Machine Learning-based Beam Size Stabilization at ALS

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OWLE ML Seminar

BERKELEY LAB

U.S. DEPARTMENT OF ENERGY | Office of Science

ACCELERATOR TECHNOLOGY & APPLIED PHYSICS DIVISION ATAP

ALS ADVANCED LIGHT SOURCE

The Advanced Light Source at Berkeley Lab

The Advanced Light Source at Berkeley Lab

184" cyclotron yoke (construction 1940)

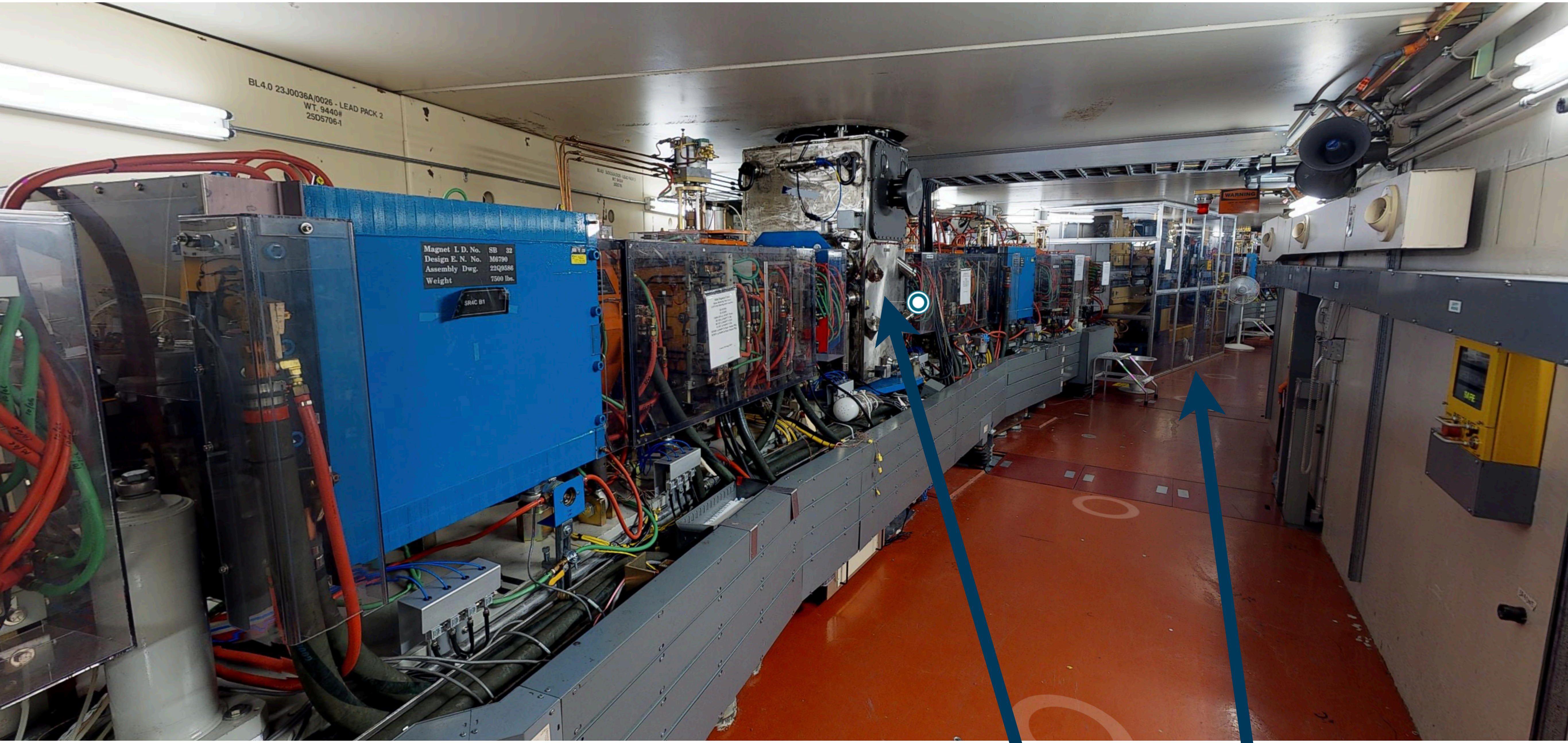
ALS Linac (50 MeV, ~1990)

ALS Booster Ring (1992)

The Advanced Light Source at Berkeley Lab

1.9 GeV Storage Ring, 196.8 m, 1993

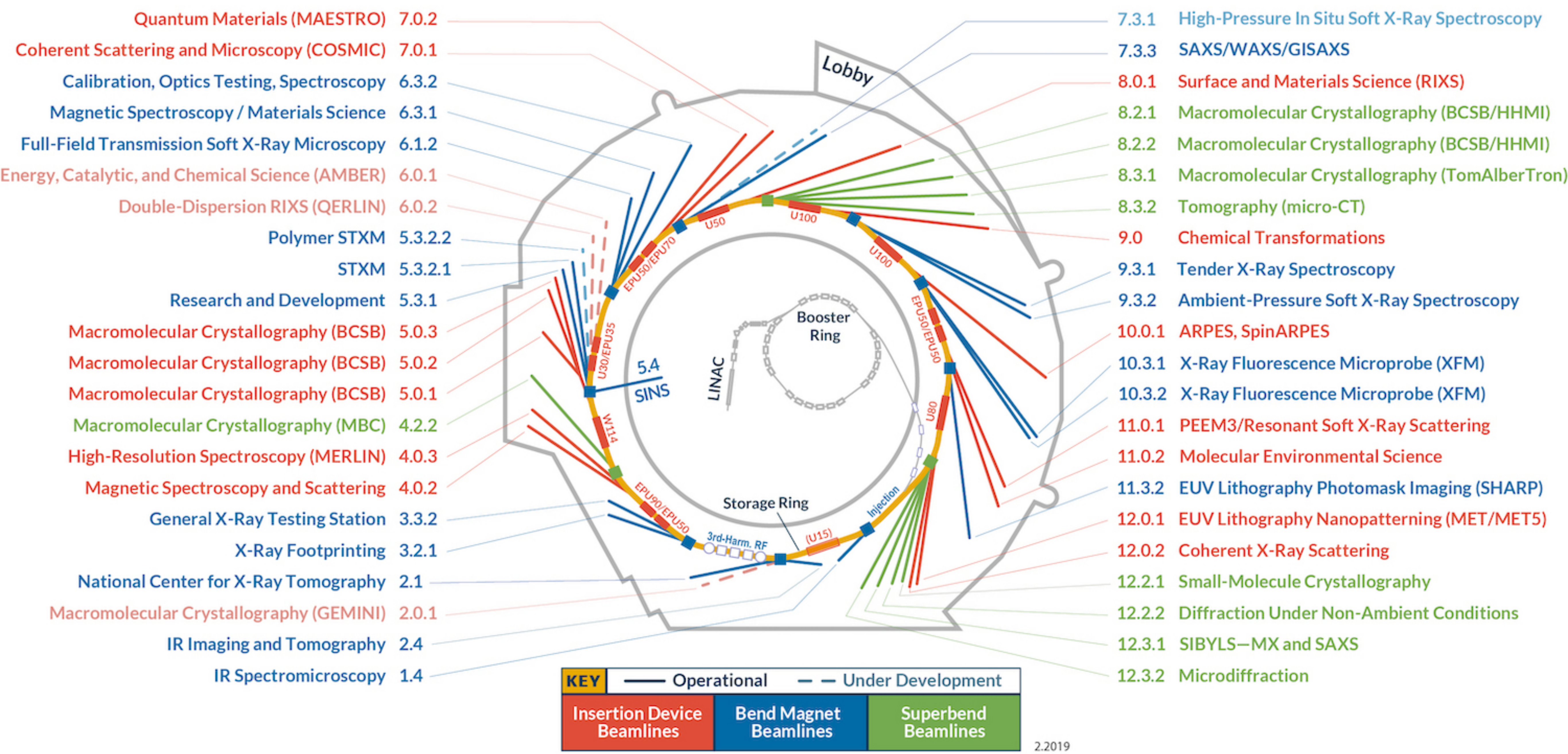
The Advanced Light Source at Berkeley Lab



Triple-bend achromat lattice (12 sectors, 3 with superbends, 10 ID straights)

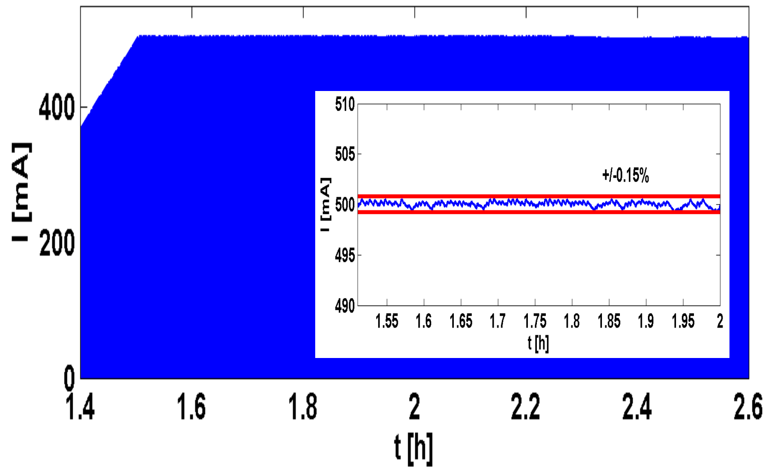
The Advanced Light Source at Berkeley Lab

≈40 beamlines, ≈5000 hrs/y, ≈2000 users/y



Many Successful Efforts to Stabilize Electron Beams

- **Top-off** keeps ALS stored current variation <0.2%



Courtesy: C. Steier, PAC'09

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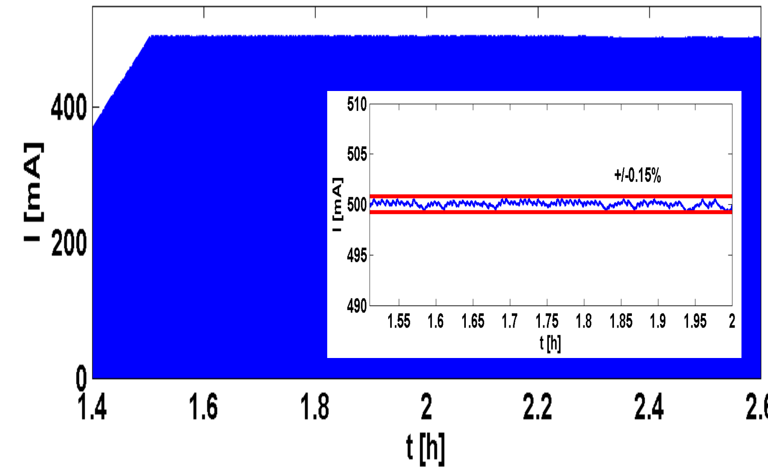

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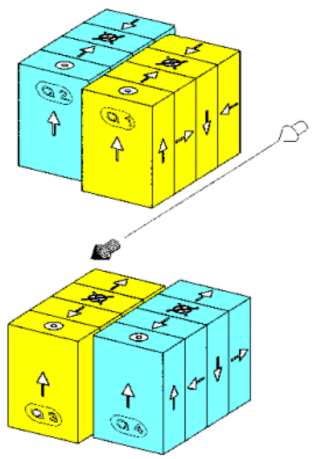

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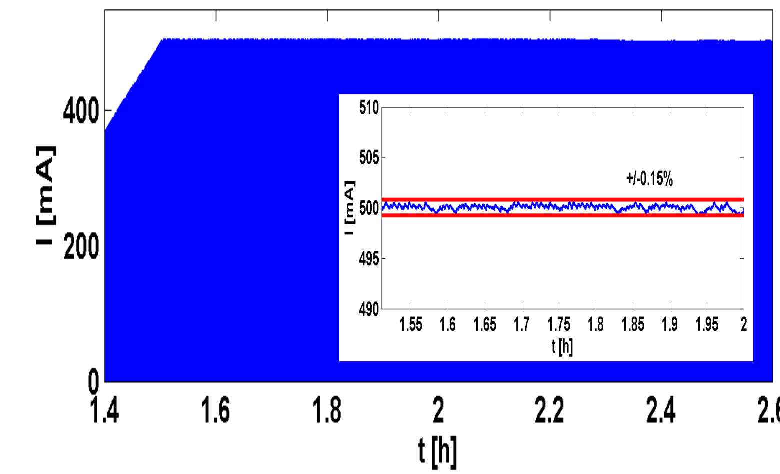

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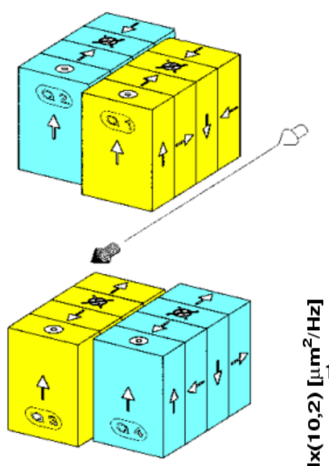

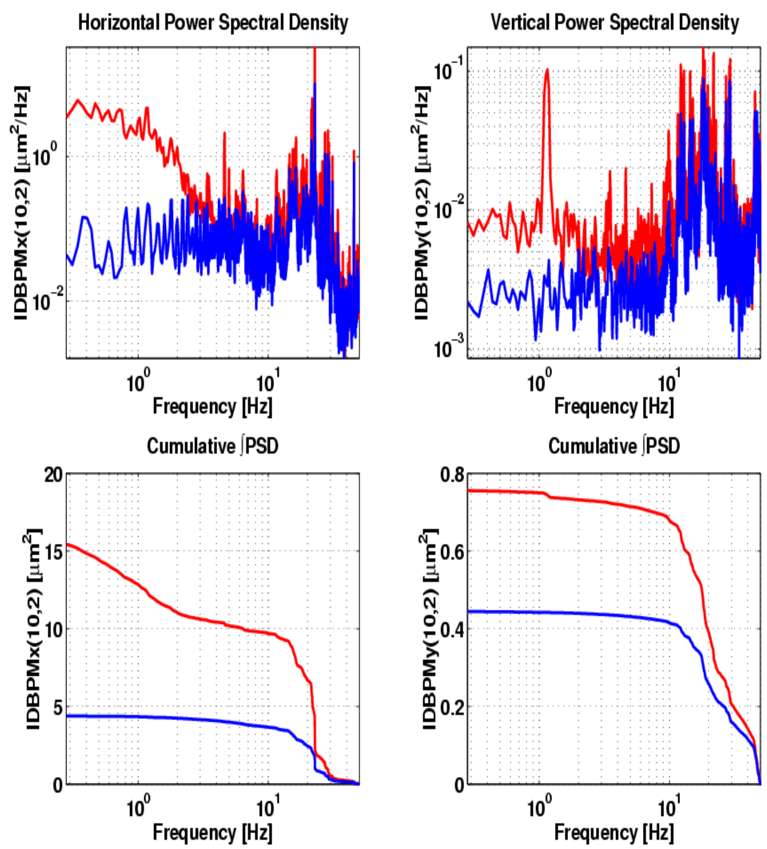

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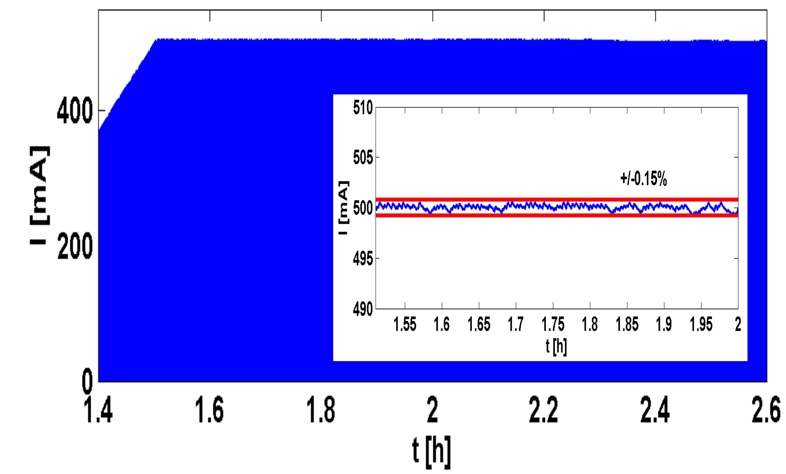
- **Top-off** keeps ALS stored current variation <0.2%
- At low energy, ALS strongly affected by insertion device (ID) imperfections & continuously changing EPU gaps/phases
  - **Orbit feedback** and ID feed-forwards stabilize source positions/angles to **sub-micron** level at many tens of Hz
  - **ID feed-forwards** & tune feedback stabilize optics at source points
  - **ID skew feed-forwards** stabilize source size
    - require recording lookup tables (time consuming)
    - tables are imperfect and **machine drifts** over time



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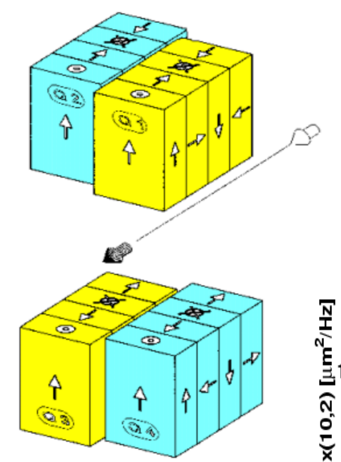
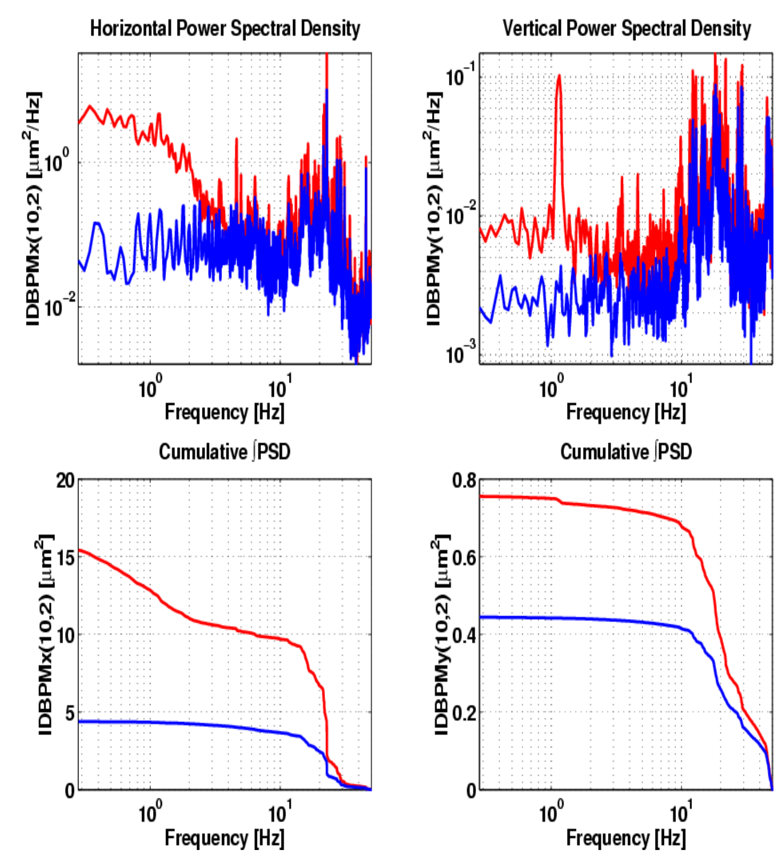
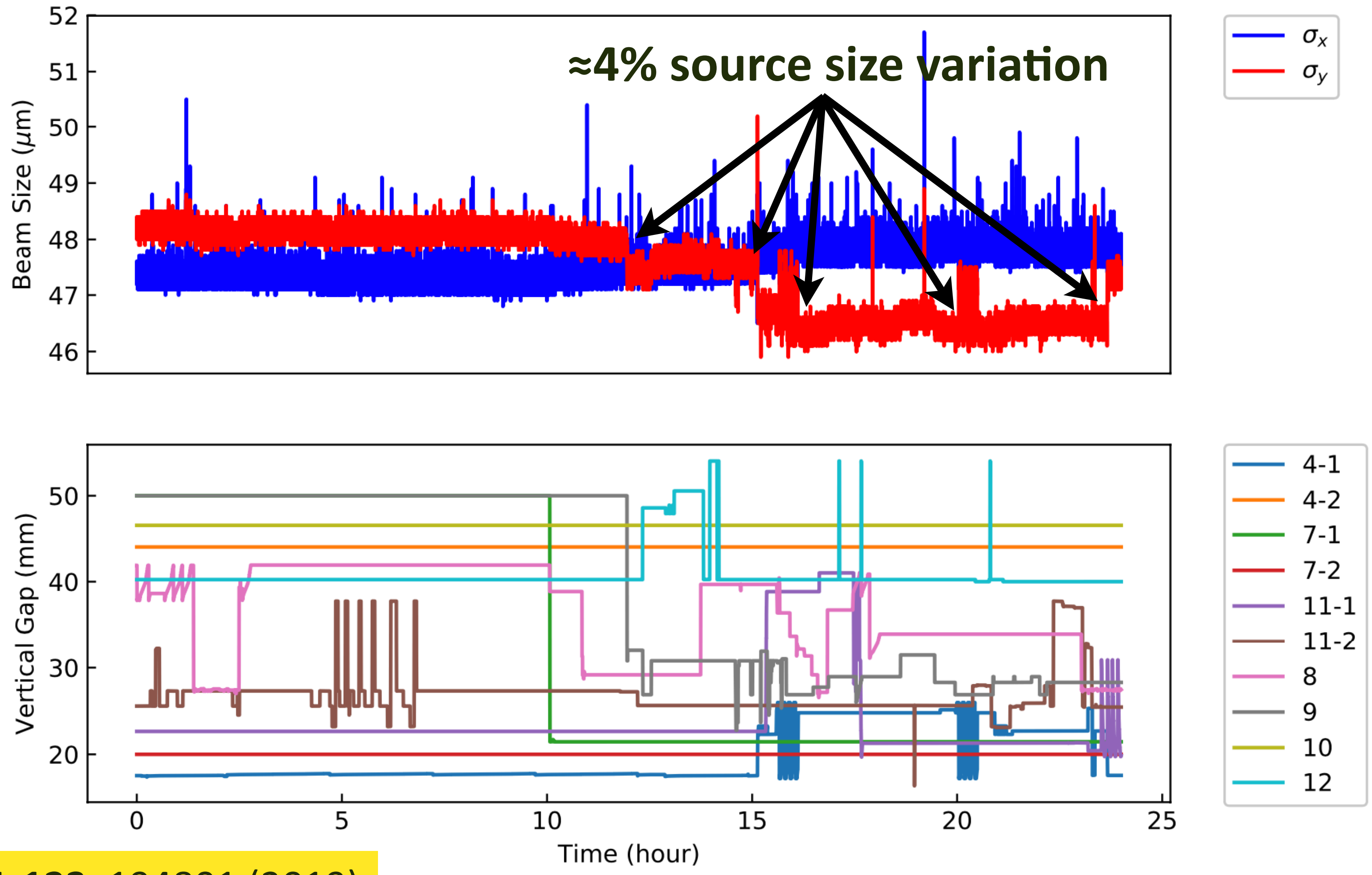




Thermal, Ground, Water Table, etc.

The Problem: Beam Size vs. ID Motion

- Nevertheless, during routine user ops observe vertical source size variations when ID configurations change



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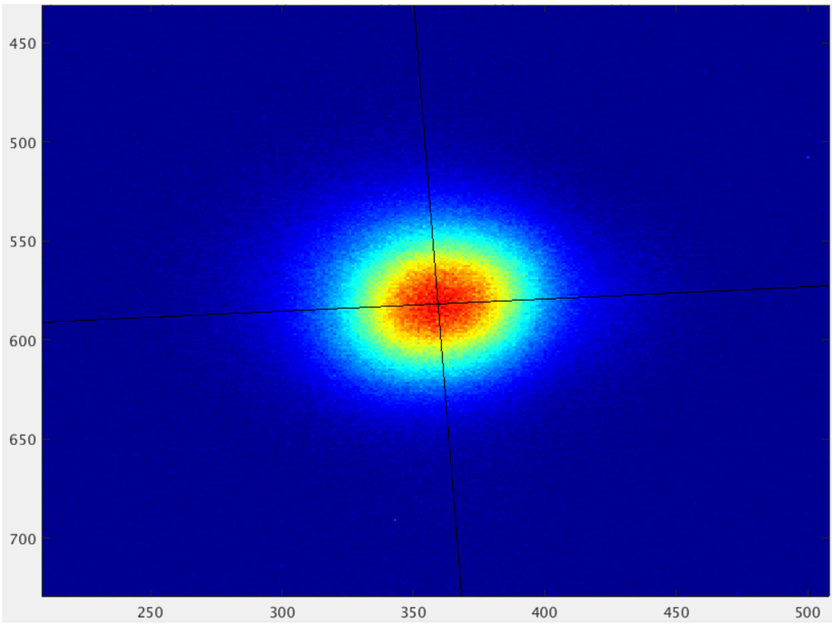
ALS Diagnostic Beamline 3.1



SR from 1st arc dipole ("round beam") → KB mirrors → C filter → 1-3 keV x-rays → LYSO scintillator crystal → visible → CCD

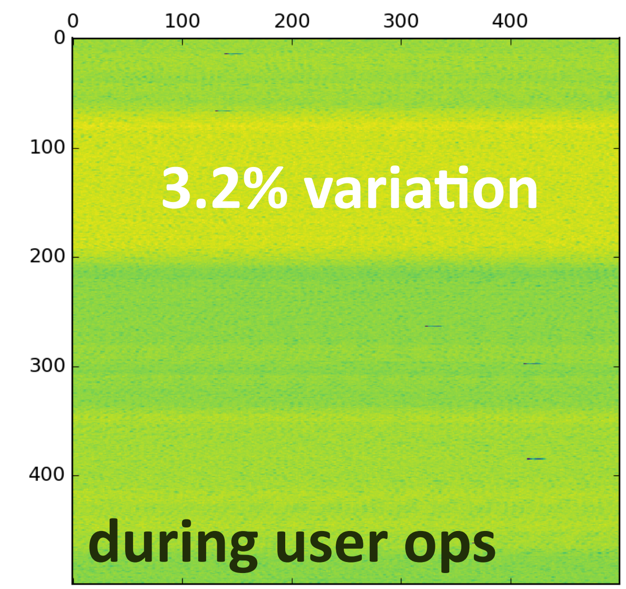
Rev. Sci. Instrum. **67**, 3368 (1996)

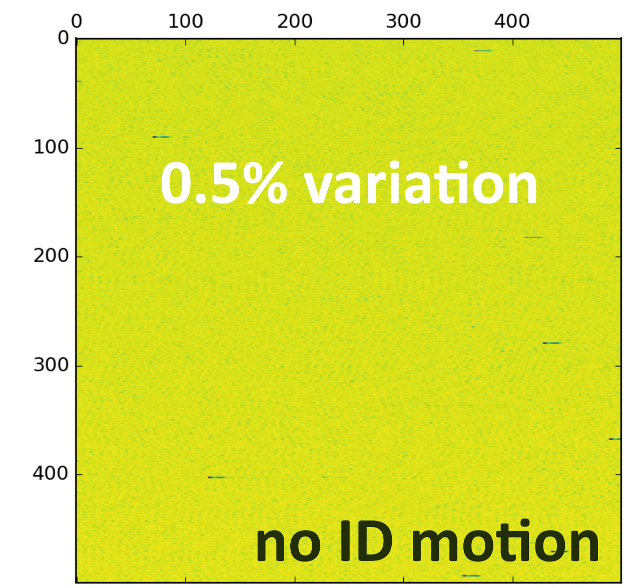
- Traditionally, 3rd-gen. sources considered <10% acceptable, but...

How this Problem Affects Sensitive Experiments

- Vertical source size fluctuations show up as intensity variations at highly sensitive beamlines, such as the STXM at ALS beamline 5.3.2.2
  - STXM zone plate focal length ≈1 mm ➔ no independent & reliable I_0 measurement
  - Very small spot size in focus (>20 nm ➔ scan >10×10 μm^2)
  - Fast raster scanning for differential measurements ➔ no averaging (≈1 ms/pixel, 1 s/line, 6 min/scan)
  - Monochromator plane is H ➔ V source size fluctuations directly affect experimental noise floor

- 4th-gen. rings such as ALS-U will be equipped with many more such highly sensitive beamlines: STXM, XPCS, ptychography, etc.





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Need to Solve This Problem at the Source

- Why use **Machine Learning (ML)** to attack this issue?
  - ML can model highly nonlinear processes and is extremely flexible
  - ML does not require a priori understanding underlying physics (e.g. machine drift) → but allows extracting valuable system information a posteriori
  - ML can substantially outperform conventional fitting (polynomial regression)
- ML requires reproducible events → confirmed in experiments
- ML ideally requires large data sets for training → ALS digital control system can provide that

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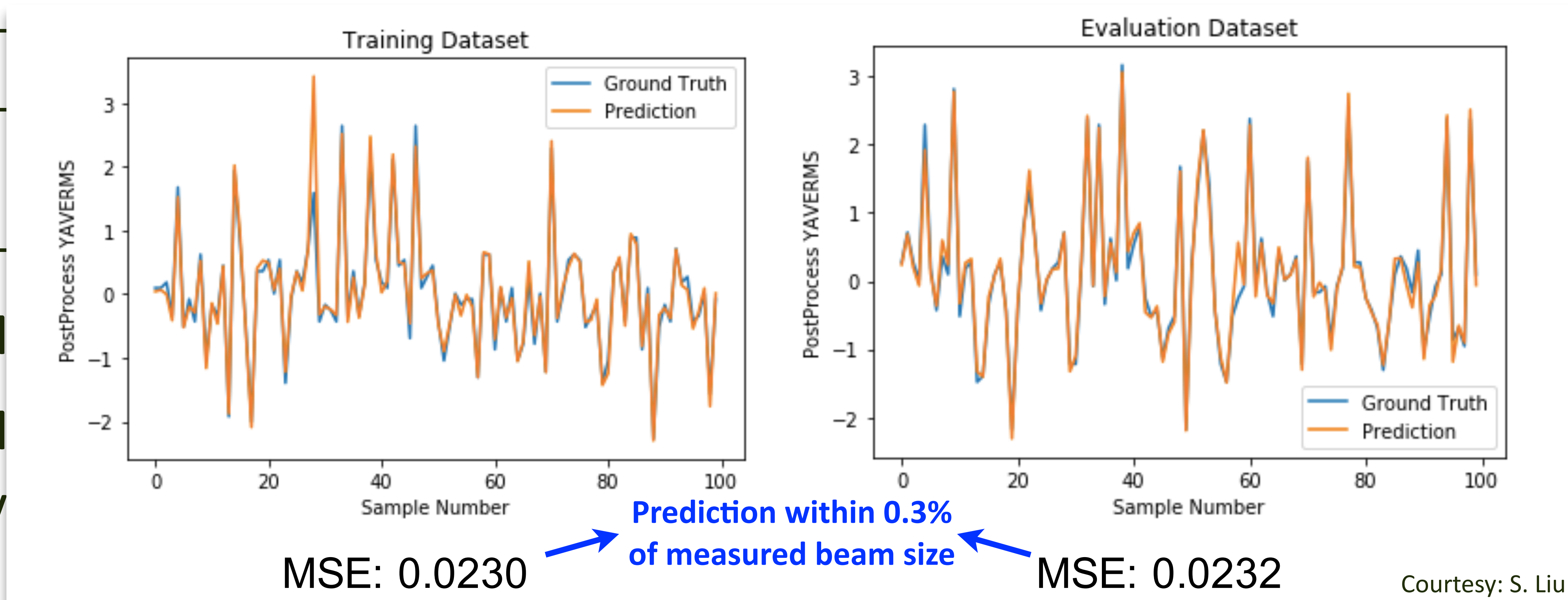
- Why use **Machine Learning (ML)** to attack this issue?
  - –
  - –
  - –



- M
- M … l
  sy

- First example: offline analysis of user ops data
  - 26 ID parameters ("input") → predict V beam size @ BL3.1 ("output")
  - Recorded 8 Msamples @ 10 Hz → 6 Msamples used for training, 2 Msamples for validation → training took 30 min on powerful GPU

Need to Solve This Problem at the Source

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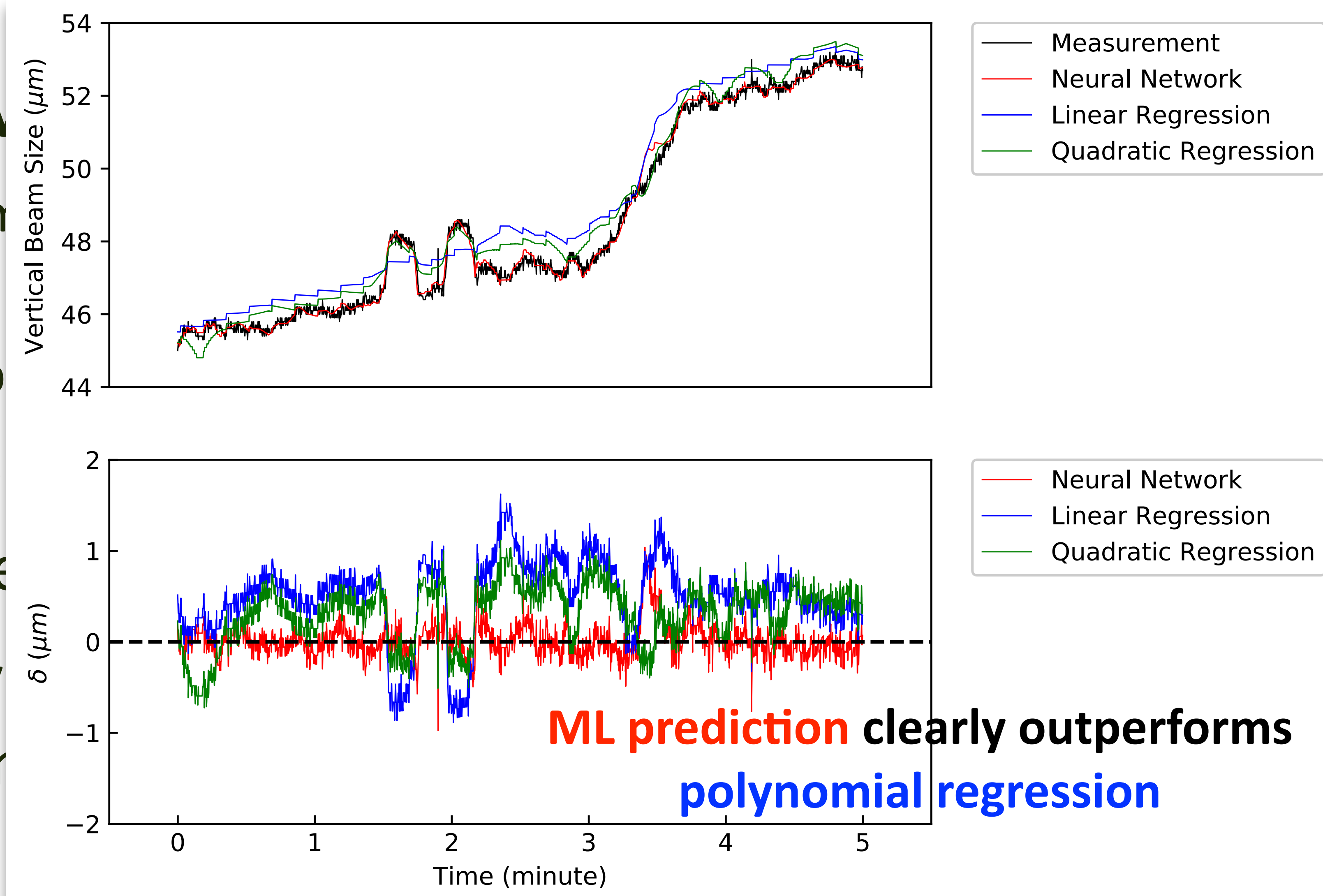
  - ML can m
  - ML does … machine drift) → b … ori
  - ML can s … egression)
- ML require … ents
- ML ideally … al control system car



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From Prediction to Correction

- Introduced "dispersion wave parameter" (DWP) to modify standard ALS dispersion wave (skew quadrupole excitation pattern) → allows adjusting vertical emittance (global conserved quantity)

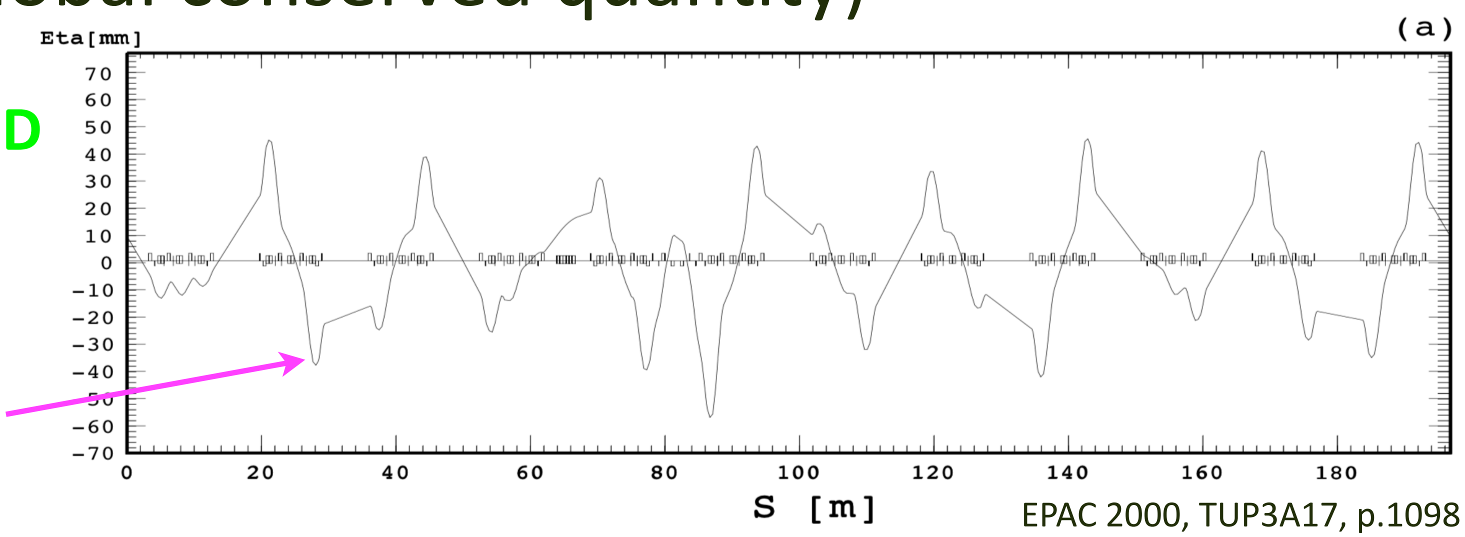
SQSF SQSD

$$\vec{K} = \vec{K}_0 + (\chi_0 + \chi)\Delta\vec{K}, \quad \vec{K} \in \mathbb{R}^{16+16}$$

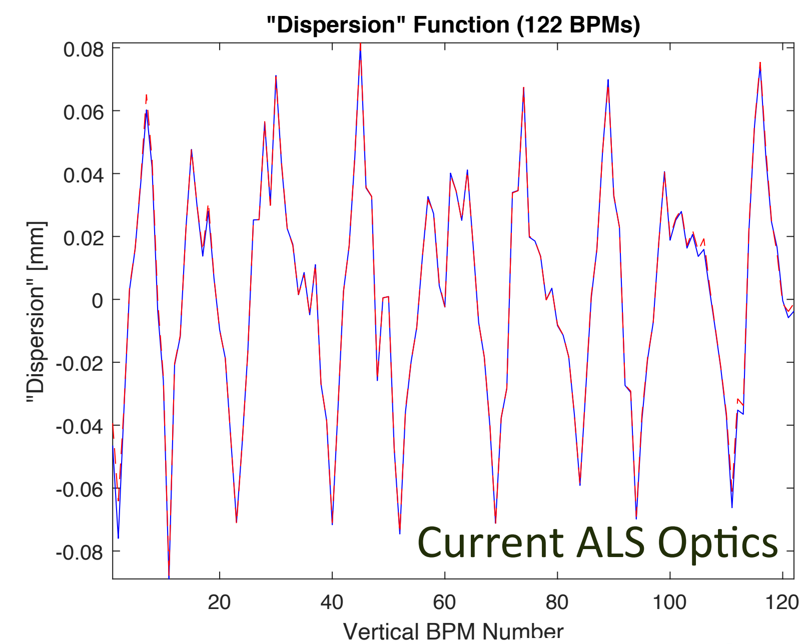
LOCO & Setup

DWP

Dispersion Wave



EPAC 2000, TUP3A17, p.1098

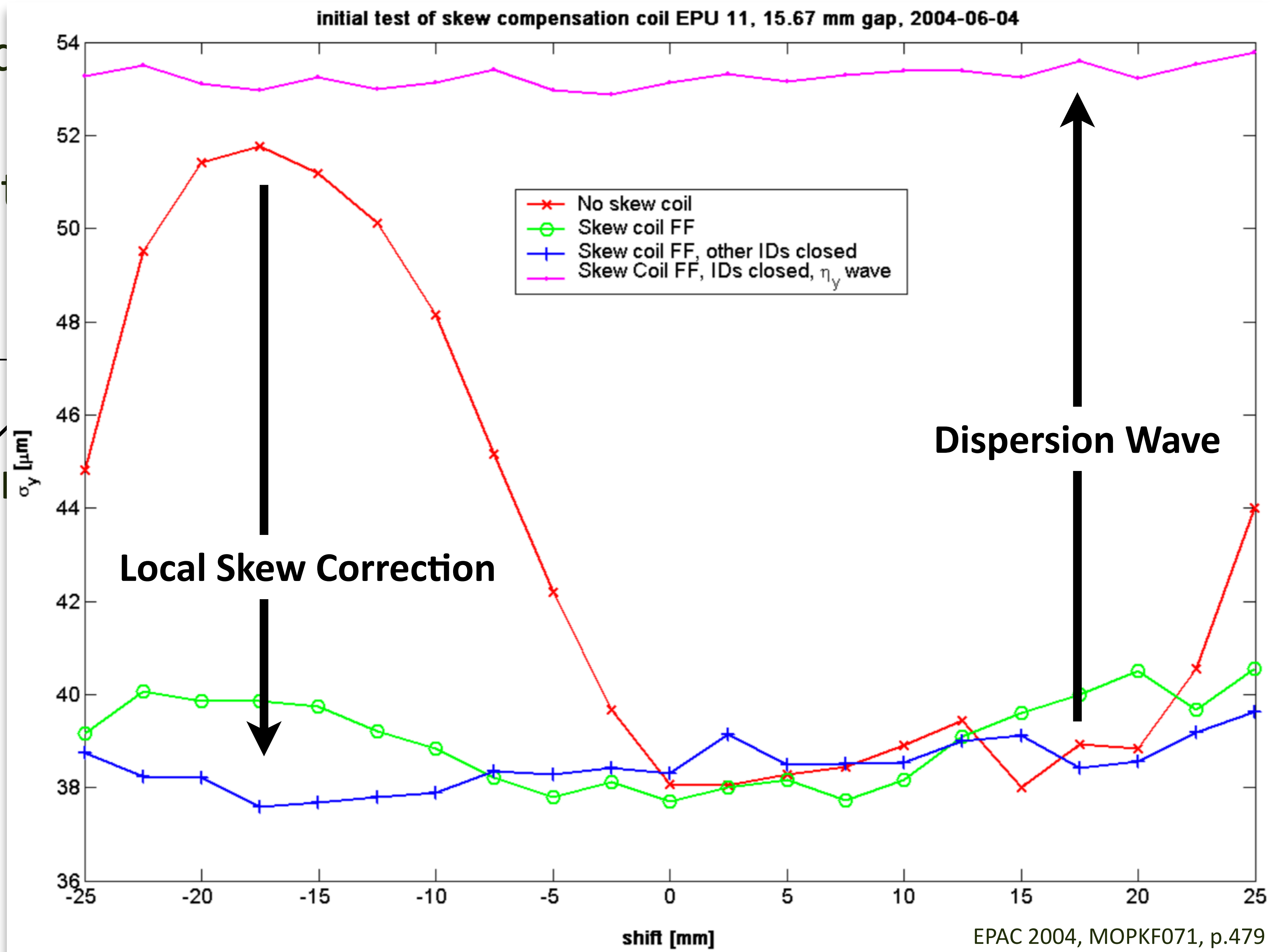


From Prediction to Correction (cont.)

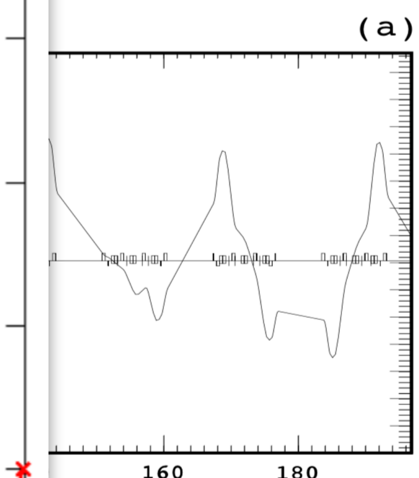
- Introd… …ndard ALS d… …lows adjust…

$\vec{K} = \vec{K}_0 + \ldots$

LOCO & Setu…



EPAC 2004, MOPKF071, p.479



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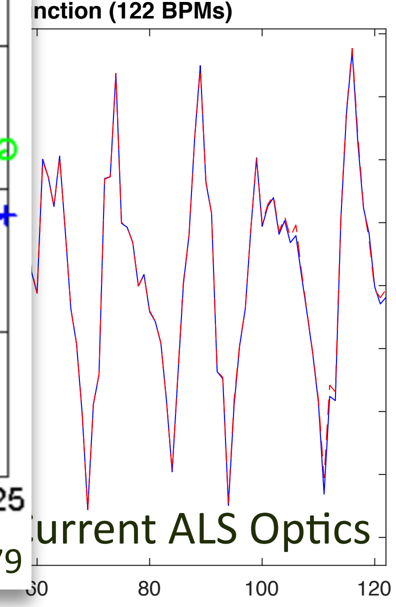

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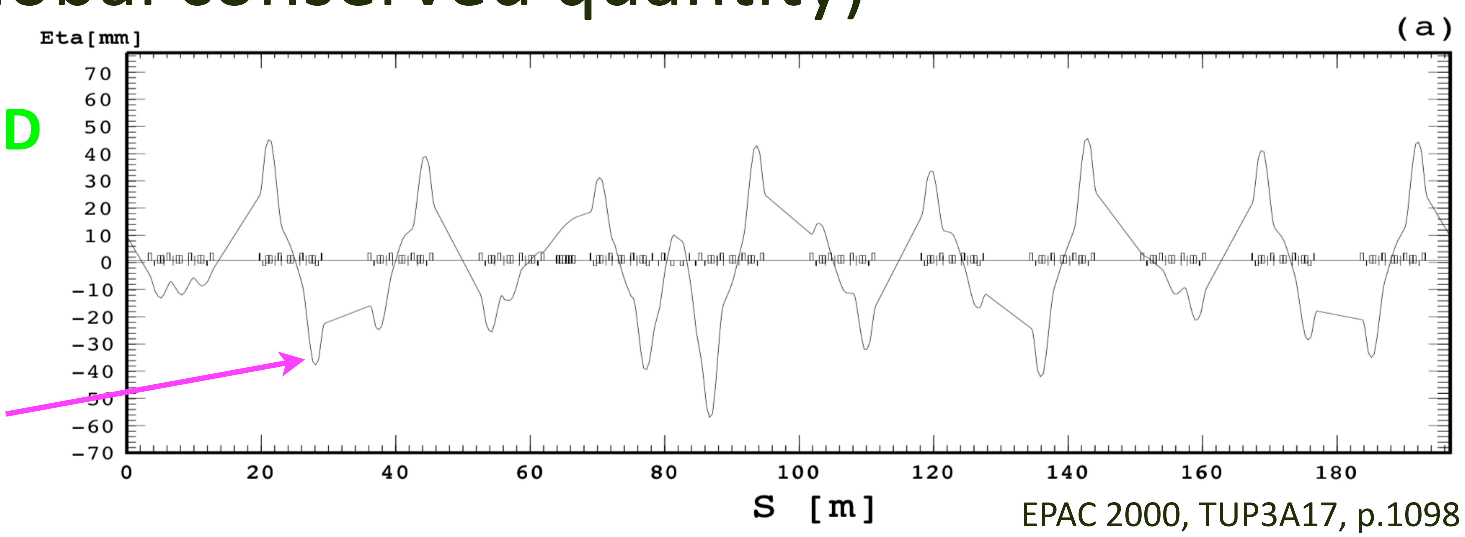
LOCO & Setup

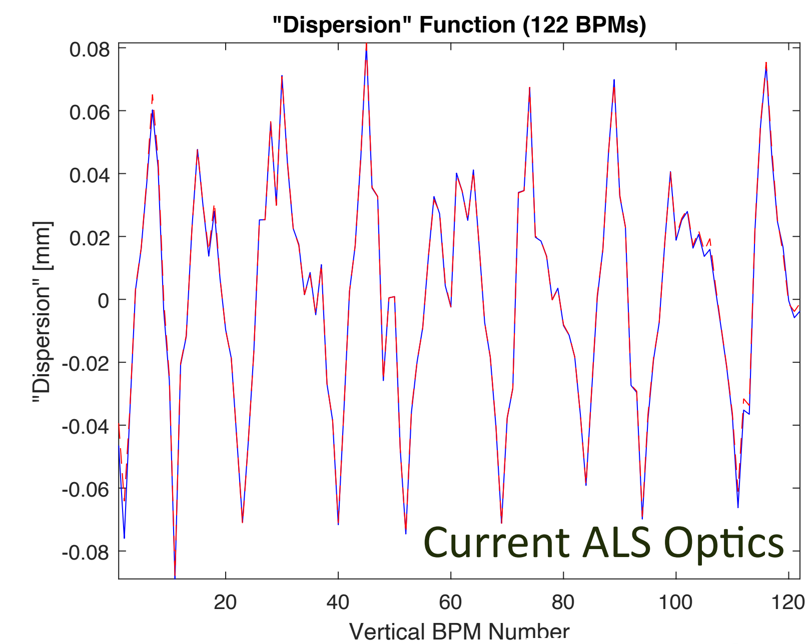
DWP

Dispersion Wave



EPAC 2000, TUP3A17, p.1098

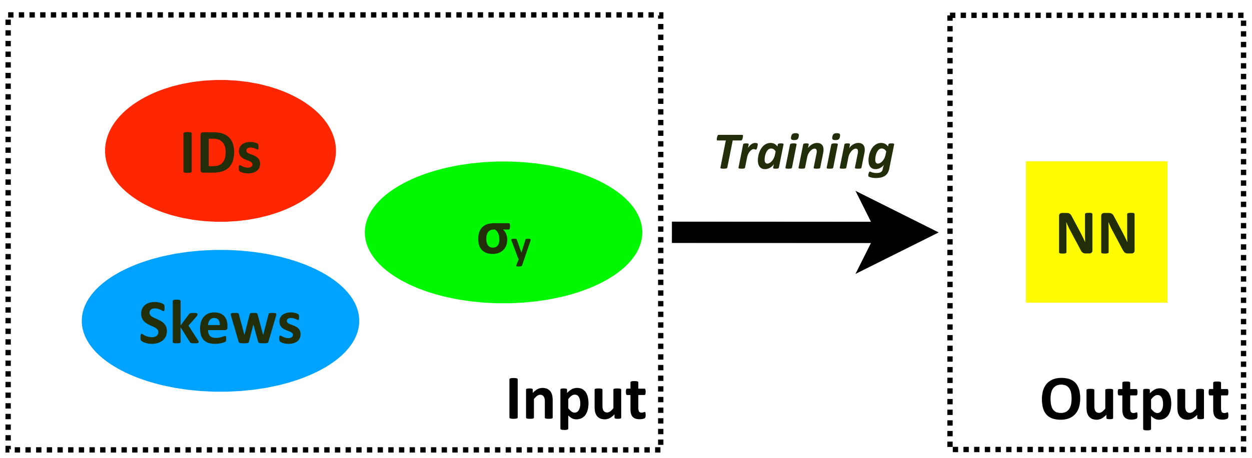
- Observed varying ID configurations affect primarily vertical dispersion ➔ ε_y
- Can therefore stabilize beam size globally by adjusting DWP



Building a NN-based ID Feed-Forward

- Training: measure beam sizes while scanning DWP & various ID configurations → acquire data at 10 Hz → input for ***training*** of NN (DL)

Deep Learning

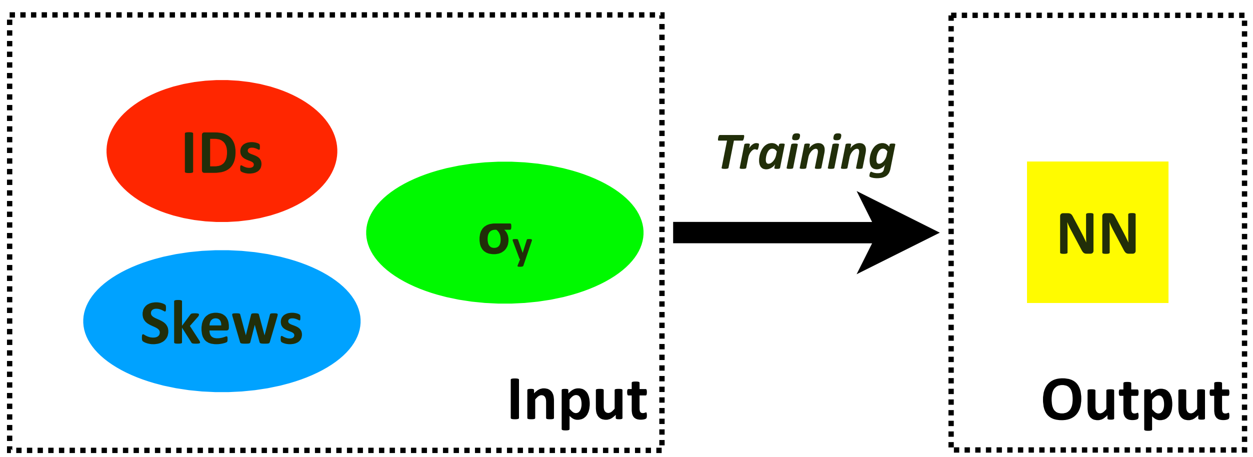


- ***Requires only large amounts of data & reproducibility***

Building a NN-based ID Feed-Forward

- Training: measure beam sizes while scanning DWP & various ID configurations ➔ acquire data at 10 Hz ➔ input for ***training*** of NN (DL)
- Result of DL is ***prediction*** for DWP required to keep beam size constant for arbitrary ID configurations ➔ run as NN-based ID FF

Deep Learning



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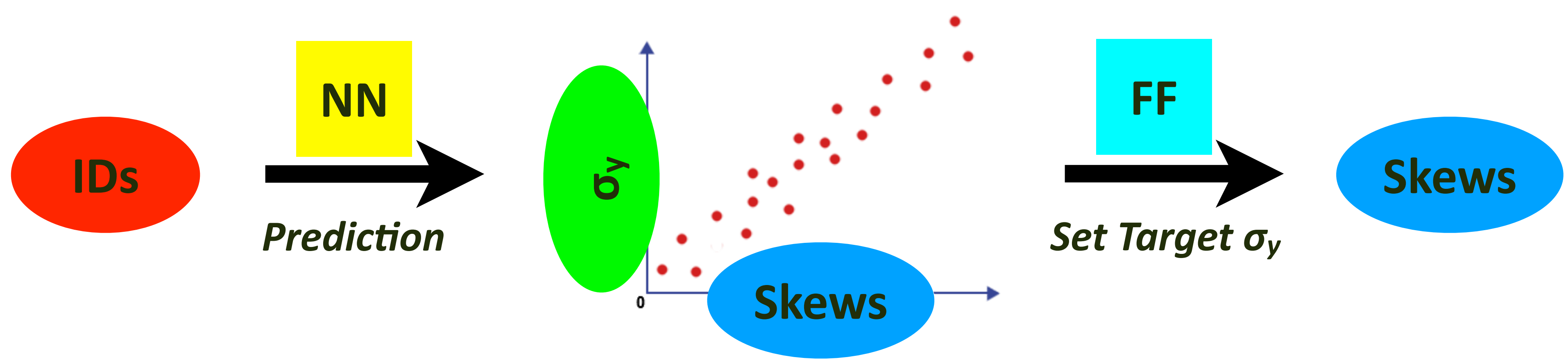
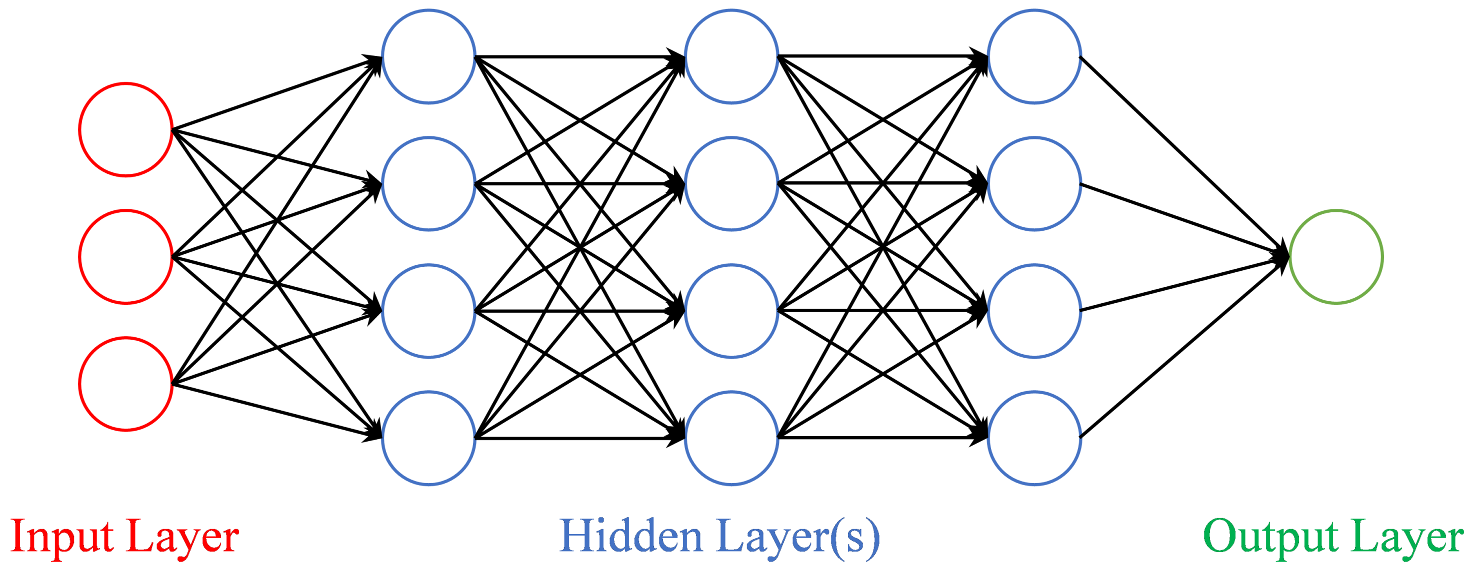
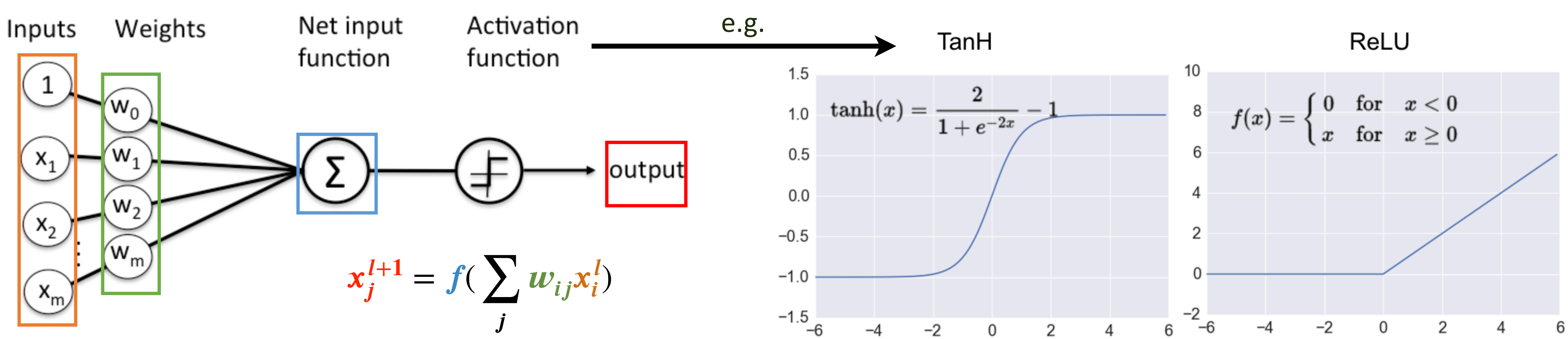
Application during ops



How a Neural Network (NN) Works

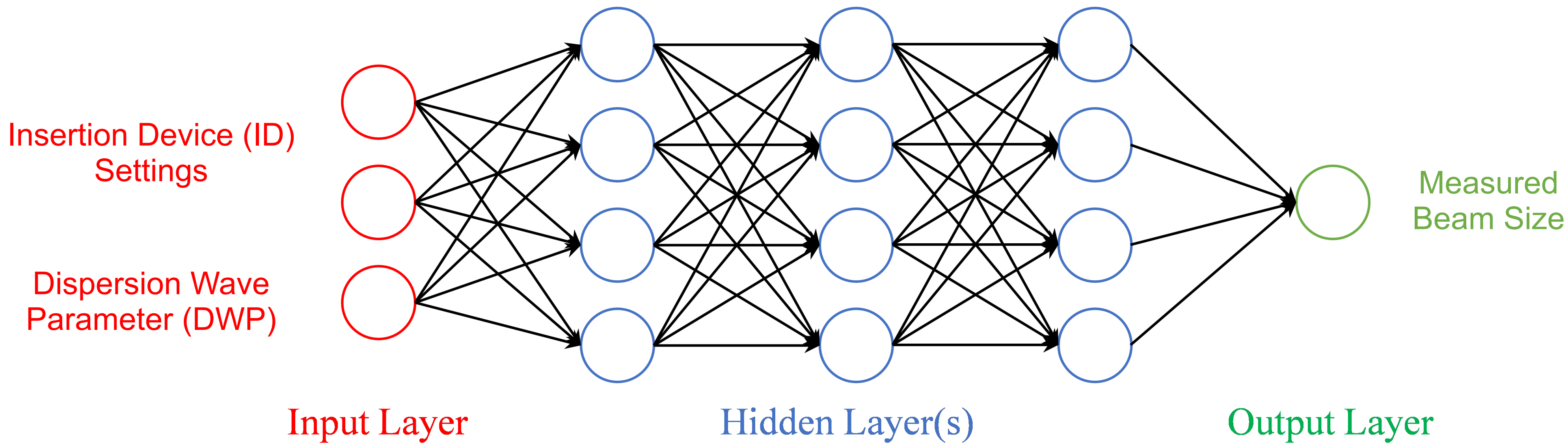


Courtesy: S. Liu



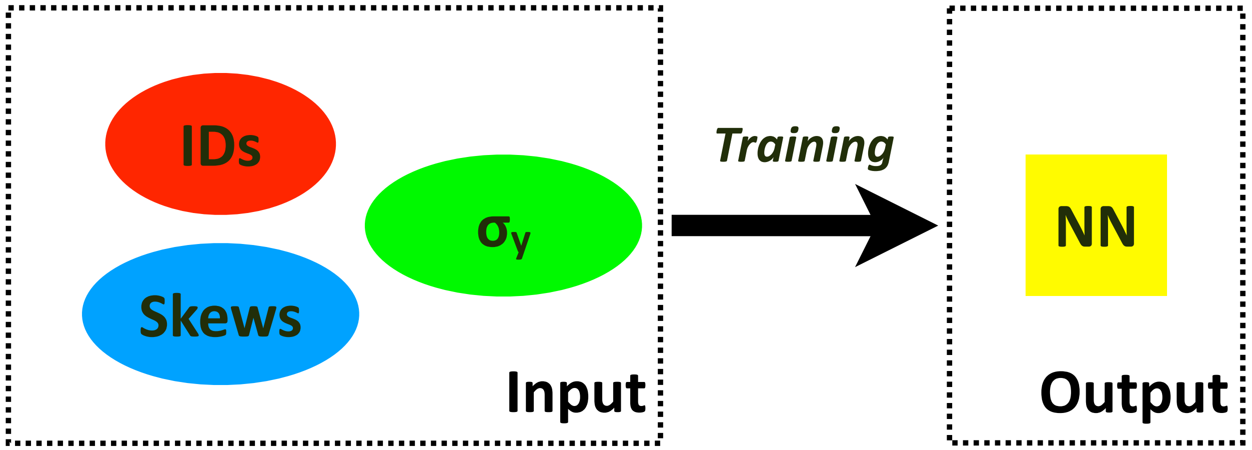
$$x_j^{l+1} = f\Big(\sum_j w_{ij} x_i^l\Big)$$

Deep Learning: How we Trained the NN



Input Layer: ID settings (22-35 Dimension) and DWP (1 Dimension)
Three Hidden Fully Connected Layers: 128, 64, 32 neurons in each layer
Output Layer: Vertical Beam Size (1 Dimension)

Regularization: L_2 regularizer with $\lambda = 10^{-4}$
Optimization: Adam Optimizer with learning rate $\alpha = 10^{-3}$



	Raw Data		With Square Features	
Architecture	Training MSE	Evaluation MSE	Training MSE	Evaluation MSE
128-64	0.0265	0.0268	0.0257	0.0260
256-64	0.0243	0.0245	0.0259	0.0262
512-128	0.0243	0.0247	0.0243	0.0247
128-64-32	0.0238	0.0242	0.0243	0.0245
256-128-64	0.0236	0.0240	0.0240	0.0246
256-128-64-32	0.0245	0.0249	0.0245	0.0248

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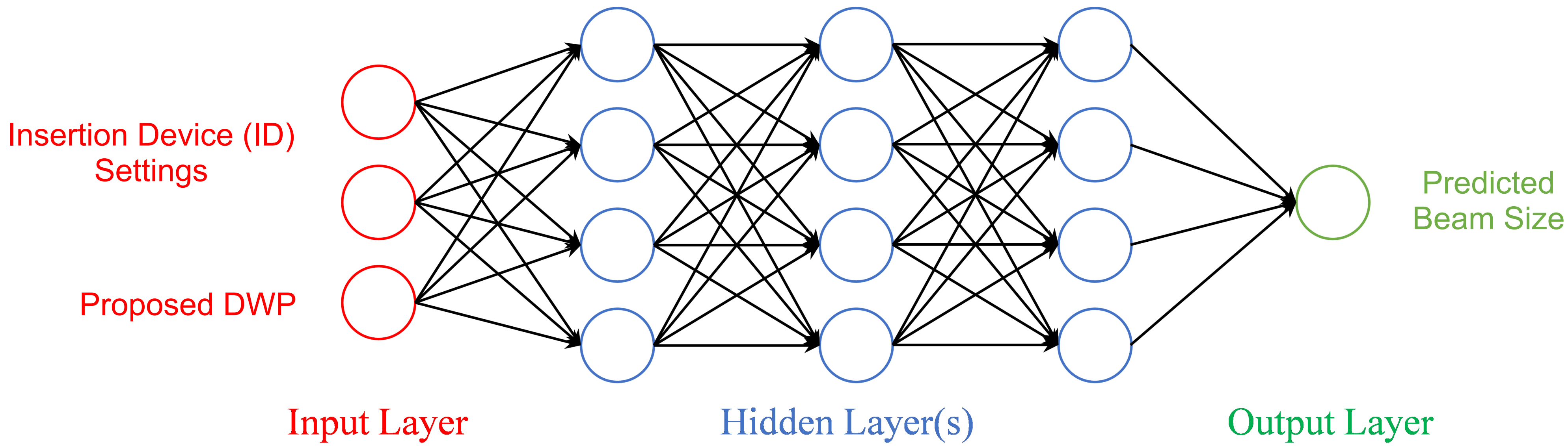
Resulting NN Enables ID Feed-Forward at ≈3 Hz



Proposed DWPs

-0.06
….
0
…
0.06

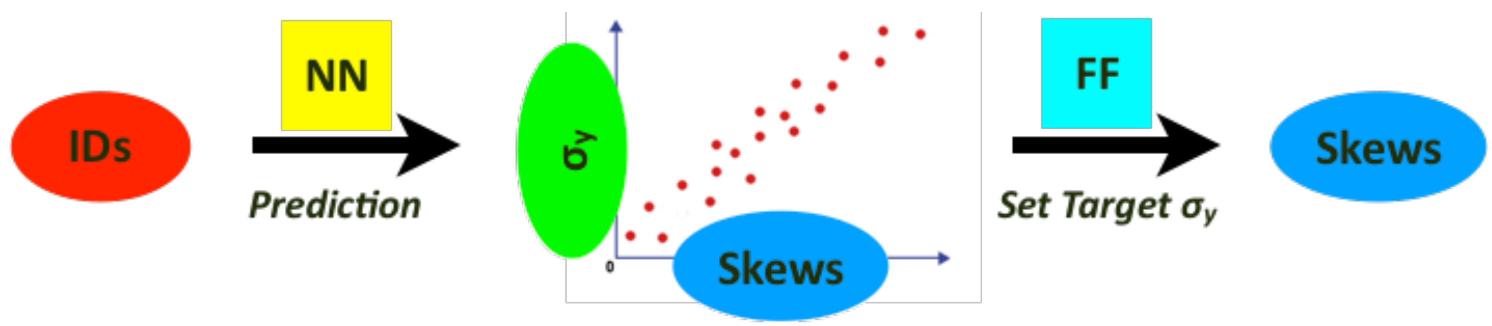
Measured ID Settings → Neural Network

Predicted Beam Sizes

50.3
….
52.1
…
54.0

Compare with Target → Beam Size

Choose proper DWP



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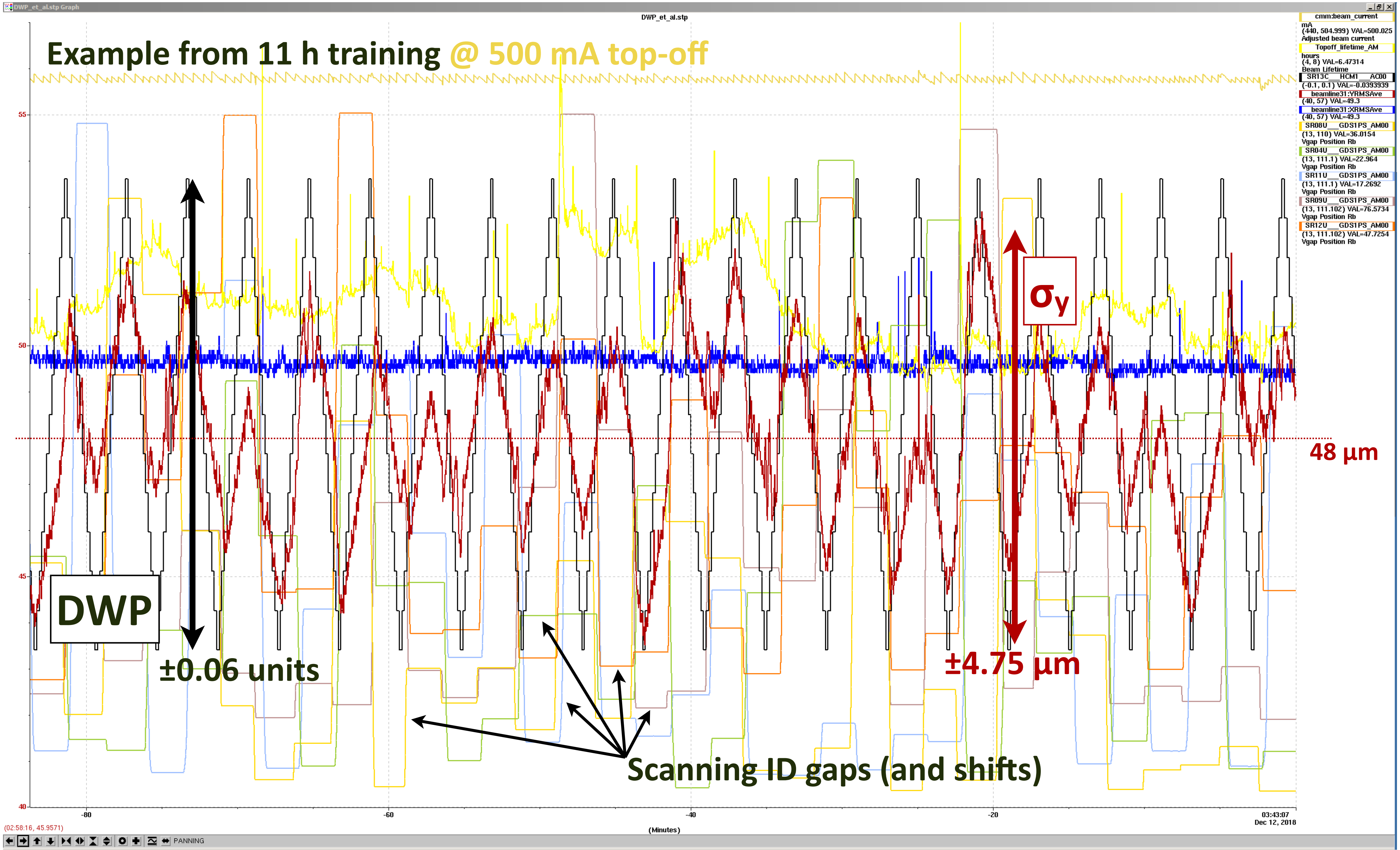
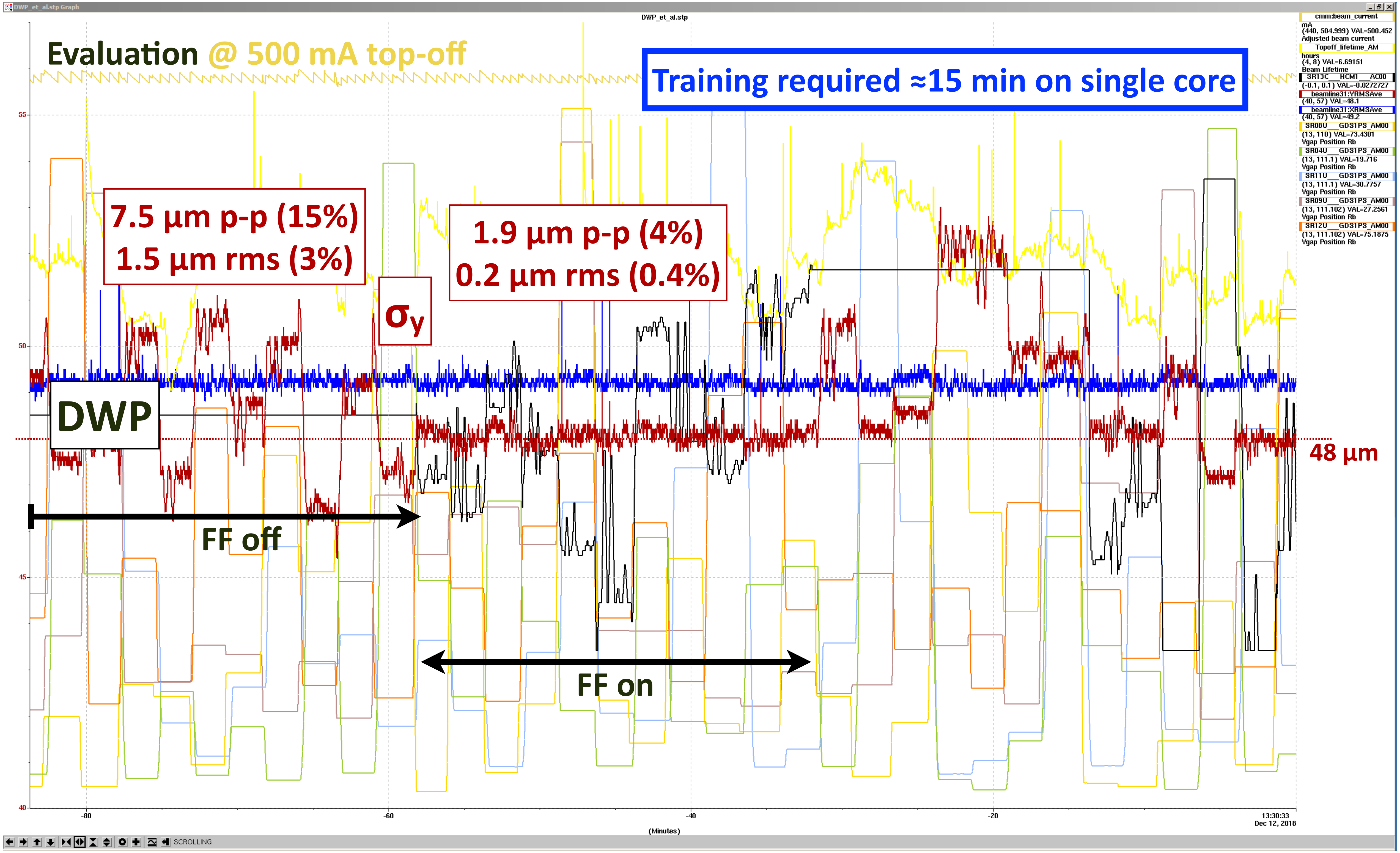
Physics Shift: Data Collection for NN Training

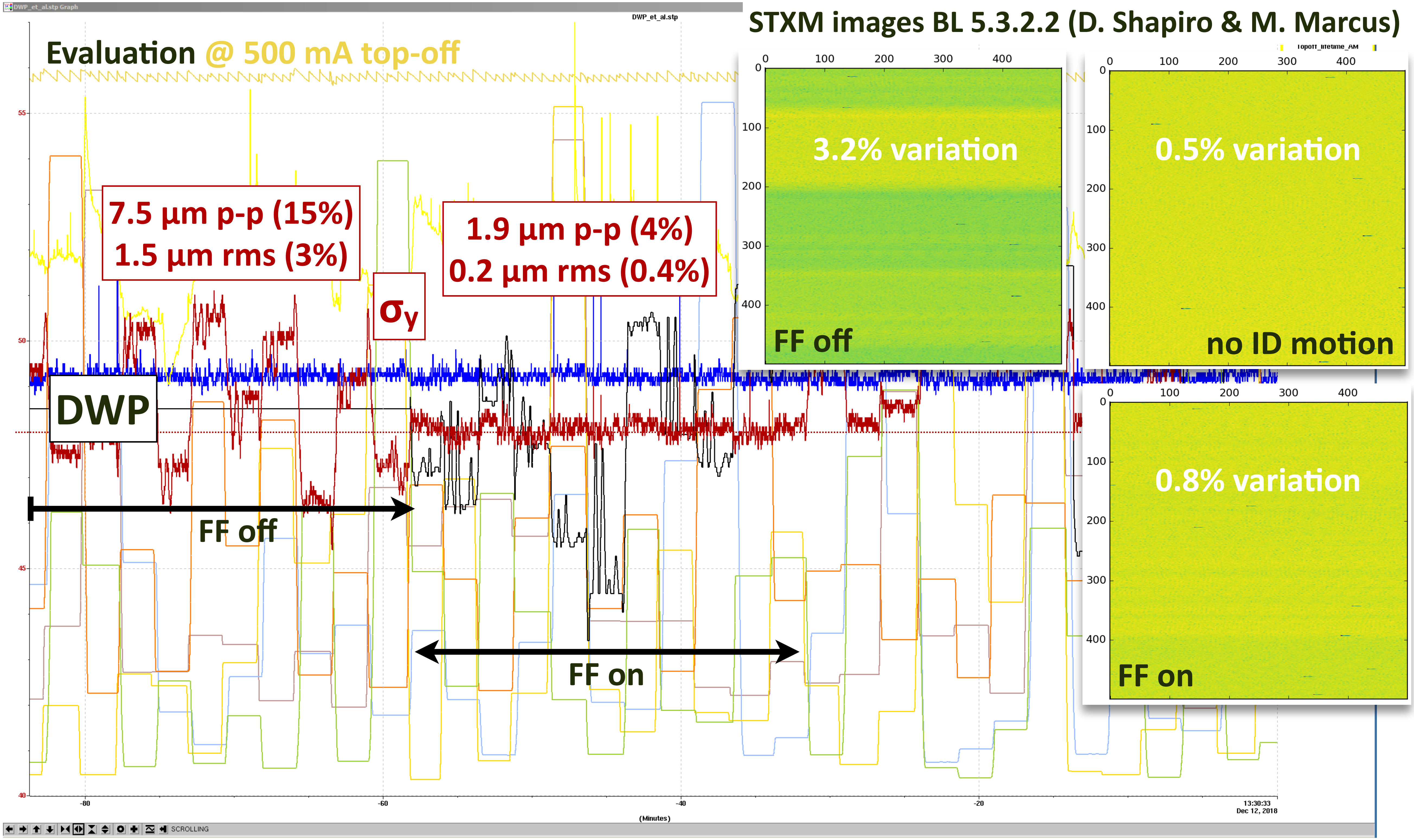


Physics Shift: Running NN-based ID Feed-Forward



Physics Shift: Running NN-based ID Feed-Forward

STXM images BL 5.3.2.2 (D. Shapiro & M. Marcus)



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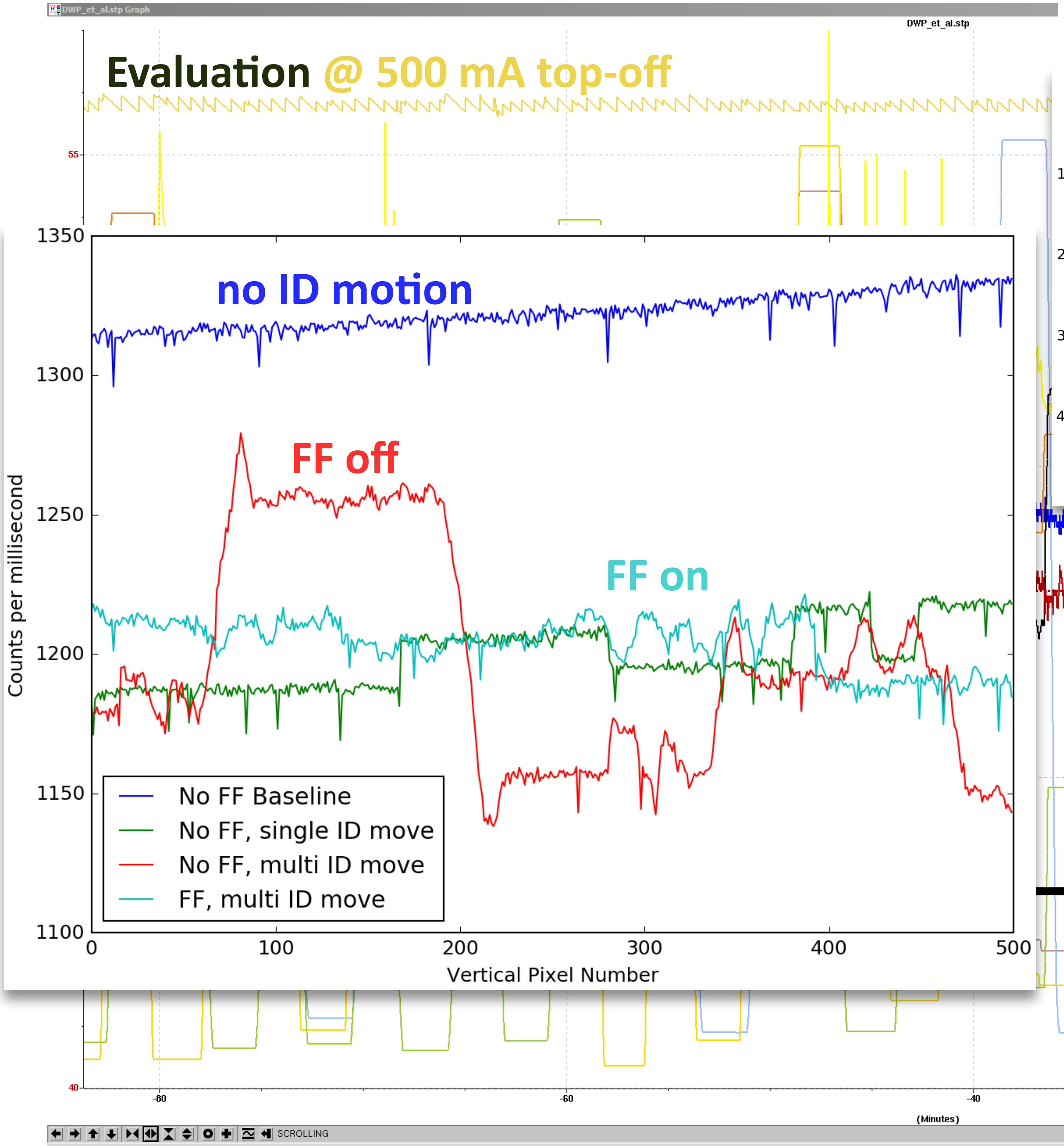

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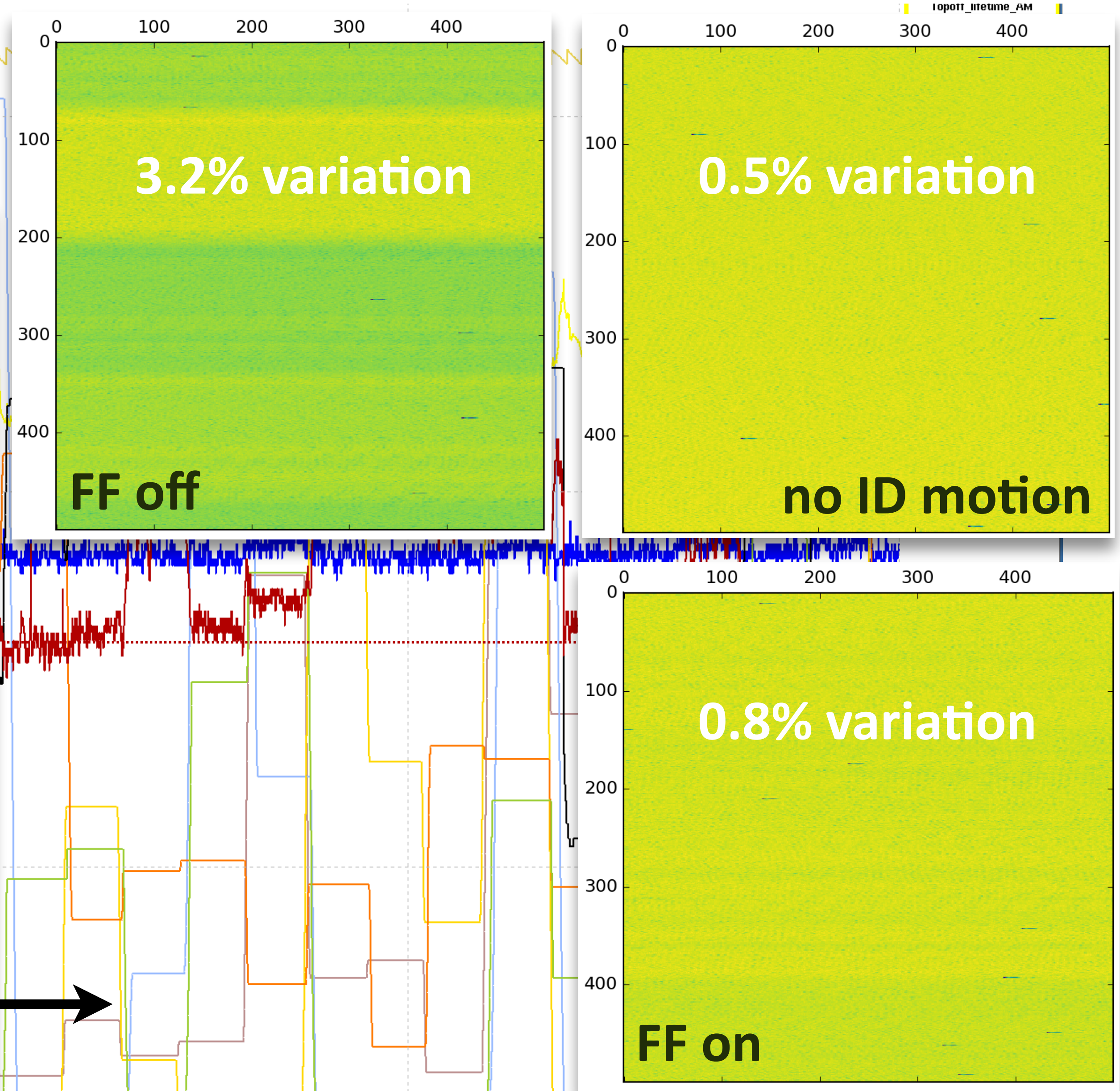

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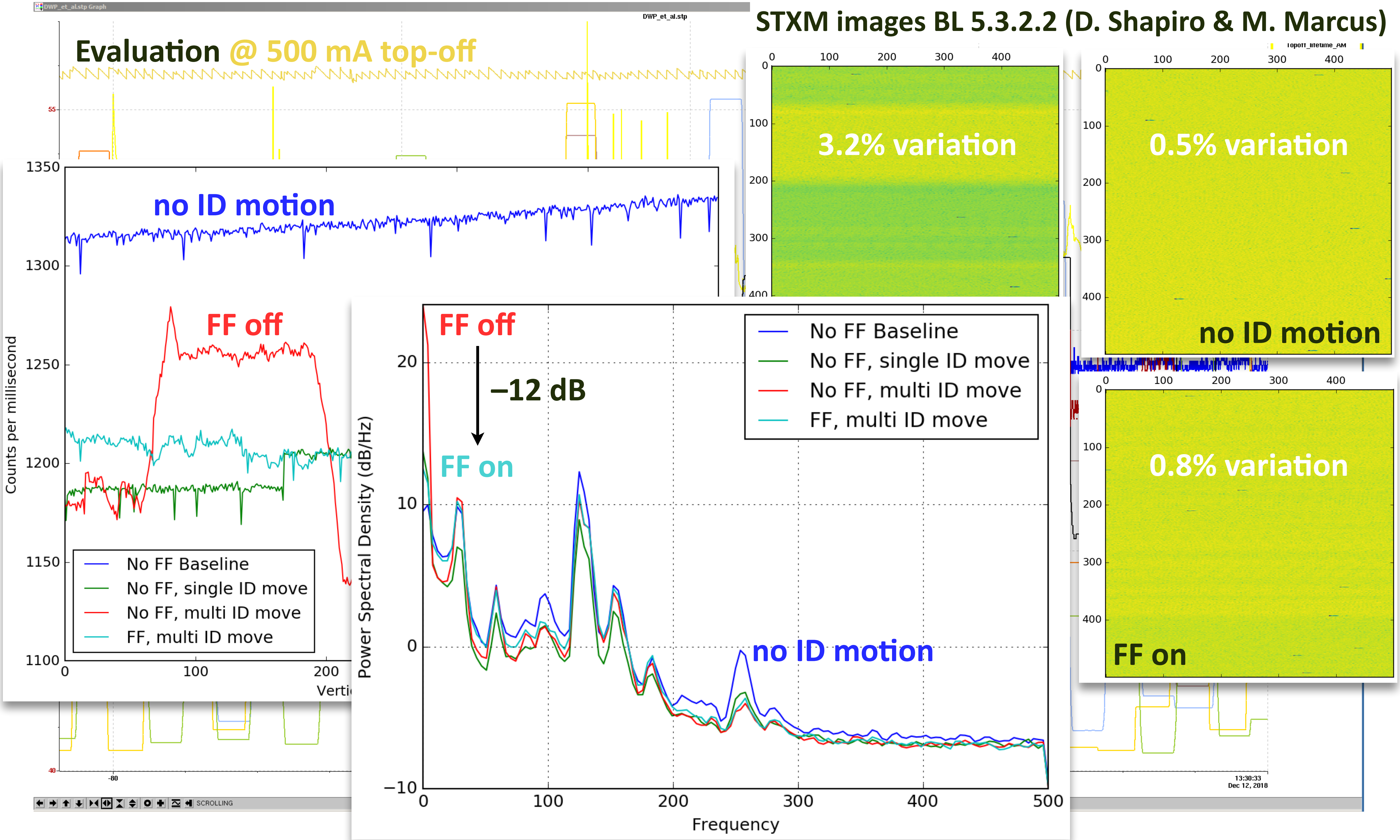
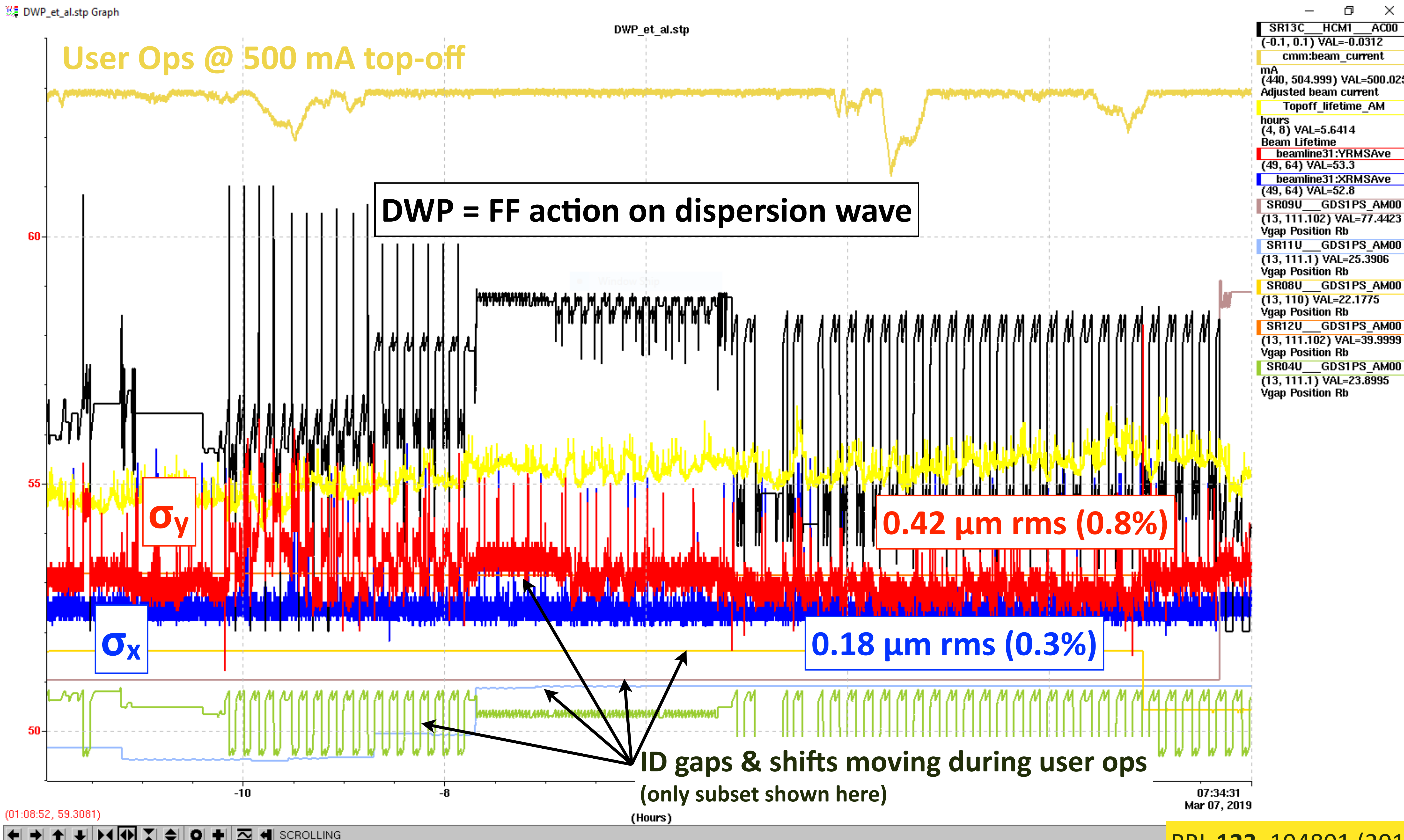


Towards First Experiments During User Ops

- Use machine shift to acquire training data by scanning operational IDs in a quasi-randomized fashion (favoring operational gap range) → train NN
- Put this NN into FF operation during user ops and evaluate

Stabilization Confirmed During First User Ops Trial



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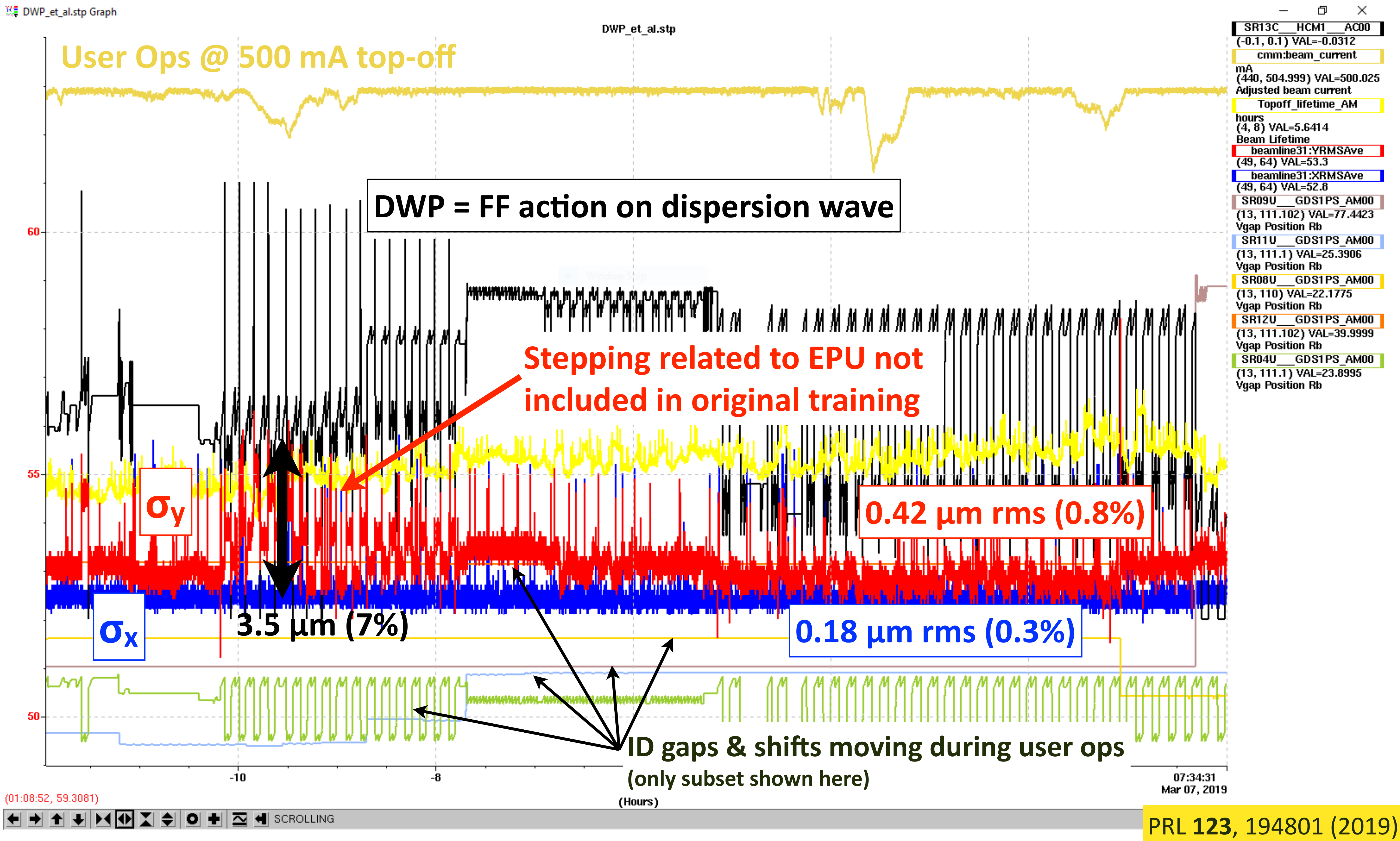

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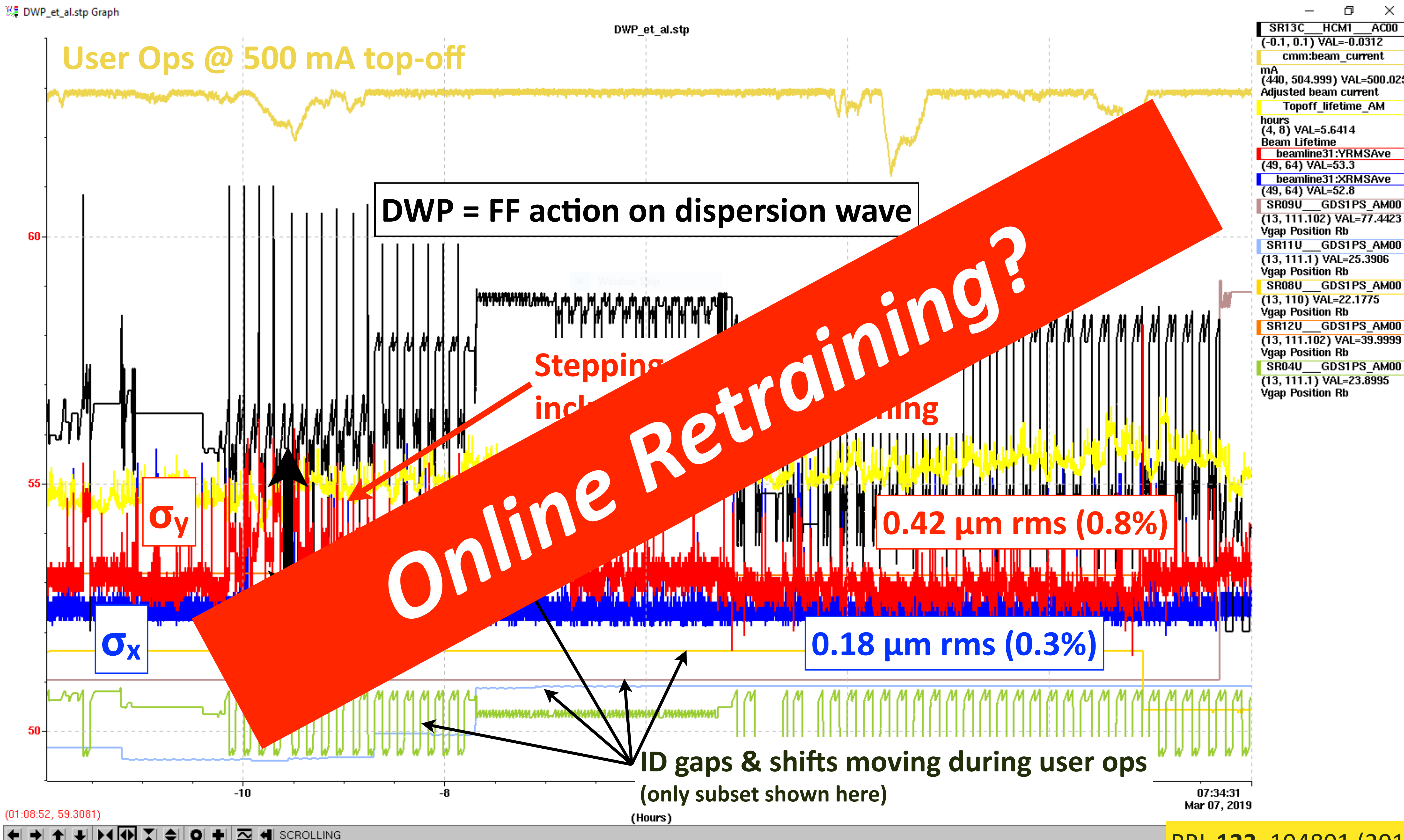

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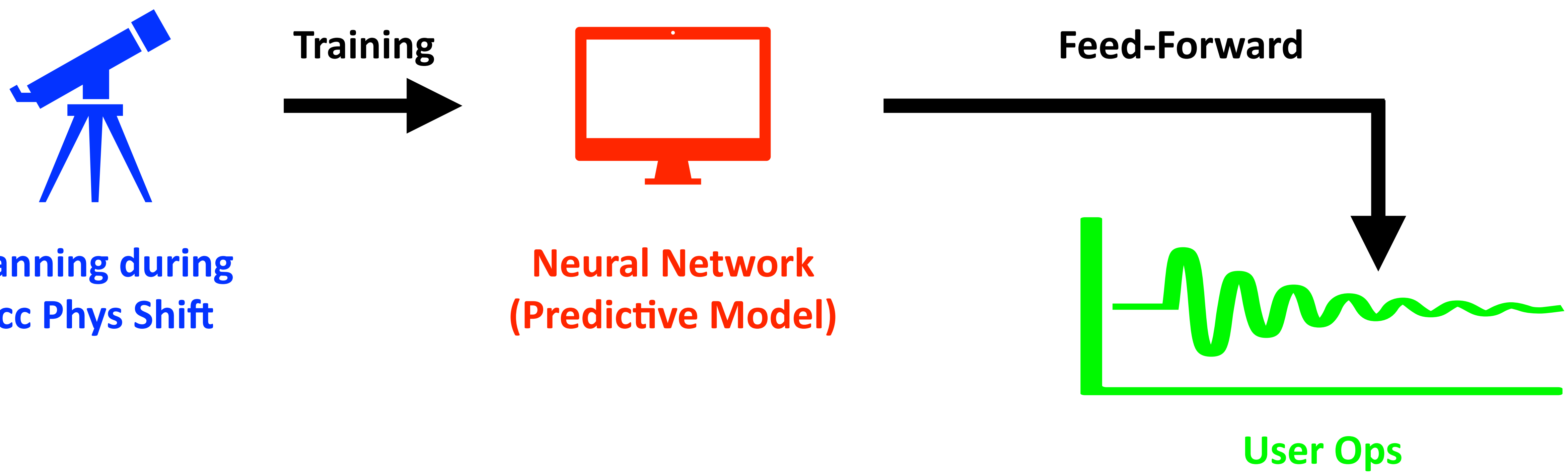
Online Retraining: Improve NN with User Ops Data

So far: "Conventional" Machine Learning



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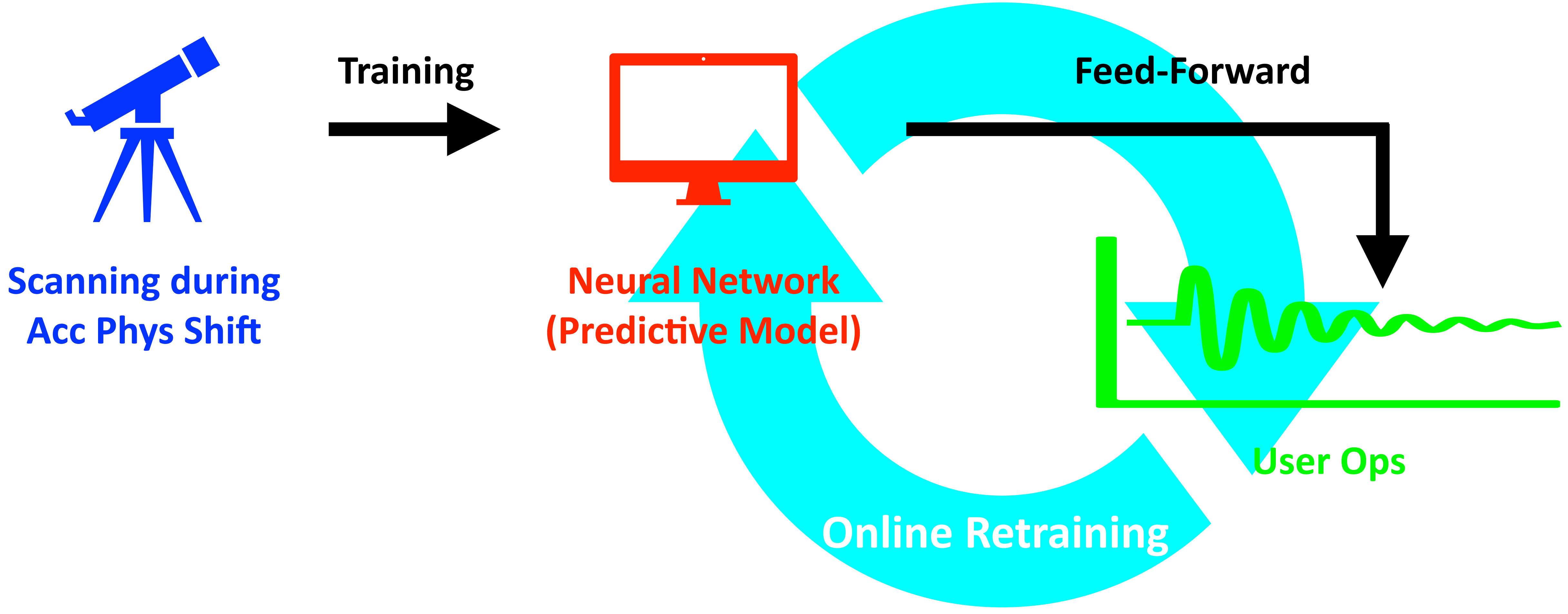
Online Retraining: Improve NN with User Ops Data

Online Retraining: apply user ops data to improve NN → swap NN used for ID FF on the fly



NN can be continuously online retrained during user ops to improve FF performance (exploiting huge amounts of data acquired during user ops)

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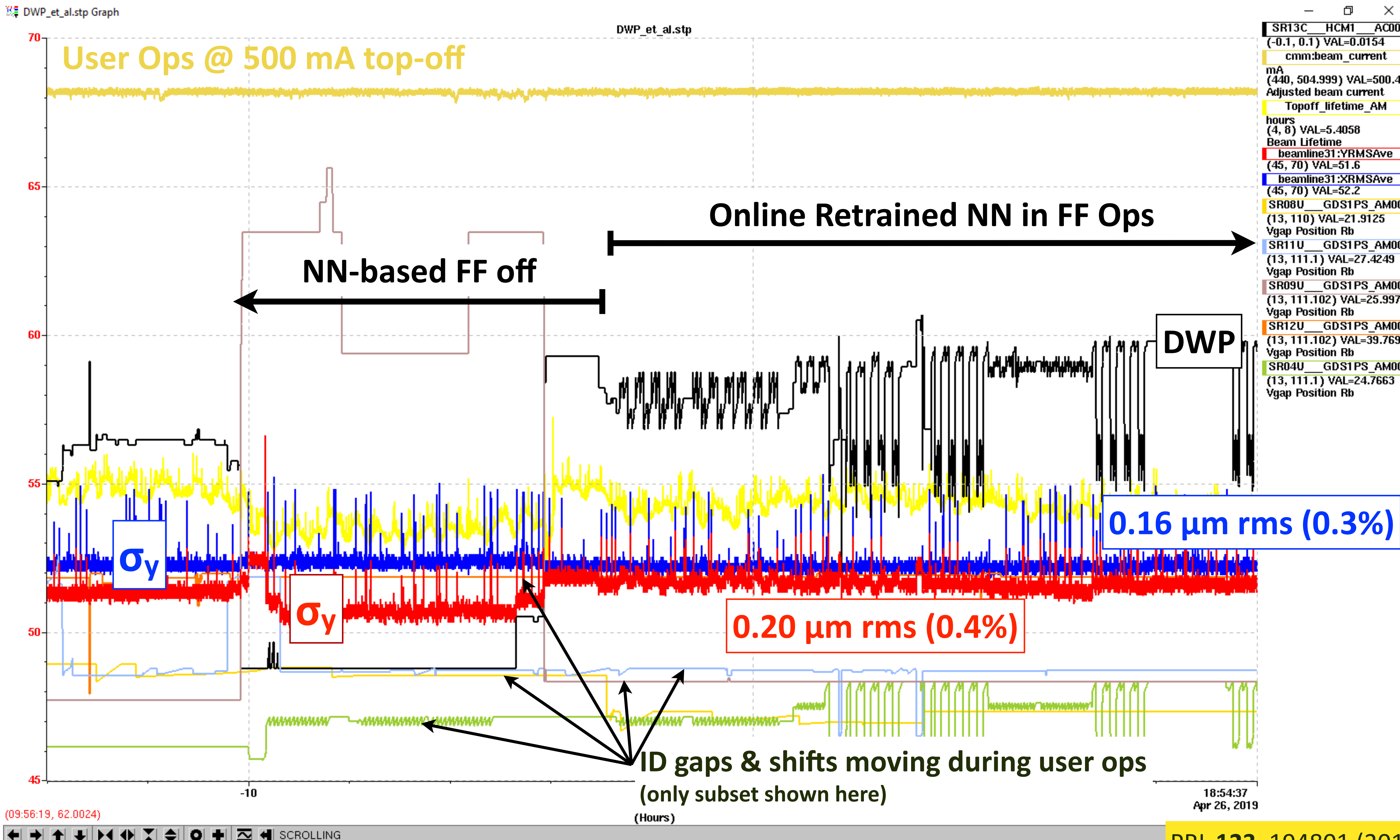
Substantial Improvement After Online Retraining



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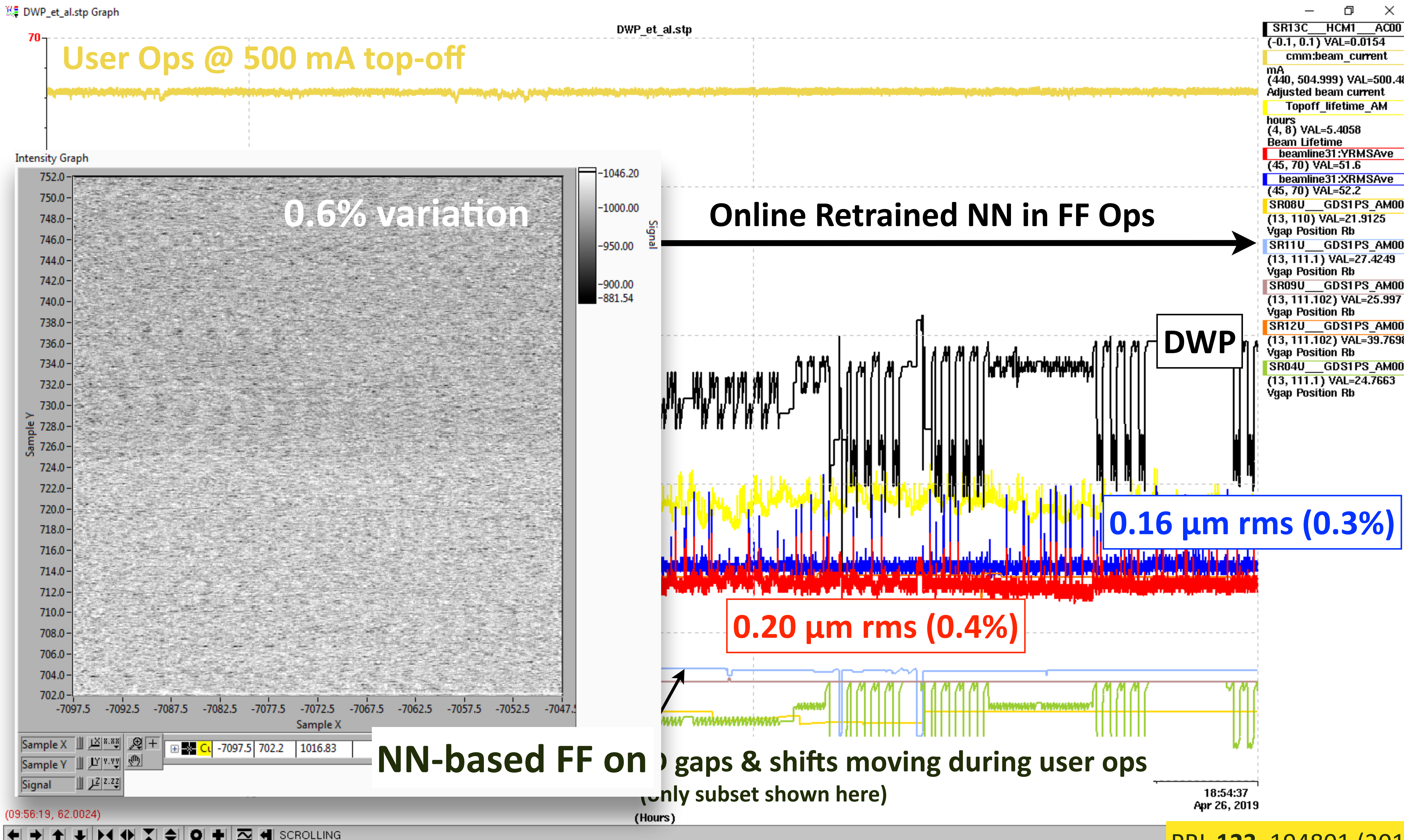

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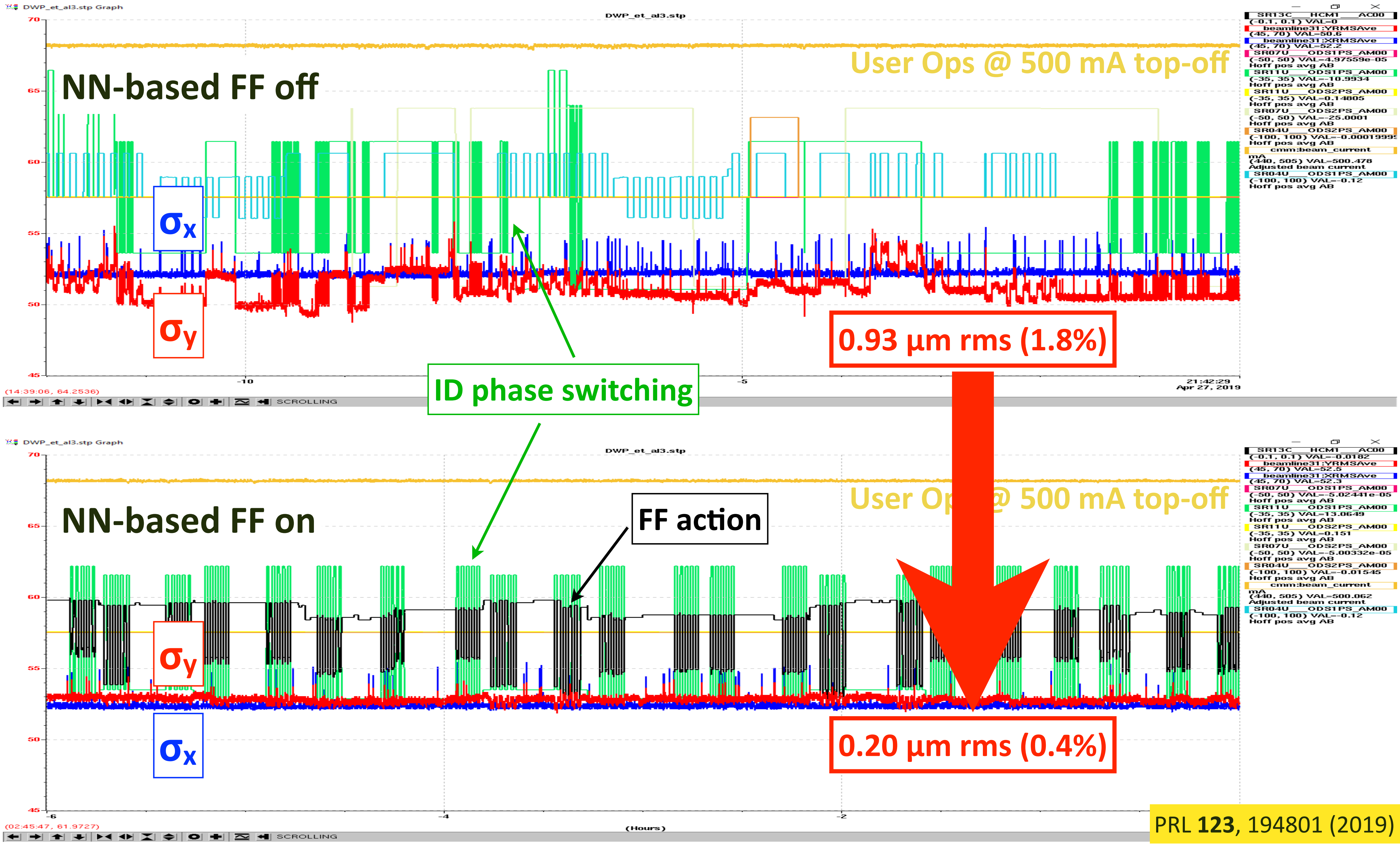
Results: NN-based FF Off vs. On During User Ops



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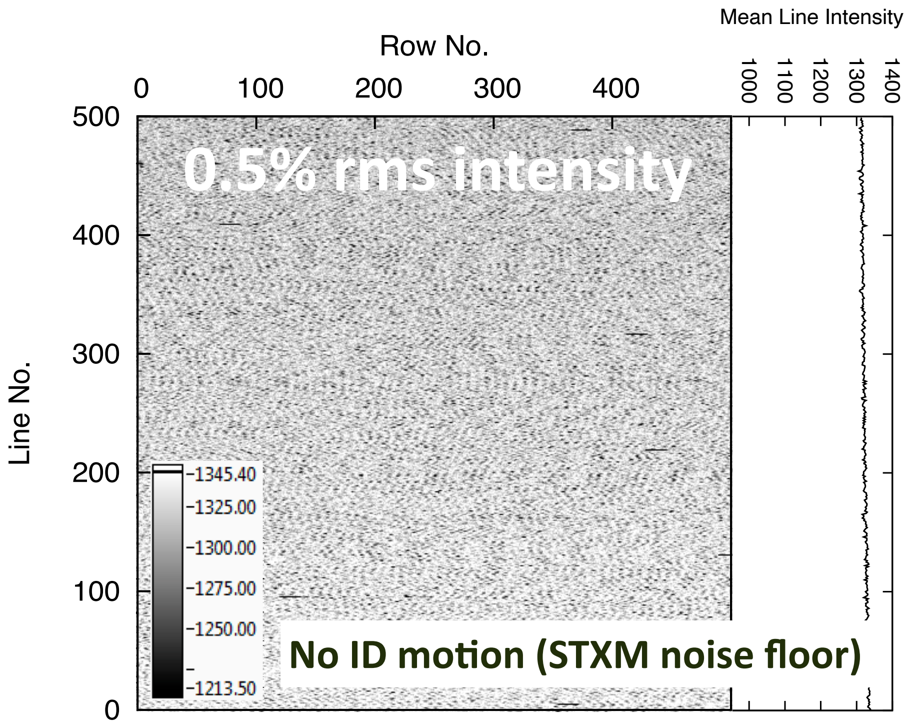
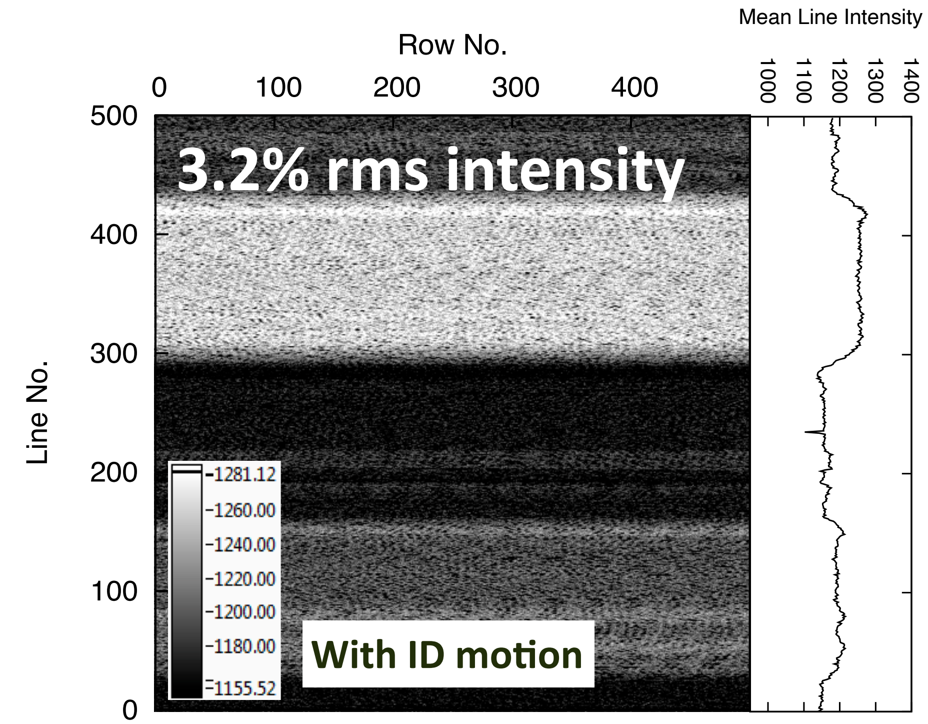
Stabilization Confirmed at Experiment

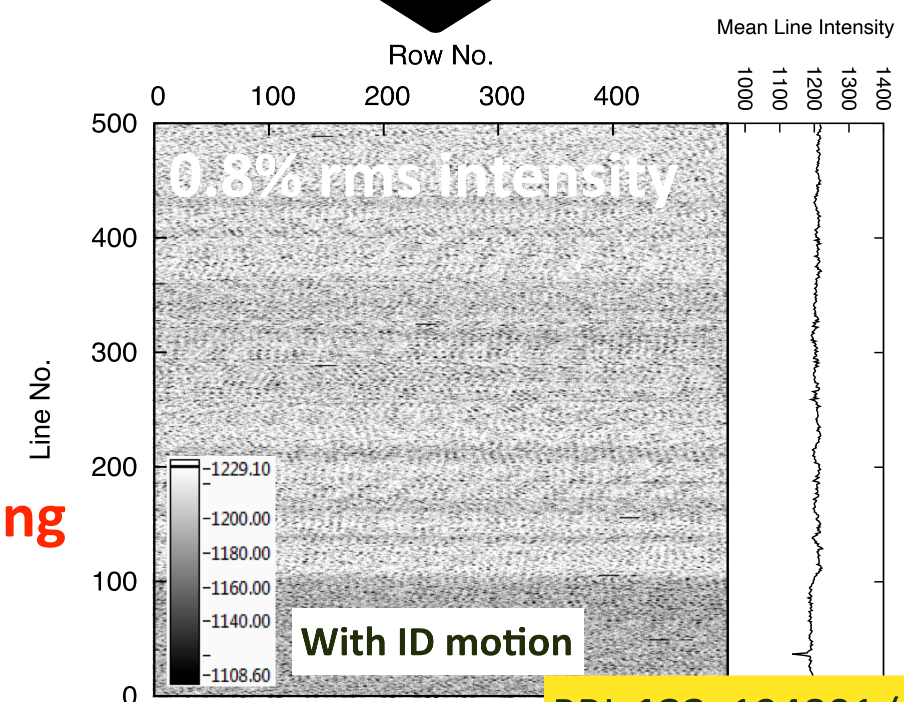
ALS Beamline 5.3.2.2



ID Motion

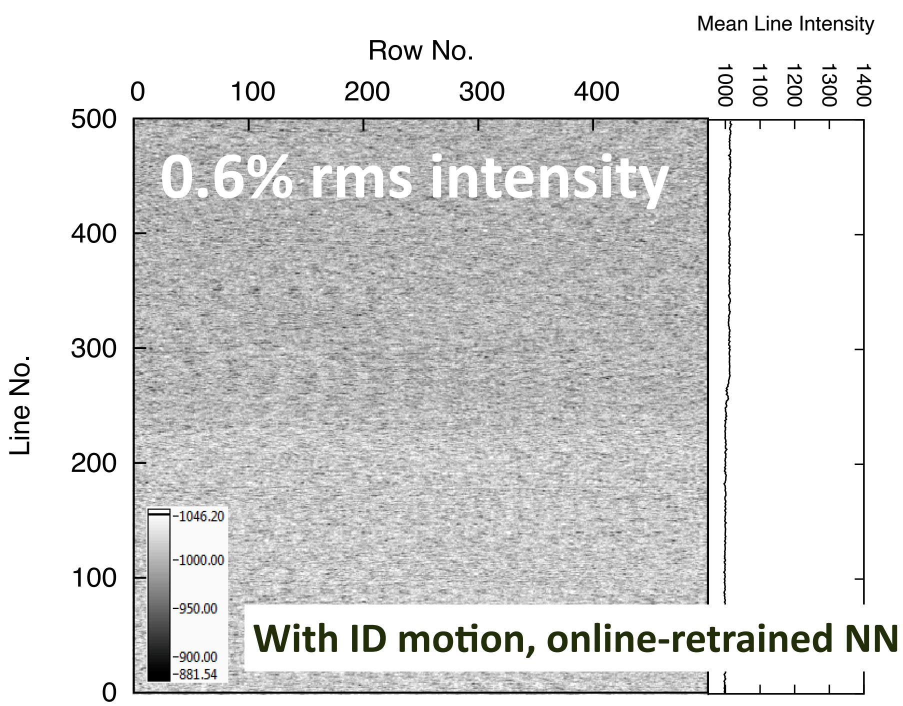


NN-based FF on



Online Retraining

Noise reduced to almost floor level



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Thank You!

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