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INTEGRATING SIMULATION AND MACHINE LEARNING FOR PROTON STORAGE RING BEAM ANALYSIS*

E.-C. Huang†, C. A. Leon, P. M. Anisimov, A. Scheinker
Los Alamos National Laboratory, Los Alamos, NM, USA

Abstract

The Proton Storage Ring (PSR) at the Los Alamos Neutron Science Center (LANSCE) compresses a 625-µs-long proton beam into a 290-ns pulse for neutron production at the Lujan Center. The data-acquisition system for the Beam Position Monitors (BPMs) in the PSR was upgraded over the past year from a multiplexer system to independent readouts, significantly increasing the data output.

To leverage this improved capability, we developed a new analysis package based on existing MAD-X model to provide critical ring information like betatron tunes and injection offsets in real time. Furthermore, a Convolutional Neural Networks (CNN's) are trained on this simulation data to learn mappings between raw BPM signals and those key parameters for a more precise measurement. A combination of a physics-based fit with a CNN correction was found to produce the best results.

INTRODUCTION

The Proton Storage Ring (PSR) at the Los Alamos Neutron Science Center (LANSCE) is a critical component in the delivery of high-intensity proton pulses for neutron production. Designed for accumulation and compression, the PSR receives an 800-MeV H^- beam from the linac, strips the electrons via a thin foil, and accumulates the resulting protons over a 625-µs injection window. The accumulated beam is then extracted, forming a short pulse approximately 290 nanoseconds in duration base to base, which is directed to the Lujan Center spallation target. With a circumference of approximately 90 meters and a revolution time of ~360 ns, the PSR operates at a repetition rate of up to 20 Hz, delivering a nominal charge at 5 µC per pulse.

The PSR operates under high space-charge conditions, which introduces challenges in maintaining beam stability and minimizing losses. Effective tuning of the ring requires careful adjustment of beam optics parameters such as the betatron tune (ν_x, ν_y), closed orbit (CO), and injection offsets (x_0, x_0', y_0, y_0'). The initial injection offsets are critical as the production beam are painted vertically to minimize the number of foil hits from circulating beam. At the beginning of the run cycle, these quantities are measured and tuned up in the "single-shot" mode. The single-shot mode injects only one 290-ns-long (or shorter) minipulse into the PSR during the whole 625-µs accumulation window for the Beam Position Monitor (BPM) measurements. Furthermore, in the single-shot mode, the RF buncher and bump magnets for transverse painting are turned off.

The original BPM system is built upon a multiplexer system [1] that was only equipped with one readout each for the top, bottom, left, and right plates for all 20 BPMs. To measure beam positions for all BPMs, the system needs to cycle through each of the BPM. Procedures are built around this limitation to switch between turn-by-turn/time mode and azimuth mode for closed orbit measurements. One would also need to be careful in the BPM selections. The online analyses built for these procedures rely on linear approximations obtained from responses matrices with very limited visualization capabilities. As a result, the PSR tune-up process is often tedious and error prone.

Over the past year, LANSCE finally replaced the multiplexer system with an individual data acquisition (DAQ) system. With the new system, we can obtain the first 30 to 40 turns (the 201.25 MHz structure from the linac dissipates after 30 turns) of beam positions for all BPMs within a single pulse. This enables us to significantly improve our online analysis methods. In this proceeding, we will demonstrate the updated analysis package based on MAD-X [2] and the new ML-based method to even further improve the precision. The model-based method is heavily built upon the RingScan work [3], which automatically switches the multiplexer through all BPMs.

MADX-BASED ONLINE ANALYSIS

Figure 1 shows an example of the measurements of all BPMs over 40 turns from a sample dataset taken during the RingScan work. Oscillation patterns for each BPM (row) and the phase advance of the betatron oscillation are both apparent. In addition to the beam positions, the new DAQ also outputs the signal intensity and beam phases relative to reference 201.25-MHz signal.

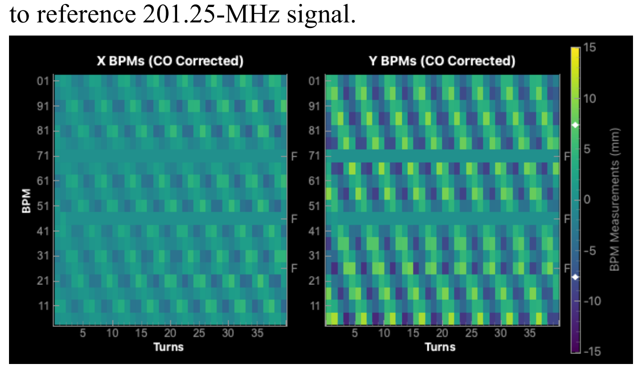

Figure 1: BPM measurements with closed-orbit corrections applied for all 20 BPMs over 40 turns.

To obtain the betatron tunes, x & y data from each BPM are fitted into a simple cosine function:

$$x_i(n) = A_i \cdot \cos\left(2\pi\nu_{x,i}n + \phi_{x,i}\right) + c_{x,i},$$

where i is the BPM number, A_i is the betatron oscillation amplitude, $\nu_{x,i}$ is the betatron tune measured at this BPM

* Work supported by LANL's LDRD program under 20250783MFR
† en-chuan@lanl.gov

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for x, n is the turn number, $\phi_{x,i}$ is the phase offset, and $c_{x,i}$ is the closed orbit offset. The fitting routine is the same for y. For individual BPM, due to the Nyquist range and the cosine function being even, the fitted ν_i is between 0 and 0.5. However, combining all BPMs and observing the betatron phase advance (the changes of ϕ_i), the integer part of the tune can be derived. However, with the target tune for x & y at 3.19 and 2.18, respectively, it is unlikely that the actual tune falls into a different integer part. Furthermore, an R-squared cut at 0.9 is applied to individual BPM fitting to ensure data quality.

All the focusing quads in the PSR share the same power supply, likewise for all the defocusing quads. Therefore, the power supply currents for the focusing quads and defocusing quads are treated as fitting parameter in MAD-X to obtain the same measured tune for x & y. As a result, the model will have the same phase advances as the machine. Using the Twiss parameters (α, β, ϕ) obtained from the MAD-X model, a linear transfer matrix is constructed for each BPM location in both horizontal and vertical planes. These matrices describe the propagation of the beam's transverse phase-space coordinates from the injection point to each BPM. The beam position at each BPM is expressed as a linear combination of the initial injection offset and angle. A least-squares minimization is then applied across all active BPMs that satisfy the R-squared criterion, enabling robust estimation of the injection offsets. This approach leverages redundant measurements and model-based transport to infer the initial beam parameters with high precision, even in the presence of noisy or partially missing BPM data. The comparison between derived values from simulated data and their true values are shown in Fig. 2.

To support real-time operation, a dedicated tuning software package has been developed to perform all analyses online with an update interval of approximately 1–2 seconds. A set of interactive visualization panels is provided to aid operators and physicists, including displays for raw BPM measurements, cosine fits for each BPM, closed orbits, inferred injection offsets, fractional tunes, betatron phase advances, and comparisons between measured and predicted first-turn trajectories. This framework enables both rapid diagnosis and intuitive understanding of the machine state.

ML-BASED ANALYSIS

In additional to the above Physics-Based Fit, we tested two models: a convolutional neural network (CNN) that just used the BPM data and a residual convolutional neural network (Res-Net) that uses both the BPM data and the Physics-based Fit predictions. For the 6 variables of tunes (ν_x, ν_y) and injection offsets (x_0, y_0, x'_0, y'_0), the Res-Net essentially acts to anticipate the error and correct the Physics-Based Fit's predictions, while also giving energy offset ($\Delta E/E$). The CNN model consists of convolutional layers, followed by a flattening operation and finally a dense network. The "images" are relatively small for ML, 20x30, (see Fig. 1) and there are only two "channels" x and y (as opposed to the 3 RGB channels for most images). Thus, there is no need for maxpool layers or striding greater than 2. This has the added benefit of not throwing away data while still being computationally fast. Also, since the data is oscillatory, the regularly used activation function of ReLU would throw out a great deal of data. Hence, we use hyperbolic tangent for the activation function. Finally, to bottleneck the data we decreased the number of filters before flattening. We use L_2 regularization. The ResNet is similar, except it also takes in the 6-variable prediction from the Physics-Based Fit.

As seen in Fig. 2, in general the spread of error for the Conventional Fit is generally larger than that of the ML models. Note, in Fig. 2 we take the fractional components for the spreads for illustration purposes. Occasionally, the Conventional Fit would deduce the integer part of the tune from the phase advance calculations.

To get a robust measure of the spread, we use the interdecile range, the difference between the 90% and 10% decile. Since in operation we would be getting information ~1 Hz, the occasional outliers are normally disregarded by operators. The results can be seen in Table 1. Note that here we used integer plus fraction for the tunes. The ResNet does the best for five out of the seven variables. It finishes second best for the other two. Hence, a combination of Conventional Fit with an ML-based correction can improve predictions while also providing information on energy offset.

Table 1: Interdecile Range (10-90%) of Errors Between Three Different Methods

	Physics Fit	**CNN**	**Res-Net**
ν_x	0.053	0.016	**0.013**
ν_y	**0.003**	0.022	0.004
x_0(mm)	1.586	0.298	**0.266**
y_0 (mm)	0.507	0.460	**0.299**
x'_0(mrad)	0.414	**0.046**	0.139
y'_0(mrad)	0.215	0.125	**0.047**
ΔE/E (%)	-	0.005	**0.002**

FUTURE PLAN

In our current analysis procedure, the following requirements are implemented: (1) operation in single-shot mode, (2) RF buncher turned off, and (3) injection chicane for transverse painting disabled. While single-shot mode is mandatory to observe the betatron oscillation in the PSR, turning off the RF buncher enhances signal strength but is not strictly necessary. Disabling the injection chicane can be accommodated through model modifications.

Looking ahead, we plan to leverage the present beam current ramp-up procedure to create a single-shot scenario in production. This ramp-up is designed to reduce the burden on the RF-feedforward system. By shifting the implementation of the current ramp-up from a beam deflector to the beam chopper, we can ensure that only a single

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minipulse is injected for the first 10 turns. This adjustment will allow us to perform the analysis during regular production runs, significantly enhancing our operational efficiency.

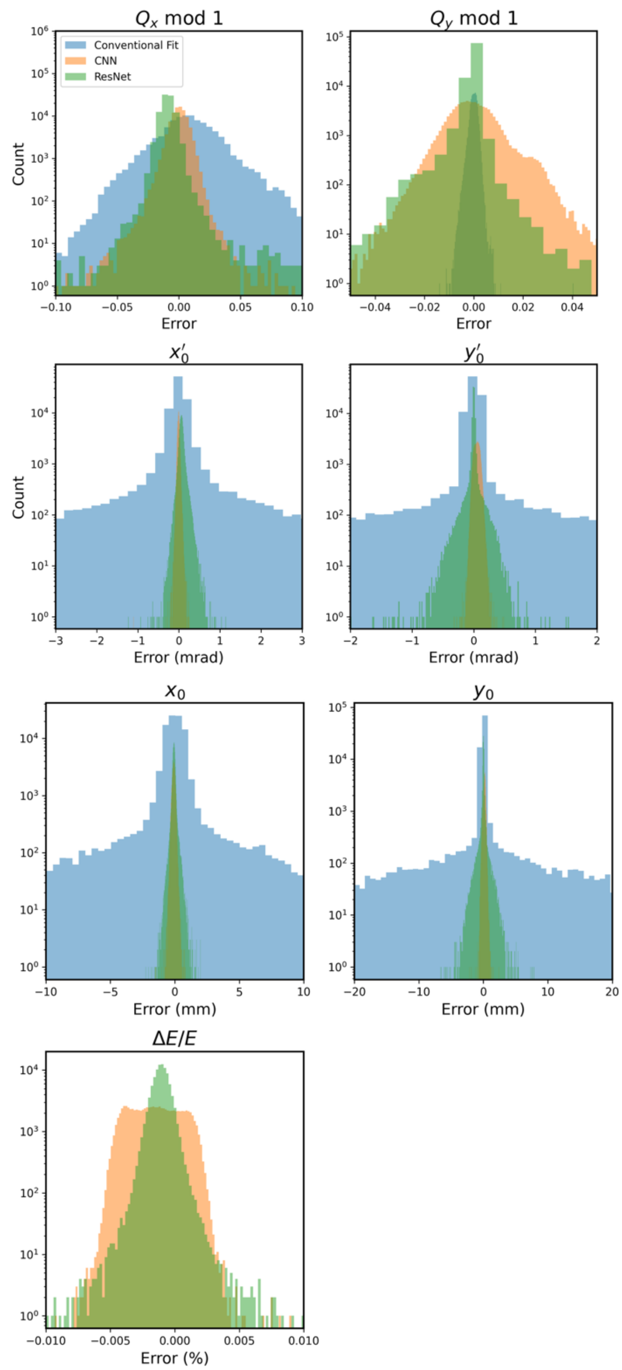

Figure 2: Histogram of errors between fitted and truth values for the tune, injection offset, and energy offset for the three methods.

Furthermore, the data used contain all the BPMs without noise generated from the PSR model. The Physics-Based Fit is not sensitive to the missing of BPM data, and it actively throws away results with a bad cosine fit. A missing BPM would only slightly impact the final precision. However, the ML models can be tested under a more realistic scenario by adding noise and missing data from selected BPMs.

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