

Design and study of a spiral focusing structure for the FFA at CSNS

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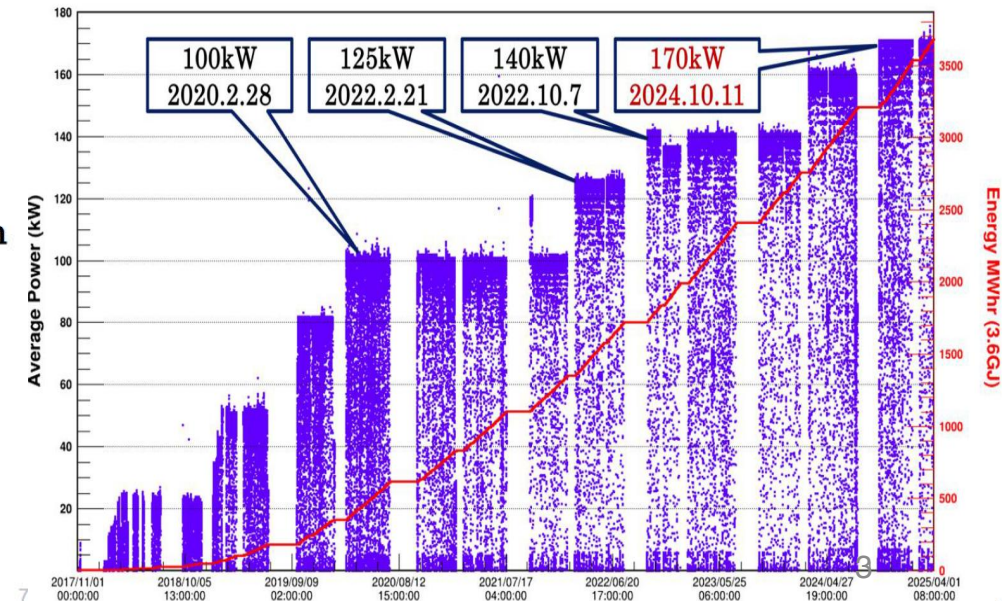
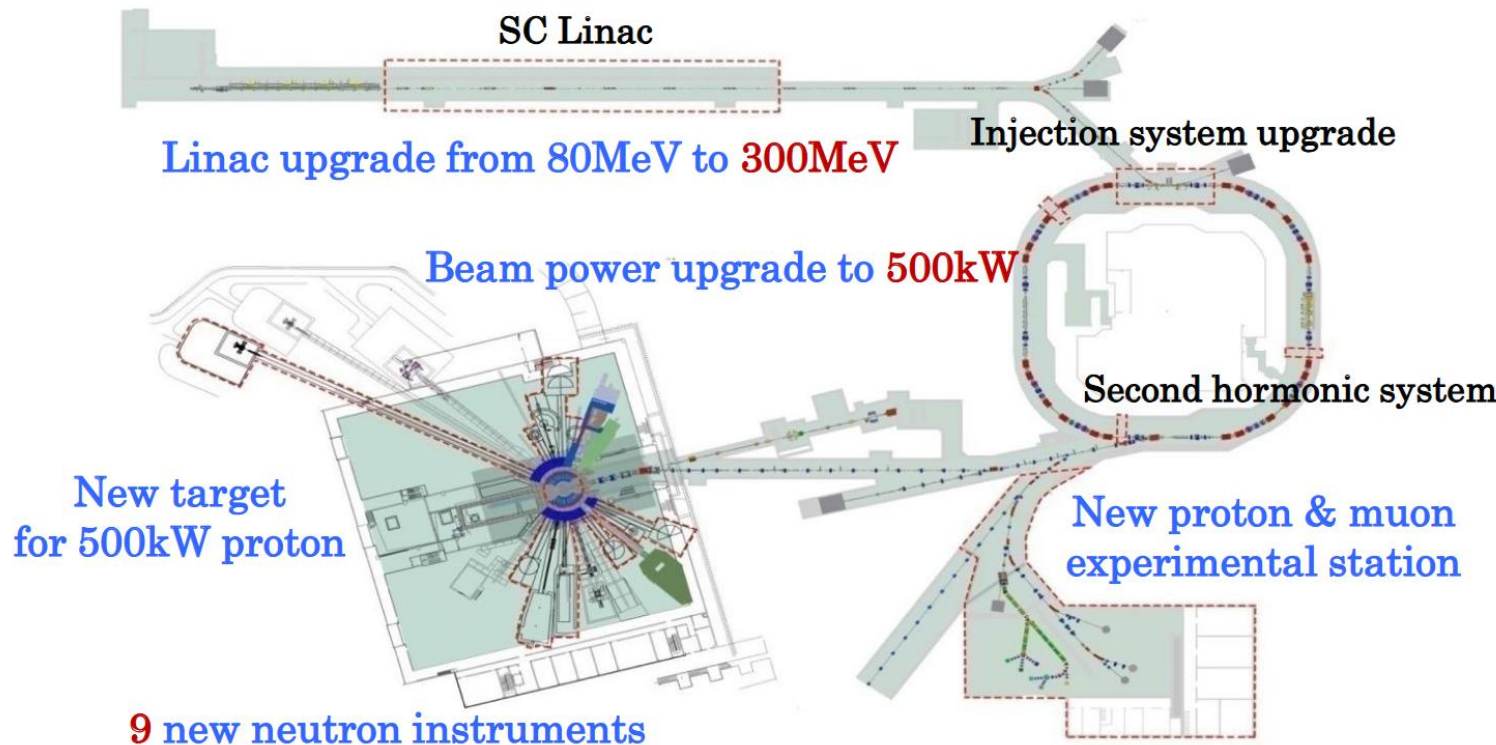
Content



1. Introduction: The CSNS Upgrade and the FFA project
2. Design Requirements: Key parameters and constraints for the accelerator
3. Lattice Design Challenges: A review of the initial design and its limitations
4. Optimization Strategy: An overview of our Machine Learning-enhanced approach
5. Lattice Study and Results: Comparison of candidate structures and the final design
6. Summery

China Spallation Neutron Source (CSNS)

- Located in southern China, Guangdong Province
- The beam power has been increased to 170 kW
- Beam power will be achieved to 500 kW in CSNS-II
- Linac energy upgrade from 80 MeV to 300 MeV



A High-Intensity Proton FFA:

- Injector: 300 MeV beam from the upgraded CSNS Linac

- The repetition rate of linac will upgrade to 50 Hz
- 25 Hz for RCS and 25 Hz for other applications

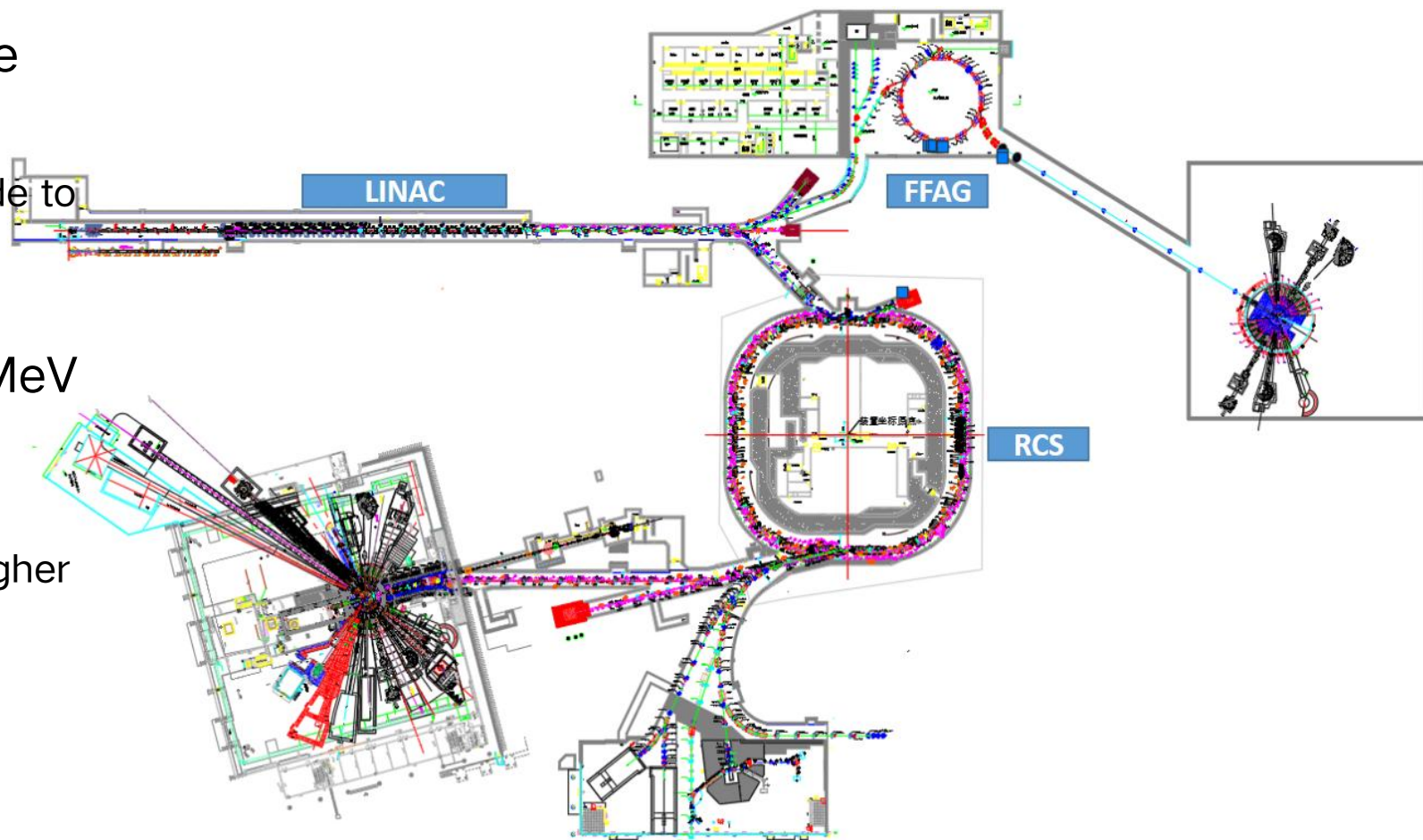
- Extraction energy of FFAG 600 MeV

- Repetition rate of FFAG 25 Hz

- Limited by the repetition rate of linac
- Capable of operating at 200 Hz or higher

- Average beam power 50 kW

- Average beam current 83.4 μA



Multi-application:

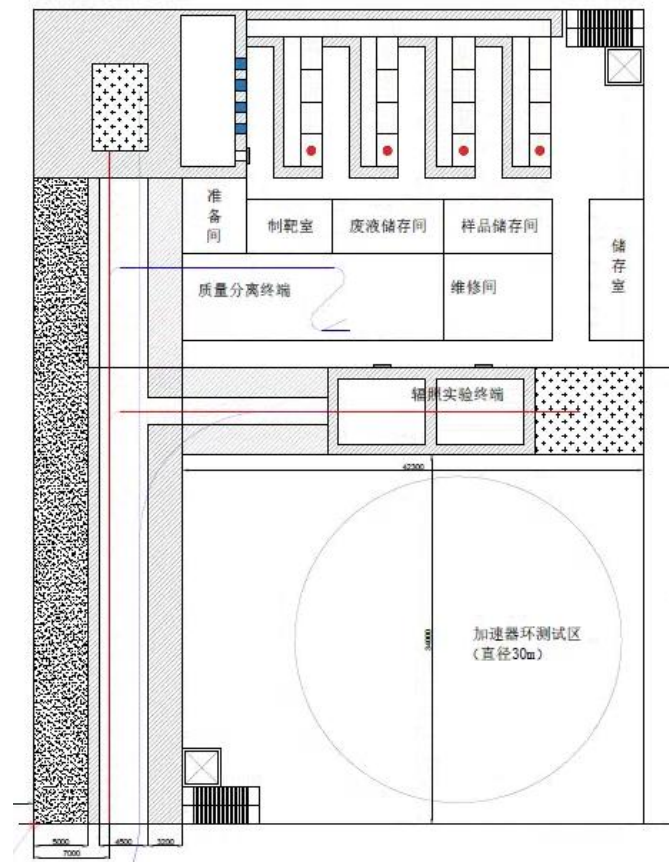
- White Neutron Source/High Repetition Rate Muon Source /The production of alpha medical isotopes/Preliminary technical research for CSNS-III

Key Design Requirements & Constraints

■ Basic Requirements

- **300 MeV to 600MeV** at injection and extraction
- FFAG type: Scaling
- Limited space for accelerator $< \text{Ø}24\text{m}$
- Normal-conducting magnet with **variable air gap**
 - Magnetic fields: $B < 1.66$ [T]
 - Beam excursion (ΔR) < 0.8 [m]
- Enough space for Injection/Extraction and RF cavity
 - Drift space > 1.8 [m]
- Physical dynamic aperture: $DA > 800$ [π mm.mrad]
(Experience from CSNS/RCS)

$$B(r) = B_0 \left(\frac{r}{r_0} \right)^k$$

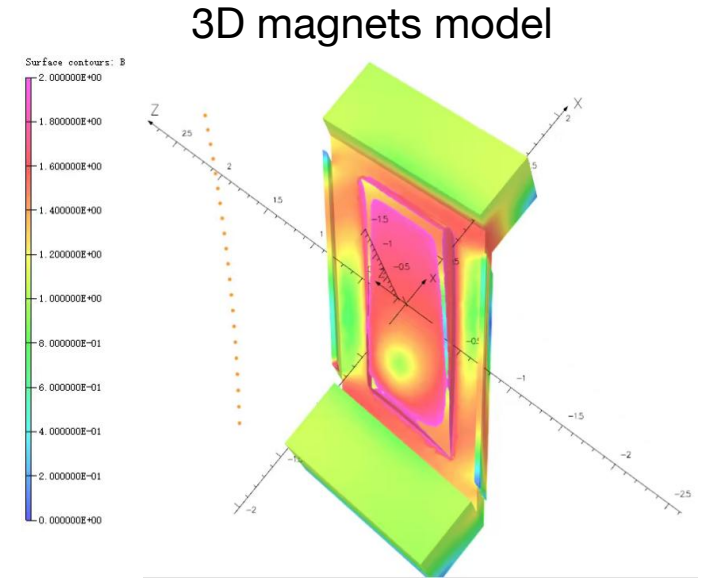
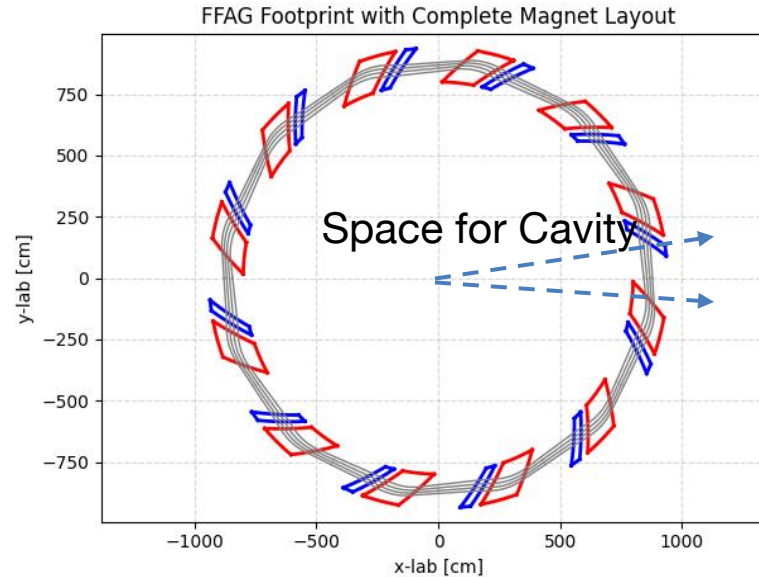


CSNS Linac End Experimental Hall (Under Construction)

Initial Lattice Design & Challenges

Spiral Magnet Parameters

Particle Type	Proton
Injection Energy (MeV)	300
Extraction Energy (MeV)	600
Super periodicity N	12
Peak Magnetic Field in F (T)	1.66
Peak Magnetic Field in D (T)	0.67
R_{ms1}	0.282
R_{ms2}	0.280
Spiral Angle (°)	43.563
Filling Factor P_f	0.485
Field Index K_i	5.449
F Magnet Width (°)	9.314
D Magnet Width (°)	2.627
F-D Magnet Gap (°)	2.608
Straight Section Width (°)	13.129
Cell tunes (ν_r/ν_z)	0.233/0.14

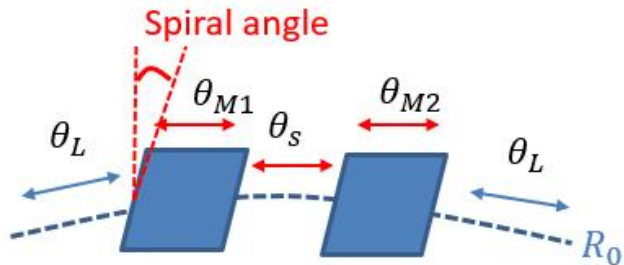


- Advantage: Provided a long drift space
- Disadvantage
 1. Small Vertical Tune: This leads to a large vertical beta function (β_z), complicating beam injection.
 2. Large F-Magnet Size: The focusing magnets were over 2 meters wide, making them excessively heavy and creating significant manufacturing challenges for the vacuum chamber.
- Conclusion: A more advanced, optimized lattice structure is required
 1. **16-cell FD or 12-cell FDF**
 2. **Lattice parameters need to be optimized for larger DA, smaller β_z , B_{max} and longer drift space**

Multi-Objective Optimization problem

- Goal: Find an optimal lattice design that satisfies all competing requirements simultaneously

	parameters	Search range
1	Spiral angle	[20°~60°]
2	Filling factor	[0.4~0.58]
3	D magnets Width θ_{M2}	[0.8~1]
4	F/D gap θ_s	[0.38~0.5]
5	Ki	[4~12]
6	B_d/B_f	[0.35~1.2]



	Objectives	Description	Direction	Purpose
1	L_{drift}	Drift space	Maximize	>1.8m
2	B_m	Maximum magnetic field	Minimize	<1.66T
3	ΔR	Beam excursion	Minimize	<0.8m
4	β_{z0}	Beta functions at straight section center	Minimize	$\beta_z < 8m$
5	β_{z-max}	Beta functions in cells	Minimize	Reduce bunch envelope
6	DA	Particle stability	Maximize	Increasing beam intensity
Supporting role for DA fast optimization				
7	Q_{z_shift}	Vertical tune shift in DA	Minimize	Increase large amplitude particle stability
8	$Tune_Diffsion$	Tune diffusion rates	Minimize	

- Method: Multi-Objective Genetic Algorithm (NSGA-II).

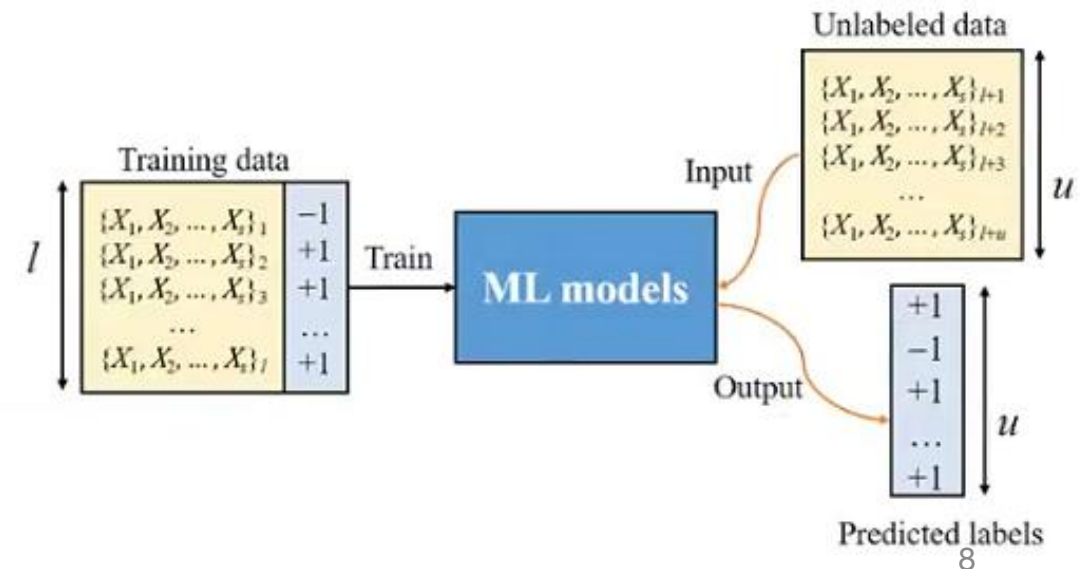
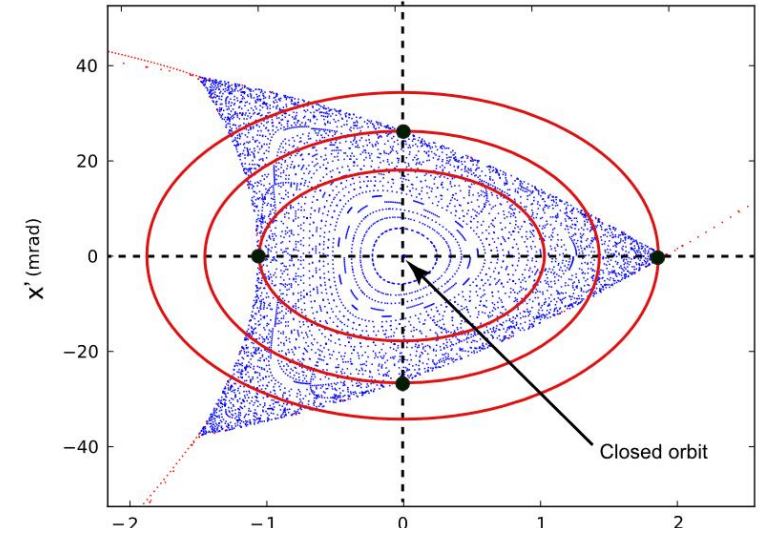
Challenges and Solutions

Key Optimization Challenges:

- High Computational Cost: Accurate Dynamic Aperture (DA) calculation requires multi-turn tracking and iteration (Binary search), which is extremely time-consuming for a population-based optimization algorithm.
- Finding the Global Optimum: Genetic algorithms may get trapped in local optima.

Our Solution:

- DA calculation with few turns.
- Employ a surrogate model to learn the system dynamics, allowing for rapid and exhaustive exploration of the parameter space to predict the true global optimum.



Predicting Long-Term Stability

- Problem: Short-term tracking (~100 turns) does not guarantee long-term stability.

- Solution: Use Frequency Map Analysis (FMA) metrics as reliable indicators

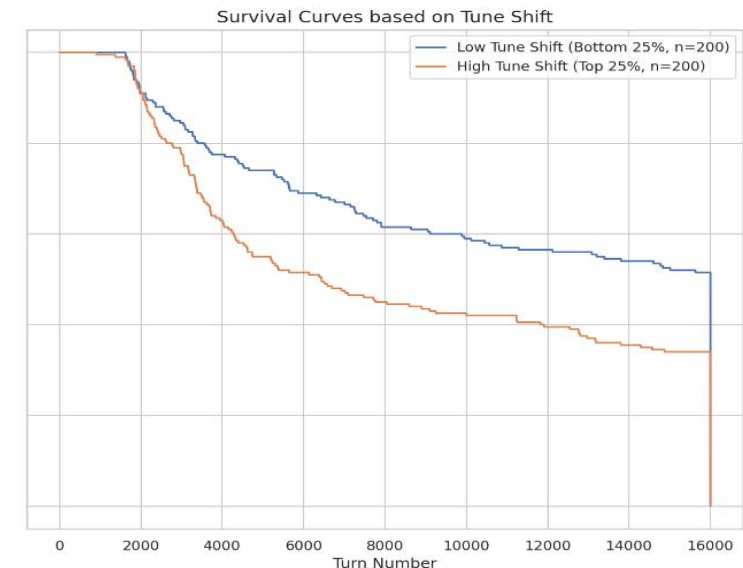
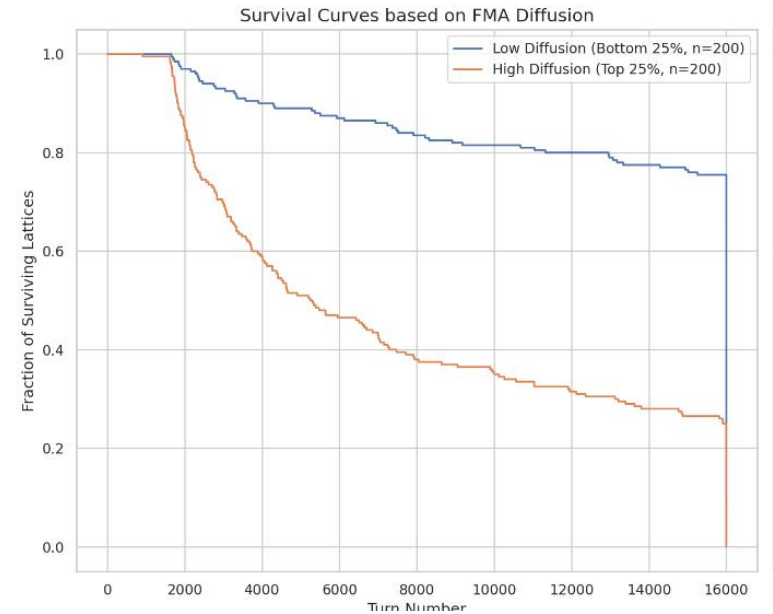
- Tune Shift: frequency (tune) change with amplitude.
- Tune Diffusion: the rate of frequency change, indicating chaos.

- Experiment:

- We took 800 lattice samples, all with good short-term DA
- We tracked them in short-term DA for 1000 turns.

- Result:

- Lattices with low tune diffusion and low tune shift showed significantly higher survival rates.
- This confirms these metrics are good proxies for long-term stability and can be used to accelerate optimization.



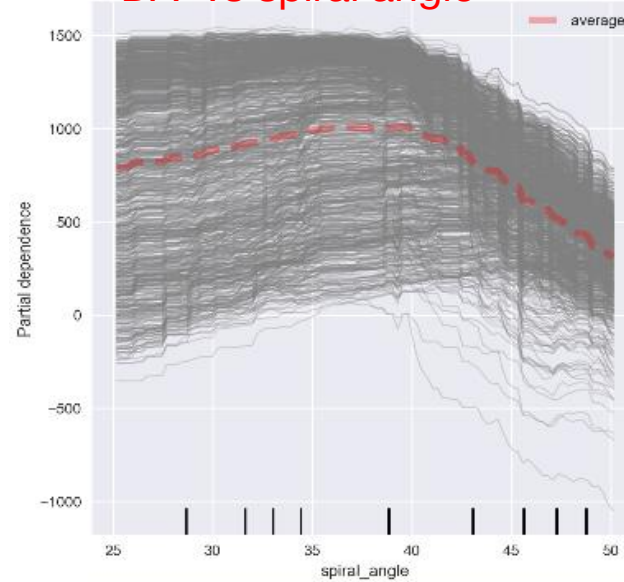
Finding the global optimum

- Developing a surrogate model to understand the complex, non-linear system dynamics of the scaling FFA, rapidly identify the region of the global optimum
- Method:
 - Initial Sampling: Generate ~1000 diverse lattice configurations using Latin Hypercube Sampling
 - Simulation: Run tracking code for this initial dataset.
 - Train Surrogate Model: Develop an XGBoost model, which offers good **interpretability**, to learn the mapping from lattice parameters to performance objectives (e.g., DA)
- Key Advantage: Speed
 - This trained model can predict the performance for thousands of parameter combinations in few seconds

Surrogate Model for Rapid System Analysis

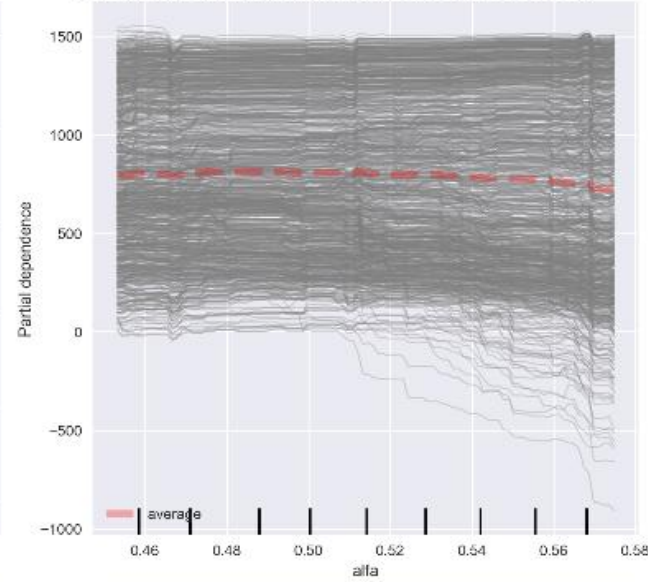
- Experiment:
 - Taking 16-cell FD for example
 - Lattice Parameters effects on DA
- Initial Finding:
 - The model predicted that the optimal solutions for DA would be found when the spiral angle is near 40 degrees

'DA' vs spiral angle

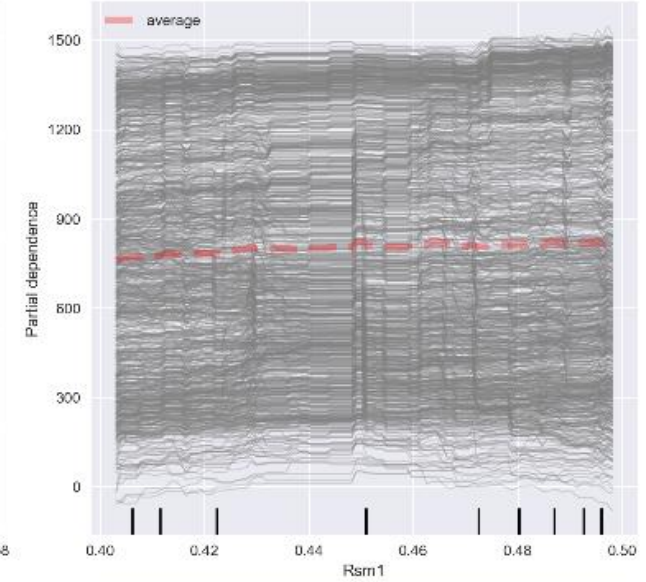


'DA' vs alfa

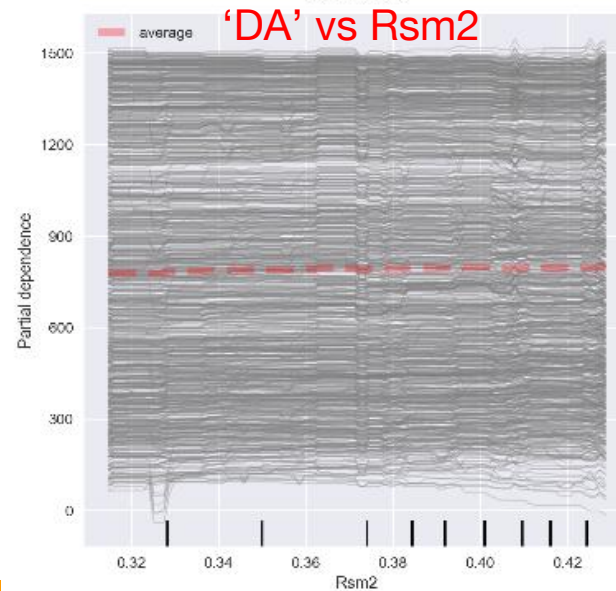
ICE and PDP Analysis: Parameter Effects on DA



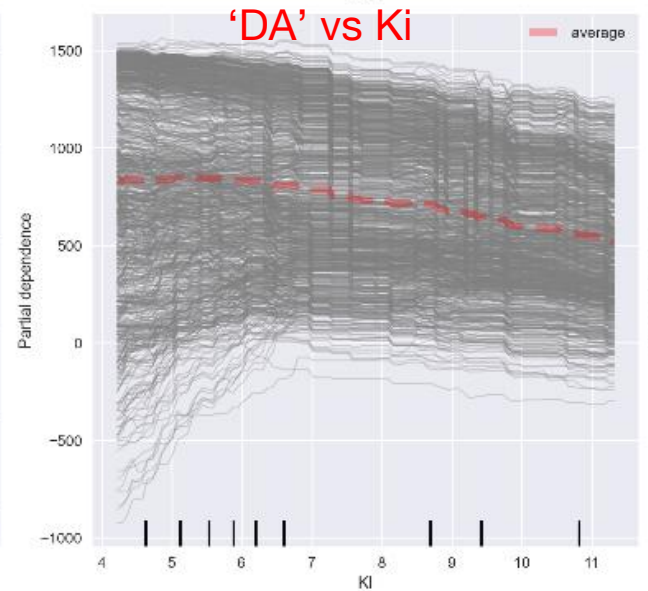
'DA' vs Rsm1



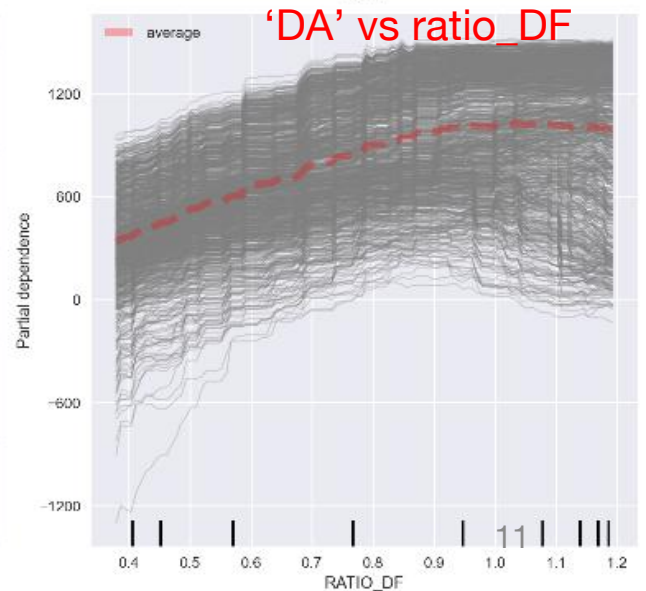
'DA' vs Rsm2



'DA' vs Ki



'DA' vs ratio_DF



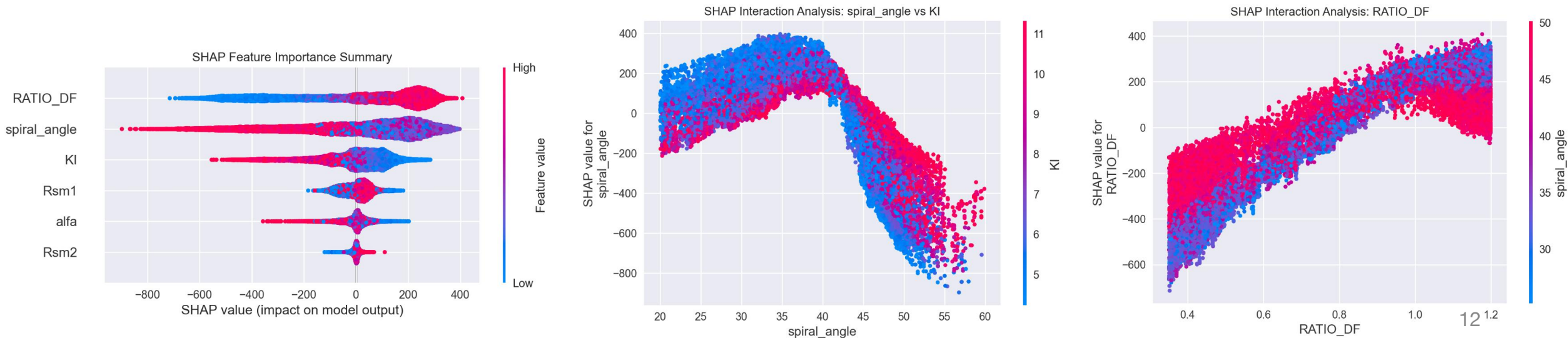
Model Interpretability: Understanding the Physics

Beyond Prediction: Gaining Physical Insight

- Our model is not a "black box." We use SHAP (SHapley Additive exPlanations) to understand why the model makes its predictions.
- This allows us to analyze the complex, non-linear interactions between parameters.

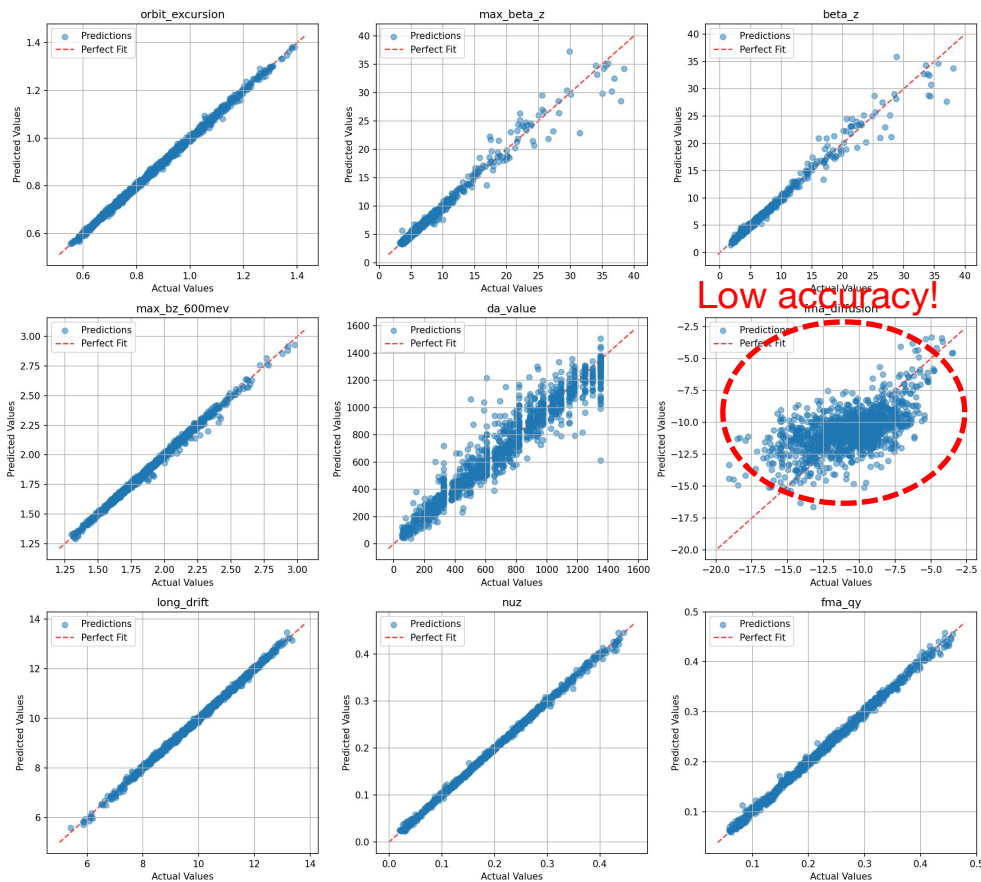
Example Insights:

- Feature Importance: Confirms that spiral_angle, RATIO_DF (F/D magnet strength ratio), and Ki (field index) have the most significant impact on the dynamic aperture.
- Parameter Interaction : We can visualize how two parameters interact. For example, the contribution of the spiral angle to DA peaks around 40 degrees. When the RATIO_DF is high, a slightly smaller spiral angle is needed to maintain a large DA.



Optimization Algorithm

- Using real tracking code (Not surrogate model) to calculate the objectives (DA calculated with 100-turns)
- Tracking code: Fixfield (Thanks to J.B's help) with 6 orders magnetic expansion precision for nonlinearity
- Developing a python script to interface with Fixfield (C/C++), facilitating its integration with model optimization frameworks or Machine Learning (works done like PyZgoubi)



```
bz_f = B_f
bz_d = B_f * ratio_D_F
latt_gen = LatticeFileGenerator(periodicity=int(Ncells), filepath=lattice_filepath)
cell1 = Cell(cell_id=1, cell_type="ffag-spi-enge", step_size=0.001, collimators=(10, 13, 0.25),
            opening_angle_deg=angle)
magnet1 = Magnet(r_center=(long_drift + theta_f / 2), r0=rm, b0=-bz_f, k=Ki, spiral_deg=spiral_angle,
                fringe_en_angle_deg=-omega1, fringe_en_A=0.14, fringe_en_order=6.0, fringe_en_c1=c1_param,
                fringe_ex_angle_deg=omega1, fringe_ex_A=0.07, fringe_ex_order=6.0, fringe_ex_c1=c1_param)
cell1.add_magnet(magnet1)
magnet2 = Magnet(r_center=(long_drift + theta_f + theta_s + theta_d / 2), r0=rm, b0=bz_d, k=Ki,
                spiral_deg=spiral_angle, fringe_en_angle_deg=-omega2, fringe_en_A=0.07,
                fringe_en_order=6.0, fringe_en_c1=c1_param, fringe_ex_angle_deg=omega2,
                fringe_ex_A=0.14, fringe_ex_order=6.0, fringe_ex_c1=c1_param)
cell1.add_magnet(magnet2)
magnet3 = Magnet(r_center=(long_drift + theta_f + theta_s + theta_d + theta_s + theta_f / 2), r0=rm, b0=-bz_f, k=Ki,
                spiral_deg=spiral_angle, fringe_en_angle_deg=-omega3, fringe_en_A=0.07,
                fringe_en_order=6.0, fringe_en_c1=c1_param, fringe_ex_angle_deg=omega2,
                fringe_ex_A=0.14, fringe_ex_order=6.0, fringe_ex_c1=c1_param)
cell1.add_magnet(magnet3)
latt_gen.add_cell(cell1)
latt_gen.generate_file()
```

FFA magnets definition: User-friendly interface for interacting with Fixfield

Optimization Results of 16-cell FD and 12-cell FDF

- Two structure have the same fringe field coefficients for a fair comparison
- Generation=200, Pareto solution sets filtered by $B_{\max} < 1.66\text{T}$, $\beta_{z_0} < 8\text{m}$, $\Delta R < 0.8\text{m}$

Fig.1 Spiral angle Vs DA

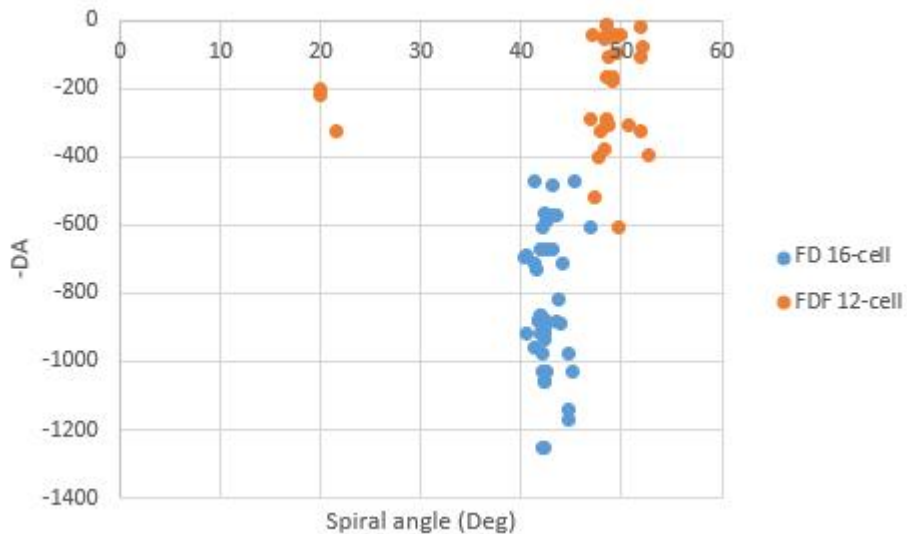


Fig.2 B_{\max} Vs DA

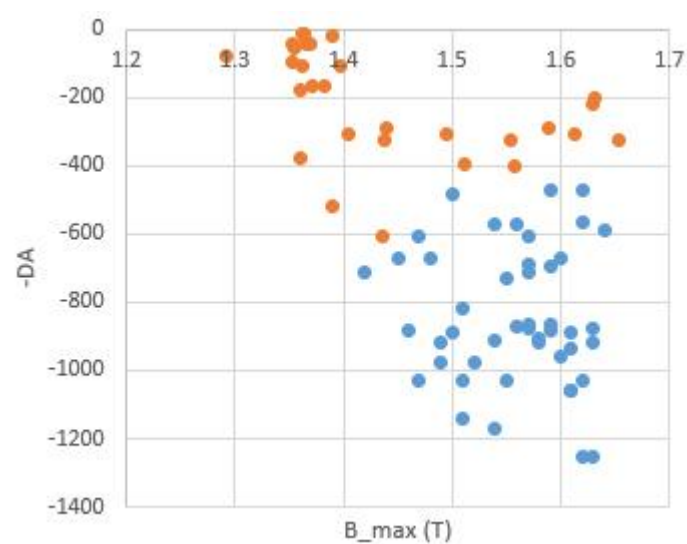
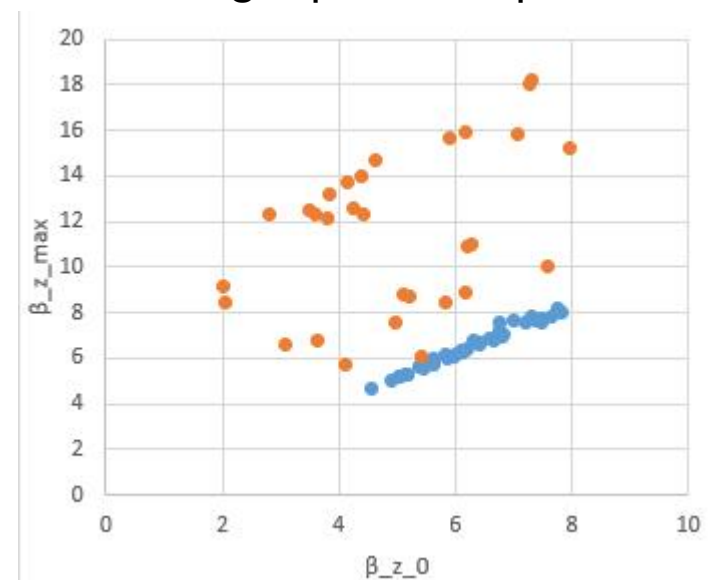


Fig.3 β_{z_0} Vs β_{z_max}

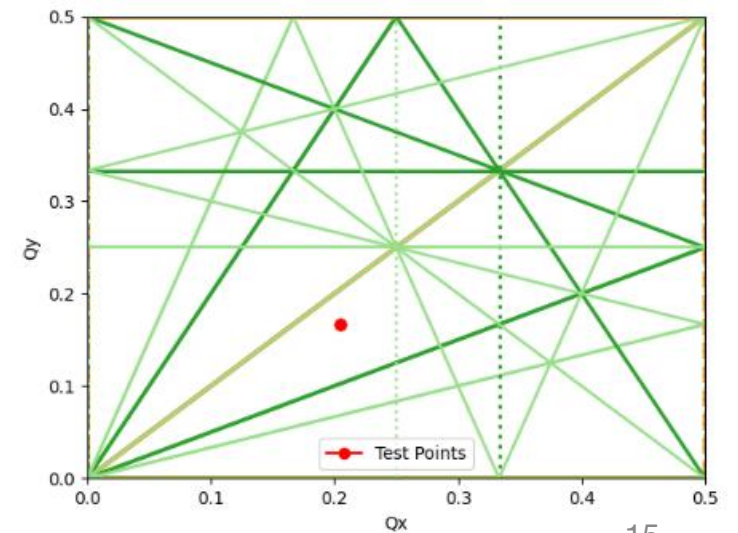
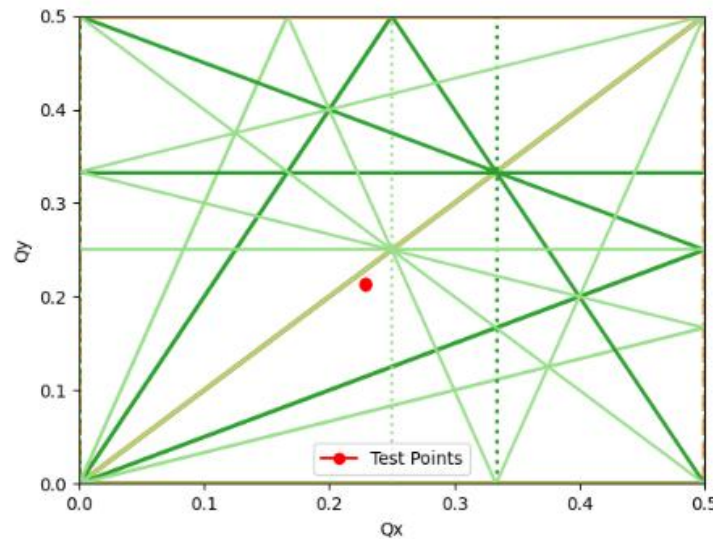
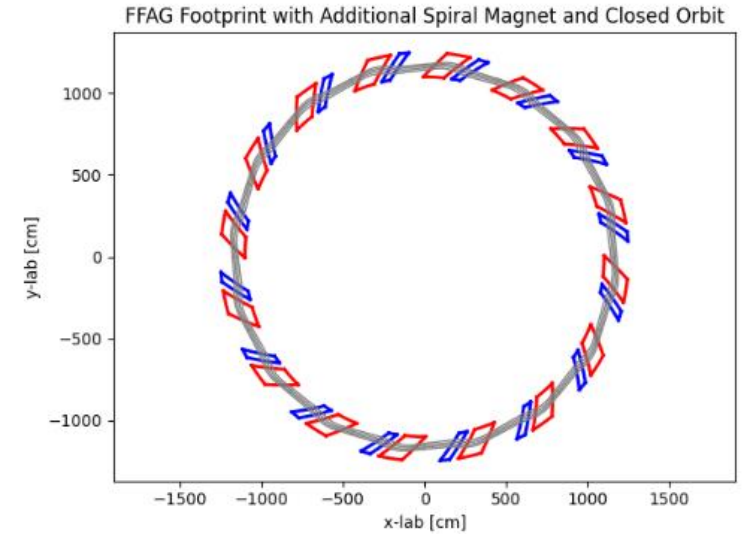
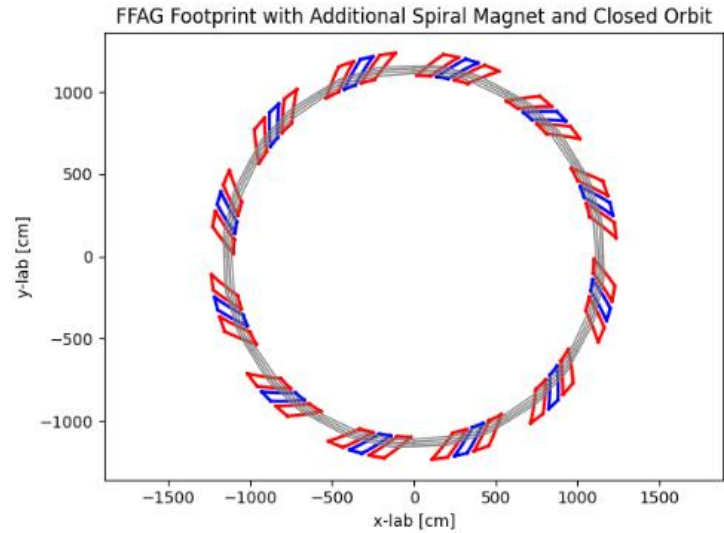


Validation of the Surrogate Model:

- The highest-performing solutions for the FD structure (in blue) are tightly clustered with a spiral angle around 42 degrees.
- This results matche the optimal region predicted by the surrogate model analysis.

Final Design Parameters: 16-Cell FD Lattice

	FDF 12-cell	FD 16-cell
Spi_angle	47.272	42.343
Alfa	0.55	0.523
Rsm1	0.83	0.406
Rsm2	0.458	0.387
Ki	6.054	7.678
Bd/Bf	0.357	0.762
DA	520.912	936.401
ΔR (m)	0.761	0.784
B_max(T)	1.389	1.608
β_z_0 (m)	5.046	5.609
β_z_{max} (m)	6.097	5.982
Drift (m)	1.986	1.872
Qx	2.743	3.28
Qz	2.475	2.572



Summary

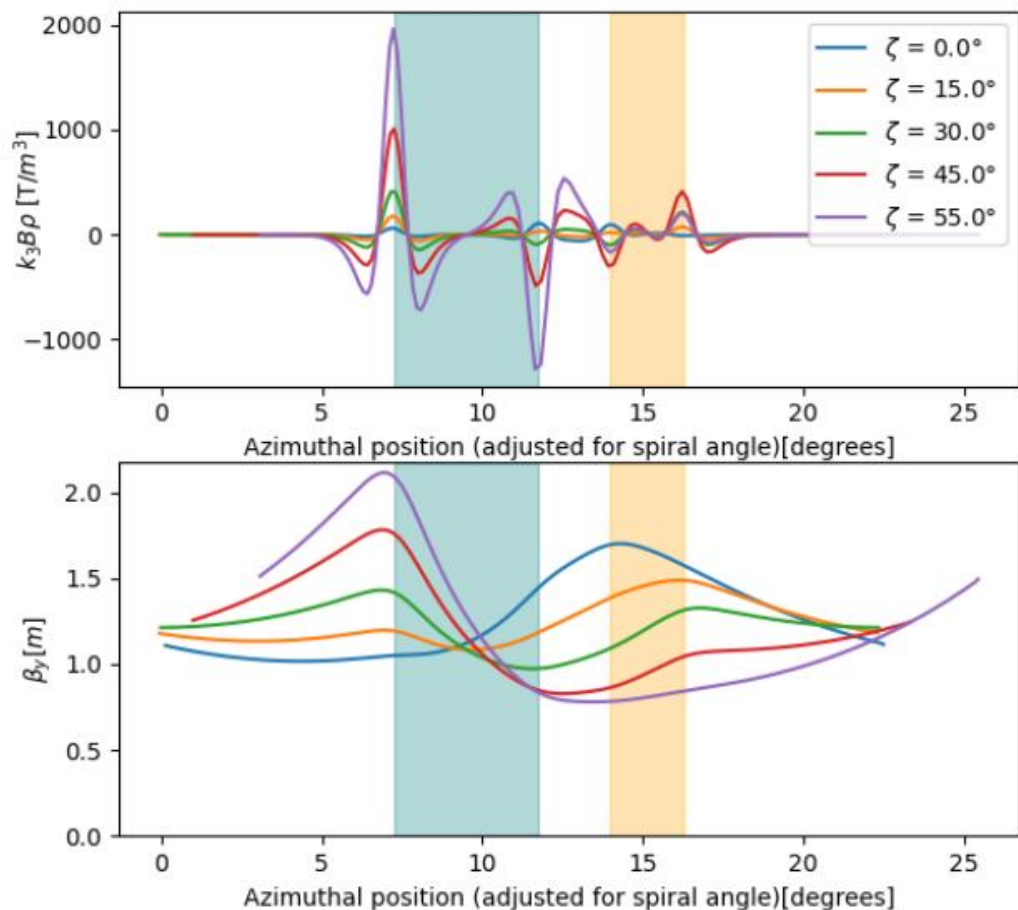
- A compact, high-intensity FFAG accelerator at CSNS, but initial lattice designs were unfeasible.
- Method: We developed an efficient optimization workflow by enhancing a genetic algorithm with machine learning.
 - This approach overcomes the extreme computational cost of traditional methods.
 - It allowed us to confidently identify a global optimum solution.
- Result: A 16-cell spiral FD lattice is a good choice
 - The design meets all strict physical and beam dynamics requirements.
 - It demonstrates superior stability and a larger dynamic aperture compared 12-cell FDF structures.
- However, as the injection scheme is closely coupled with the lattice design, the final parameters will require further fine-tuning.

Thank you for your attention

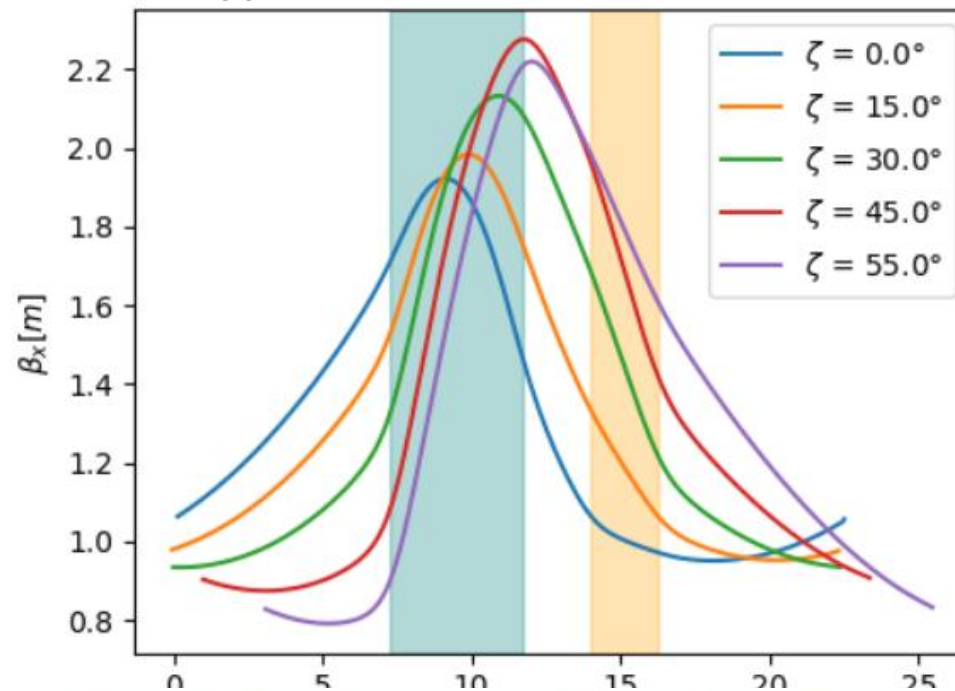


Back up

- Octuple component in fringe field is the limited source for DA, How to reduce the impact of Octuple component to tune shift requires the cooperation of the spiral angle



M. Topp-Mugglestone. Nonlinear Dynamics of Scaling FFAs. IPAC 2023



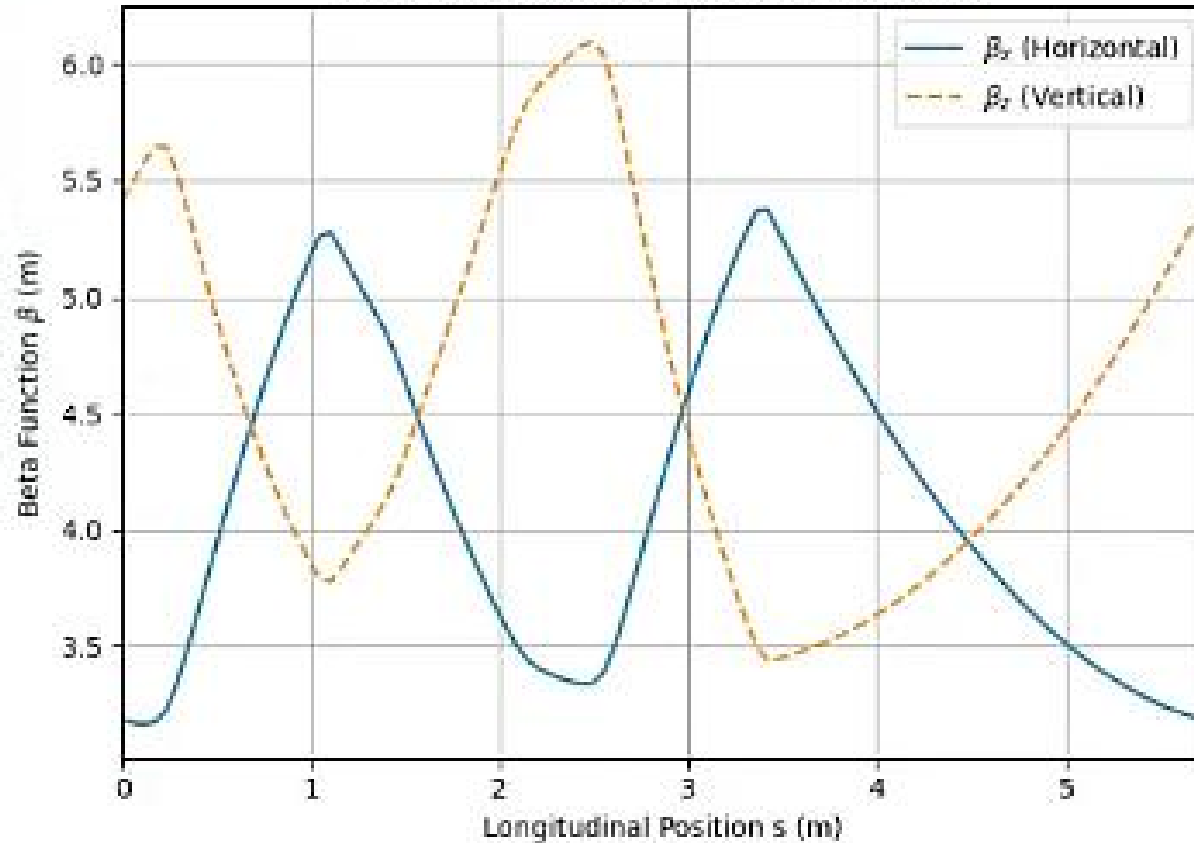
Tune shift with octupole B4 and amplitude J_x, y .

$$\Delta Q_y = \frac{q}{p} \frac{3B_4}{8\pi} (\beta_y^2 J_y - 2\beta_y \beta_x J_x)$$

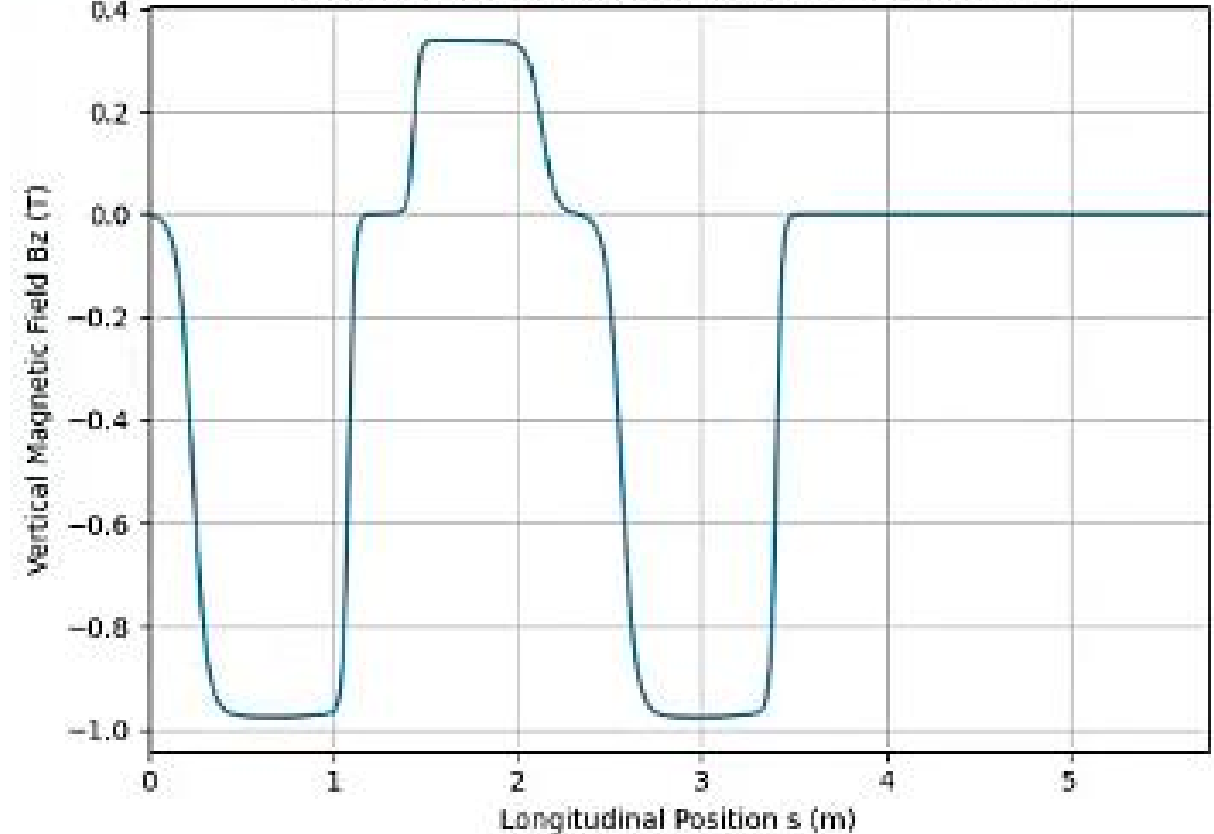
Back up

- FDF, linear optics results (Fixfield code simulation)

Beta Functions along One Super-period



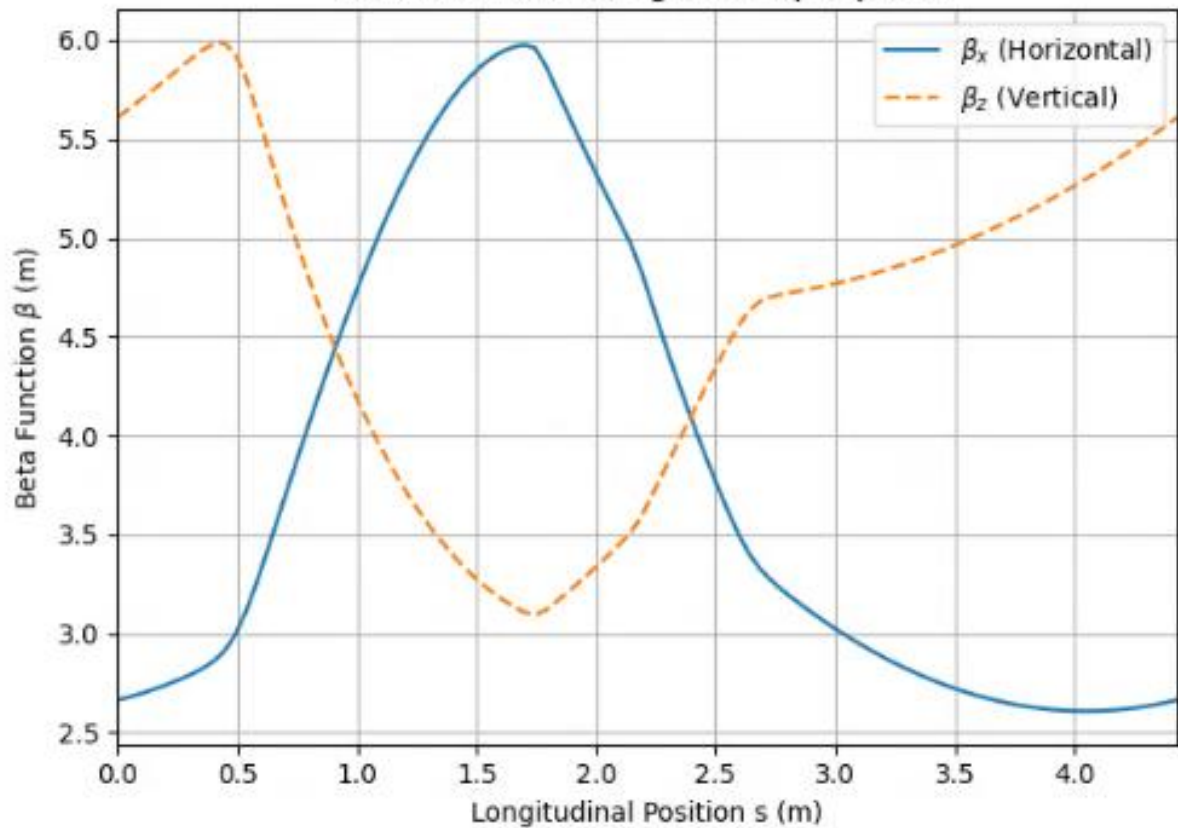
Magnetic Field B_z along the Trajectory (One Turn)



Back up

- FD, linear optics results (Fixfield code simulation)

Beta Functions along One Super-period



Magnetic Field B_z along the Trajectory (One Turn)

