ISBN: 978-3-95450-261-5 ISSN: 2673-7000 doi: 10.18429/JACoW-NAPAC2025-THP014

BEAM LOSS MODELING AND MITIGATION DUE TO INTRA-BEAM STRIPPING *

S. Kakkar† 1, V. Morozov[2], L. Lee[1], N. Evans[2], A. Zhukov[2], A. Hoover[2]
[1]University of Tennessee, Knoxville, TN, USA
[2]Oak Ridge National Laboratory, Oak Ridge, TN, USA

Abstract

Intra-Beam Stripping (IBS) is a critical beam loss mechanism in high-intensity H- linacs and presents a significant limitation to increasing beam power. This work presents a computational framework to evaluate and mitigate IBS-induced beam losses along the Spallation Neutron Source (SNS) LINAC. The calculation is based on an analytic theory and involves evaluation against simplified analytically solvable cases. We then applied our algorithm to Gaussian bunches with a known probablity density functions(PDFs). We next extended our algorithm to arbitrary bunch distributions using Neural Spline flow (NSF) models trained on PyORBIT tracking data. In the future, we plan to validate our algorithm experimentally and apply it to design effective mitigation strategies.

INTRODUCTION

High-intensity H- linear accelerators are crucial components of modern accelerator facilities, enabling high beam power for a range of scientific and practical applications. The SNS at Oak Ridge National Laboratory (ORNL) relies on these machines to deliver high-power beams for ambitious experimental programs. However, a persistent challenge for those accelerators is the control and mitigation of beam loss. Even small, uncontrolled losses can lead to radiation activation, increased maintenance, and ultimately limit facility upgrades and operations [1].

IBS is one of the primary mechanisms causing beam loss in these accelerators. It is due to the close electromagnetic interactions within dense H- bunches that lead to the loss of the electrons, and its effect increases with higher beam intensity (Fig. 1). Lebedev and Nagaitsev [2] developed foundational analytical models widely used for IBS predictions, but those often assume ideal Gaussian beam distributions and overlook complex, realistic beam shapes [3].

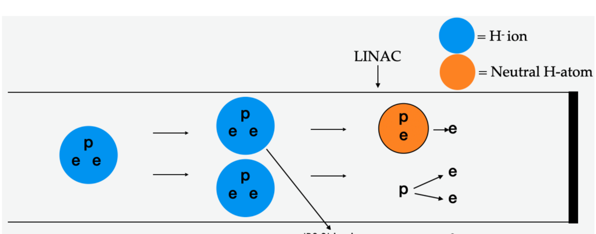

Figure 1: Electron stripping from H⁻ ions due to IBS.

This work aims to bridge the gap by expanding established analytic models with simulation-based and machine learning techniques. We combine Lebedev's foundational theory with neural network methods trained on detailed tracking data to model even the most complex, non-Gaussian bunch profiles and include collective effects like space charge. By carefully benchmarking this approach and applying to practical scenarios at SNS, we aim to provide more accurate IBS loss rate predictions and contribute to developing effective mitigation strategies for current and future high-intensity H- linacs.

LOSS RATE CALCULATION

The particle loss rate due to intra-beam stripping (IBS) is modeled using analytical expression developed by Lebedev and Solyak [2]. The general form of this loss rate is given by:

$$\frac{dN}{dt} = \frac{N^2}{2}\int |\mathbf{u}|\, \sigma_H(|\mathbf{u}|)\, f(\mathbf{v}_1, \mathbf{r}_1)\, f(\mathbf{v}_2, \mathbf{r}_2)\, \delta(\mathbf{r}_1 - \mathbf{r}_2)\, d\Gamma_1\, d\Gamma_2$$

Here:

- $\frac{dN}{dt}$ is the total particle loss rate due to intra-beam stripping.
- N is the number of particles in the bunch.
- $\mathbf{u} = \mathbf{v}_1 - \mathbf{v}_2$ is the relative velocity between two interacting particles.
- $\sigma_H(|\mathbf{u}|)$ is the H^- stripping cross-section, which depends on the relative velocity.
- $f(\mathbf{v}_1, \mathbf{r}_1)$,$f(\mathbf{v}_2, \mathbf{r}_2)$ are the 6D phase space density functions of two particles.
- $\delta(\mathbf{r}_1 - \mathbf{r}_2)$ ensures that only particles at the same position interact.
- $d\Gamma_1$, $d\Gamma_2$ are the phase space volume elements for each particle.

Monte Carlo Integration Approach

The loss rate integral is high-dimensional and cannot be solved analytically for realistic beam distributions. We evaluate it numerically using a Monte Carlo method, where random pairs are sampled from a specified distribution and the integrand is computed for each sample.

All calculations are performed in the rest frame of bunch, where the reference particle is at rest. This makes it easier to describe particle motion using transverse angles and momentum spread along the beam direction. In this frame, it is simpler to calculate both the relative velocity between

* This manuscript has been authored in part by UT Battelle, LLC under Contract No. DE-AC05-00OR22725 with the U.S. Department of Energy. This research used resources at the Spallation Neutron Source, a DOE Office of Science User Facility operated by the Oak Ridge National Laboratory.
† nlns1@ornl.gov

ISBN: 978-3-95450-261-5 ISSN: 2673-7000 doi: 10.18429/JACoW-NAPAC2025-THP014

particles and how they are distributed in phase space. Since intra-beam stripping depends on both of these–how particles move relative to each other and how they are spread out–the rest frame is a natural and practical choice for the calculation.

Benchmarking with Gaussian Distribution

To check the accuracy of our loss rate calculation method, we first apply it to an ideal case where the beam has a Gaussian distribution in phase space. This distribution is fully defined using Twiss parameters and beam emittance, which are used to construct the beam's covariance matrix. In this setup, both the bunch distribution and the sampling distribution are modeled as the same Gaussian. This gives a clean benchmark to test the Monte Carlo integration and compare it against known theoretical predictions.

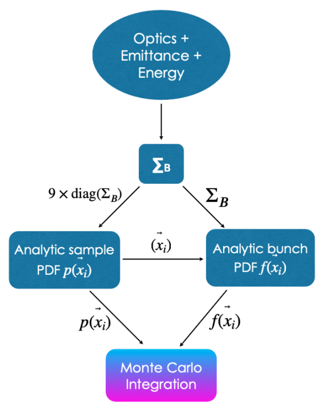

Figure 2: Benchmarking workflow using a Gaussian beam. The beam covariance matrix Σ_B is built from optics, emittance, and energy. Phase space coordinates $\vec{x}_i$ are sampled and evaluated using analytic PDFs for Monte Carlo integration. Here, $\vec{x}_i$ denotes phase space coordinates and Σ_B is the beam covariance matrix.

This benchmarking setup, see Fig. 2, allows us to validate the Monte Carlo integration procedure using a simple Gaussian distribution. Since the beam distribution is known, we can predict how the loss rate should behave under ideal conditions. This gives a reference point to confirm that the sampling, integration, and overall calculation are implemented properly before moving on to more realistic beam data.

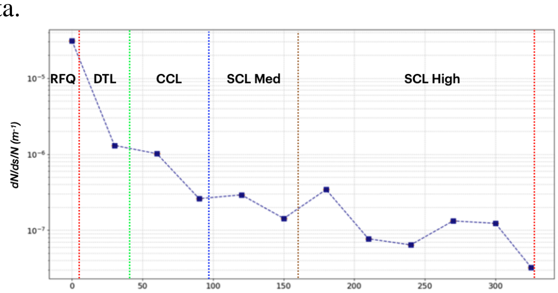

Figure 3: Beam loss rate per meter computed using Gaussian beam model, sampled every 30 meters along the LINAC. Colored markers indicate major LINAC sections (RFQ, DTL, CCL, SCL Med, SCL High).

Figure 3 gives an initial look at the beam loss pattern using a simplified Gaussian distribution. Sampling every 30 meters provides a general trend along the LINAC, but it misses the finer details of the loss profile. Still, it's a helpful reference point to make sure Monte Carlo sampling, integration process, and loss rate formula are all working as expected.

LOSS RATE CALCULATION WITH MACHINE-LEARNED PDF

To model beam loss under realistic conditions, we move beyond the analytic Gaussian assumption and use tracked particle to represent the true distribution. Phase space data at various locations along the SNS LINAC are obtained from PyORBIT simulations [4], which includes beamline optics and collective effects such as space charge. This data captures, non-Gaussian features and correlations present in the beam.

To efficiently use this high-dimensional data in Monte Carlo loss rate integral, we train a neural network to approximate the underlying phase space probability distribution function (PDF). This gives us smooth, realistic model of how particles are distributed in phase space.

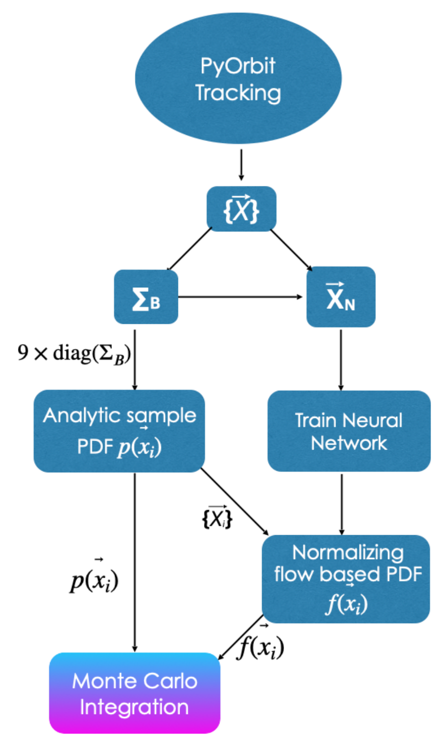

Figure 4: Workflow for computing loss rate using machine-learned PDFs trained on tracked phase space data.

Figure 4 above outlines the procedure we follow to compute the beam loss rate using realistic distributions. We begin by tracking the bunch through the full LINAC using PyORBIT, generating 6D phase space data at various positions. This data is used in two ways: (1) to compute the

6th North American Particle Accel. Conf. (NAPAC2025), Sacramento, CA, USA JACoW Publishing
ISBN: 978-3-95450-261-5 ISSN: 2673-7000 doi: 10.18429/JACoW-NAPAC2025-THP014

covariance matrix for constructing an analytic sample distribution, and (2) to train a neural network that models the true bunch PDF. Once trained, the model PDF is evaluated at the same Monte Carlo sample points drawn from the Gaussian. This method ensures accurate loss rate estimation by weighting contributions from sampled points based on their probability under the true distribution.

RESULTS AND DISCUSSION

We calculated the IBS loss rate along the SNS LINAC using two different modeling approaches: an analytic Gaussian-based using Twiss Parameters and a machine-learned model trained on tracked phase space data from PyORBIT. Although both use Monte Carlo integration to evaluate 9D loss rate integral, but the underlying beam distribution differ significantly.

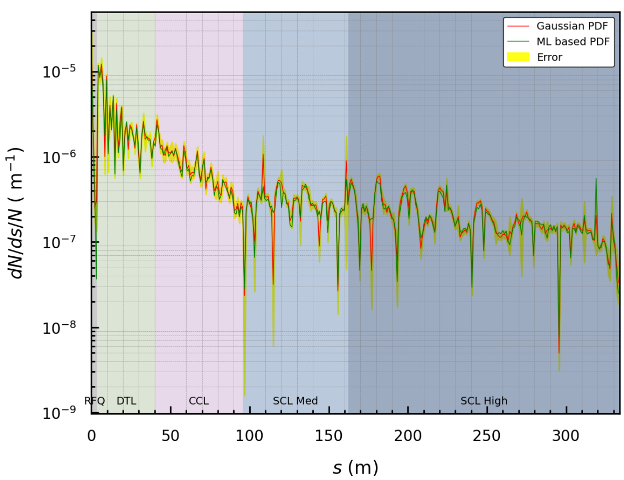

Figure 5: Beam loss rate computed using Gaussian and machine-learned PDFs along the SNS linac.

Figure 5 represents the resulting loss rates by two approaches. The red curve shows the result using a Gaussian approximation constructed from Twiss parameters-including beam's γ, α, β, emittances–which were used to generate synthetic phase space data. The green curve represents the loss rate computed using machine-learned PDFs trained on fully tracked 6D phase space data from PyORBIT simulations. In both cases, Monte Carlo integration was carried out using one million samples to evaluate the 9D loss rate integral at every meter. The error from Gaussian based Monte Carlo is shown by yellow band; ML-based curve lies within this band, confirming model accuracy. The error was calculated using standard Monte Carlo expression and validated across multiple random seeds to ensure consistency. These simulations were run on a high-performance workstation with 64 CPU cores, allowing the full LINAC loss rate to be computed in about two hours.

The strong agreement between two curves shows that the machine-learned PDF captures the key features of the beam. More importantly, it opens the door to modeling loss rates using realistic, non-Gaussian distributions–giving us flexibility to move beyond idealized assumptions in future.

Reconstruction of Phase Space using ML

To validate how well the machine-learned PDFs represent the real beam, we compared their generated phase space distributions with the tracked data from PyORBIT at a fixed location (s = 95.57 m) in the CCL region. Figure 6 shows the projections from the trained ML model, while Fig. 7 shows the same projections from PyORBIT simulations.

Although the projections are not identical, the overall structure and shape are very similar across all planes–transverse $(x, x'), (y, y')$, and longitudinal (z, δ). This consistency suggests that ML model is able to capture the key features of the beam distribution. To further support this comparison, we also include RMS values from both cases in Table 1.

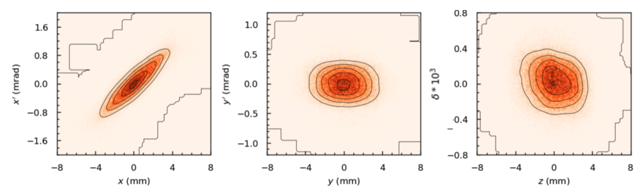

Figure 6: Phase space distributions by ML model.

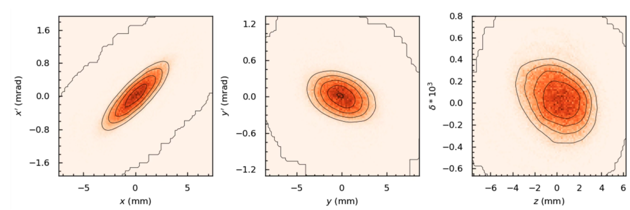

Figure 7: Phase space distributions by PyORBIT tracking.

Table 1: RMS Values

Coordinates	ML Model	PyORBIT
x (mm)	1.9846	1.8222
x' (mrad)	0.5131	0.4502
y (mm)	1.9105	1.9343
y' (mrad)	0.2162	0.2390
z (mm)	1.8114	1.8232
δ	0.1975	0.2046

CONCLUSION

This study shows that machine-learned PDFs offer a reliable and flexible alternative for estimating beam losses in realistic accelerator conditions. Without relying on idealized assumptions, the ML approach adapts to the true beam shape and still delivers results that align well with traditional methods. Its ability to generalize across non-Gaussian cases makes it a powerful tool for future applications, such as modeling complex beam dynamics and optimizing designs for the future accelerator upgrades.

ISBN: 978-3-95450-261-5 ISSN: 2673-7000 doi: 10.18429/JACoW-NAPAC2025-THP014

REFERENCES

[1] S. Henderson, "The SNS beam power upgrade", in *Proc. EPAC'04*, Lucerne, Switzerland, Jul. 2004, paper TUPLT170, pp. 1527–1529. https://accelconf.web.cern.ch/e04/papers/TUPLT170.pdf

[2] V. Lebedev, N. Solyak, J.-F. Ostiguy, A. Alexandrov and A. Shishlo "Intrabeam stripping in H^- linacs", " Jul. 2012, arXiv:1207.5492 [physics.acc-ph] doi:10.48550/arXiv.1207.5492

[3] M. A. Plum, "Beam loss mechanisms in high intensity linacs", in *Proc. HB'12*, Beijing, China, Sep. 2012, paper MOI1C03, pp. 36–40. https://accelconf.web.cern.ch/HB2012/papers/moi1c03.pdf

[4] A. Shishlo, S. M. Cousineau, J. Holmes, and T. Gorlov, "The particle accelerator simulation code PyORBIT", in *Procedia Comput. Sci.*, vol. 5, pp. 1272–1281, 2015 doi:10.1016/j.procs.2015.05.312