Thesis abstract Emmanuel Goutierre

« Machine Learning-Based Particle Accelerator Modeling »

Particle accelerators rely on high-precision simulations to optimize beam dynamics. These simulations are computationally expensive, making real-time analysis impractical. This thesis seeks to address this limitation by exploring the potential of machine learning to develop surrogate models for particle accelerator simulations.

The focus is on ThomX, a compact Compton source, where two surrogate models are introduced: LinacNet and Implicit Neural ODE (INode). These models are trained on a comprehensive database developed in this thesis that captures a wide range of operating conditions to ensure robustness and generalizability.

LinacNet provides a comprehensive representation of the particle cloud by predicting all coordinates of the macro-particles, rather than focusing solely on beam observables. This detailed modeling, coupled with a sequential approach that accounts for cumulative particle dynamics throughout the accelerator, ensures consistency and enhances model interpretability.

INode, based on the Neural Ordinary Differential Equation (NODE) framework, seeks to learn the implicit governing dynamics of particle systems without the need for explicit ODE solving during training. Unlike traditional NODEs, which struggle with discontinuities, INode is theoretically designed to handle them more effectively.

Together, LinacNet and INode serve as surrogate models for ThomX, demonstrating their ability to approximate particle dynamics. This work lays the groundwork for developing and improving the reliability of machine learning-based models in accelerator physics.