

First Attempts at Applying Machine Learning to ALS Storage Ring Stabilization*



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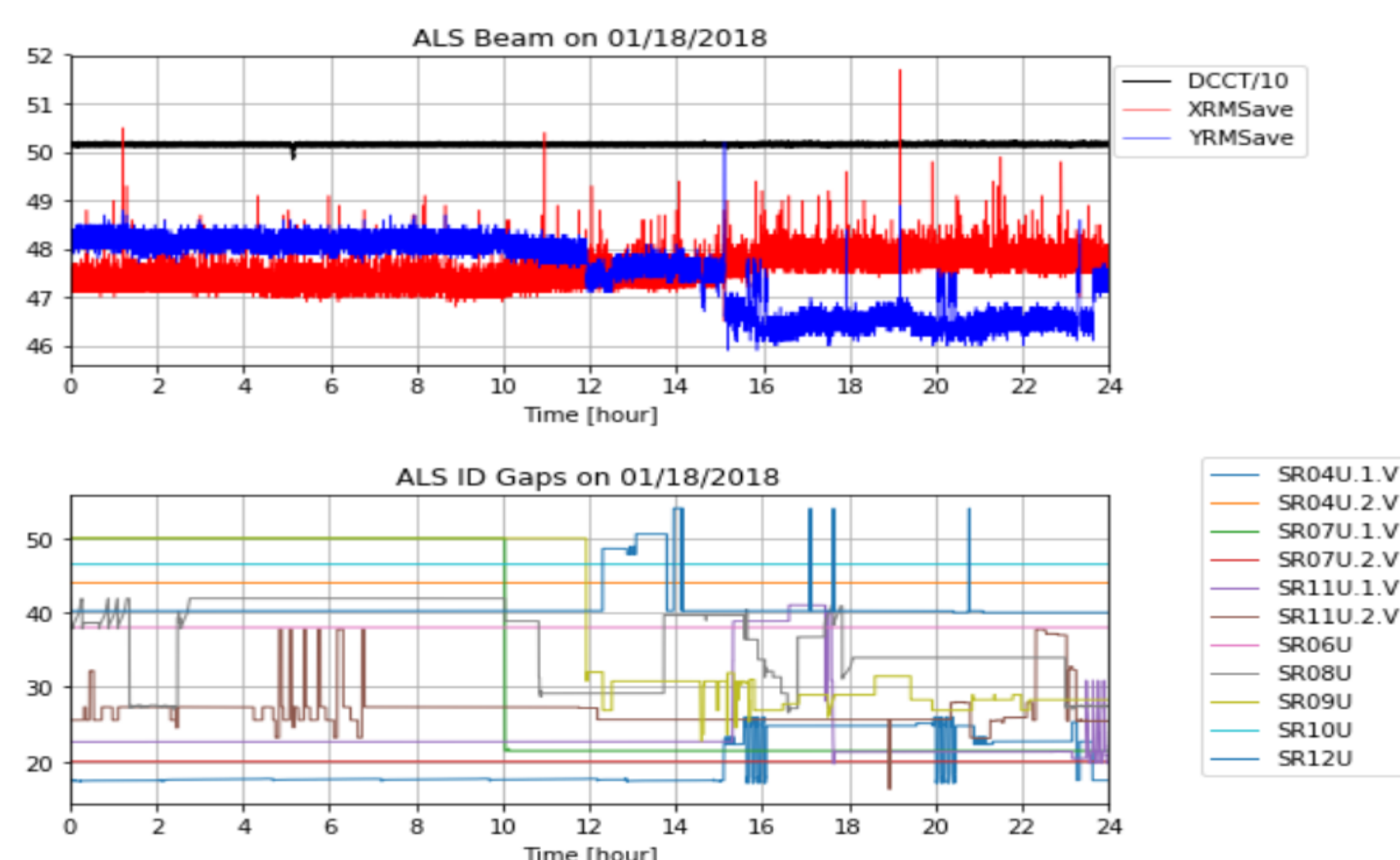


Introduction

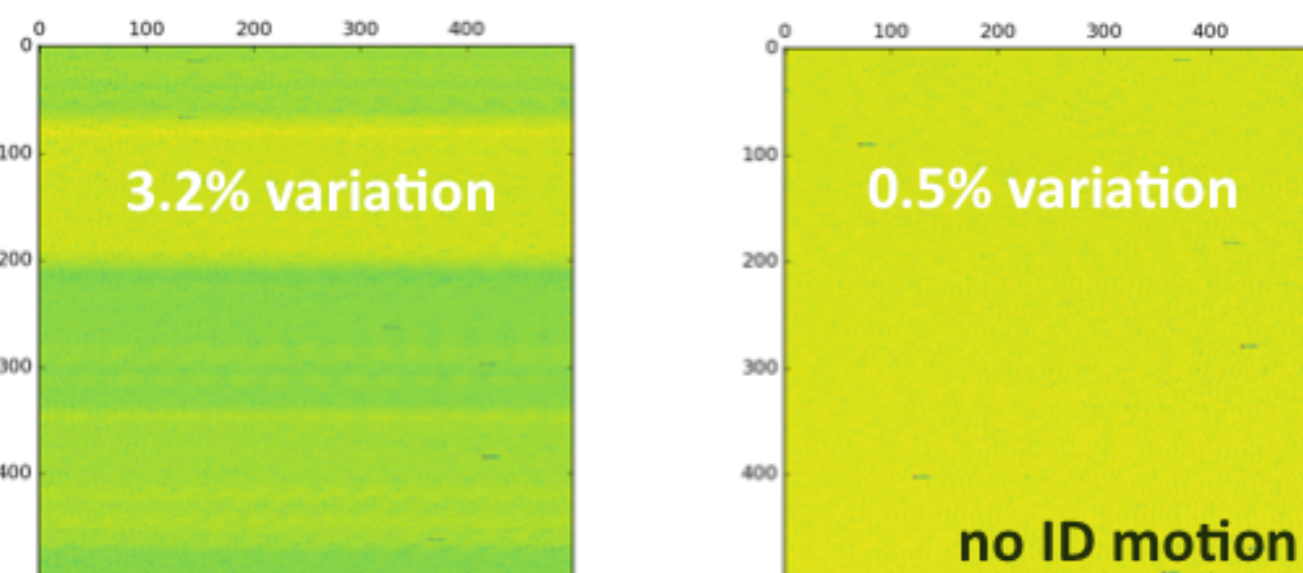
- Overall source stability relies on maintaining constant source position/angle and intensity (beam size & current).
- Source position/angle stability on the sub-micron level is routinely achieved through orbit feedback (FB) and ID feed-forwards (FFs).
- Top-off injection maintains constant current on the sub-percent level over the entire user time.
- Source **size** stability finally, is achieved through optics corrections → systematic (eg. ID FFs) as well as random error corrections (eg. tune FB) are routinely employed.
- ID gap/phase compensation is based on lookup tables for skew quadrupole corrections; recording these lookup tables requires large amounts of dedicated machine time.
- Lookup tables are imperfect; in addition, the machine drifts (eg. temperature, ground settlement) → ID compensation deteriorates with time.
- Machine Learning offers a solution to this problem that is stable over time and requires little dedicated machine time.

Source Size Stability

- In addition to orbit FBs, the ALS employs local optics corrections to compensate for perturbations from ID gap/phase motion → local and global quadrupole and skew quadrupole corrections.
- At 2 GeV ALS is susceptible to ID focusing and skew errors.
- Local ID FFs are used to correct systematic focusing and skew quadrupole errors resulting from ID motion.
- These ID FF tables are, however, imperfect and their performance deteriorates with time as the machine drifts.
- Over a 24-hour user shift we see multiple steps of the vertical beam size despite all orbit FBs and ID FFs running. The cause of these steps are ID gap/phase changes:



- These changes of source size are not just observed at the diagnostic beamline. We can also see them as intensity fluctuations at user beamlines.
- A good example is ALS beamline 5.3.2.2 (STXM) where variations of vertical source size translate directly to intensity fluctuations in the STXM scans:



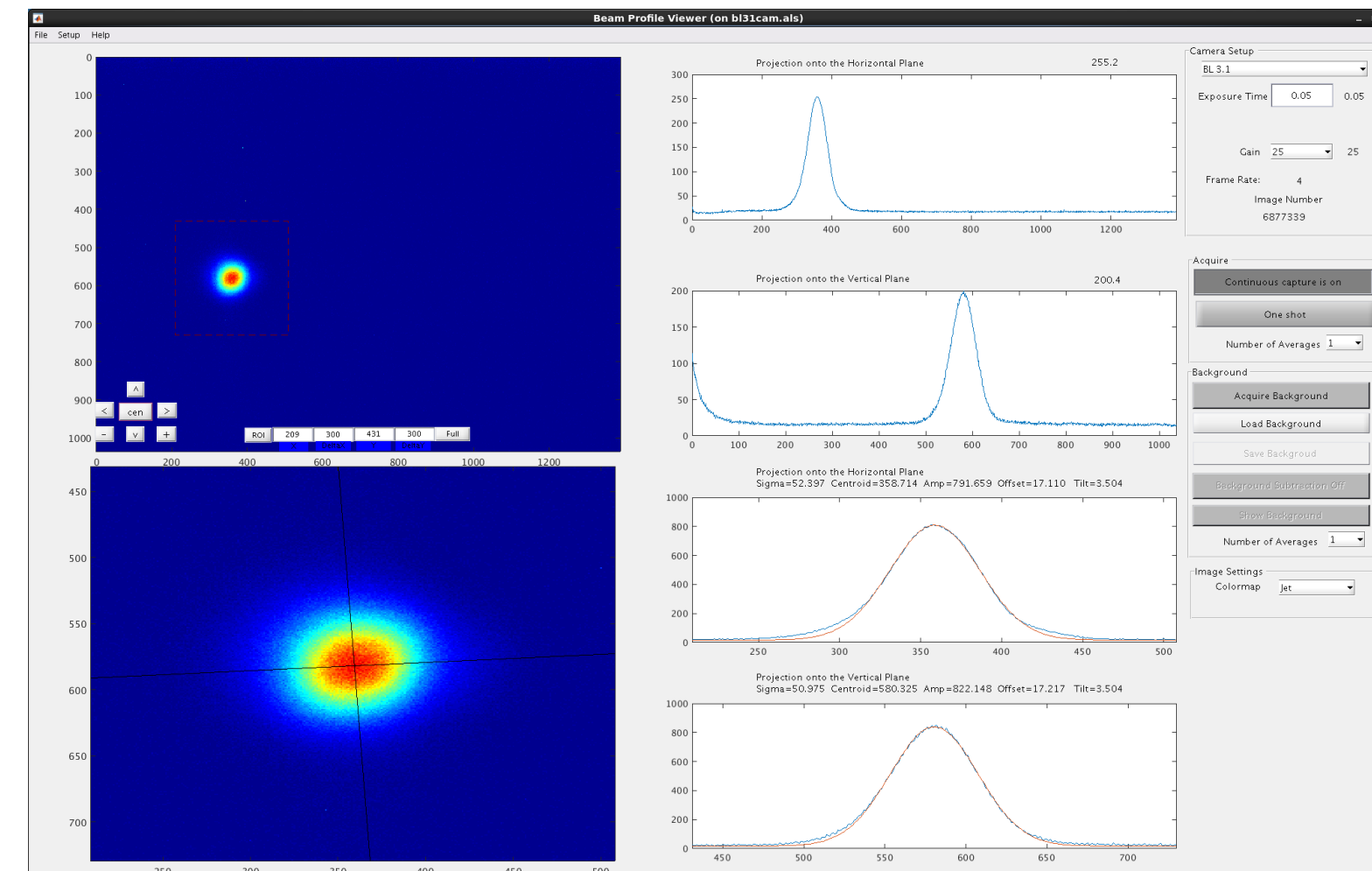
- This limits the STXM resolution; since the beamline cannot average out or normalize such fluctuations, the only solution lies in stabilizing the source.

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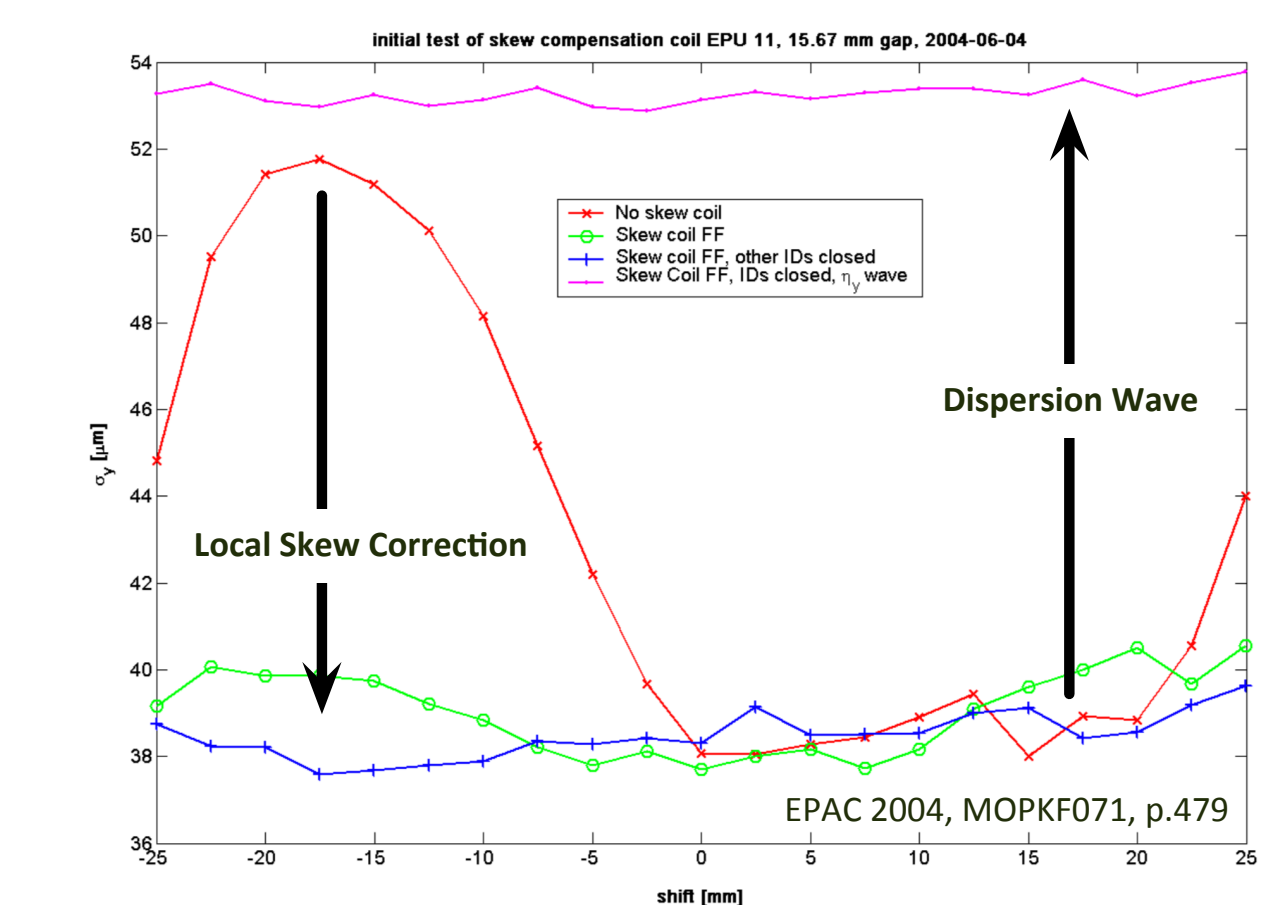
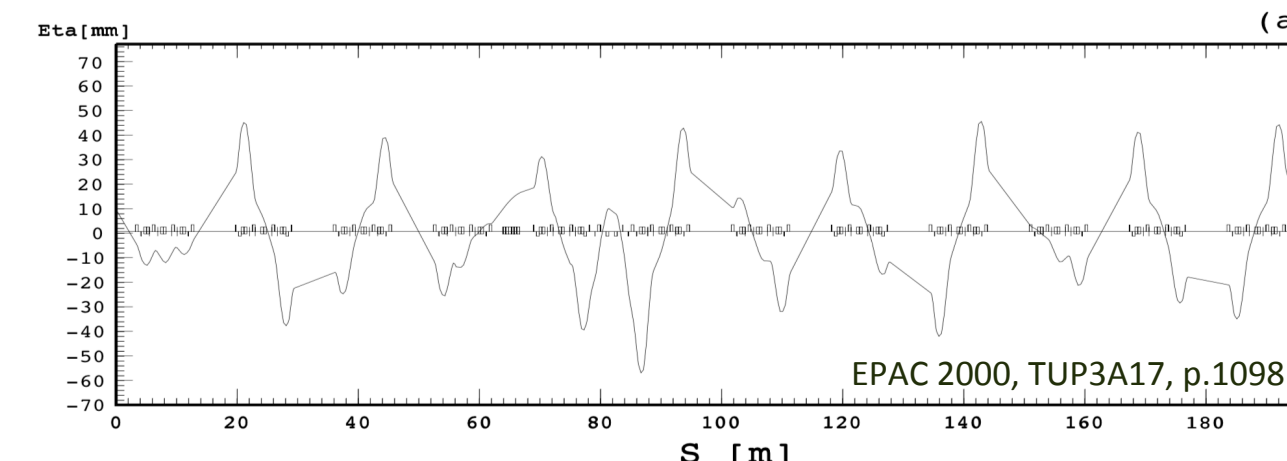
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Vertical Beam Size & Dispersion Wave

- ALS diagnostic beamline 3.1 can be used to measure vertical beam size with high accuracy at ~5 Hz:

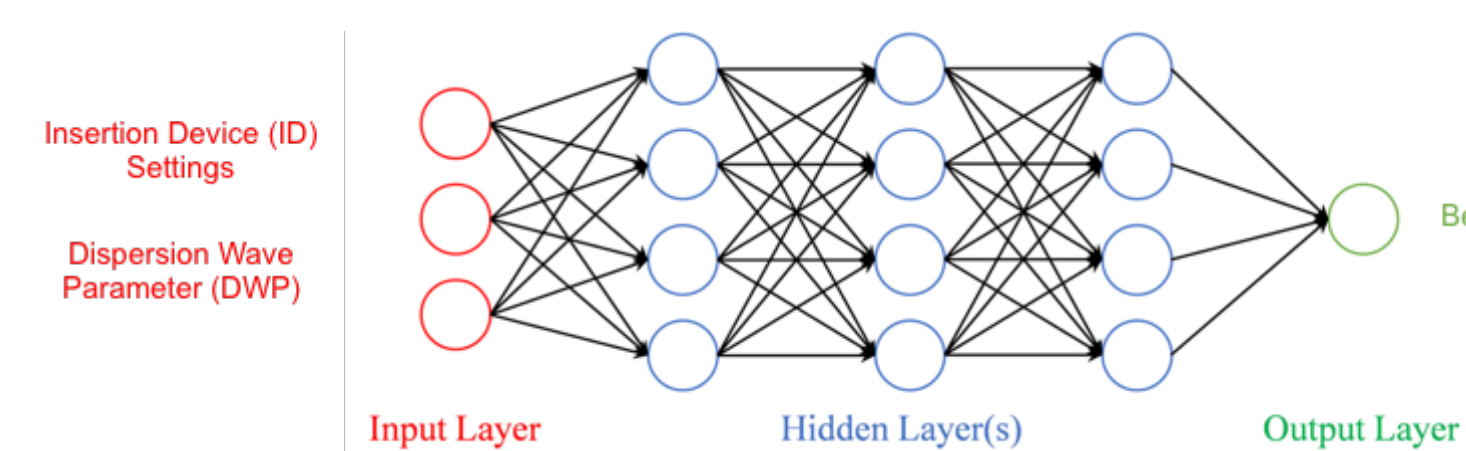


- Vertical beam size at source points is determined by a dispersion wave (which excites vertical emittance, a global conserved quantity) relying on 32 skew quadrupoles:



Neural Network & Training

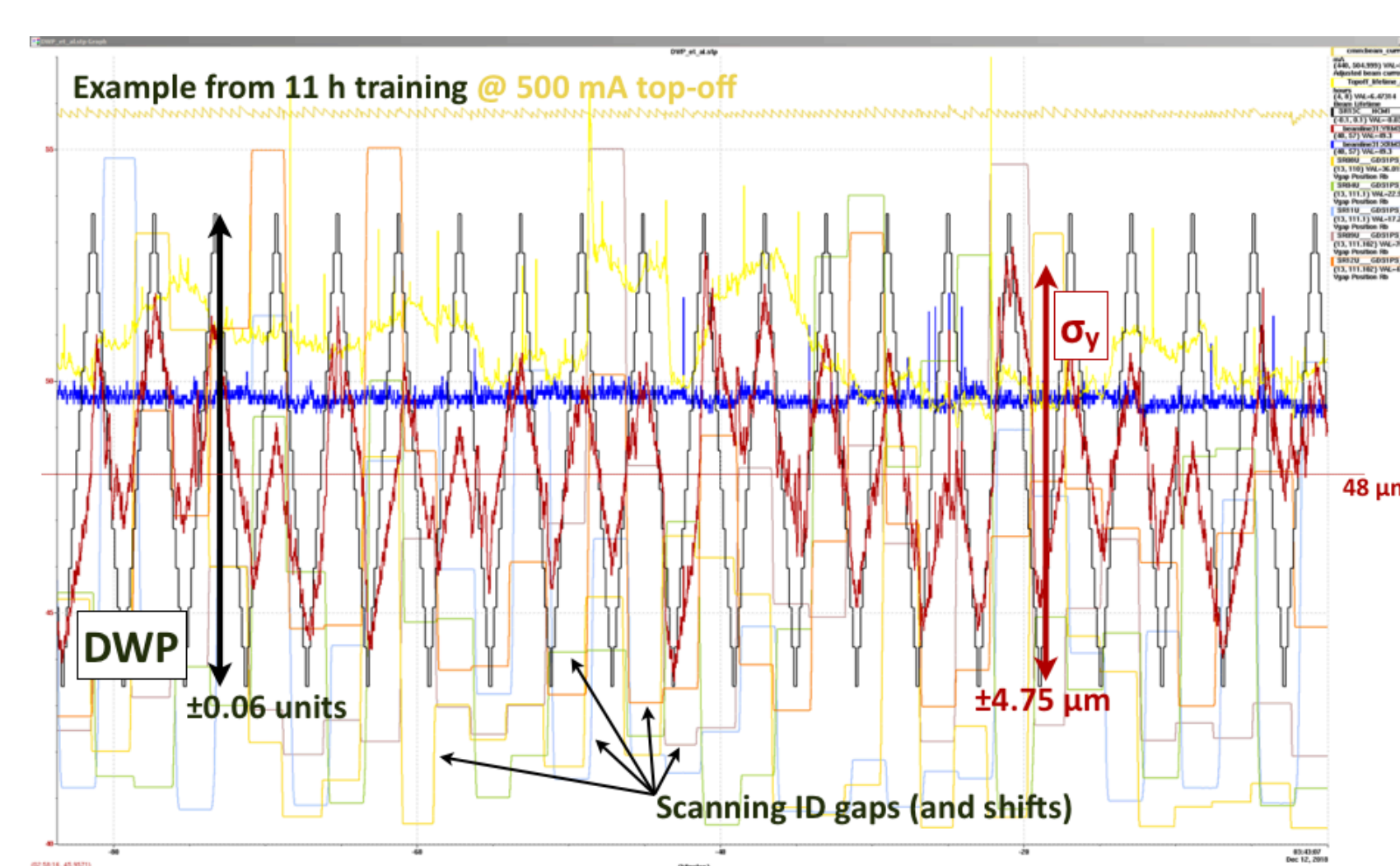
- A neural network (NN) can deliver accurate predictions for beam size as a function of ID gap/phase configurations and skew quadrupole settings described by the dispersion wave parameter (DWP):



- The configuration of this NN has been heavily optimized to achieve best predictions (**hyper parameter tuning**):

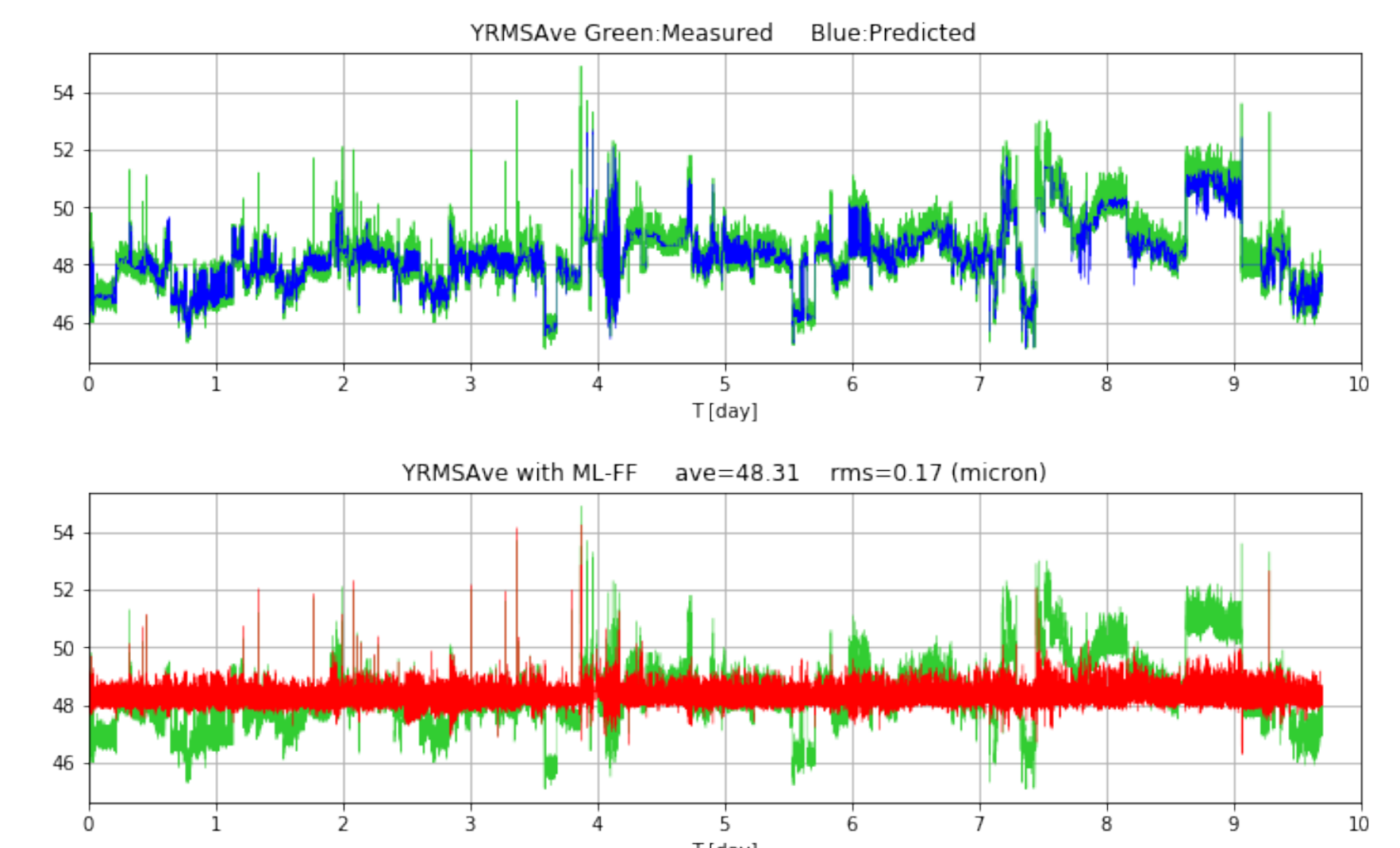
Architecture	Raw Data		With Square Features	
	Training MSE	Evaluation MSE	Training MSE	Evaluation MSE
128-64	0.0265	0.0268	0.0257	0.0260
256-64	0.0243	0.0245	0.0259	0.0262
512-128	0.0243	0.0247	0.0243	0.0247
128-64-32	0.0238	0.0242	0.0243	0.0245
256-128-64	0.0236	0.0240	0.0240	0.0246
256-128-64-32	0.0245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

- The NN is trained using 10 Hz data including all ID and skew configurations as well as the beam sizes as measured at the diagnostic beamline (roughly 35 parameters in total).
- This training data can be acquired during a machine physics shift where we continuously scan ID configurations to mimic user operations while also changing the vertical beam size:

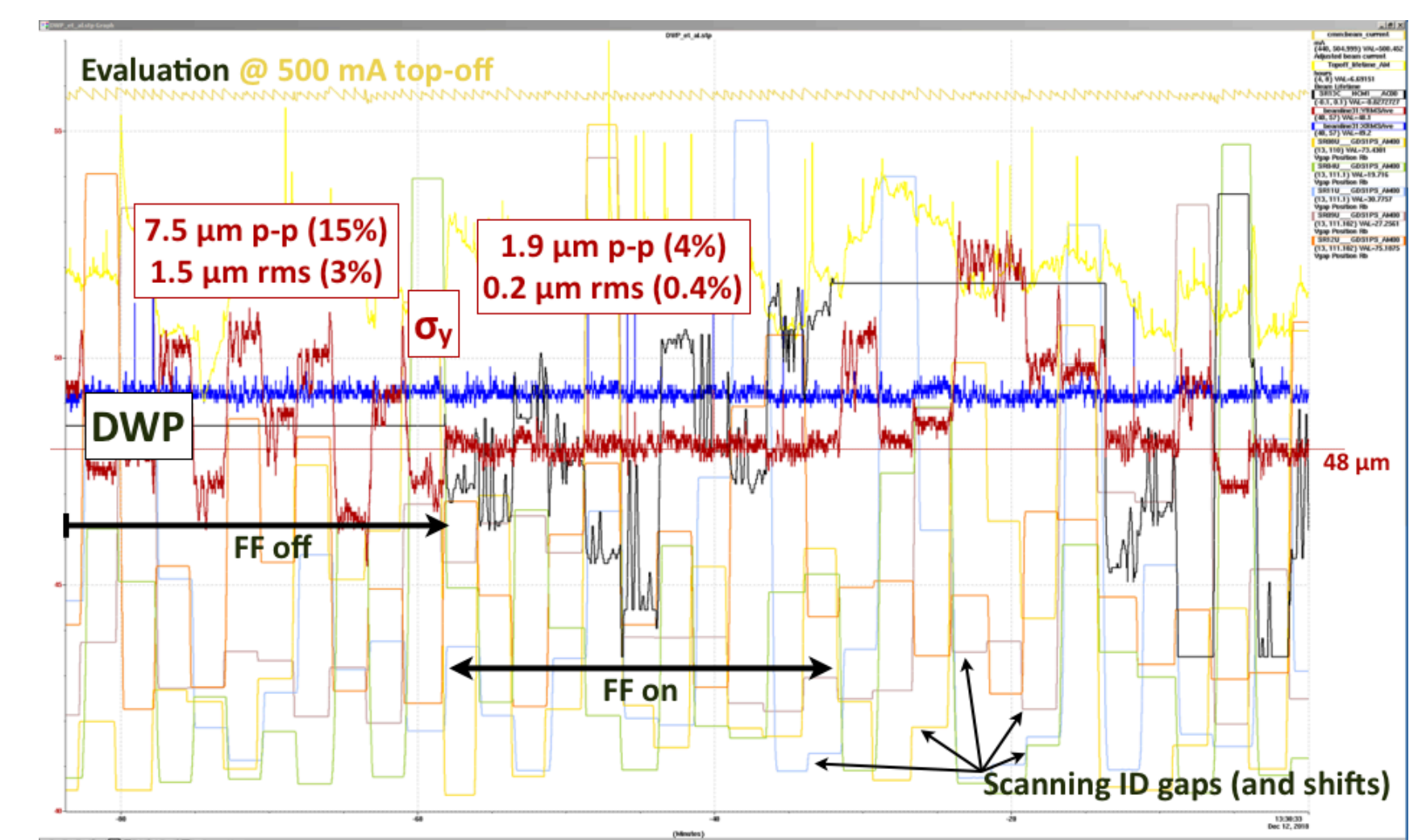


Machine Learning Results

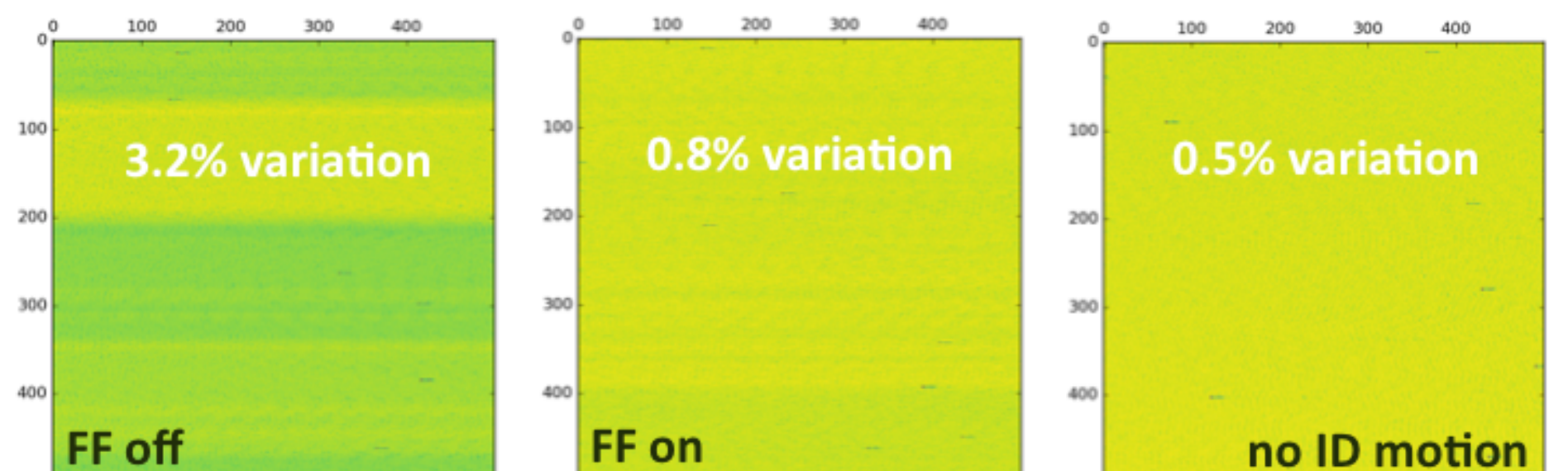
- Simulations using user operations data showed that the predictions of such a NN could be very accurate → residuals are on sub-percent level:



- This allows using such NN predictions to run a NN-based FF.
- The NN is fed current ID configurations along with many possible skew quadrupole settings at ~3 Hz → its predictions are expected beam sizes for each skew quad setting.
- The NN-based FF then picks the beam size that matches our target to determine the required skew quad configuration → this is then downloaded to the skew quad power supplies.
- First tests at the ALS during machine physics shifts showed a dramatic increase of source size stability:



- The vertical source size was stabilized by almost one order of magnitude rms, and by about a factor 4 peak-to-peak.
- As expected, since this stabilization was based on a global property (vertical emittance), it could therefore also be confirmed at other source points.
- The sensitive 5.3.2.2 STXM beamline saw a 4-fold reduction of rms intensity fluctuation when the NN-based FF was running:



Outlook

- With successful stabilization confirmed at the most sensitive beamline, the NN-based FF was put into operation during user shifts.
- Over the course of many days the NN-based FF ran successfully achieving sub-percent level rms stability of the vertical beam size in ALS without manual intervention.
- With the NN-based FF now running during user operations, large amounts of user data can be collected and used for **online retraining**.
- Online retraining allows to retrain the NN based not only on original training data (dedicated shifts) but also on data obtained during user ops, with ID configurations as set by users.
- Confirmed rms stability was further improved (up to +100%) over extended periods of time without requiring any additional dedicated machine time.