E327: FY23 Progress and Plans for FY24

Virtual Diagnostic for phase space prediction and customization at FACET-II

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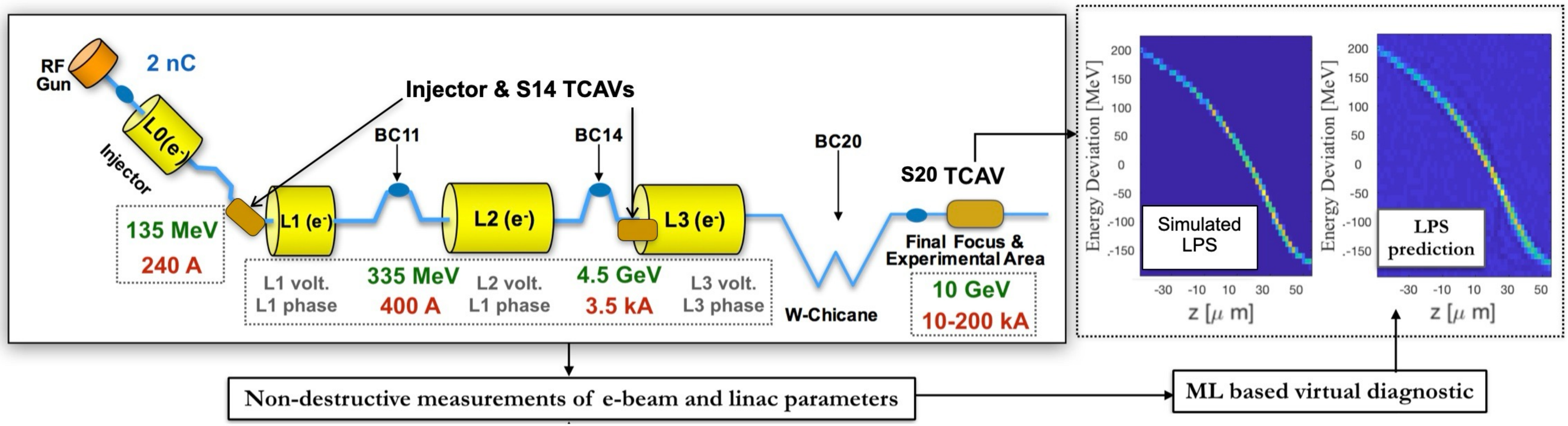
FACET-II

SLAC NATIONAL ACCELERATOR LABORATORY

Stanford University | U.S. DEPARTMENT OF ENERGY

E327 Science Goals

C. Emma and A. Edelen et al., PRAB 21, 112802 (2018)



Science Goal	Definition of Success
Implement a single-shot non-destructive ML diagnostic to predict the e-beam LPS along the linac.	LPS virtual diagnostic operational. Successful LPS prediction in S20 first, then S14 and Injector.
Use the ML-diagnostic to customize/control the LPS for different experiments.	Successful optimization of LPS for main beam configurations (single bunch full comp, single bunch long beam, two bunch).

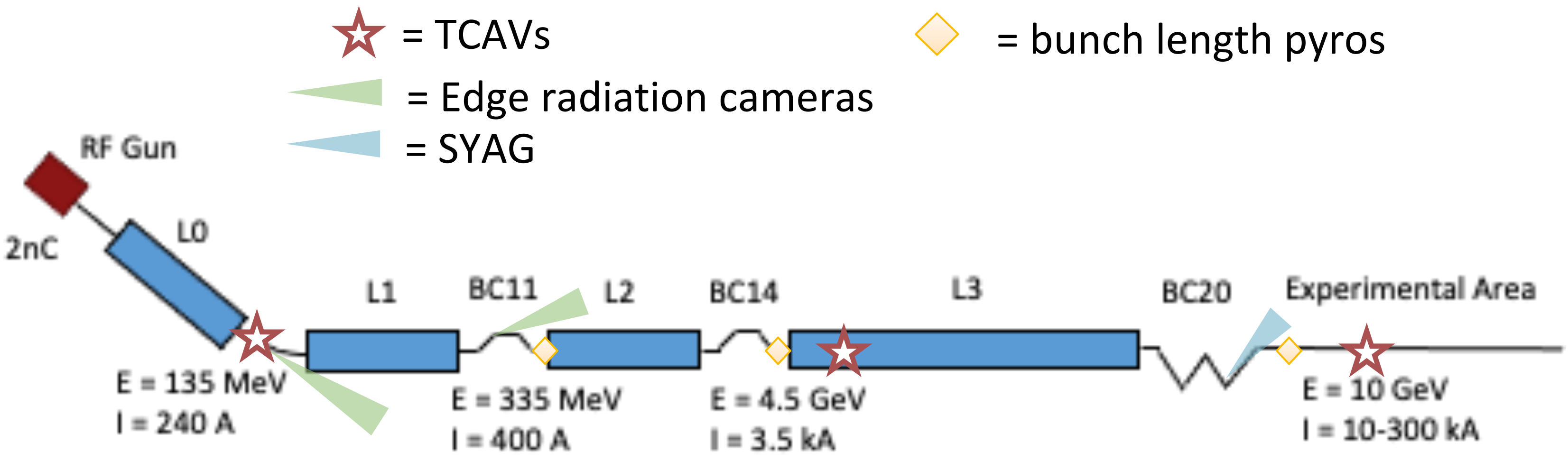
E327 Experimental timeline

- Phase 1: LPS prediction
  - Software/diagnostic commissioning for LPS virtual diagnostic
  - Training of ML models to predict LPS in single bunch 2nC config in S20
  - Extend to S10 and S14 TCAVs
  - Extend to 2 bunch, long bunch configurations
  - Development of LPS virtual diagnostic GUI for facility/users

- Phase 2: LPS optimization
  - Optimization for machine setup of multiple beam configurations (single bunch 2nC, 2 bunch, long bunch)
  - Extend to LPS control for same beam configurations

E327 adopting phased approach to LPS prediction/optimization.

E327 Diagnostics and Observables



First experiments

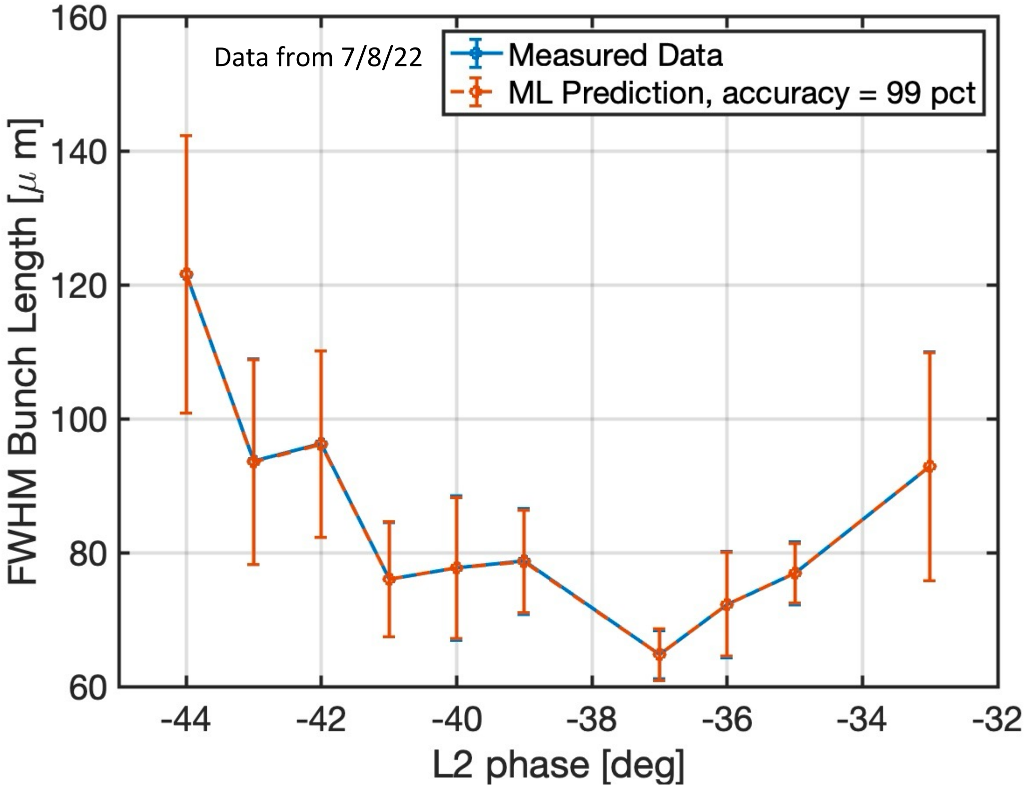
Scanned machine parameters:
L1,L2,L3 RF phase & amplitude
BC11, BC14,BC20 peak current set points

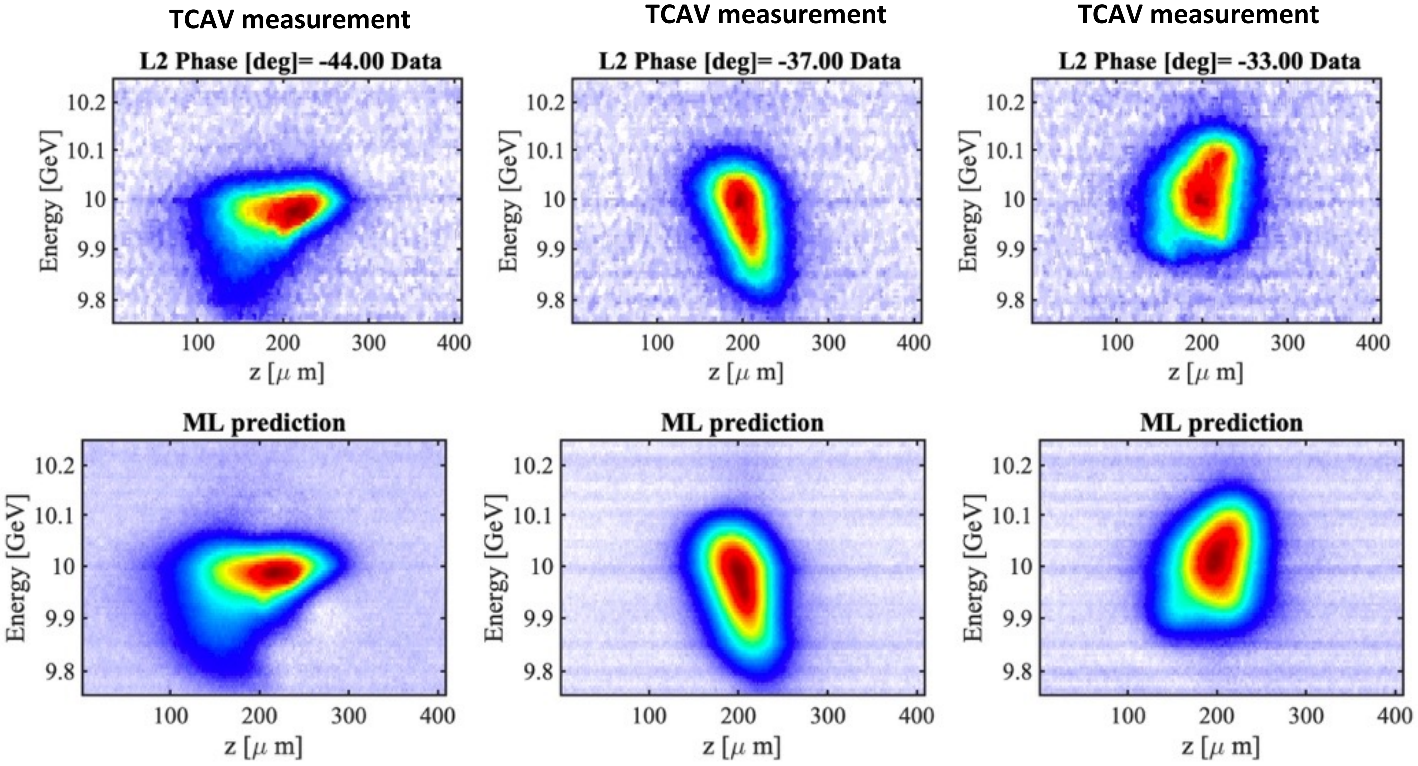
Inputs to ML model:
L0,L1,L2,L3 voltage & phase readbacks,
BC11,BC14, BC20 current monitor
SYAG, EOS, Edge radiation, THz spectrum

- DAQ used to collect/analyze scalar + image data during TCAV operation
- S10 and S20 TCAVs have both been used to measure LPS in injector and at IP (S14 TCAV not online yet).
- ~150 scalar diagnostics (e.g. BPMs, toroids, RF readbacks, BLEN pyros) and multiple image diagnostics (SYAG, EOS) were correlated with bunch length/LPS variations

Diagnostics along the linac used to predict phase space in injector and experimental area

First Results from FY22



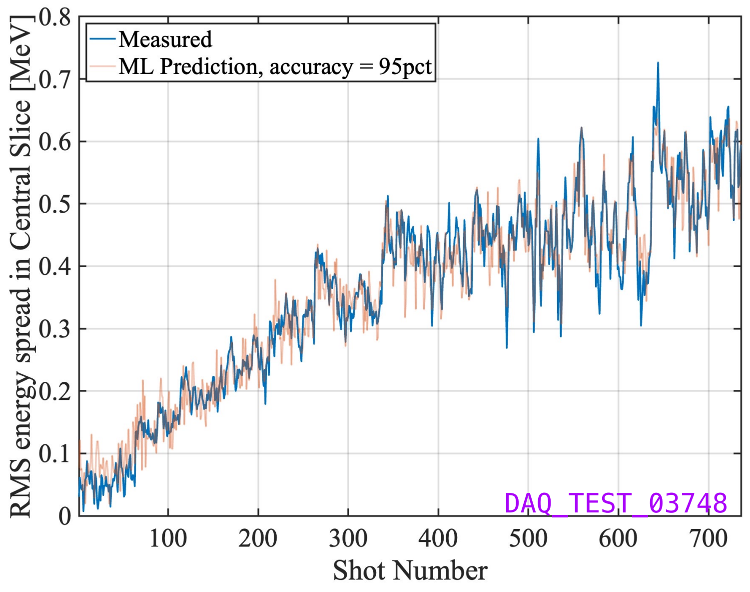


- Demonstrated Neural network prediction of FWHM bunch length and LPS in FACET experimental area with good prediction accuracy

ML based LPS diagnostic feasibility demonstrated at FACET-II. Upcoming work focused on robustness + multiple locations/beam configurations

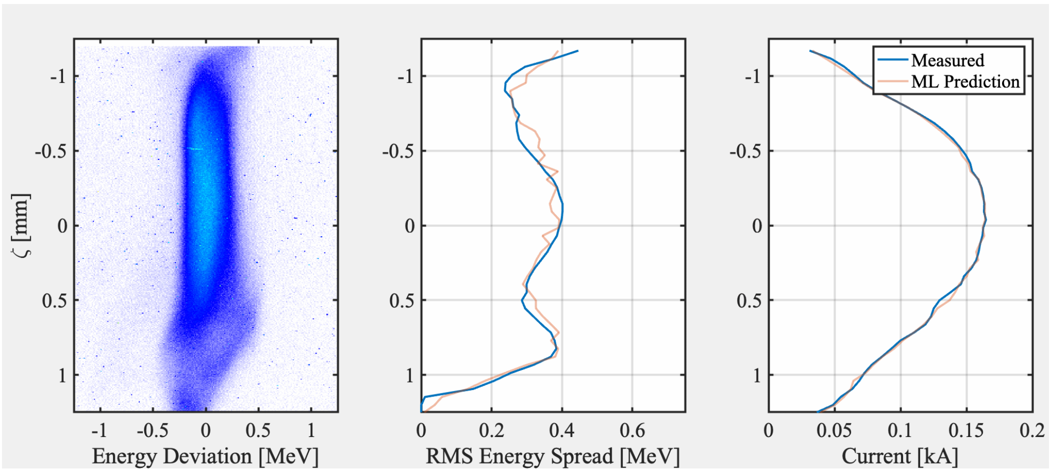
Latest results from FY23 – no dedicated beam time but…

Single shot prediction of RMS heating

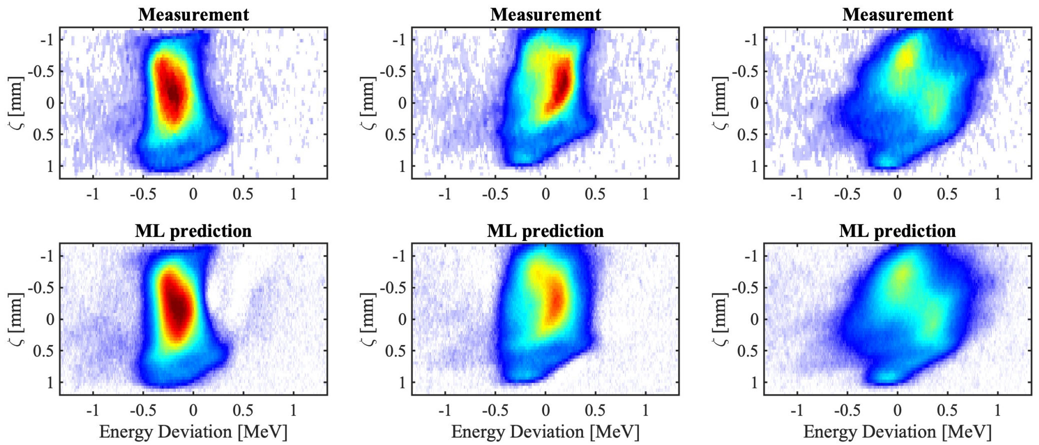


Injector scalars used as ML inputs: magnet, RF, water, BPM, laser energy used to non-destructively predict heating as measured on TCAV0.

Single shot prediction of longitudinal current/energy spread profile at injector exit with laser heater



Current profile predicted with excellent accuracy. RMS energy spread prediction is noisier and prediction accuracy is lower for some shots.



Single shot prediction of LPS

LPS at injector exit predicted with heater on/off. LPS is under-sampled in zeta while maintaining full energy resolution

Note – only 773 shots used in training!

Leveraged laser heater commissioning data to predict of heating, current/energy spread profile and LPS

E327 Plans for FY24

- Characterization of LPS diagnostic prediction accuracy over time. Retraining studies with beamtimes spaced at different intervals.

- Use of LPS diagnostic for e-beam setup and for online PWFA optimization:
  - Reduction of beam jitter (synergy with E325 + E331)
  - LPS tuning/control using downstream PWFA diagnostics (synergy with E325 + E331)

- ML based prediction of two-bunch and long bunch 2D LPS with the laser heater

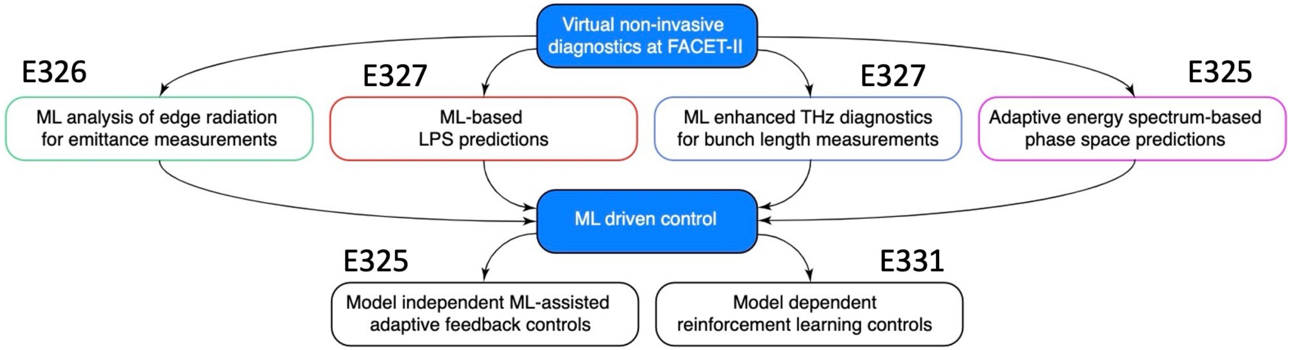
Conclusion

- LPS prediction feasibility demonstrated in experiment + sim at multiple locations in the linac
- Next steps are to focus on *robustness*, *multiple beam configurations*
- Challenges to robustness are machine drifts both periodic (e.g. diurnal w/ temp) and random.
- Uncertainty quantification + additional diagnostics (e.g. spectral methods) will be important especially for ultra-short bunches going forward
- Incorporate new reconstruction methods to aid full phase space characterization (e.g. work done at FlashForward and/or by Ryan Roussel)

Collaboration

- SLAC: C. Emma, B. O'Shea, A. Hanuka, A. Edelen, G. White, S. Gessner, L. Gupta, R. Roussel, S. Miskovich, W. Neiswanger
- LANL: A. Scheinker

FACET-II Pyramid of ML



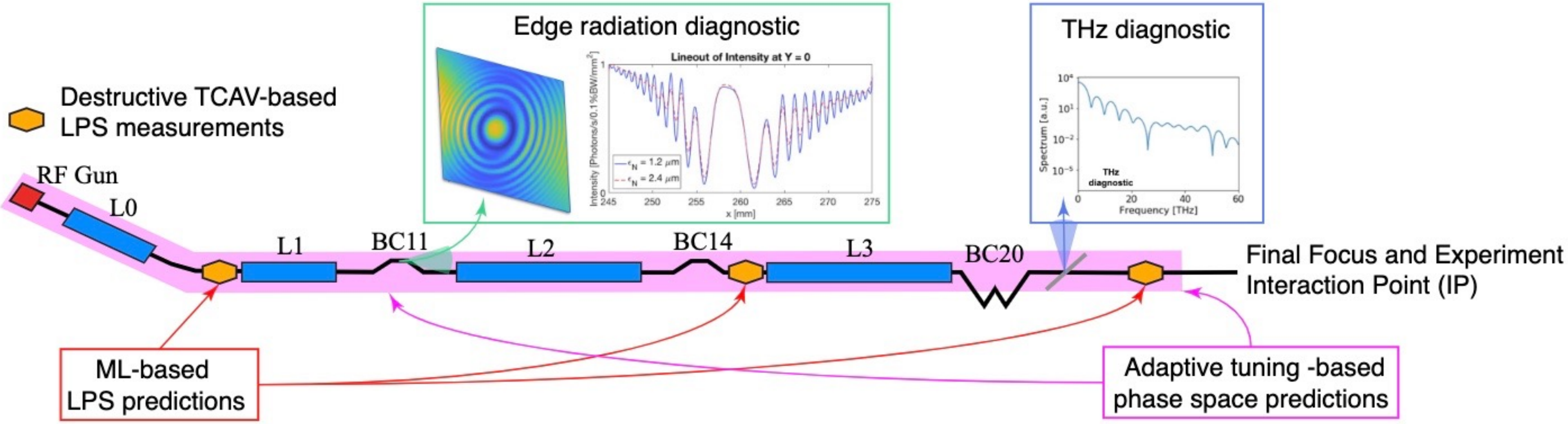
Questions?

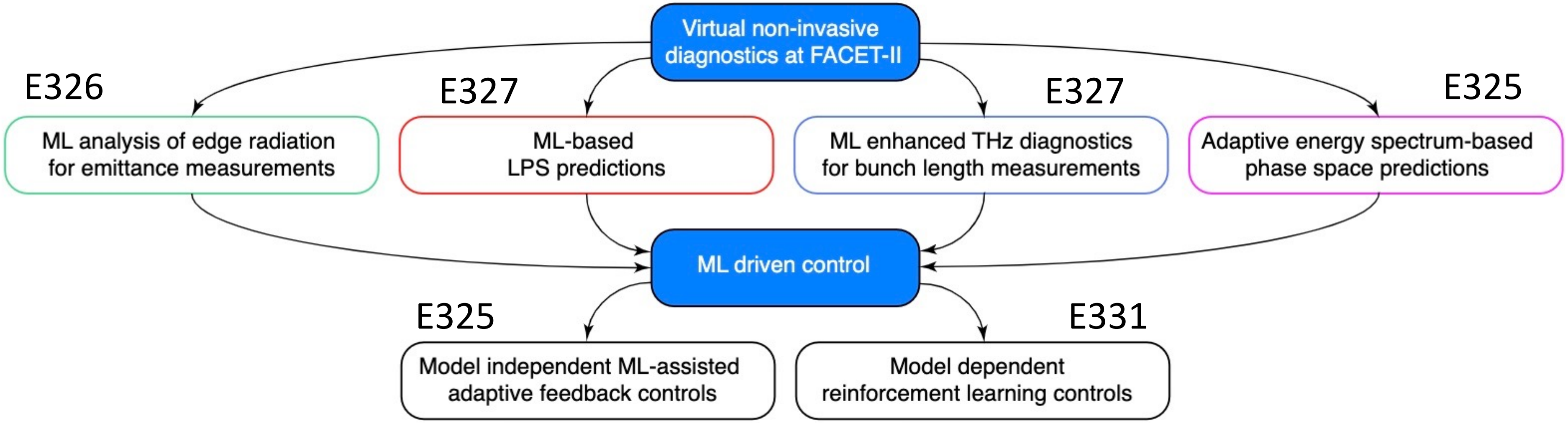
Backup Slides

Publications

1. C. Emma and A. Edelen, et al., “Machine learning based longitudinal phase space prediction of particle accelerators”, PRAB **21**, 112802 (2018)
2. Scheinker, A., Emma, C., Edelen, A., and Gessner, S.. Mon . "Advanced Control Methods for Particle Accelerators (ACM4PA) 2019". LANL Workshop Report, United States. doi:10.2172/1579684. https://www.osti.gov/servlets/purl/1579684.
3. A. Hanuka, C. Emma et. al., “Accurate and confident prediction of electron beam longitudinal properties using spectral virtual diagnostics” *Scientific Reports,* **11**, Article number: 2945 (2021)
4. C. Emma, A. Edelen, A. Hanuka, B. O’Shea, A. Scheinker, “Virtual diagnostic suite for electron beam prediction and control at FACET-II” *Information* 2021, 12(2), 61; https://doi.org/10.3390/info12020061

Landscape of AI/ML Activities at FACET-II





Synergistic experiments, individual success enhances all research + facility operation

Current and RMS energy spread variation DAQ TEST_03748 Laser heater waveplate scan