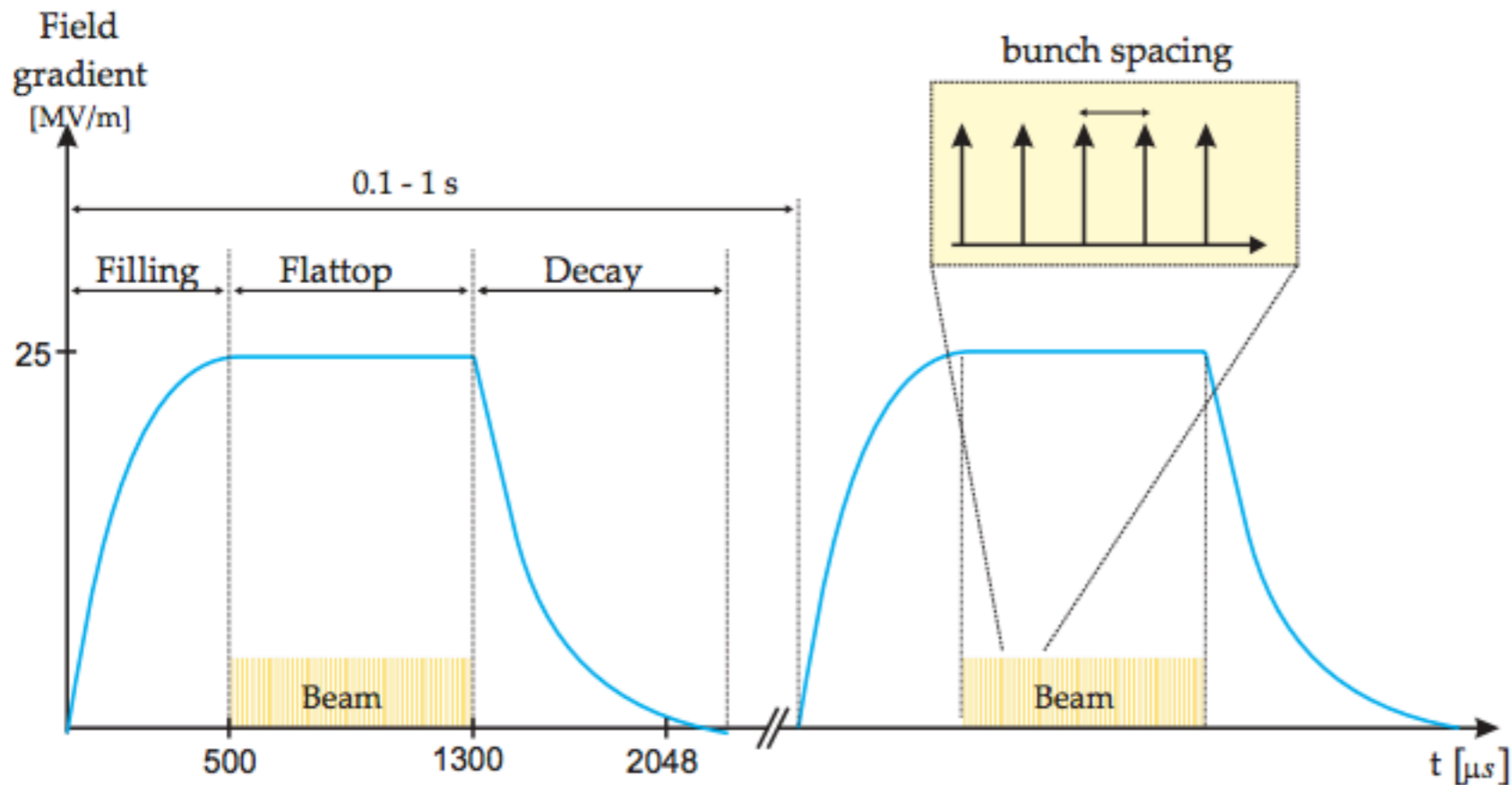
Iterative learning control

(Study of work by Christian Schmidt and others)

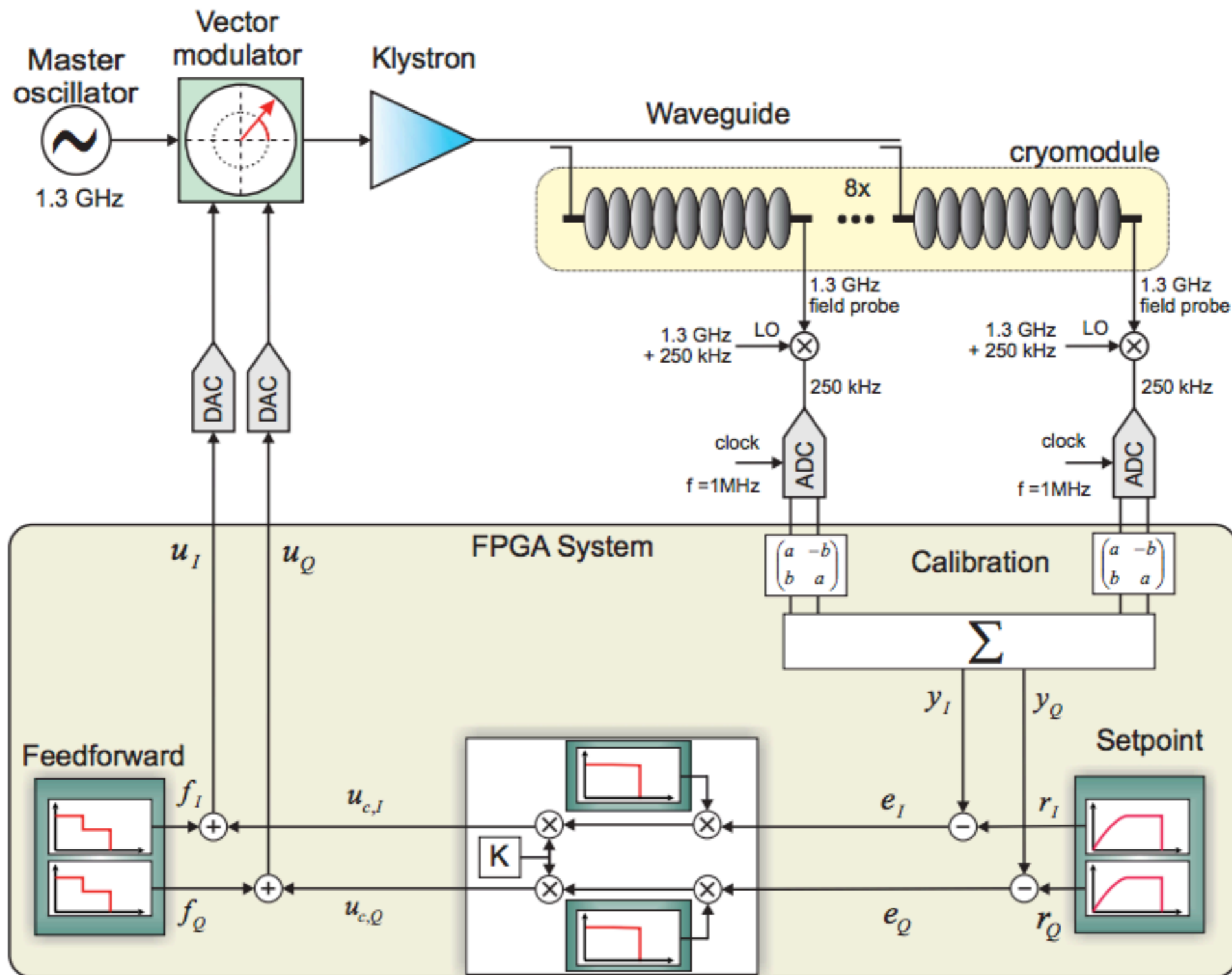
Free Electron Laser in Hamburg (FLASH) at DESY



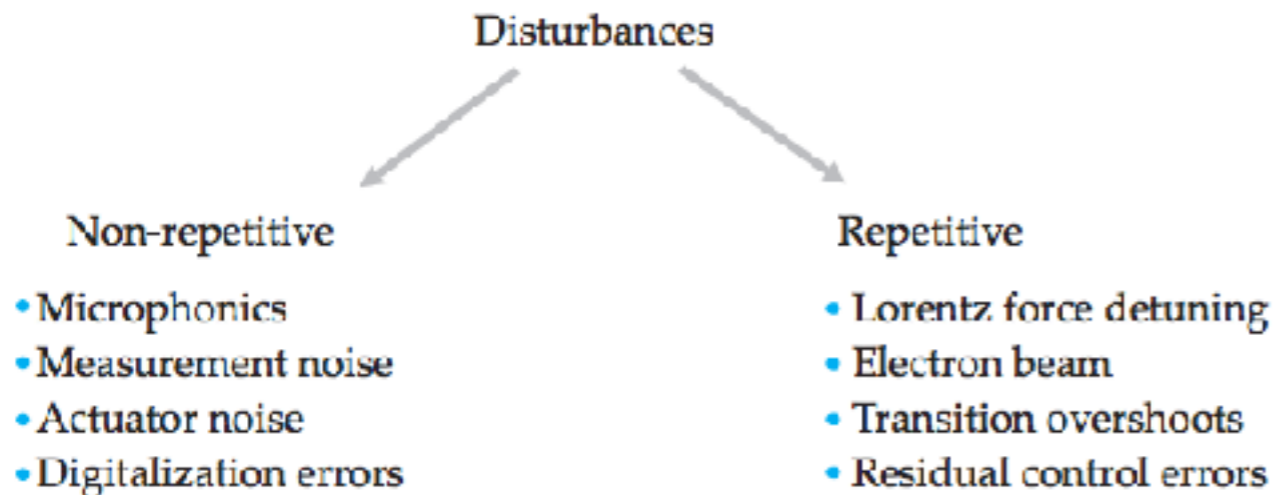
- pulsed RF Operation due to the thermal losses



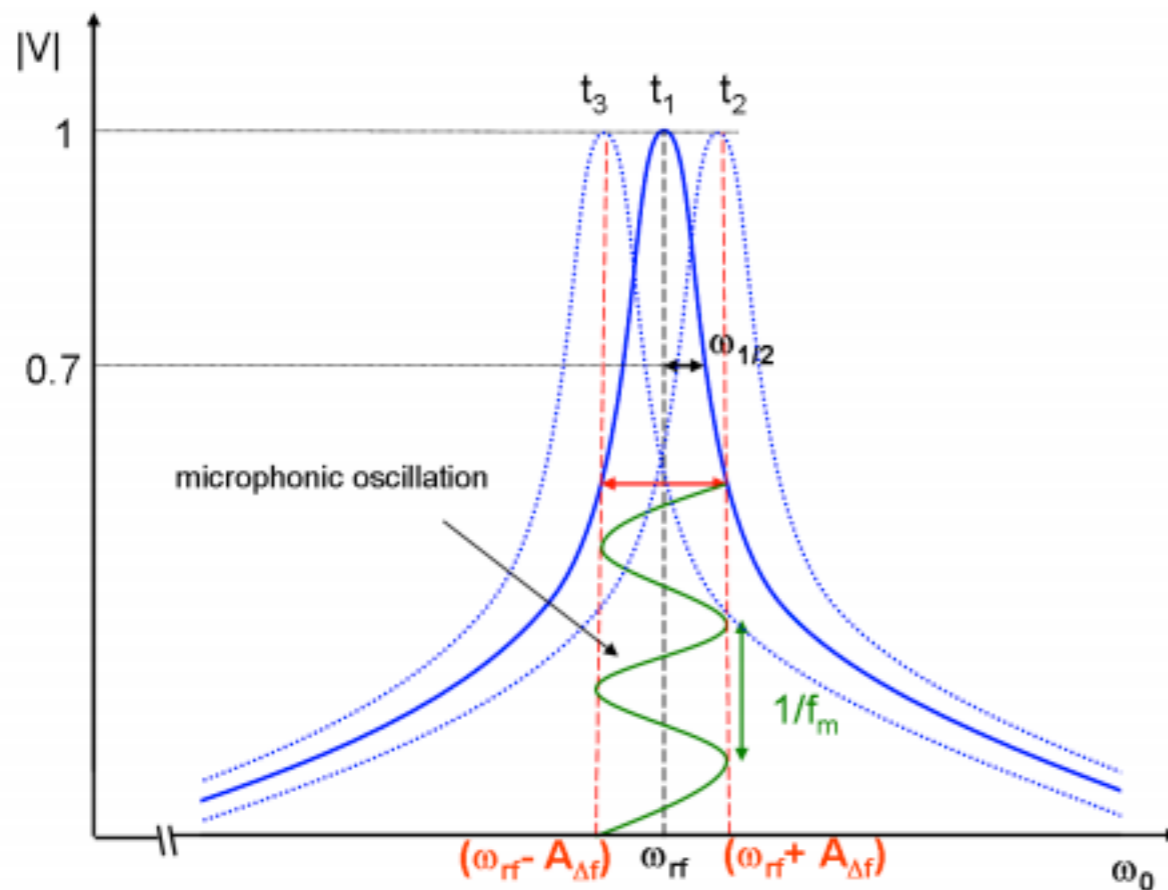
FLASH LLRF



Disturbances - microphonic



- typically in a range up to a few hundred hertz, which in pulsed operation appears as fluctuations from pulse-to-pulse.

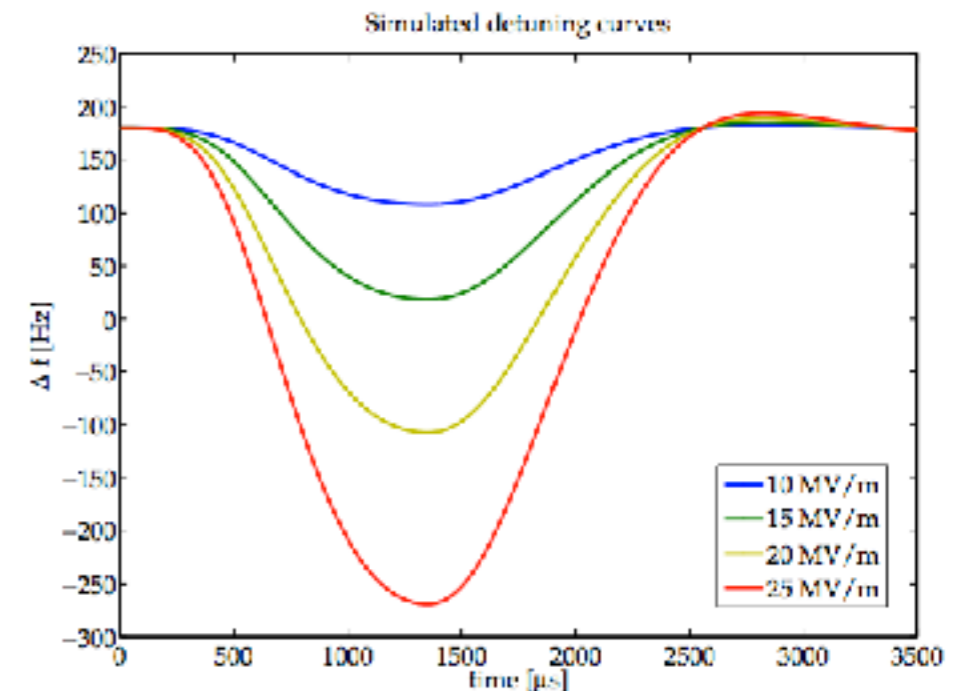
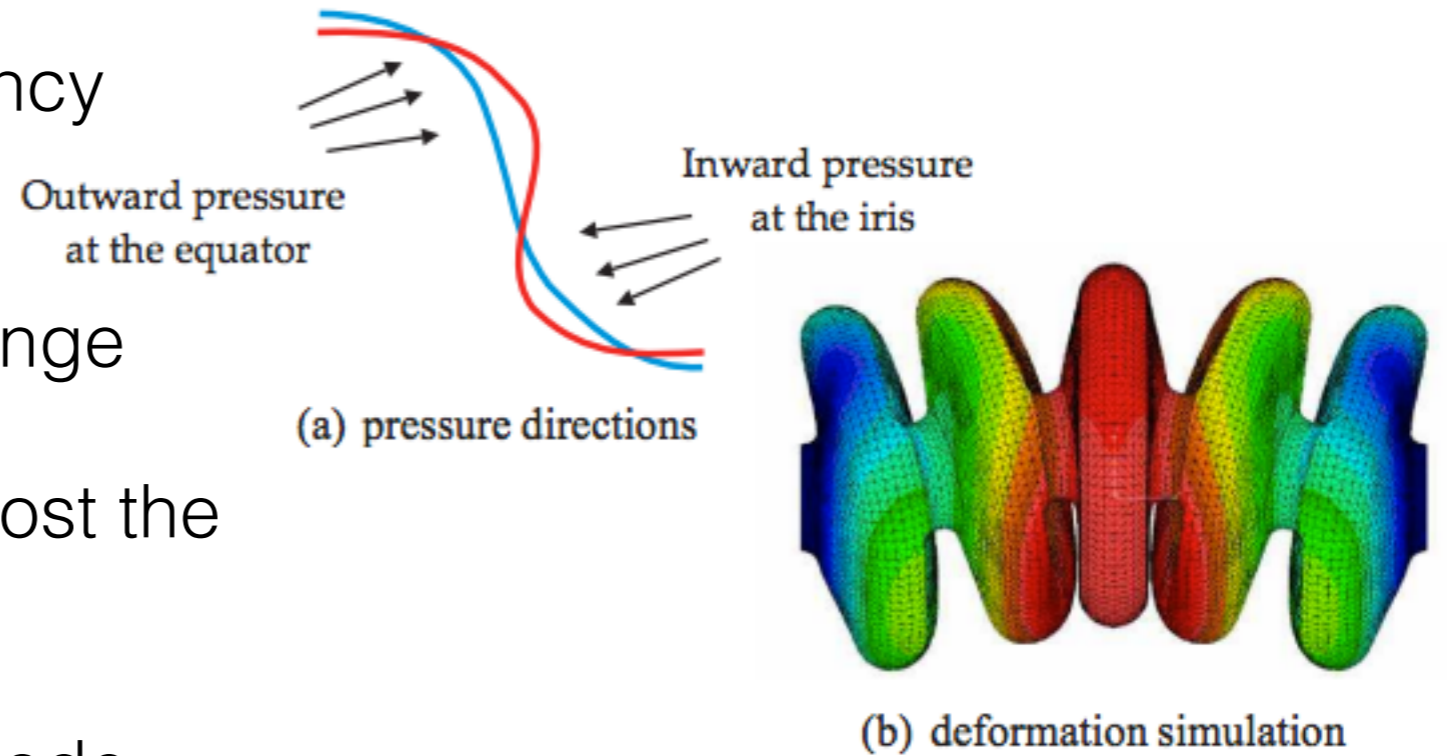


The amplitude or resonance frequency change for FLASH type of cavities is typically $\sigma A \Delta f \approx 6 \text{ Hz}$

- Can use (mechanical) feedback loop to compensate

Disturbances - Lorentz force detuning

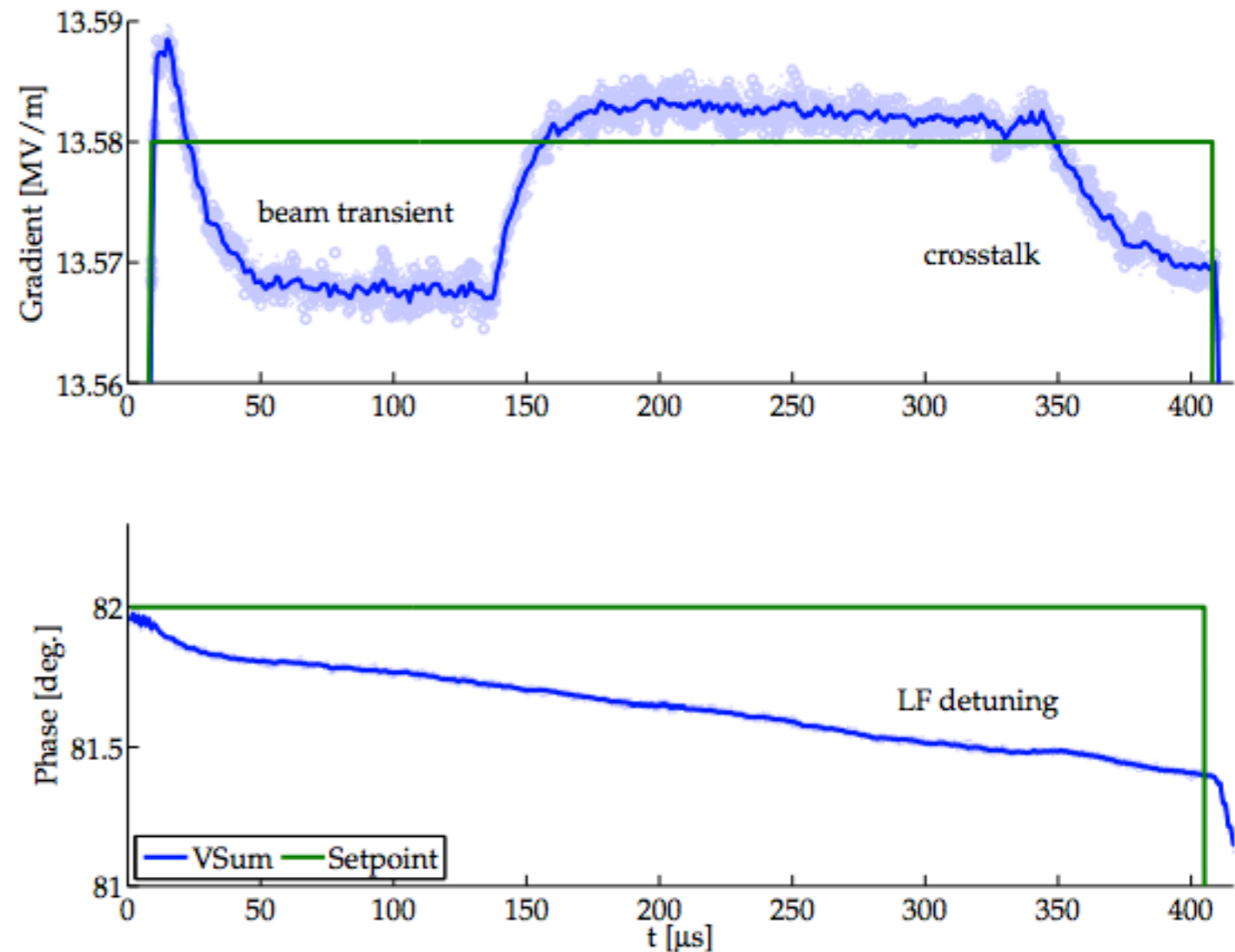
- stronger resonance frequency deviation
- If the RF field does not change from pulse-to-pulse, the deformations will show almost the same behavior
- For the pulsed operation mode only the transient response is measurable (Deformations are disappeared before the next pulse starts, so the effect is repeated with the next pulse)



$$\Delta \ddot{\omega}(t) + \frac{1}{\tau_m} \Delta \dot{\omega}(t) + \omega_m^2 \Delta \omega(t) = \omega_m^2 \Delta \omega_T - 2\pi K \omega_m^2 \cdot E_{acc}^2(t)$$

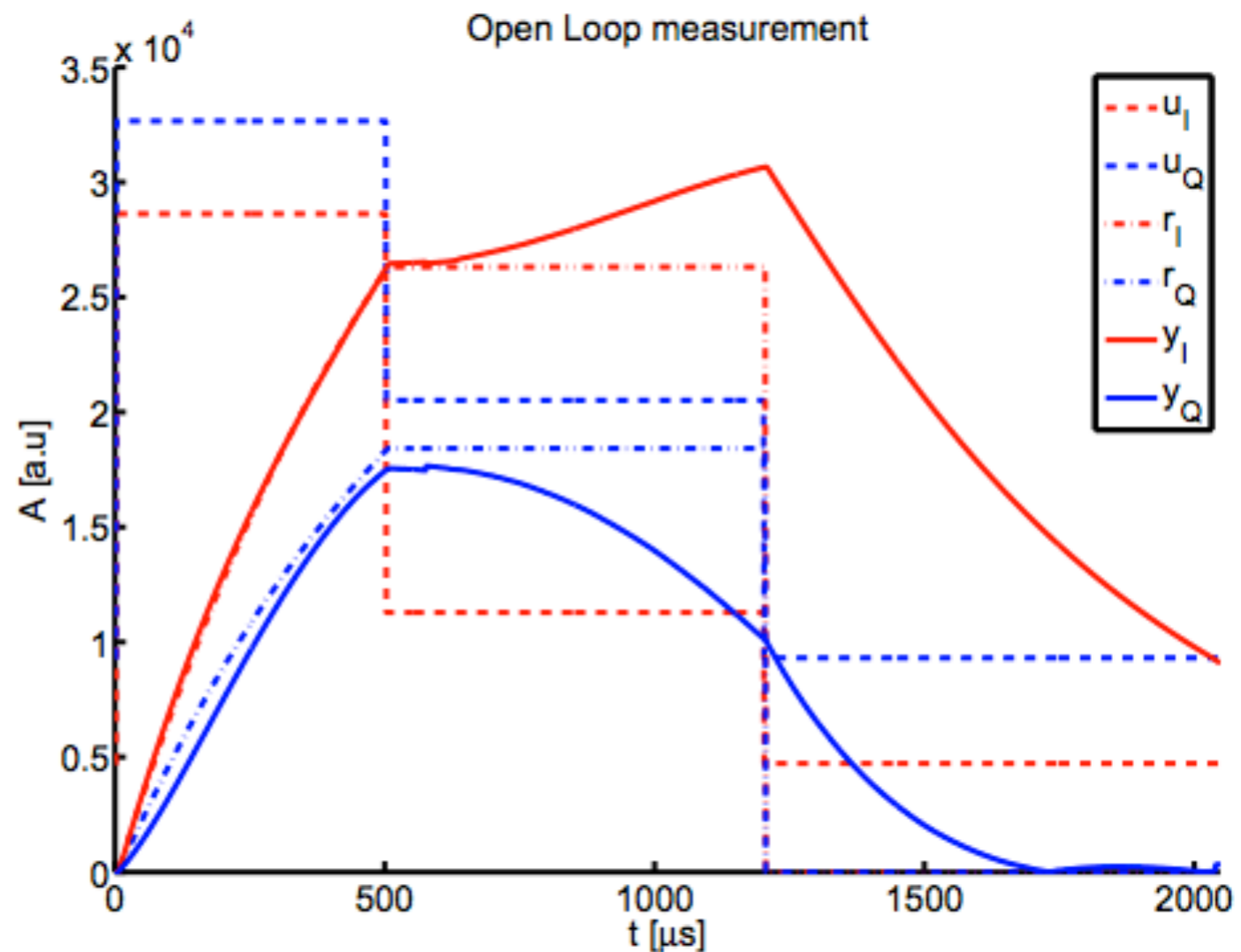
Disturbances - beam loading

- repetitive disturbance source, therefore predictable (if operation state remains)
- Shown with proportional feedback loop closed



RF open-loop response and feedback control

- Proportional gain controller has limit gain due to measurement noise and HOM (8/9 pi mode)
- Phase lag due to digitalization
- Tradeoff between in-pulse and pulse-to-pulse errors
- Out of scope - designing a MIMO feedback controller via generalized plant and weighting filter with HIFOO - see [1]

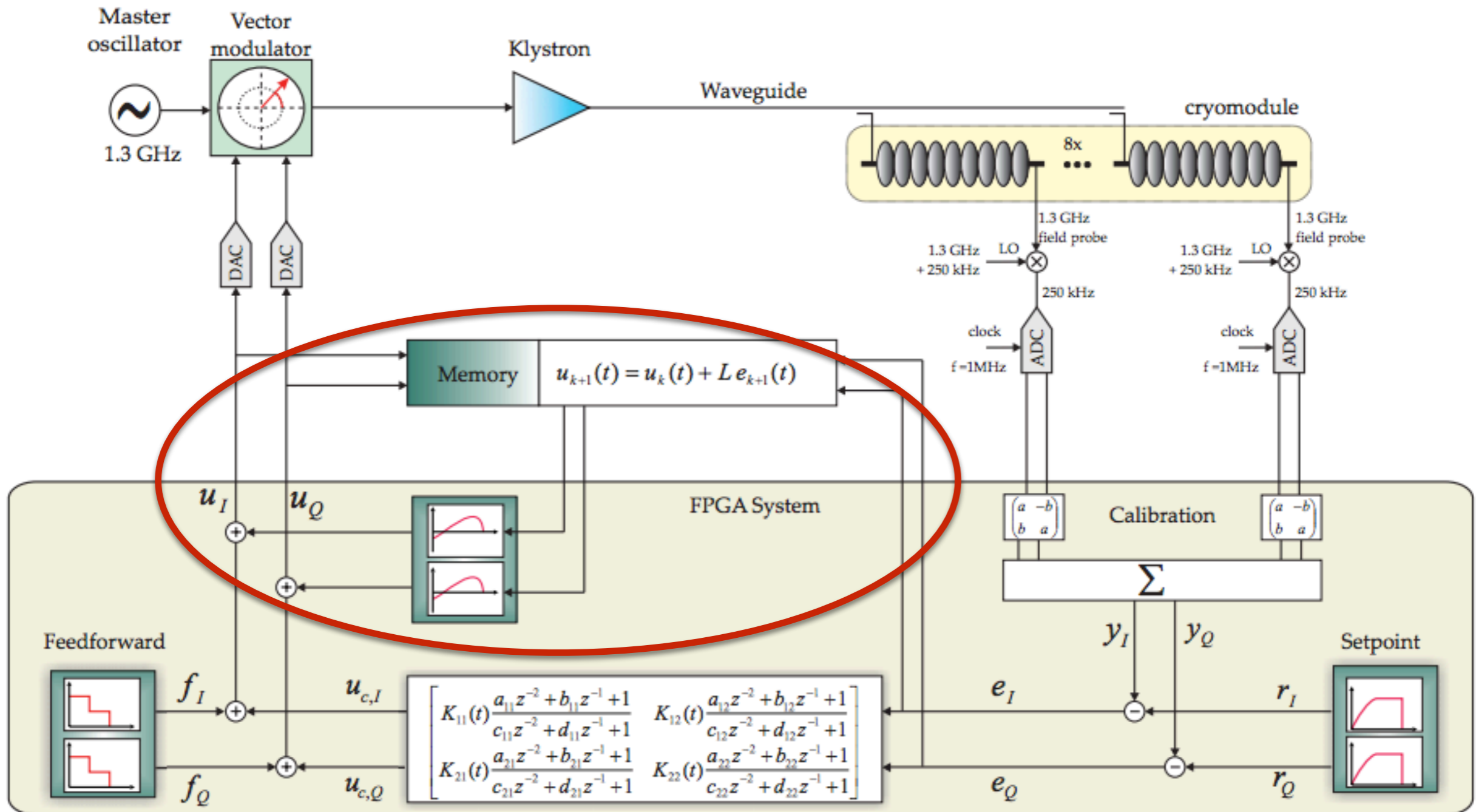


Feedforward control

- Residual field errors due to the low BW of the feedback loop and limitations on the gain
- Predictable disturbance - can compensate with RF modulation
- How to calculate? Constant during operation? Optimal?

Iterative learning control - take information from previous trials to optimize the control inputs on the next trial

FLASH LLRF - NOILC Feed forward



Norm-optimal iterative learning control

- General iterative control - $u_{k+1}(t) = Q(u_k(t) + L e_k(t))$
to ensure some error metric $\|e_k\| \rightarrow 0$ as $k \rightarrow \infty, k \in \mathbb{N}$

- Given a system
$$\begin{aligned} x(t+1) &= A x(t) + B u(t); \\ y(t) &= C x(t) \end{aligned}$$

- NOILC - optimize u_{k+1} iteratively

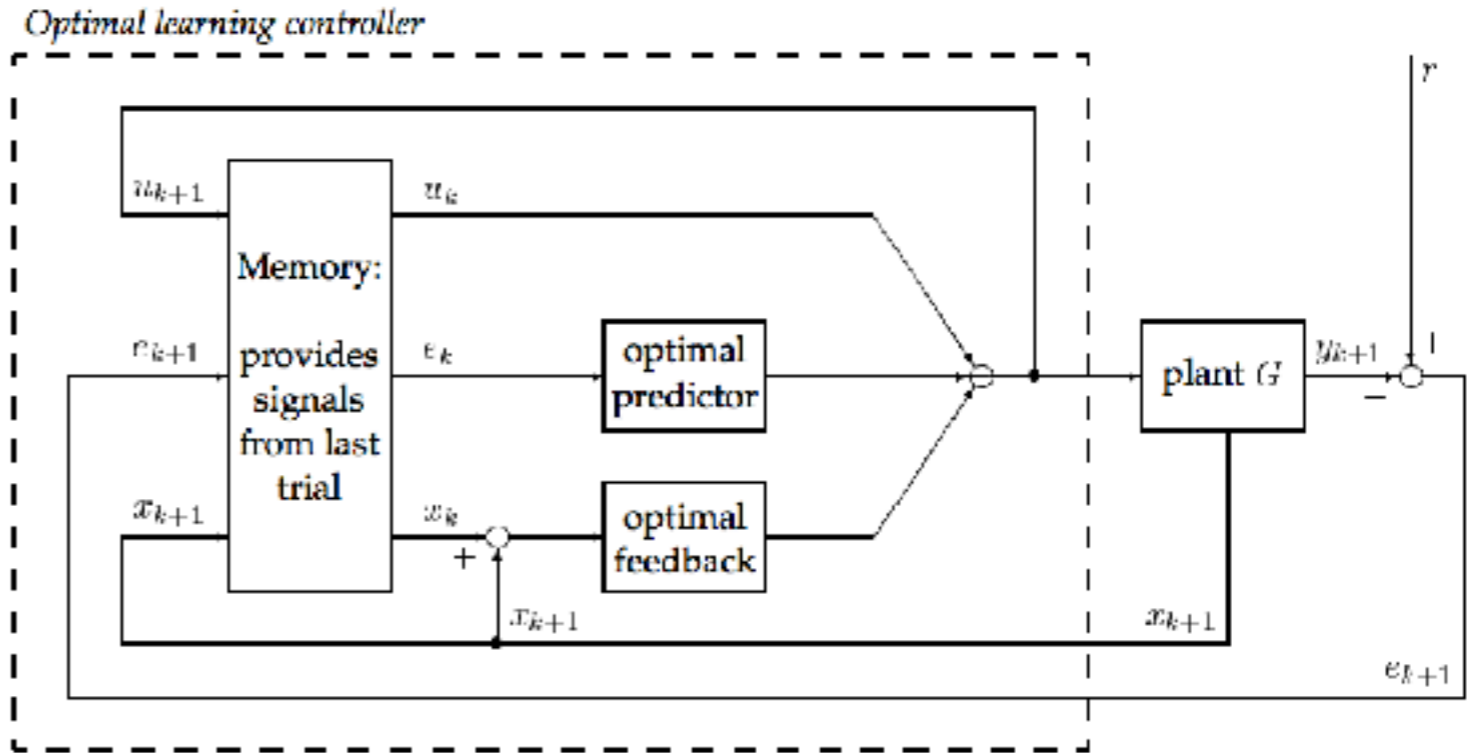
$$u_{k+1} = \arg \min_{u_{k+1}} \{J_{k+1}(u_{k+1}) : e_{k+1} = r - y_{k+1}, \quad y_{k+1} = G u_{k+1}\}$$

per selected performance index

$$J_{k+1} = \sum_{t=1}^N [r(t) - y_{k+1}(t)]^T Q(t) [r(t) - y_{k+1}(t)] + \sum_{t=0}^{N-1} [u_{k+1}(t) - u_k(t)]^T P(t) [u_{k+1}(t) - u_k(t)]$$

NOILC - solution

- Problem stated has a solution [2]:



- Matrix gain

$$K(t) = A^T K(t+1)A + C^T Q(t+1)C - A^T K(t+1)B(B^T K(t+1)B + R(t+1))^{-1} B^T K(t+1)A$$

- Predictive component

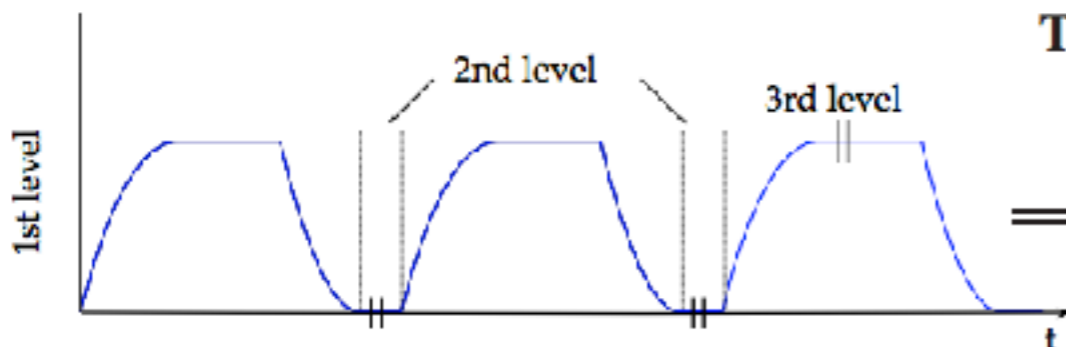
$$\xi_{k+1}(t) = (I + K(t)BR^{-1}(t)B^T)^{-1} (A^T \xi_{k+1}(t+1) + C^T Q(t)e_k(t)) ; \quad \xi_{k+1}(N) = 0$$

- Input update

$$u_{k+1}(t) = u_k(t) - (B^T K(t)B + R(t))^{-1} B^T K(t)A[x_{k+1}(t) - x_k(t)] + R^{-1}(t)B^T \xi_{k+1}(t)$$

Implementation note - F-NOILC

- Extensive calculations to update input values.
- Can rearrange for pre-calculation of a lot of terms in advance and minimize real-time calculations
- Note - need to recalculate with model changes (if any)
- See for ex. [3]



First level (before operation):

$$K(t) = A^T K(t+1)A + C^T W_1(t+1)C - [A^T K(t+1)B \cdot \{B^T K(t+1)B + W_2(t+1)\}^{-1} \cdot B^T K(t+1)A] \quad ; \quad K(N) = 0$$

$$\alpha(t) = \{I + K(t)BW_2^{-1}(t)B^T\}^{-1}$$

$$\beta(t) = \alpha(t)A^T$$

$$\gamma(t) = \alpha(t)C^T W_1(t+1)$$

$$\omega(t) = W_2^{-1}(t)B^T$$

$$\lambda(t) = (B^T K(t)B + W_2(t))^{-1} B^T K(t)A$$

Second level (between trials):

$$\xi_{k+1}(t) = \beta(t)\xi_{k+1}(t+1) + \gamma(t)e_k(t+1) \quad ; \quad \xi_{k+1}(N) = 0$$

Third level (between each sample interval):

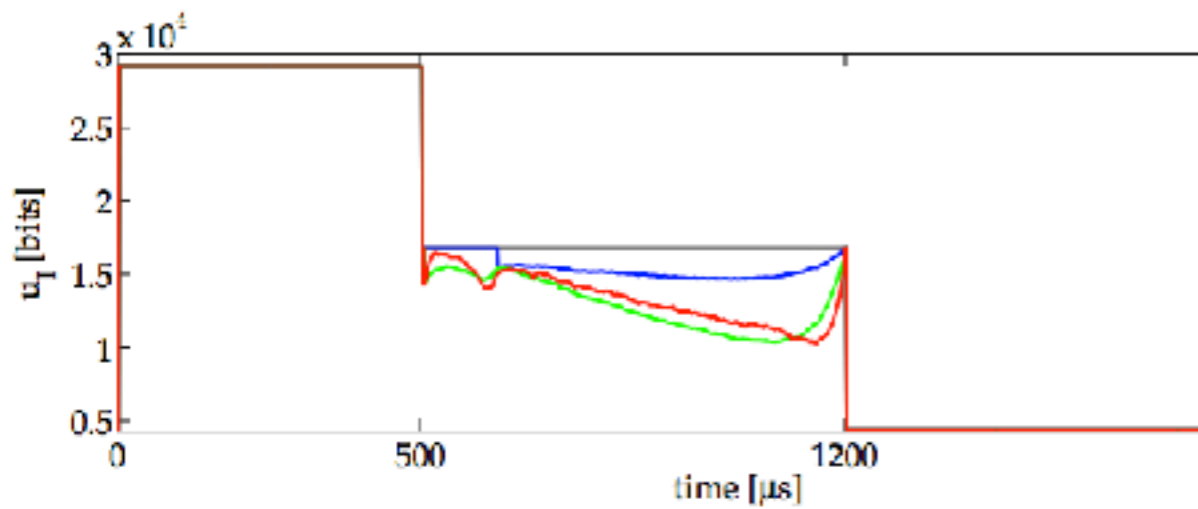
$$u_{k+1}(t) = u_k(t) - \lambda(t)\{x_{k+1}(t) - x_k(t)\} + \omega(t)\xi_{k+1}(t)$$

Out of scope - system identification

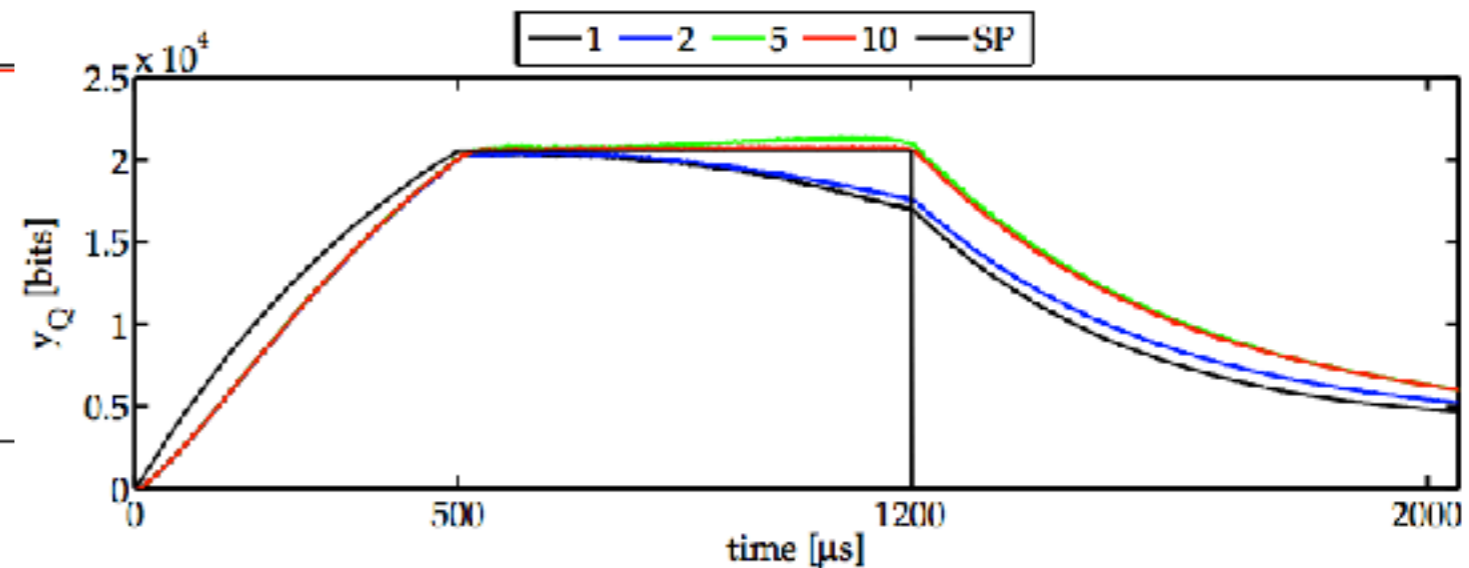
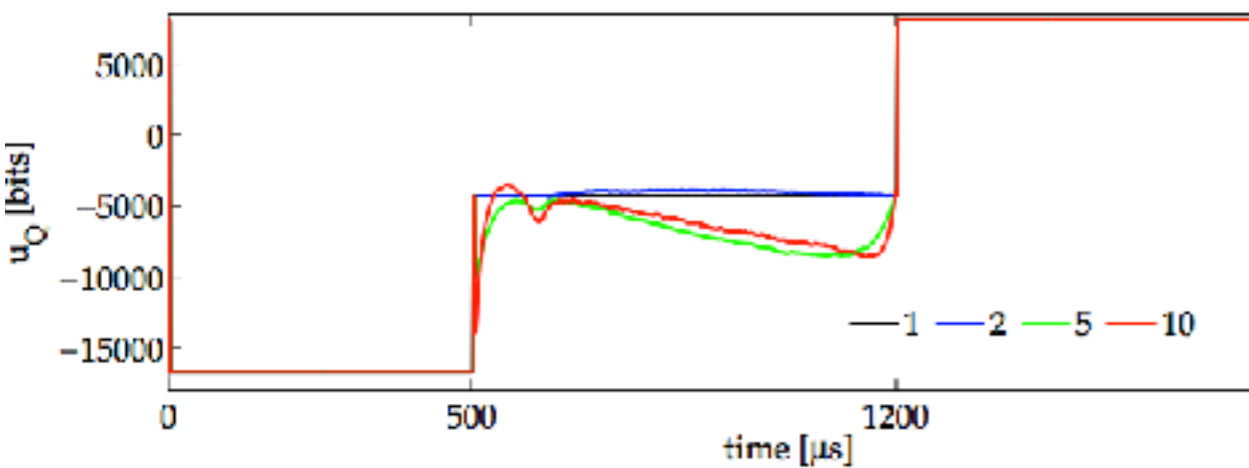
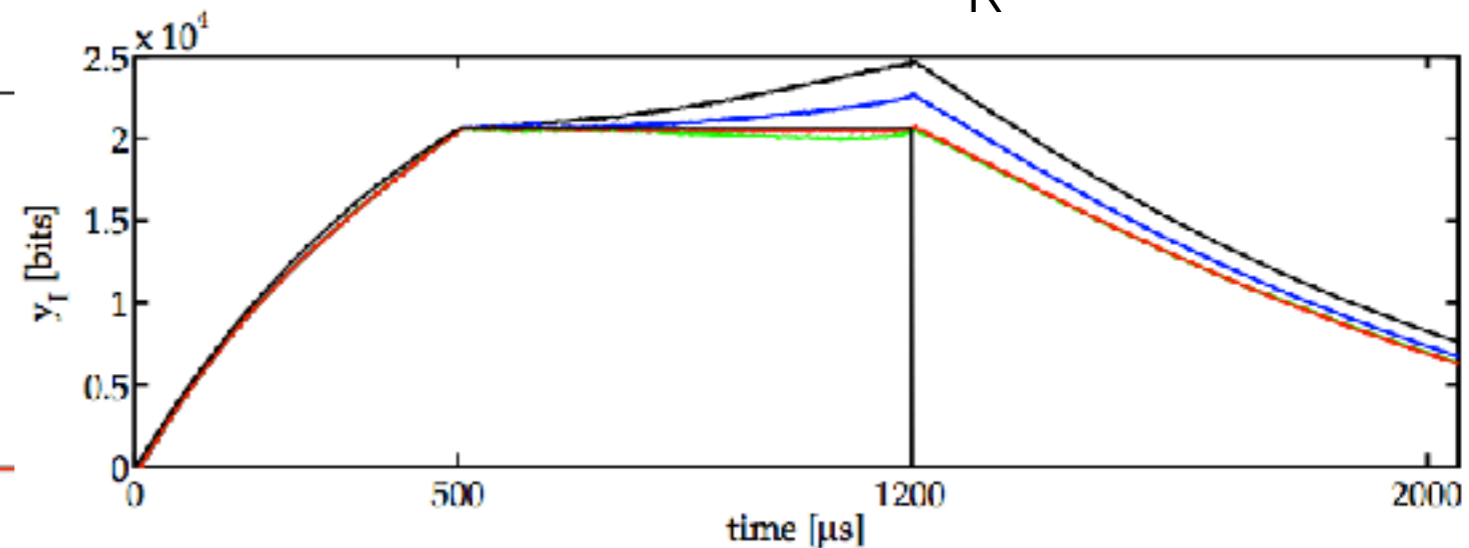
- Requires A, B, C, D...
- Black-box model for system identification
- Model validation

Experimental results - open-loop ILC (no beam, LFD only)

System input $u_k(t)$

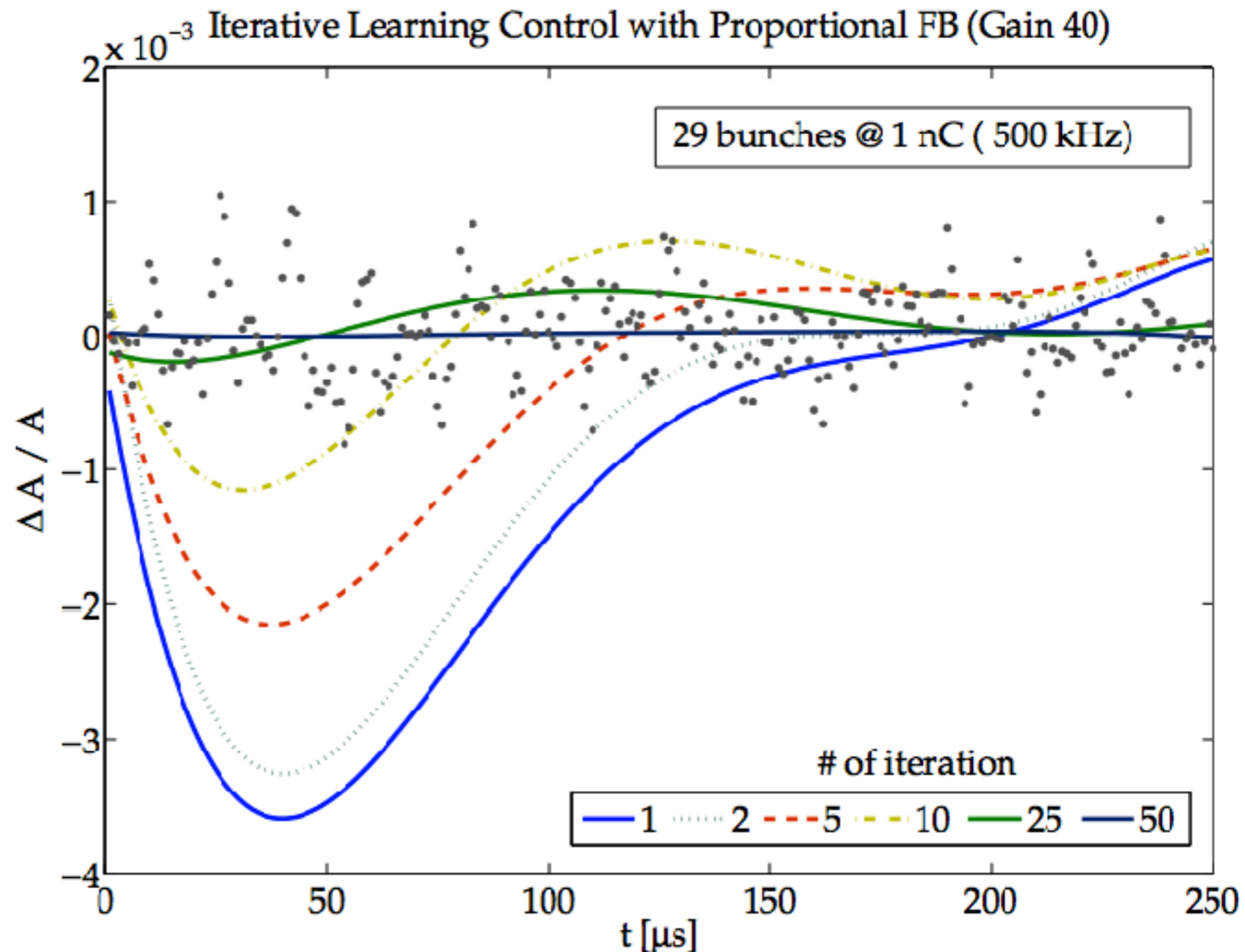


System output $y_k(t)$

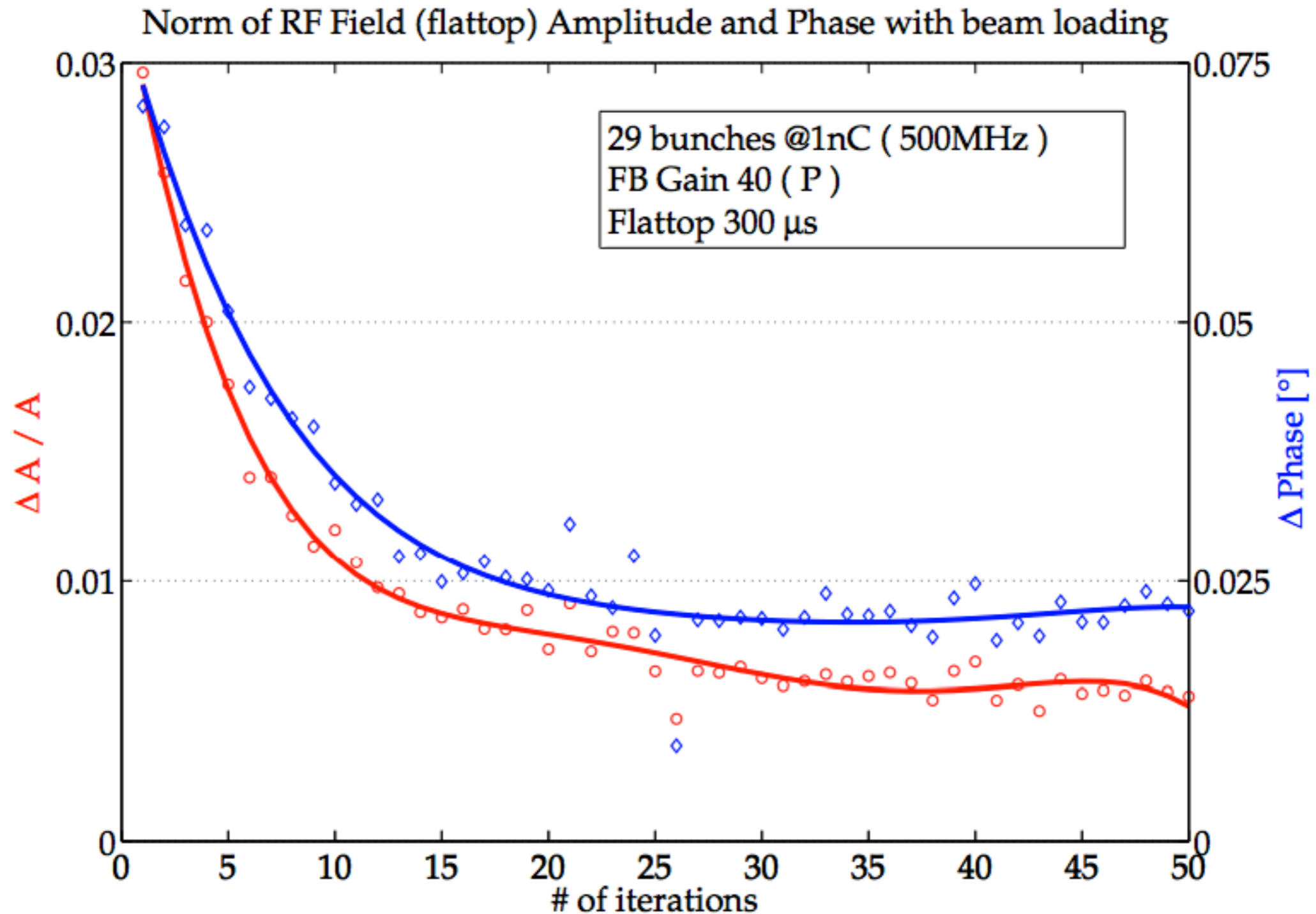


Experimental results - closed-loop ILC (P controller)

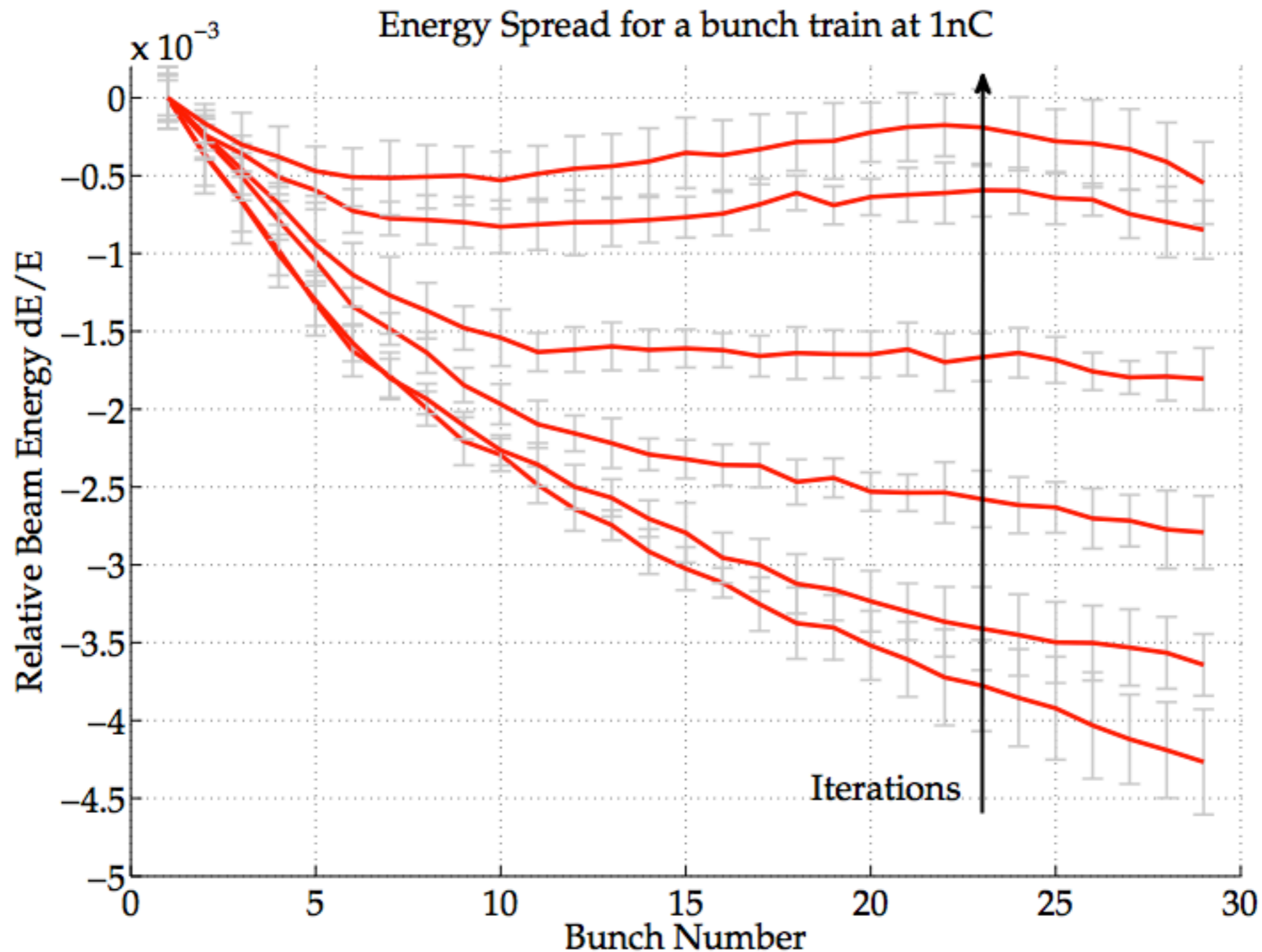
- Fitted curves of RF field amplitude changes due to feedforward adaptation
- Dots represent the measurement points after 50 iterations showing that only **non repetitive fluctuations are left over**



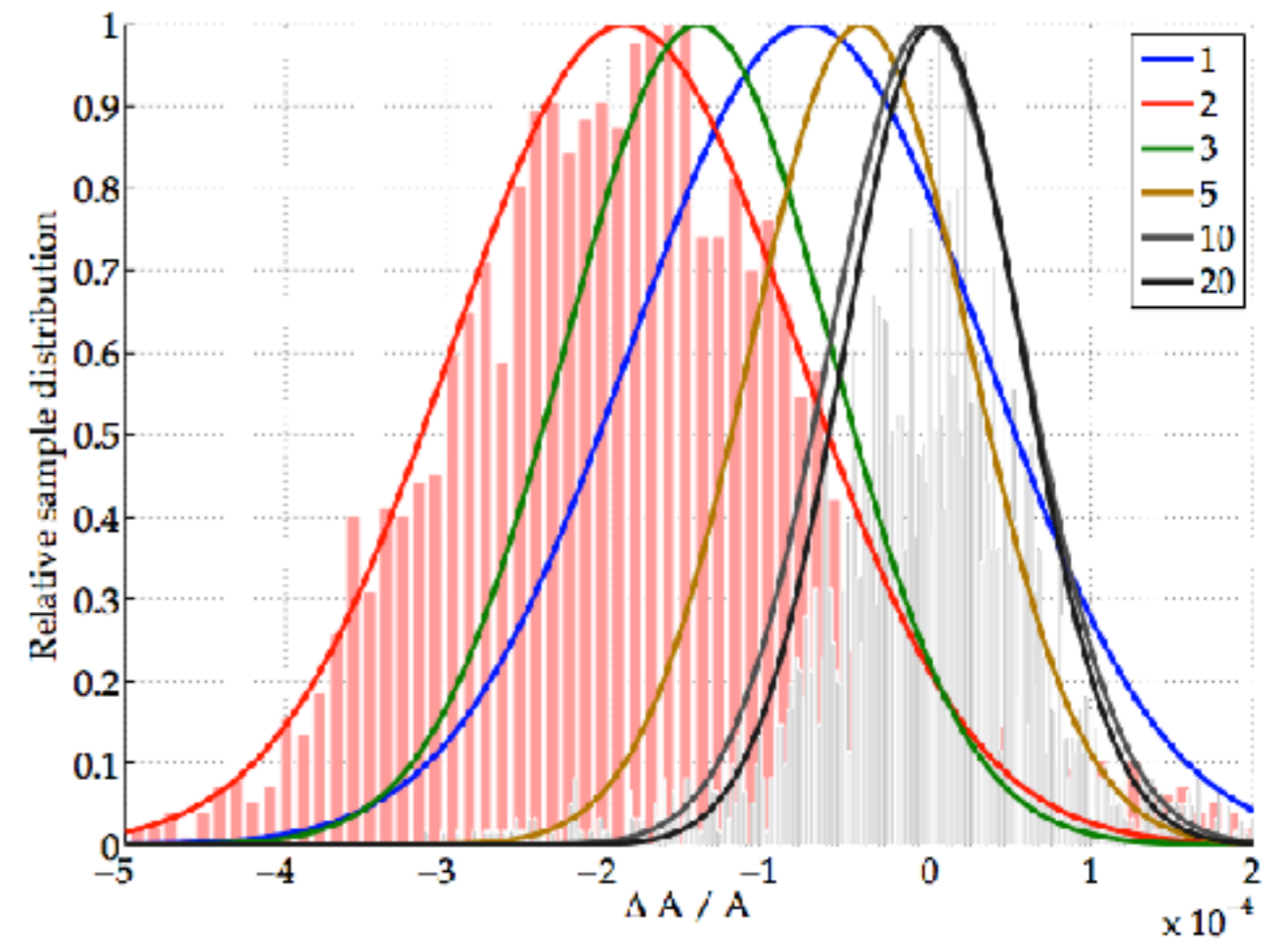
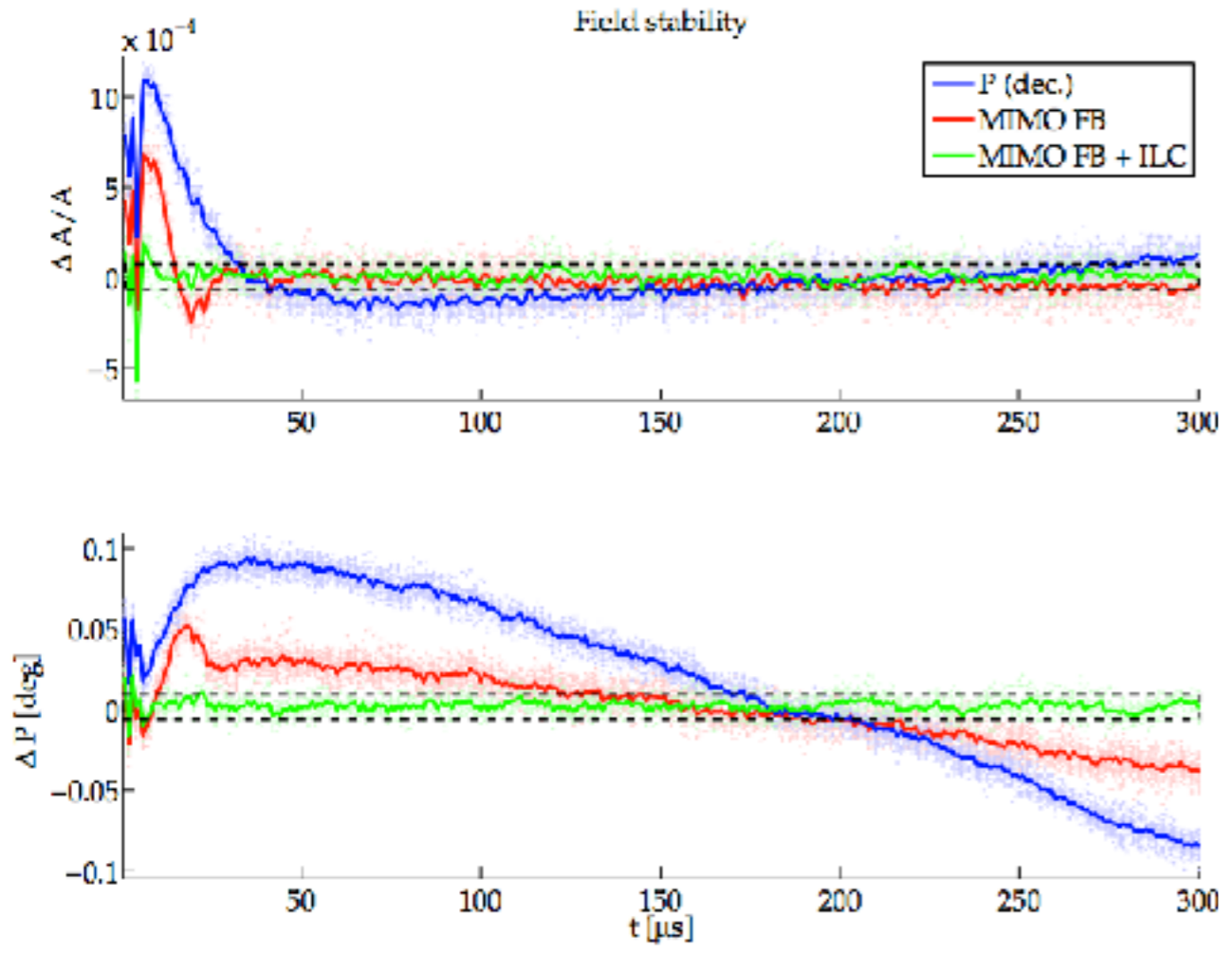
Experimental results - ILC convergence (P controller)



Experimental results - pulse train energy spread (P controller)

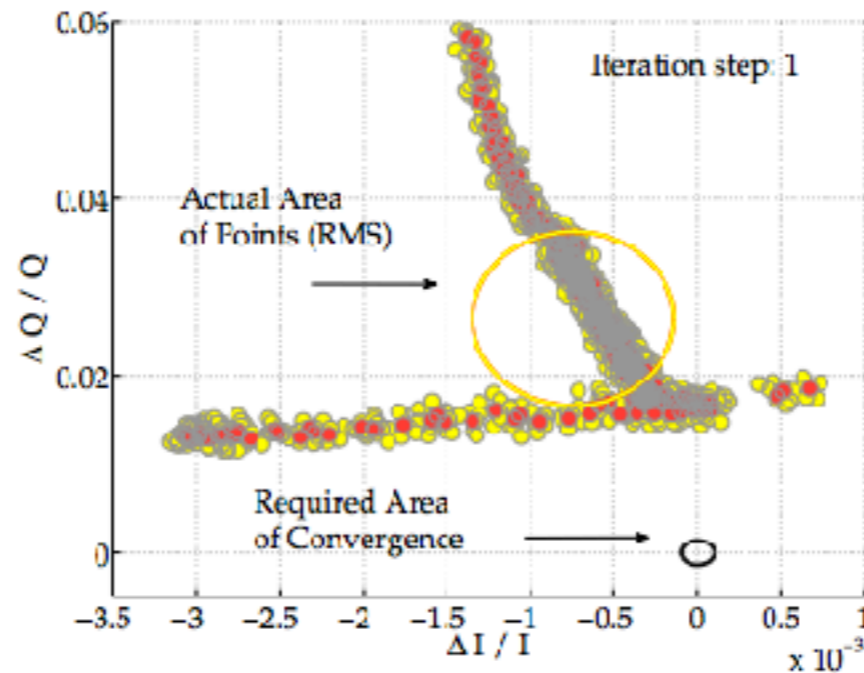


ILC and MIMO controller

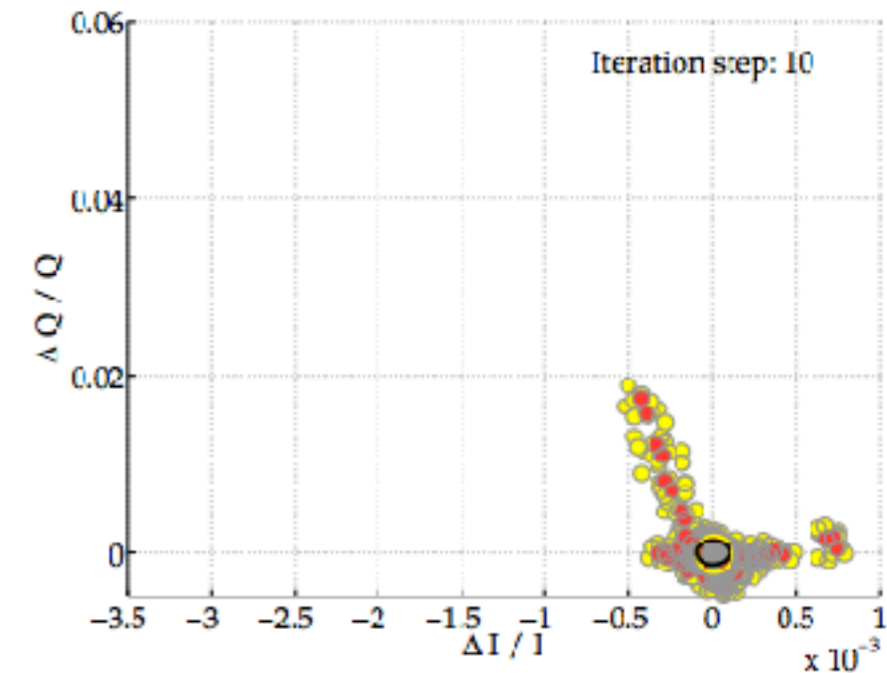


ILC long term adaptation

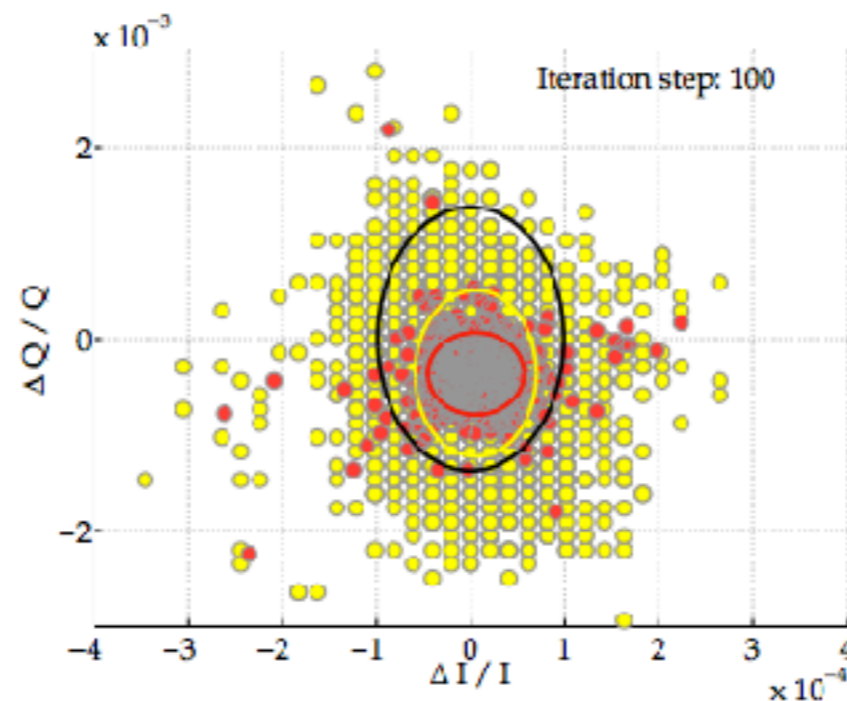
- I/Q domain
- yellow dot - data point
- red dot - 5 sample average
- yellow/red ovals - rms error
- black oval - system requirement
- System converges nicely.
what happen next as iteration number increase?



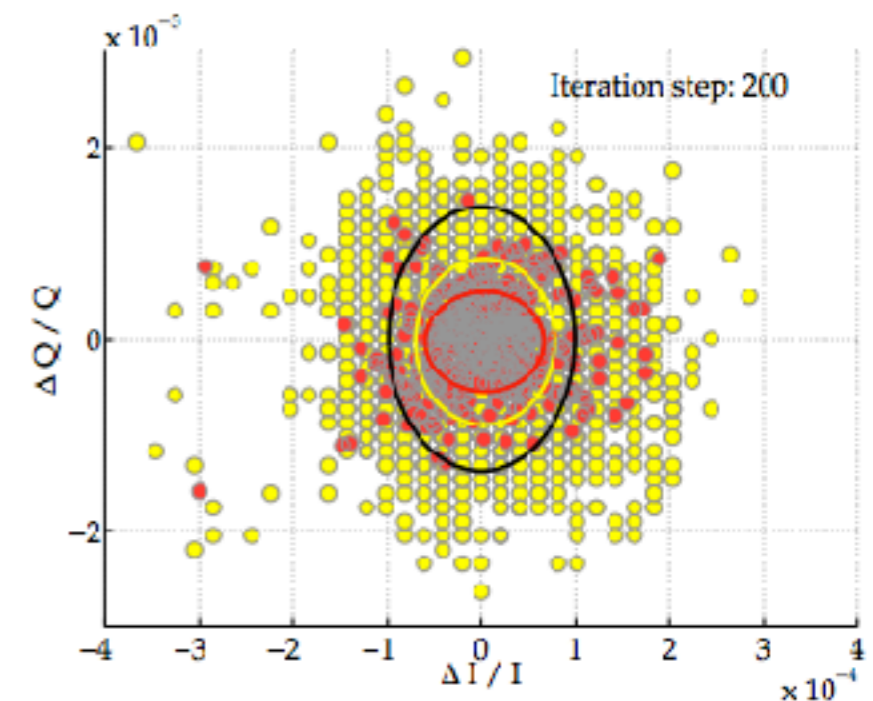
(a)



(b)



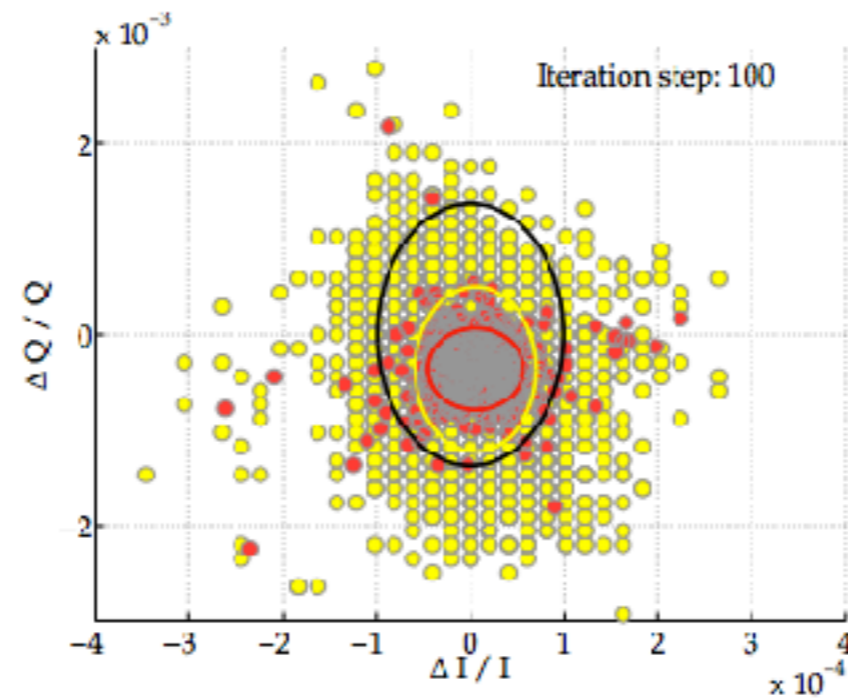
(c)



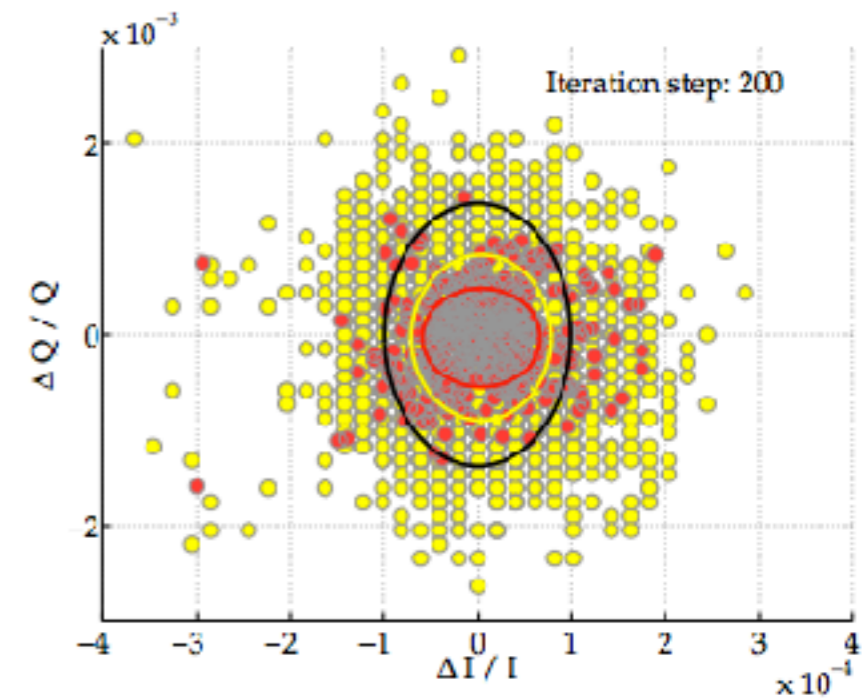
(d)

ILC long term adaptation (cont.)

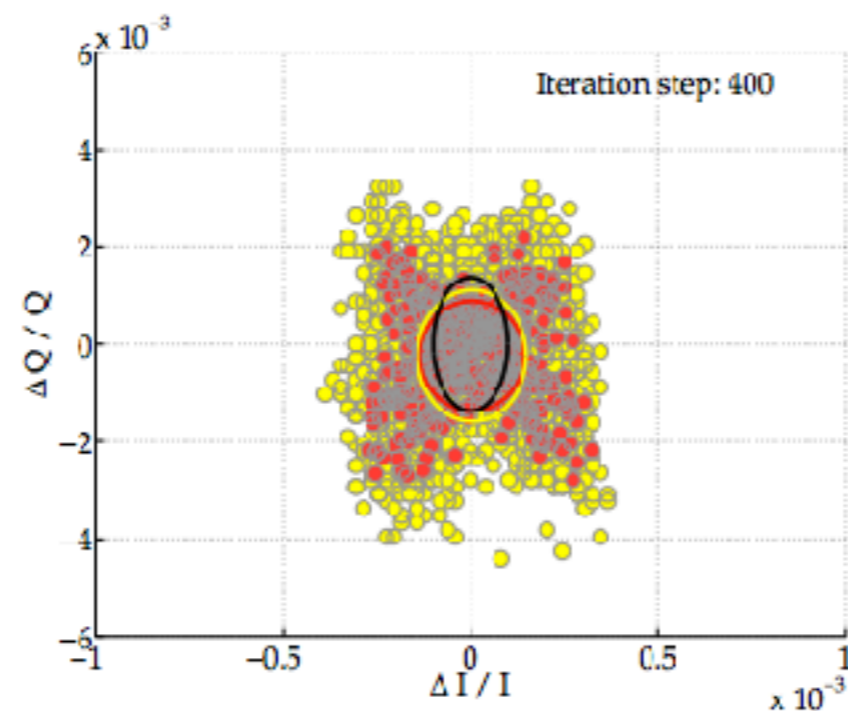
- ILC induced oscillations
- What can caused this?



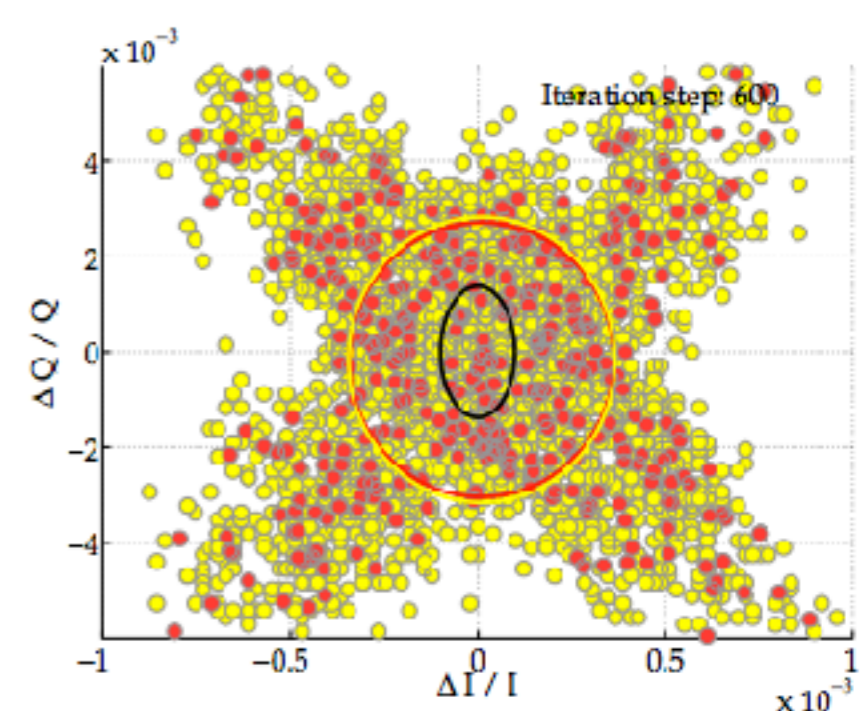
(c)



(d)



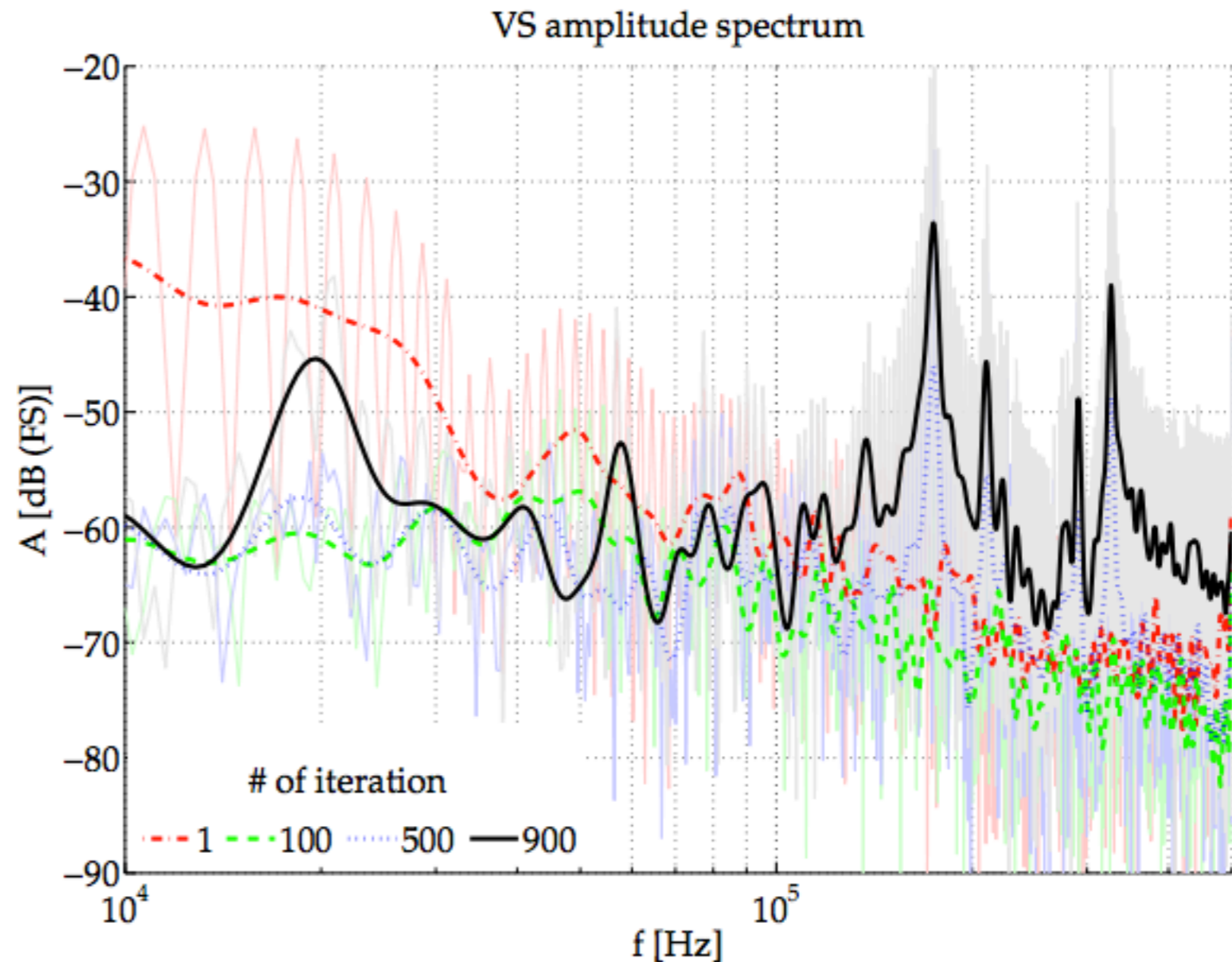
(e)



(f)

ILC - implications of model limitation

- Spectrum analysis of vector sum shows that as iterations increase, peaks occur at frequencies consistent with $8/9\pi$ mode of the cavity
- Limitation of the system model used for ILC derivation



References

Following references were used in this presentation for strictly educational purpose:

- [1] C. Schmidt (2010): *RF System Modeling and Controller Design for the European XFEL* (Doctoral thesis)
- [2] N. Amann, D.H. Owens, E. Rogers: *Iterative learning control for discrete-time systems with exponential rate of convergence*, IEE Proc. Control Theory Appl., vol. 143, no. 2, pp. 217-224, 1996.
- [3] J.D. Ratcliffe, P.L. Lewin, E. Rogers, J.J. Htnen, D.H. Owens: *Norm-Optimal Iterative Learning Control Applied to Gantry Robots for Automation Applications*, IEEE Transactions on Robotics, Vol. 22, No. 6, 2006