APPLICATION OF DEEP LEARNING METHODS FOR INSERTION DEVICE EFFECTS IN THE SSRF

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Abstract

A deep-learning-based feedforward scheme has been developed to compensate insertion-device (ID) effects in the Shanghai Synchrotron Radiation Facility (SSRF). Neural networks predict orbit and betatron-coupling perturbations caused by ID gap and phase changes. The orbit model reduces residual closed-orbit distortion (COD) to below 2 um and shortens preparation time by about a factor of 50 compared with conventional feedforward-table measurements. A coupling model trained with turn-by-turn (TBT) beam-position-monitor (BPM) data reaches an R^2 value above 0.95. These results show that deep learning can support fast and reproducible ID compensation during light-source operation.

INTRODUCTION AND ID COMPENSATION CHALLENGES

Insertion devices are essential to synchrotron radiation facilities because they provide tunable photon energy, polarization, and brightness. Their gap, phase, and polarization changes also modify magnetic field integrals and local focusing, which can drive COD, tune drift, beta-beating, coupling, and beam-size variation. These effects directly appear as photon-beam position, angle, flux, and brightness fluctuations.

SSRF is a 3.5 GeV third-generation light source with a 432 m storage ring, a nominal emittance of about 3.9 nm rad, and 27 operational IDs, including IVUs, CPMUs, EPUs, wigglers, and a Superconducting wiggler (SCW). Representative measurements show the scale of the compensation problem: 20EPU60 gap changes produce COD up to about +/-80 um horizontally and +/-60 um vertically, while 09EPU58 gap changes alter the horizontal and vertical beam sizes by about 3 um and 28 um, respectively. Thus, ID compensation must address both orbit and coupling.

The conventional SSRF feedforward system uses correction coils, quadrupoles, skew quadrupoles, response matrices, and look-up tables. It is robust but time-consuming: a planar-ID gap table typically takes about 0.5 h per ID, while a two-dimensional EPU gap-phase table can take about 4 h for one mode. A full measurement campaign for 27 IDs can exceed 60 h and must be repeated after lattice changes, ID maintenance, or BPM recalibration. Deep learning is introduced to learn the mapping from ID states to beam response from a compact data set, while the measured response matrix remains the basis for bounded and interpretable correction.

Previous SSRF feedforward and ID beam-dynamics studies provide the operational baseline [1-3]. Related machine-learning correction and stabilization studies at MAX IV and ALS are reported in Refs. [4-6]. Broader ML-based optics correction, BPM fault detection, magnet-error reconstruction, physics-informed modeling, surrogate optimization, and accelerator-ML roadmaps are discussed in Refs. [7-8].

NEURAL NETWORK FOR ID ORBIT FEEDFORWARD

The orbit feedforward model is formulated as a supervised learning problem. The input vector contains the gap settings of 19 IDs. The output vector contains beam-position responses measured by 138 BPMs in both transverse planes, giving 276 output targets. Instead of measuring dense tables for each device independently, the training data are obtained by changing several ID gaps and recording the resulting global orbit response. Data are recorded every 0.2 s, so about 3000 data sets can be collected in 10 min. The model structure and training workflow are shown in Fig. 1.

The neural-network architecture contains three hidden layers. Hyperparameters were scanned for activation function, batch size, hidden-layer width, and learning rate. The best orbit model uses ReLU activation, hidden layers of [64, 128, 256], a batch size of 16, and a learning rate of 0.001. The training, test, and validation losses are 0.00692, 0.00869, and 0.00097, respectively. The model reaches an R^2 value above 0.98 over the sampled operating range.

The model was tested with randomized ID gap settings over a range of 6-30 mm. Figure 2 shows a representative testing result for ID orbit correction, where the predicted BPM responses closely follow the measured values across both transverse output ranges. The predicted perturbation is then converted into correction currents using the existing response matrix and feedforward coils. After correction, the residual COD is reduced to less than 2 um. The complete model-based preparation takes about 3.5 min, which is about 50 times faster than traditional feedforward-table measurements.

This workflow has two operational strengths. First, it sharply reduces the time required to prepare ID feedforward data. Second, it represents the combined effect of several IDs, which is closer to real operation than treating each

ID independently. The method also remains compatible with conventional correction logic: the neural network predicts the beam response, and the measured accelerator response matrix determines how to correct it.

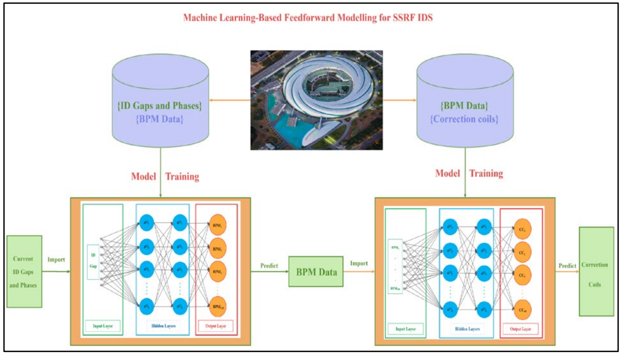

Figure 1: Neural-network architecture and training strategy for ID orbit response prediction.

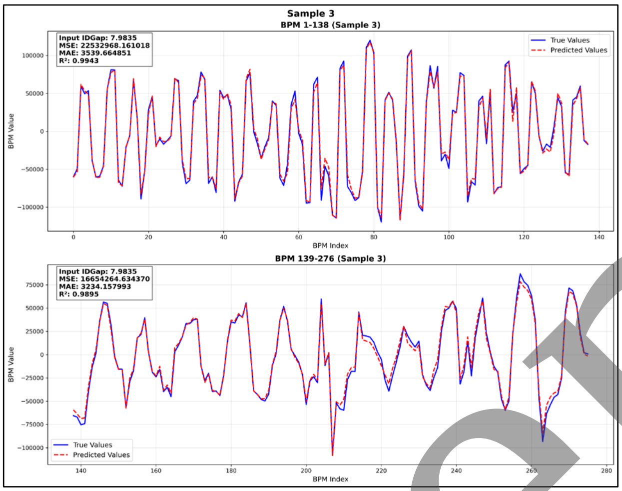

Figure 2: Testing the performance of the deep learning model for ID orbit correction. The measured and predicted BPM responses are compared for a representative randomized ID gap setting.

DEEP LEARNING FOR BETATRON COUPLING FEEDFORWARD

Orbit correction alone is insufficient for EPUs because coupling can change strongly with gap and phase. For coupling feedforward, TBT BPM data are acquired after transverse excitation by the kicker. The excited betatron amplitude is typically 200-600 um. The data include TBT signals from 138 BPMs for different EPU configurations, including 03EPU200 and 09EPU58. TBT data are used because they contain phase, amplitude, and mode-coupling information that cannot be obtained from static orbit data alone. The acquisition and preprocessing process is summarized in Fig. 3.

The raw BPM data are preprocessed before model training. Faulty BPMs are removed, and BPM coefficients are corrected using fitting results from previous SSRF experiments. Independent component analysis is then applied to transform the TBT data into betatron-coupling observables. These observables serve as output targets for the neural network; the first part corresponds to horizontal projected coupling and the second part to vertical projected coupling.

The coupling model also uses three hidden layers. Hyperparameter optimization shows that the best configuration uses a sigmoid activation function, hidden layers of [64, 128, 256], a batch size of 64, and a learning rate of 0.01. The training, test, and validation losses are 0.003460, 0.007532, and 0.004427, respectively. As shown in Fig. 4, the loss converges stably, and the model reaches an R^2 value above 0.95.

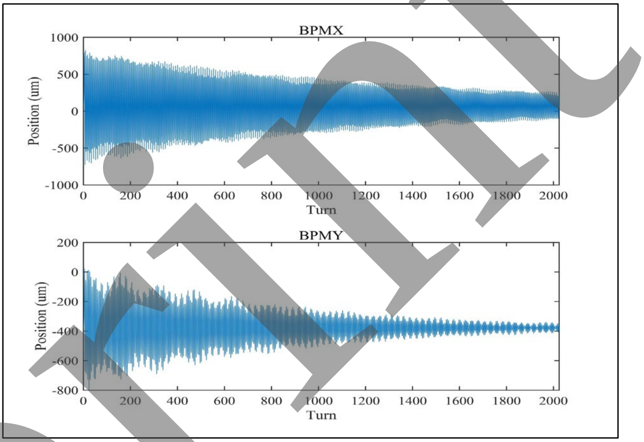

Figure 3: TBT BPM data acquisition and preprocessing flow for coupling measurement.

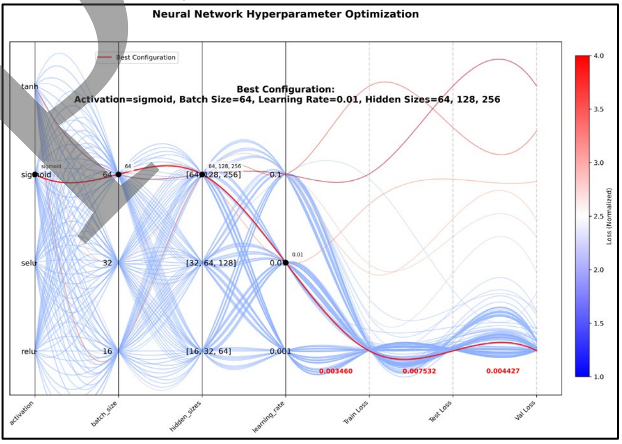

Figure 4: Hyperparameter optimization and loss convergence for the coupling neural network.

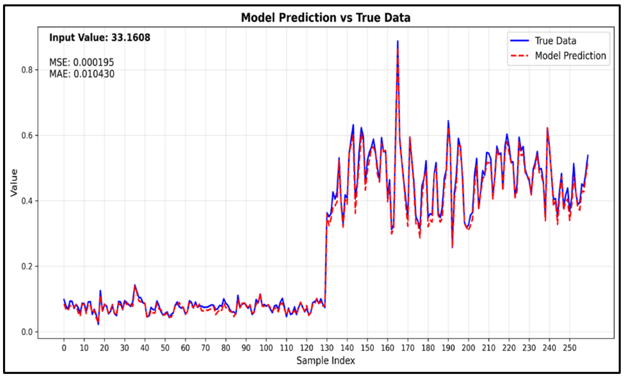

Figure 5: Horizontal and vertical coupling prediction compared with measured data.

The coupling model provides a data-driven route to skew-quadrupole feedforward. During operation, the ID state is used to predict the coupling response, and the correction is applied through available skew-quadrupole families. Figure 5 compare the predicted and measured horizontal and vertical coupling responses, respectively, showing that the model reproduces the main response patterns. Compared with repeated coupling measurements for each ID state, this model-based approach can reduce tuning time and support faster recovery after ID changes.

OPERATIONAL CONSIDERATIONS

The SSRF results show that deep learning is most useful when it is integrated with accelerator-physics constraints. The model reduces repetitive measurements, but it should not operate without limits. The training data must cover the ID gap and phase range used in user operation. Predictions outside the trained range should be flagged, limited, or rejected.

BPM data quality is also critical. Faulty BPMs, timing errors, gain drift, and calibration changes can bias both orbit and coupling models. Data-quality checks should therefore be part of the control system, not merely an offline preprocessing step. Correction currents should also be bounded by hardware and software limits, and a fallback to conventional feedforward tables should remain available.

A practical deployment path is to begin with shadow mode, in which the model predicts corrections but does not apply them. The next step is limited residual correction around conventional table values. Only after long-term validation should the learned model become the primary feedforward source. This staged approach protects the machine while allowing operators to build trust in the model.

The same strategy can be extended beyond ID orbit and coupling. SSRF has also developed online optics feedback based on convolutional neural networks, with beta-beating controlled below 1%. Reinforcement learning has been tested for beam-size stabilization, achieving beam-size fluctuation below 1 um. Together, these tools suggest a broader control-room framework in which orbit, coupling, optics, and beam-size stabilization are coordinated rather than tuned as separate tasks.

FUTURE WORK

Future work will focus on robustness, integration, and validation under user-operation conditions. The reinforcement-learning model for beam-size control will be optimized and retrained with the goal of reducing beam-size fluctuation below 0.5 um. The orbit and coupling models will be extended to more ID configurations, including EPU phase scans and simultaneous motion of multiple devices. Long-term studies are needed to quantify model drift and define retraining intervals.

Uncertainty-aware control is another important direction. A model should output not only a correction value but also a reliability estimate. This can be implemented using ensemble models, dropout-based uncertainty estimates, or validation against nearby measured points. If uncertainty is high, the correction can be limited or rejected.

The final validation should be made from the beamline-user perspective. Electron-beam COD and coupling are intermediate metrics; the ultimate goal is stable photon beam position, angle, flux, and brightness. Future studies should correlate AI-based corrections with photon diagnostics and user experiment stability.

CONCLUSION

Deep learning methods have been applied to compensate ID effects in the SSRF storage ring. A neural-network orbit model using 19 ID gap settings as inputs and 276 BPM orbit responses as outputs predicts ID-induced COD with an R^2 value above 0.98. Combined with the measured response matrix and feedforward coils, it reduces the residual COD to less than 2 um and reduces preparation time by about a factor of 50. A second neural-network model based on TBT BPM data predicts ID-induced betatron coupling with an R^2 value above 0.95. With correction limits, data-quality checks, uncertainty monitoring, and fallback to conventional tables, this method can become a practical component of high-stability synchrotron light-source operation.

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