LINAC_GEN: INTEGRATING MACHINE LEARNING AND PARTICLE-IN-CELL METHODS FOR ENHANCED BEAM DYNAMICS AT FERMILAB

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ABSTRACT

Here, we introduce Linac_Gen, a tool developed at Fermilab, which combines machine learning algorithms with Particle-in-Cell methods to advance beam dynamics in linacs. Linac_Gen employs techniques such as Random Forest, Genetic Algorithms, Support Vector Machines, and Neural Networks, achieving a tenfold increase in speed for phase-space matching in Linacs over traditional methods, through the use of genetic algorithms. Crucially, Linac_Gen's adept handling of 3D field maps elevates the precision and realism in simulating beam instabilities and resonances, marking a key advancement in the field. Benchmarked against established codes, Linac_Gen demonstrates not only improved efficiency and precision in beam dynamics studies but also in the design and optimization of Linac systems, as evidenced in its application to Fermilab's PIP-II Linac project. This work represents a notable advancement in accelerator physics, marrying ML with PIC methods to set new standards for efficiency and accuracy in accelerator design and research. Linac_Gen exemplifies a novel approach in accelerator technology, offering substantial improvements in both theoretical and practical aspects of beam dynamics.

DESIRED CAPABILITIES FOR COMPUTATIONAL TOOLS

1. **Longitudinal lattice design:** Capability to optimize the longitudinal lattice for achieving precise energy targets within cavity performance limits.
2. **Transverse dynamics:** Computation of solenoid and quadrupole focusing fields with high accuracy to ensure the avoidance of resonances in alignment with longitudinal phase advances and within magnet performance limits.
3. **Beam matching:** Fast and reliable tool for calculating and matching Twiss parameters in 6D phase-space across the linac.
4. **Beam dynamics calculations:** Capability to perform advanced three-dimensional Particle-In-Cell particle tracking simulations, incorporating both relativistic beam dynamics and the effects of 3D RF and static fields.
5. **Adaptability for innovation:** The tool must be adaptable, allowing for the seamless integration of novel concepts and custom algorithms to push the boundaries of existing codes.

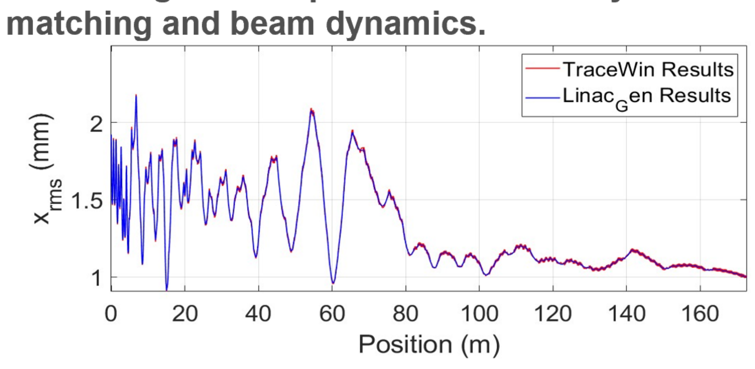
LINAC_GEN: THE EVOLUTION IN LINAC DESIGN & SIMULATION

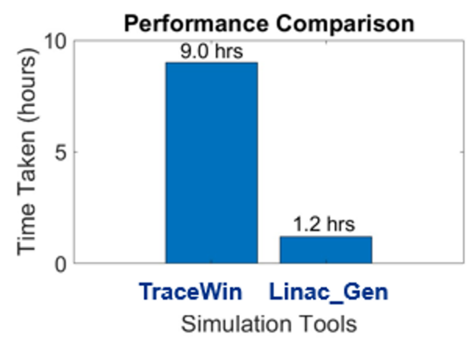
- Confronted with the limitations of current simulation tools, I developed my own simulation code employing a staged approach.
- STAGE 1: Implementation of algorithms for longitudinal and transverse lattice design while following the pre-defined design strategies to avoid emittance growth, halo formation and beam instabilities.
- STAGE-2: Implement Particle-In-Cell method to perform beam dynamics calculation with the designed lattice and compare the results with code like TraceWin.
- STAGE-3: Utilization of Genetic algorithms to achieve faster inter-section beam matching.

➢ Optimizes Twiss and lens parameters for targeted beam profiles.
➢ Handles complex, nonlinear interactions in beam dynamics.
➢ Conducts global searches to avoid local minima and find optimal solutions.
➢ Manages multi-objective optimization, balancing emittance and beam loss, x-y splitting.
➢ Takes less computational time and resources than TraceWin, ideal for real-time control systems

PERFORMANCE ANALYSIS: TRACEWIN VS. LINAC_GEN

Evaluating the computational efficiency of TraceWin and Linac_Gen for 6D phase-space matching and beam dynamics.





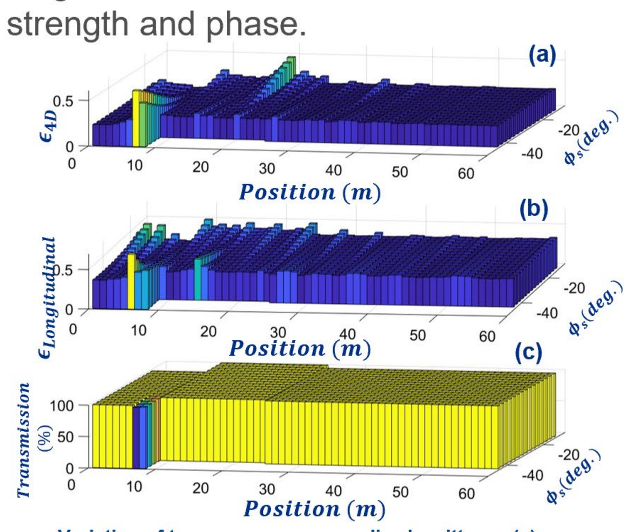
- **Computational Efficiency:**
  - TraceWin: Requires 8 to 10 hours for 6D phase-space matching and beam dynamics simulations.
  - Linac_Gen: Completes the same simulations in about 1.2 hours, making it 7 to 8 times faster.
- **Accuracy of Results:**
  - Despite the significant difference in computational speed, Linac_Gen's results closely align with those from TraceWin, showing less than a 3% discrepancy.

ML ALGORITHM IMPLEMENTATION

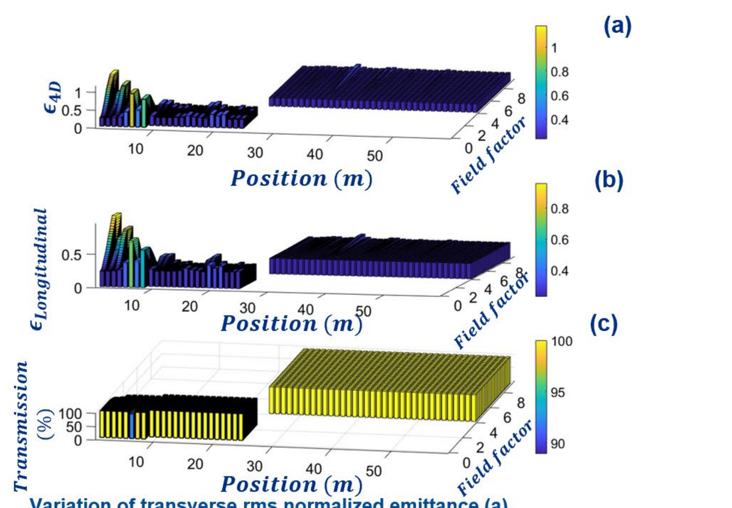
Algorithm Type	Application in Linac Design	Technical Advantage
Convolutional Neural Networks (CNNs)	Analyzing phase space images for beam profile optimization	High accuracy in spatial pattern recognition, essential for beam shaping
Long Short-Term Memory Networks (LSTMs)	Modeling time-dependent beam dynamics and predicting future beam states	Captures long-term dependencies in temporal data, crucial for dynamic stability analysis
Random Forests	Predicting linac operational parameters from historical data	Handles high-dimensional spaces effectively, important for parameter tuning
K-means Clustering	Unsupervised categorization of beam states for anomaly detection	Efficiently identifies distinct operational regimes, beneficial for diagnostics
Genetic Algorithms	Optimizing the configuration of linac components for improved beam quality	Searches through complex parameter spaces, mimicking natural evolutionary processes

DATA FOR TRAINING

- Visualizations showcase the predictive model's results, illustrating changes in transverse and longitudinal emittance and beam transmission correlated to adjustments in cavity field strength and phase.



Variation of transverse rms normalized emittance (a), longitudinal normalized rms emittance (b), and transmission with synchronous phase.



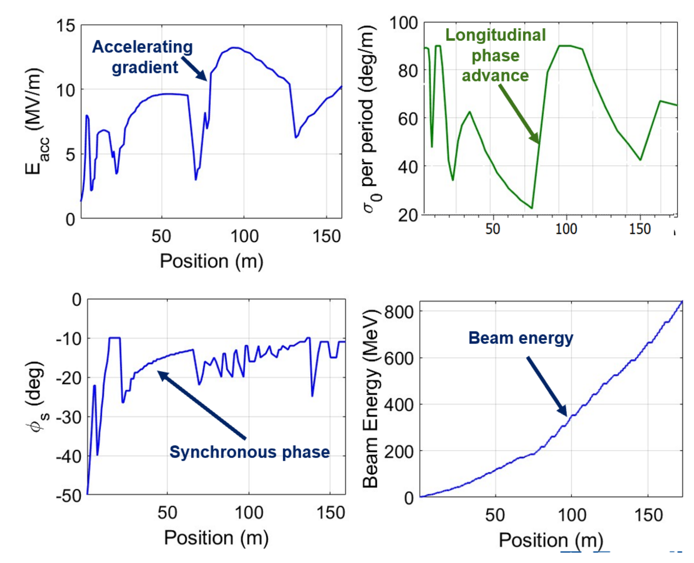
Variation of transverse rms normalized emittance (a), longitudinal normalized rms emittance (b), and transmission % with cavity field map factor.

LONGITUDINAL DYNAMICS

Custom-developed code 'Linac_Gen' utilized for optimization.

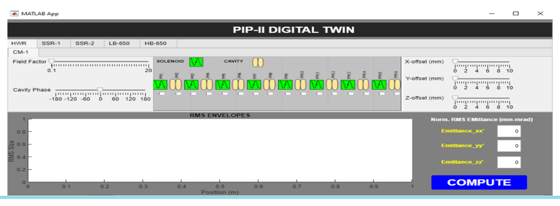
- **Considerations:**
  - Structure Phase Advance: Kept at or below 90° .
  - Energy Gain Target: From 2.1 MeV to 800 MeV.
  - Accelerating Gradient: Not to exceed E_max_cav.

Cavity type	Aperture (diameter) (mm)	Effective length (cm)	Accelerating gradient (MV/m)	E_{peak} (MV/m)	B_{peak} (mT)	R/Q (Ω)	G (Ω)
HWR	33	20.7	9.7	44.9	48.3	272	48
SSR1	30	20.5	10	38.4	58.1	242	84
SSR2	40	43.8	11.4	40	64.5	297	115
LB650	88	70.3	16.9	40.3	74.6	341	193
HB650	118	106.1	18.8	38.9	73.1	610	260



DIGITAL TWIN PREDICTIVE TRAINING

- **Electromagnetic field interactions:**
  - Predicts beam behavior in response to cavity field and phase variations, and solenoid field adjustments.
- **Structural Alignments:**
  - Forecasts the effects of element misalignments on beam trajectory, emittance and stability.
- **Beam Parameter Variation:**
  - Models the beam's reaction to changes in current, and longitudinal and transverse distribution (e.g. Gaussian vs KV)..



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CONCLUSION

- ❑ Developed 'Linac_Gen', a custom code for advanced longitudinal and transverse lattice design and beam dynamics with PIC algorithms.
- ❑ Integrated machine learning to enhance beam physics calculations, elevating analysis to new heights.
- ❑ Trained ML models with PIP-II data to create a predictive digital twin for real-time operational insights.
- ❑ Deployed the digital twin virtually for live control room scenario, mimicking comparing simulations with experimental data to optimize PIP-II operations