MACHINE-LEARNING SURROGATE MODELING OF THE RAON LEBT BEAMLINE

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Abstract

We present a machine-learning surrogate model for the RAON Low Energy Beam Transport (LEBT) beamline that enables fast prediction of beam centroids at multiple diagnostics. A dataset of `TRACK` simulations spanning steering-magnet and electrostatic-quadrupole settings is used to train fully connected neural networks (FCNNs). The surrogate model reproduces the underlying beam dynamics with high accuracy while providing orders-of-magnitude faster evaluation than conventional beam dynamics simulations. This approach supports rapid orbit studies, optimization, and future data-driven beam control applications in the RAON front-end transport system.

INTRODUCTION

The Rare isotope Accelerator complex for ON-line experiments (RAON) is a heavy-ion accelerator facility in Korea for stable and rare isotope beams [1]. The Low Energy Beam Transport (LEBT) section transports ion beams from the Electron Cyclotron Resonance Ion Source (ECR-IS) to the Radio Frequency Quadrupole (RFQ), as shown schematically in Fig. 1. This front-end section determines the injection quality for downstream acceleration. Reliable control of the transverse beam centroid in this region is essential for minimizing beam loss and preserving beam quality.

Orbit control in the LEBT is challenging because the beam energy is low and the dynamics are affected by space charge, nonlinear focusing fields, alignment errors, and uncertainties in machine settings [2,3]. Conventional correction based on linear response matrices is useful for routine tuning but can become inaccurate when nonlinearities and space-charge effects are important. High-fidelity particle tracking can model these effects, but repeated `TRACK` calculations are too expensive for fast parameter scans or online optimization.

Machine-learning (ML) surrogate models offer a practical approach for accelerating beam dynamics studies by learning nonlinear mappings between machine settings and beam responses [4–6]. In this work, fully connected neural networks (FCNNs) are trained on `TRACK` simulation data to predict beam centroids at multiple RAON LEBT diagnostics. The resulting model is implemented in the Python-based `synapticTrack` framework and provides a fast model for orbit studies and future data-driven beam control.

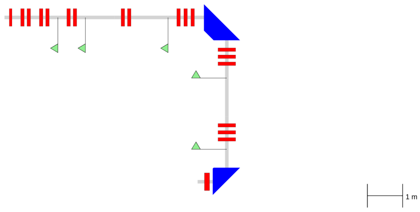

Figure 1: Schematic layout of the RAON LEBT beamline from ECRIS to RFQ. Red elements indicate focusing elements, and green symbols indicate diagnostic locations.

SIMULATION AND CALIBRATION FRAMEWORK

The `TRACK` code [7] was used to generate beam dynamics data for the RAON LEBT. The simulation model includes steering magnets, electrostatic quadrupoles (EQuads), drift sections, and diagnostic locations corresponding to four wire scanners (WSs), one Allison scanner (AS), and the LEBT exit. Ar^{8+} operating conditions were considered, and the simulations recorded horizontal and vertical beam centroids for each machine configuration.

Simulation, calibration, and ML workflows were managed using `synapticTrack`, a modular Python framework developed for this study. The framework handles `TRACK` data conversion, scanner analysis, feature normalization, visualization, and PyTorch-based surrogate model training. This common workflow allows measured and simulated data to be treated consistently during calibration and dataset generation [8].

To improve agreement with measurements, the `TRACK` model was calibrated using scanner data, as summarized in Fig. 2. Steering magnet kicks were adjusted to minimize differences between measured and simulated beam centroids, while EQuad voltages were calibrated using RMS beam-size information. The EQuads were grouped into three scaling families to reduce dimensionality and improve optimization stability. The calibrated model was then used as the reference simulation model for training-data generation.

SURROGATE MODEL DEVELOPMENT

The surrogate model was trained on a large `TRACK` dataset generated with Latin Hypercube Sampling (LHS) [9]. The 13-dimensional input vector consisted of five horizontal steering kicks, five vertical steering kicks, and three grouped EQuad scaling factors. The 12-dimensional output vector consisted of horizontal and vertical centroids at WS1–WS4, AS1, and the LEBT exit. Approximately 50,000 simulation

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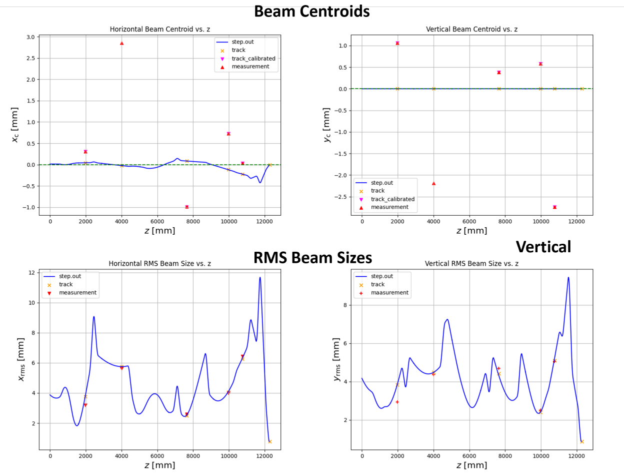

Figure 2: Calibration of TRACK simulations against measured beam centroids and RMS beam sizes. The calibrated model reproduces the measured centroid and beam-size trends at the LEBT diagnostics.

cases were generated and divided into training, validation, and test sets.

The neural-network model was implemented as an FCNN in PyTorch. Several hidden-layer configurations with 128- and 256-neuron layers were tested, together with ReLU, GELU, and LeakyReLU activation functions. The model maps the accelerator setting vector $\mathbf{x}$ to the predicted centroid vector $\mathbf{y} = f(\mathbf{x}; \theta)$, where θ denotes the trainable network parameters. The overall FCNN structure is shown in Fig. 3.

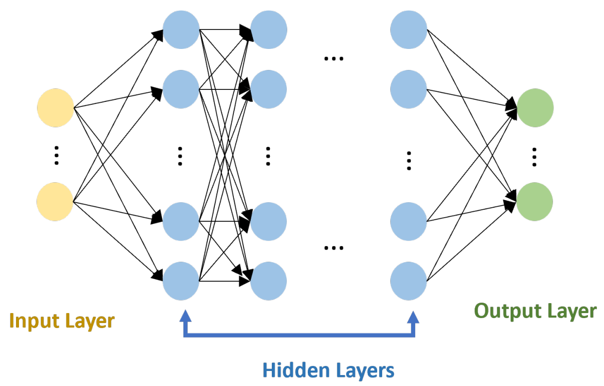

Figure 3: Fully connected neural-network surrogate model used to map steering magnet and EQuad settings to beam centroid predictions at LEBT diagnostics.

The FCNN was trained using supervised regression against TRACK results. Different loss functions and optimizers were investigated, including MSE, MAE, Huber loss, Adam, and AdamW. The best-performing configuration used MSE loss with the Adam optimizer and GELU activation. As shown in Fig. 4, the training and validation losses decrease steadily and remain close to each other, indicating stable convergence without significant overfitting. The diagnostic-by-diagnostic RMS errors remain below 0.05 mm for the best model.

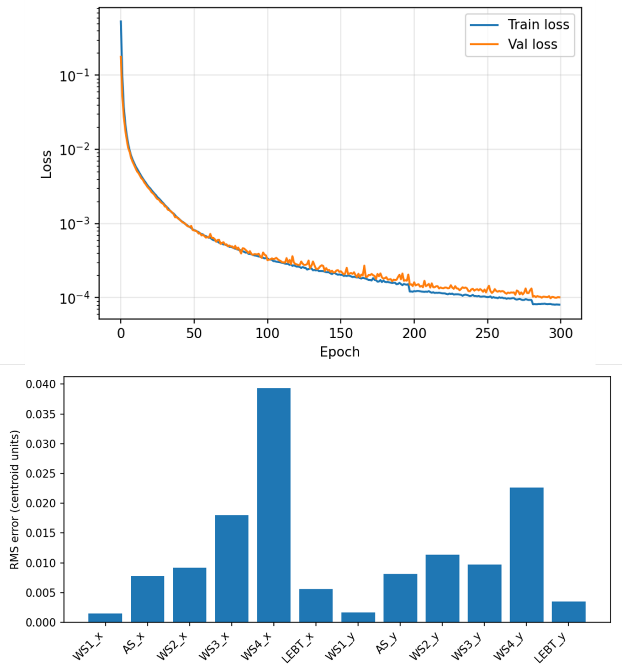

Figure 4: Training performance of the FCNN surrogate model. Top: training and validation loss evolution. Bottom: RMS centroid prediction errors for each output coordinate.

The trained surrogate reproduced the TRACK centroid response with high accuracy across all diagnostic locations. Figure 5 compares the centroid evolution predicted by TRACK and by the surrogate model for a representative test setting. The two curves are nearly indistinguishable at all diagnostic locations. In addition, the surrogate model provided sub-millisecond inference time, whereas a single TRACK run required approximately 15 s. This speedup enables rapid orbit scans, optimization, and surrogate-based control studies that would be impractical with direct tracking alone.

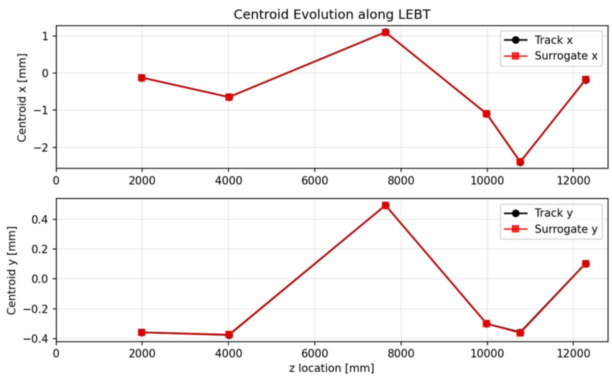

Figure 5: Comparison of TRACK simulations and surrogate-model predictions for horizontal and vertical centroid evolution along the RAON LEBT.

APPLICATION TO ORBIT CORRECTION

The trained surrogate model was applied to preliminary orbit correction studies in the RAON LEBT. The correction objective was to minimize horizontal and vertical centroid offsets at all diagnostic locations by varying steering magnet settings and EQuad scaling factors. Because the surrogate evaluates beam responses rapidly, it enables efficient exploration of the correction parameter space and can serve as a fast-response environment for optimization algorithms.

Figure 6 shows a representative orbit correction result obtained using Reinforcement Learning with the FCNN surrogate model as the beamline environment. The uncorrected orbit exhibits significant horizontal and vertical centroid deviations, while the RL-corrected orbit remains close to the target trajectory throughout the diagnostic locations. The trained RL policy determines correction settings by interacting with the surrogate model, enabling rapid optimization without repeated full TRACK simulations during policy training. The resulting correction settings were subsequently compared with full TRACK simulations and showed consistent orbit recovery trends, indicating that the FCNN surrogate captures the nonlinear orbit response required for RL-based orbit correction studies. This framework provides a practical basis for future online orbit correction, where algorithms such as PPO, SAC, or TD3 can be trained efficiently on the surrogate model and then validated with high-fidelity beam dynamics simulations.

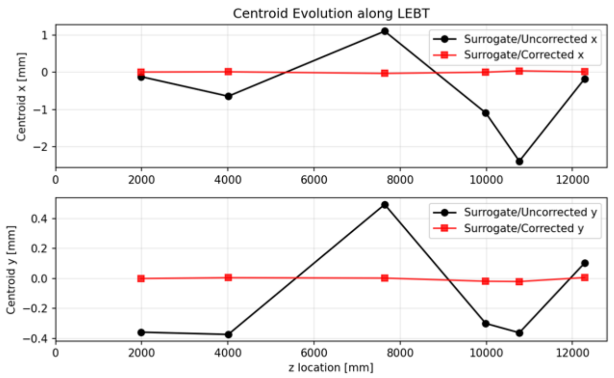

Figure 6: Preliminary surrogate-based orbit correction result. The corrected trajectory is centered close to the target orbit at all LEBT diagnostic locations.

CONCLUSION

A machine-learning surrogate model for the RAON LEBT beamline was developed using FCNNs trained on calibrated TRACK simulation data. The model predicts beam centroids at multiple diagnostics from steering magnet and EQuad settings with sub-0.05 mm RMS error and sub-millisecond inference time. The surrogate significantly accelerates orbit-response evaluation and provides a foundation for rapid orbit studies, online optimization, and future reinforcement-learning-based accelerator control in the RAON front-end transport system.

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