Injector System Design for the 4th Generation Synchrotron Radiation Accelerators

- KU-IHEP Joint Workshop -

Chong Shik Park
Department of Accelerator Science/Accelerator Physics Center
Korea University, Sejong

Outline

- Motivations
- Computerized Optimizations
- Design and Optimization of Electron Injection System
- Optimization Processes and Results
- Error Study and Results
- Summary

* Acknowledgement: Dr. Chanmi Kim of PAL

Motivation: Electron Injector Design and Optimization

- Characteristics of 4th Generation Synchrotron Radiation Light Sources
  - Higher Brightness and Coherence Synchrotron Radiation
- Importance of Injector System Design
  - The injector prepares and delivers electron beams to the main accelerator.
  - Ensures high-quality beam parameters: emittance, energy spread, and bunch length.
- Challenges in Injector Design
  - Requires precise control over multiple variables (e.g., RF phases, magnet strengths).
  - Ensuring beam stability and consistency is critical for optimal synchrotron performance.
- Why Optimization Matters
  - Manual tuning of parameters is slow and imprecise.
  - Automated optimization helps achieve the best beam quality while minimizing energy loss and errors.

Motivation: Optimizations in Accelerator Designs

- Numerous parameters (knobs) must be considered in the design and operation of an accelerator system.
  - These parameters of the accelerator system should be optimized to meet the requirements and achieve the best performance.
- Manual search of these parameters is essentially an optimization process.
  - The function to be optimized is the performance evaluated on the operating or designing system through measurements or **simulations**.
  - The knobs are the input variables of the function.
- The operator or designer of the system executes an optimization algorithm to search the parameter space for the optimum of the performance function.
  - However, this manual tuning has many limitations.
  - It is typically slow for humans **to dial in the new setpoints, to process the measured/simulation data, and to make decisions on the next move**.
- The complexity of the optimization problem is usually limited by the ability of humans to analyze and comprehend the data taken from **a high dimension parameter space**.

Computerized Optimizations

- It is obviously easy to **automate the optimization process** using computational tools.
- Automated optimization integrates all the three components
  - **Parameter variations**
  - **Performance monitoring**
  - **Selection of optimal parameters**
- This is possible using various mathematical optimization algorithms.
- Optimization of **large-scale problems with complex parameter space** becomes feasible.
  - For example, strongly coupled parameters
- Simultaneous optimization of **multiple objective performance functions** is also possible.

Optimization Methods

- Optimization is looking for the maximum or minimum of the objective function(s) within a certain parameter space.
- **The objective function** is not usually given in an analytic form.
  - Instead, the function is evaluated through measurements on a machine or calculated through a computer program(simulation)
  - The system to be optimized can be considered as a black-box.
- The relevant conditions of the system are controlled through **the input variables(parameters)**
- **Constraints** can be set conditions for the variables that are required to be satisfied.

- Objectives

$$\min f_m(x), \quad m = 1, \cdots, M$$

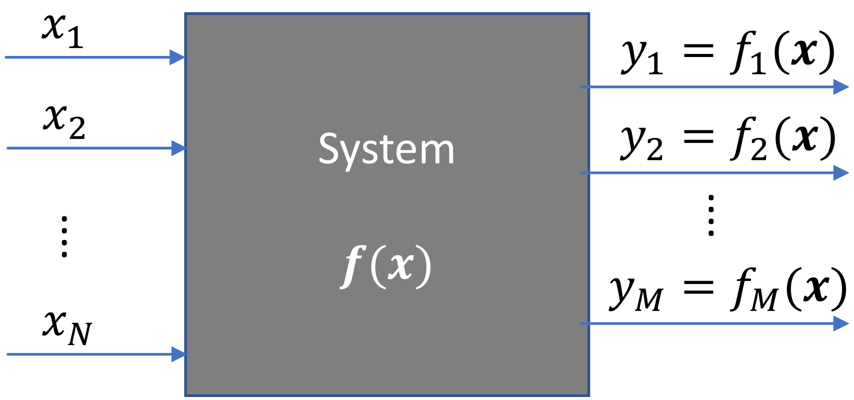
- Variables

$$x_i^L \le x_i \le x_i^U, i = 1, \cdots, N$$

- Constraints

$$g_j(x) \le 0, \quad j = 1, \cdots, J$$

$$h_k(x) = 0, \quad k = 1, \cdots, K$$



Optimization Algorithms

- **Deterministic Algorithm**
  - The convergence path from any initial point is fixed
  - Gradient-Based/Gradient-Free

- **Stochastic Algorithm**
  - **Randomly selects** the parameter values of the trial solution.
  - The convergence path is different every time.
  - **Genetic Algorithm**
  - **Particle Swarm Optimization**

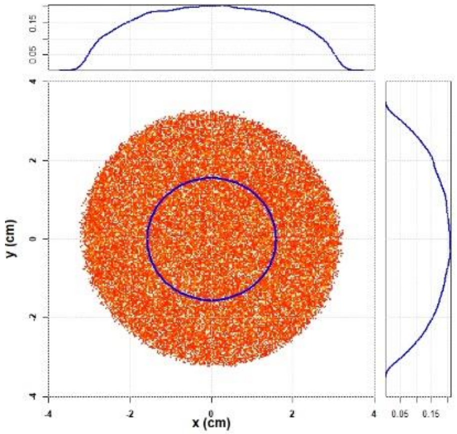
- **Model-Based Optimization – Machine Learning**
  - Builds models with the measurement/simulation data and use the models to guide the search for the optimum
  - **Gaussian Process Optimizer**
  - **Multi-Generation Gaussian Process Optimizer**
  - **Reinforcement Learning**

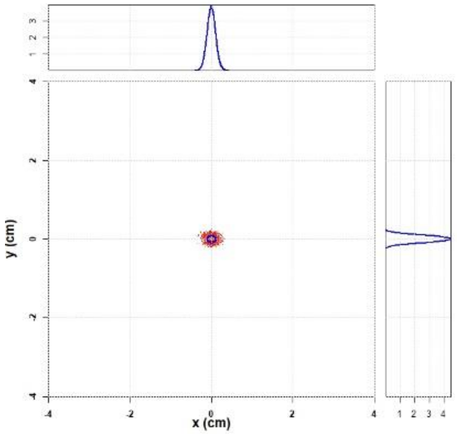
Accelerator Optimization Simulation Examples

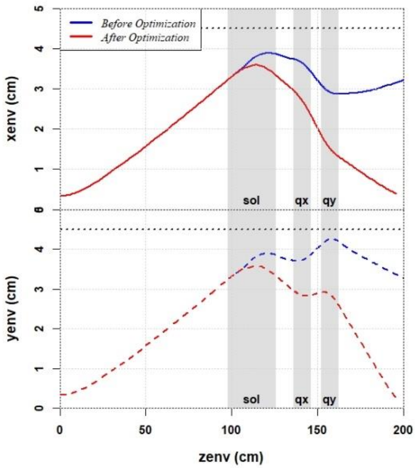
Single-Objective Optimization (SOO) and Multi-Objective Optimization (MOO)

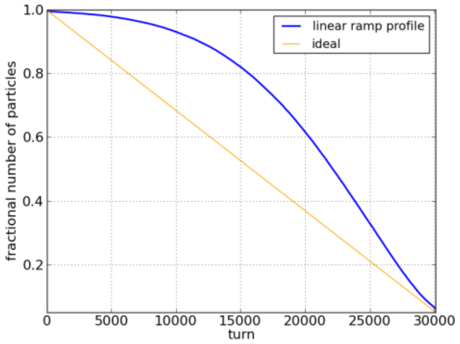
- SOO: **Injector Lattice** Optimization
  - Beam Dynamics Simulation: **Track**
  - Optimization Library: **NLopt**
- SOO: **Magnetic Fields Ramp** Optimization
  - Beam Dynamics Simulation: **Synergia**
  - Optimization Library: **NLopt**
- SOO and MOO: **Cavity Design**
  - Cavity Design: **SuperFish**
  - Optimization Library: **NLopt and pymoo**
- SOO and MOO: **Linac Beam Dynamics** Optimization
  - Beam Dynamics Simulation: **astra**
  - Optimization Library: **NLopt and pymoo**

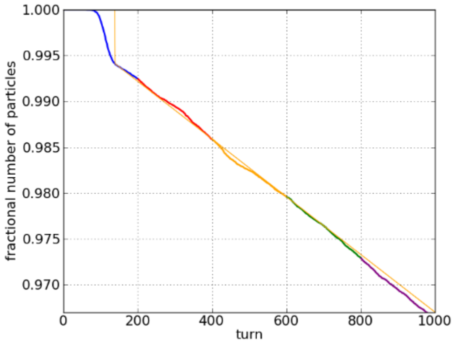
- User created **Python or R scripts** for integrating simulation codes and optimization libraries.

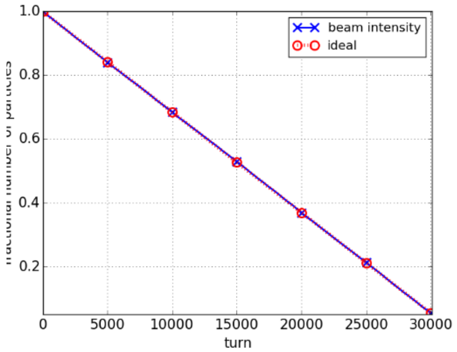




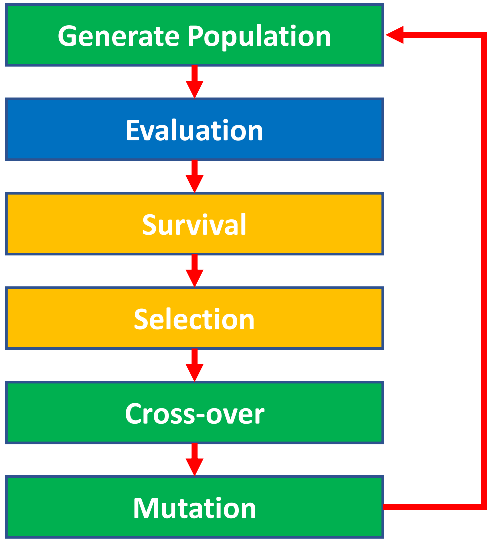




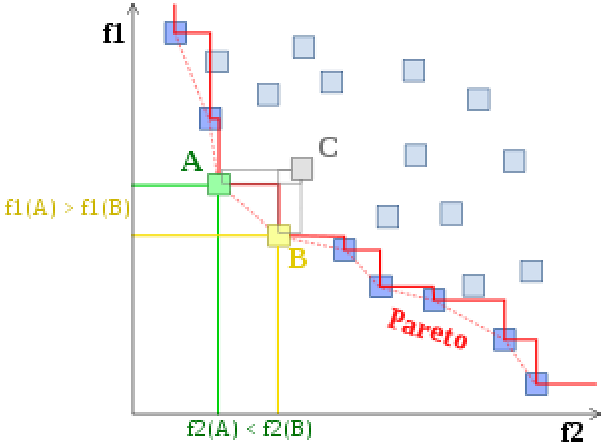




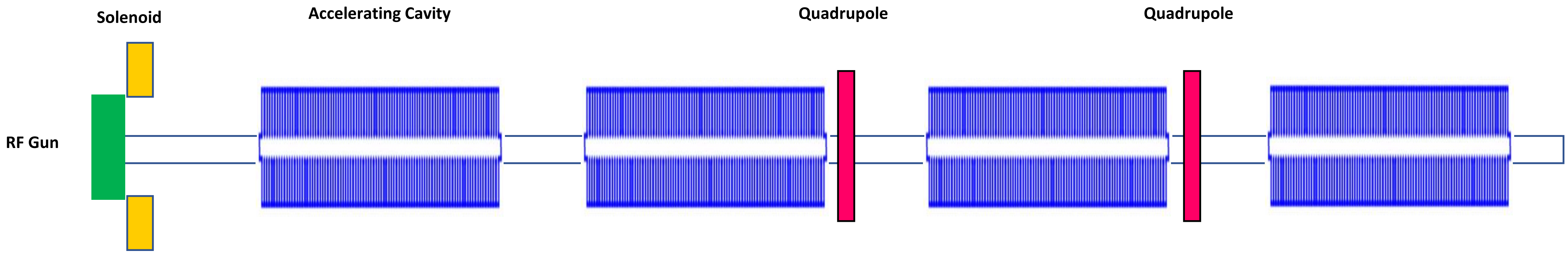
Multi-Objective Genetic Algorithm (MOGA)



- Genetic algorithms manipulate **populations** of solutions over multiple **generations**.
- In each generation, a portion of the population is replaced by a good solution selected from a new solution created through **cross-over or mutation**.
- In a **cross-over operation**, two child solutions are created by combining the parameter values of the two parent solutions.
- **Mutation operation** generates new solutions by randomly modifying the parameter values of existing solutions.
- The solution that survives the selection operation is usually better and **tends to produce better new solutions**.
- The fitness of the solution improves over time and the population gradually converges to a minimum.
- The leading front for all valid solutions in the parameter space is called **the Pareto front**.
  - Solutions in the Pareto front represents the best possible solutions.
  - The Pareto optimal set (or front) allows us to visualize the trade-off between the objectives
  - The goal of multi-objective optimization is **to find the Pareto front**.



Design of Electron Injection System for 4GSR



- Two-Step Design and Optimization

- RF cavity geometries: Superfish and pymoo
  - RF photoinjector gun cavity
  - Accelerating cavities

- Linac Parameters: Astra and pymoo
  - RF cavity input phases and gradients
  - Magnet strengths

Parameters	Values
Energy	200 MeV
Frequency	2,997.56±0.5 MHz
Emittance @ 200 MeV	< 10 nm
Relative Energy Spread (rms)	< 0.5 %
Bunch Charge (Charge Stability)	0.01 to 1 nC (2 %)
Pulse Duration	6~8 ps FWHM
Repetition Rate	2 Hz (60 Hz)

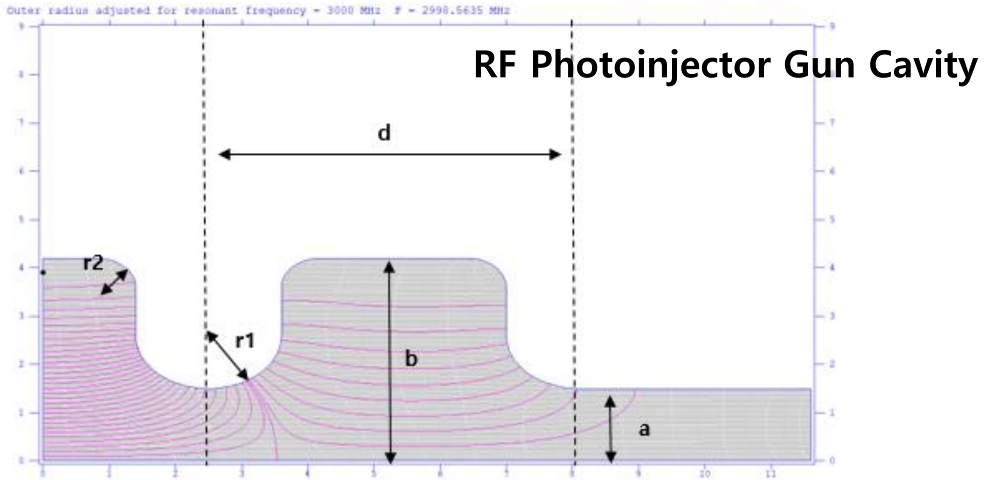
Design and Optimization of RF Cavities

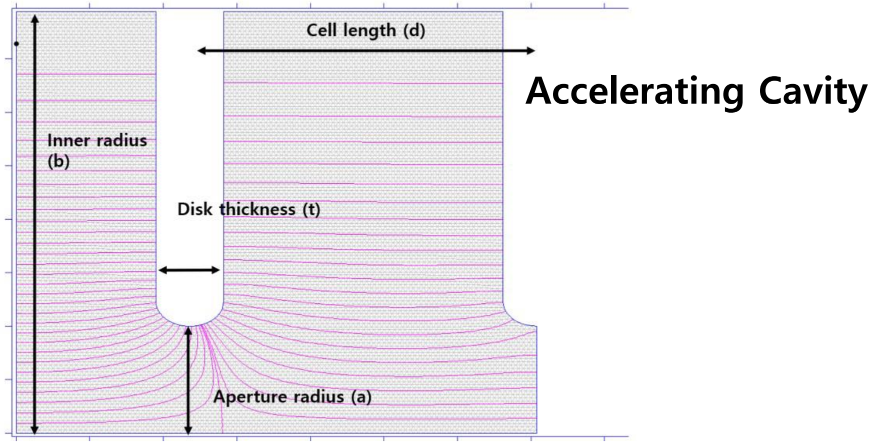
Objectives		Units
R/Q	Maximization	Ω
Stored Energy	Minimization	J

Constraints		Units
Frequency	2,997.56 ± 0.5	MHz
Transit Time Factor	> 0.6	
Quality Factor	> 14,000	

Variables	Units
Cell Length (d)	m
Gap Length (r1*2)	m
Aperture Radius (a)	m
Inner Radius (b)	m
Cell Radius (r2)	m

MOGA Parameters	
Population	300
Offspring	150
Generation	200

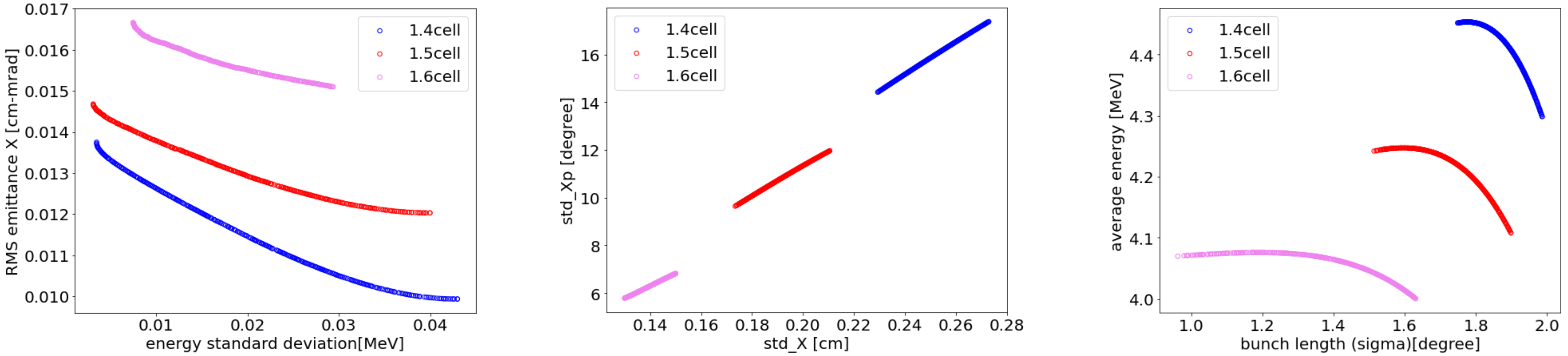




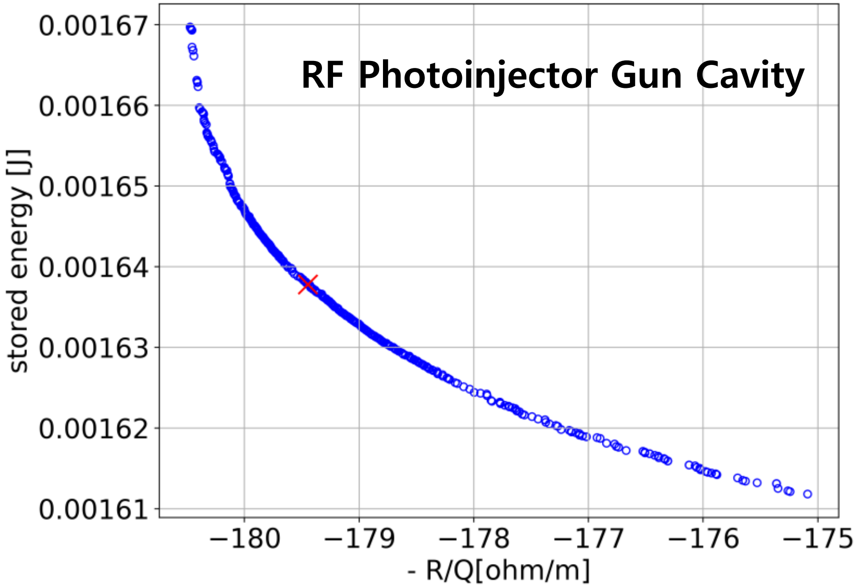
Optimization of the RF Gun Cavity Using MOGA

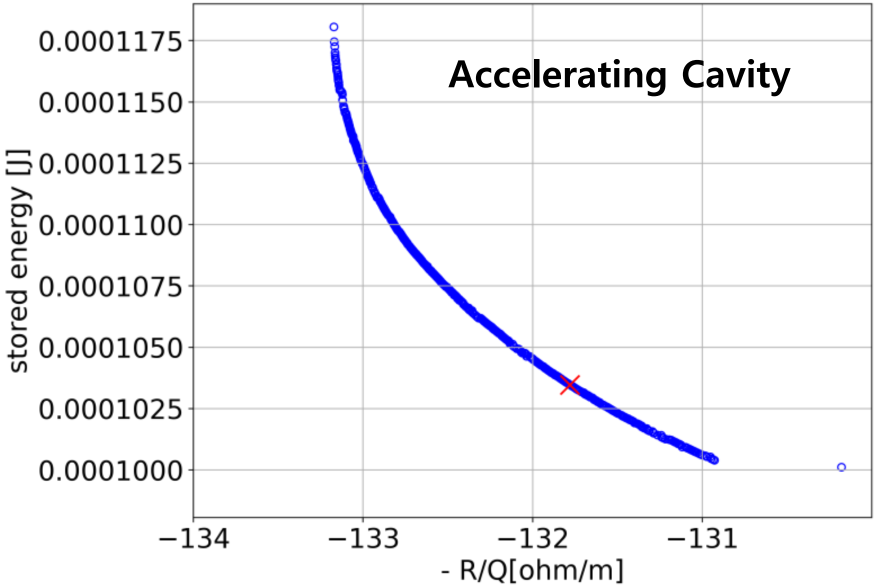
Beam Dynamics Optimization

Cell Number	Frequency (MHz)	TTF	Stored Energy (MeV)	Q	R_s (Ω)	R/Q (Ω)
1.4	2,997.561	0.715049	0.001998	16,808.0	47.280	155.042
1.5	2,997.488	0.692018	0.001637	18,008.7	64.148	179.999
1.6	2,997.488	0.615029	0.001512	18,476.6	71.472	168.362



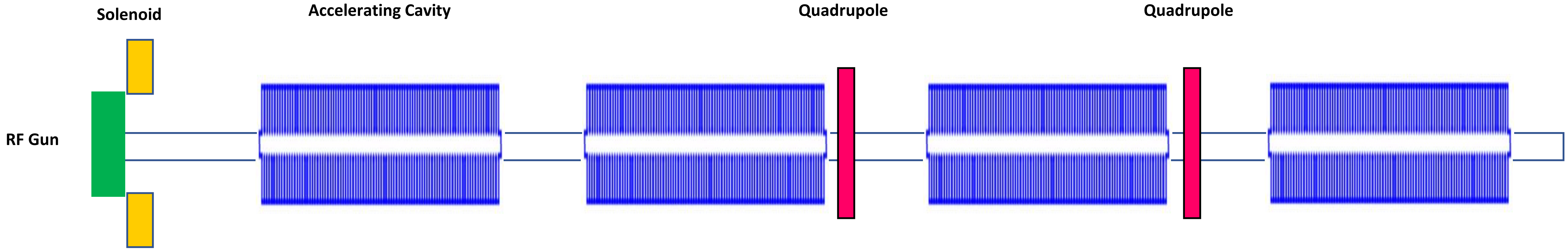
Design and Optimization of RF Accelerating Cavity





Parameters	Gun Cavity	Accelerating Cavity	Units
R/Q	179.446	131.779	Ω
Stored Energy	0.001638	0.0001035	J
Frequency	2,997.59	2,997.45	MHz
TTF	0.6920	0.7012	
Quality Factor	18,008.7	13,151.5	

Optimization of Linac Design Parameters



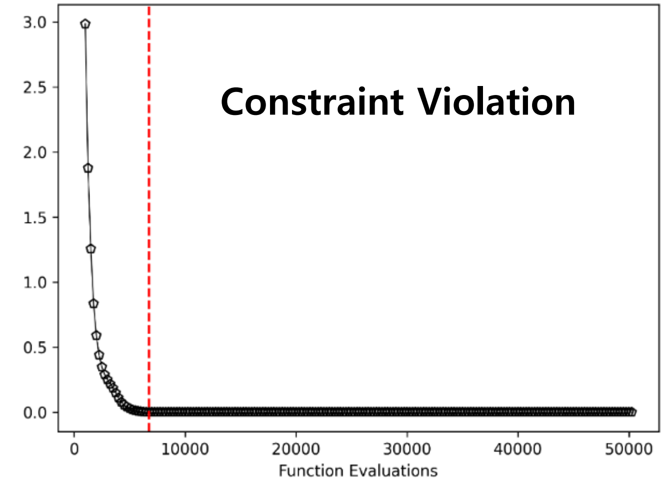
Objectives (3)		Units
Horizontal Normalized RMS Emittance	Minimization	mm-mrad
Vertical Normalized RMS Emittance	Minimization	mm-mrad
RMS Energy Spread	Minimization	

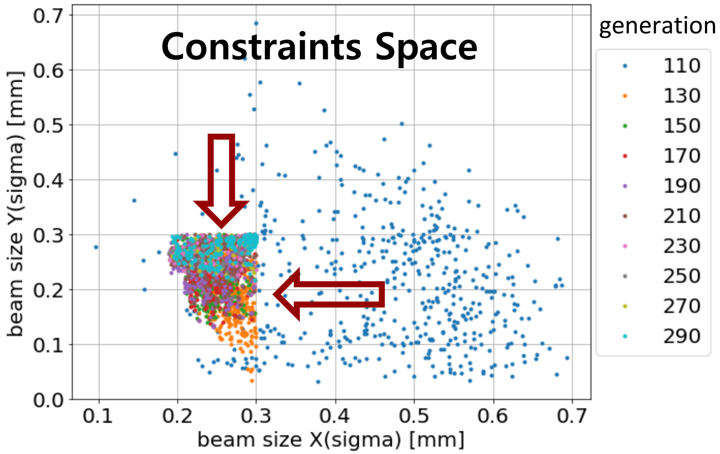
Constraints (7)		Units
Horizontal Beam Size	< 0.3	mm
Vertical Beam Size	< 0.3	mm
Horizontal Beam Divergence	< 0.266	mrad
Vertical Beam Divergence	< 0.266	mrad
Bunch Length	< 1.0	Mm
Average Energy	200	MeV
Transmission Rate	> 99.99	%

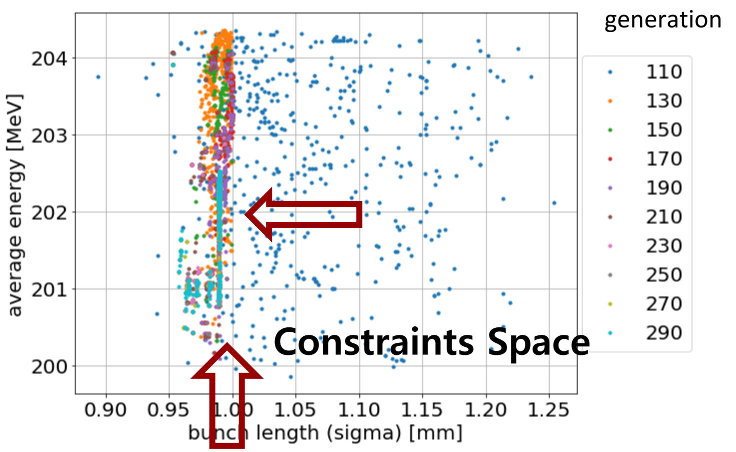
Variables (6)	Ranges	Units
RF Gun Cavity Input Phase	0 ~ 360	Degree
ACC Cavity 1 & 2 Input Phase	0 ~ 360	Degree
ACC Cavity 3 & 4 Input Phase	0 ~ 360	Degree
Solenoid Strength	0.1 ~ 0.3	T
Quadrupole 1 Strength	0 ~ 10	T/m
Quadrupole 2 Strength	-10 ~ 0	T/m

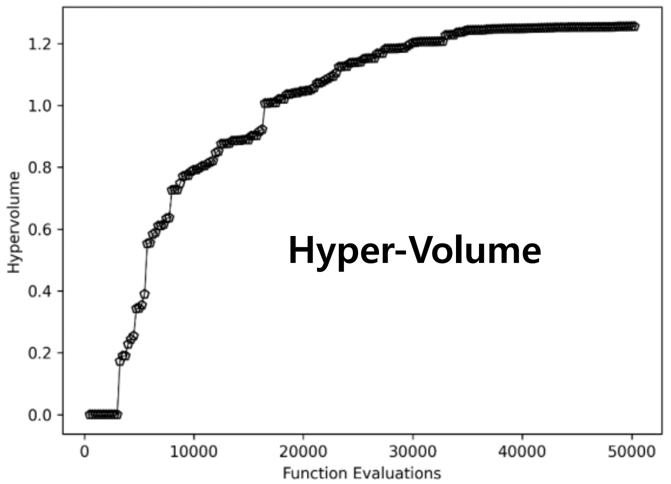
MOGA Parameters	
Population	500
Offspring	250
Generation	300

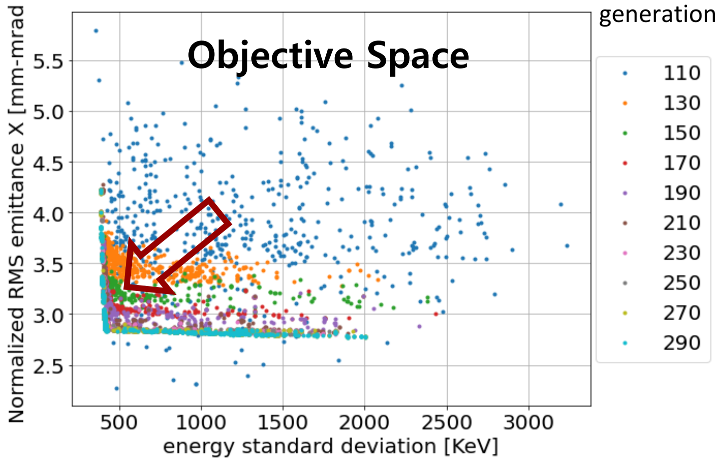
Optimization Processes

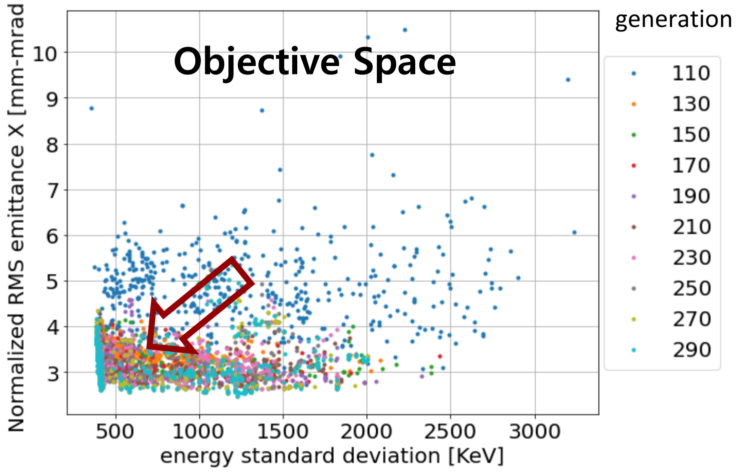




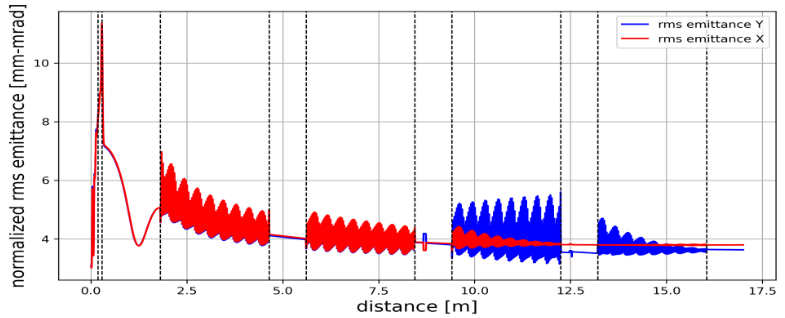


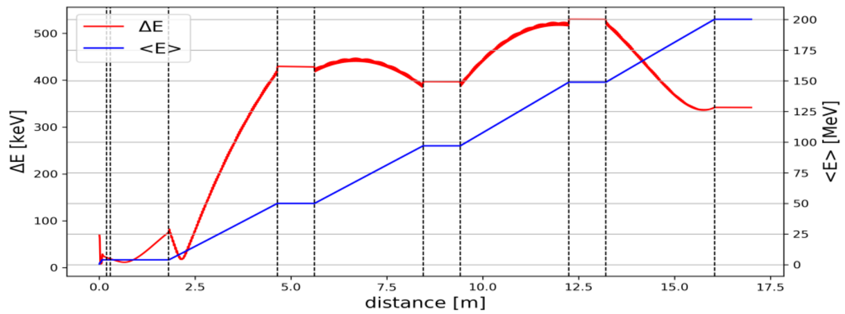


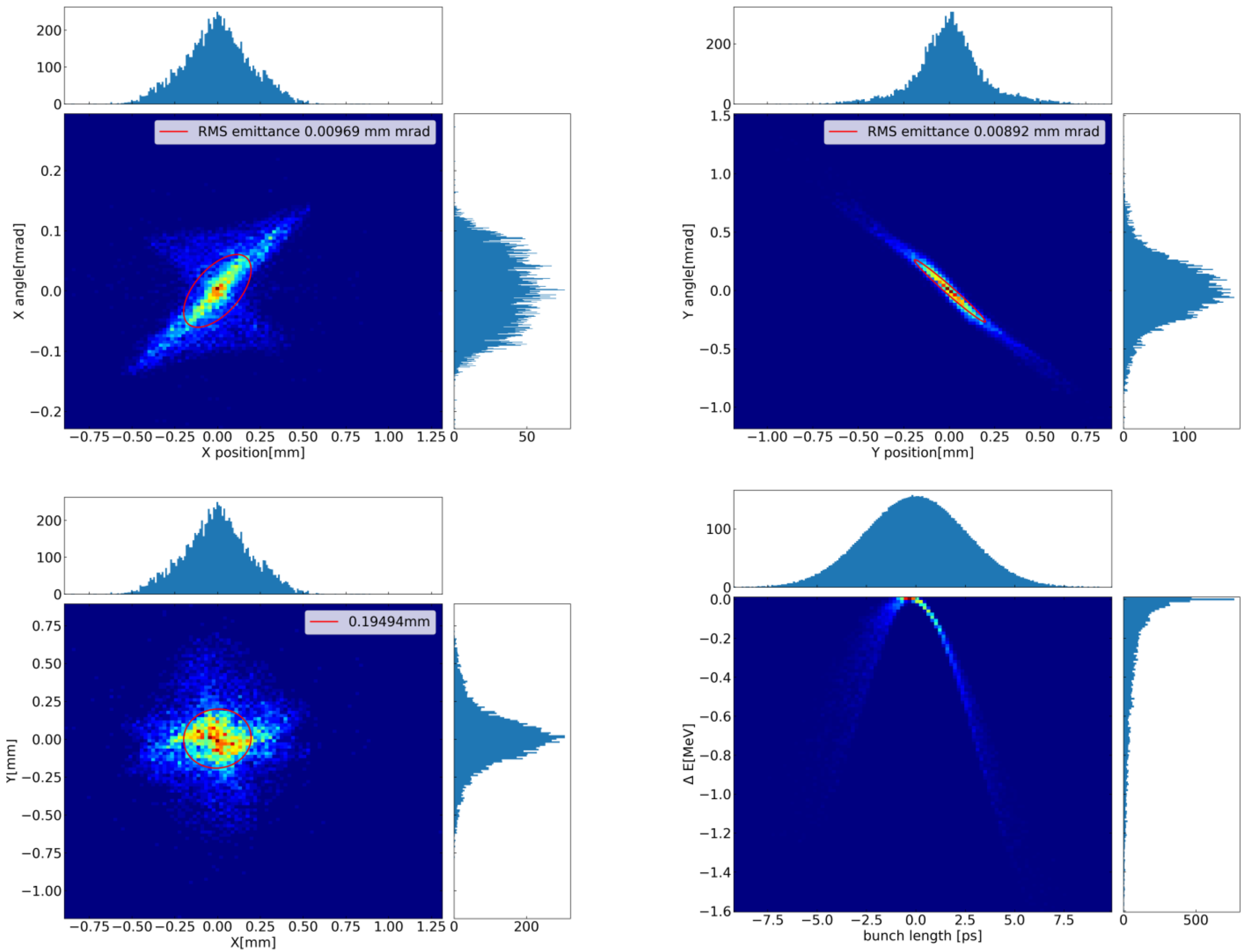




Optimization Results



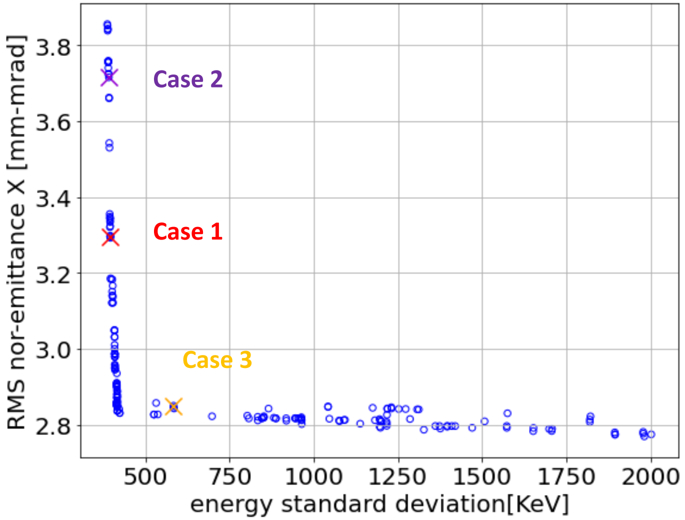


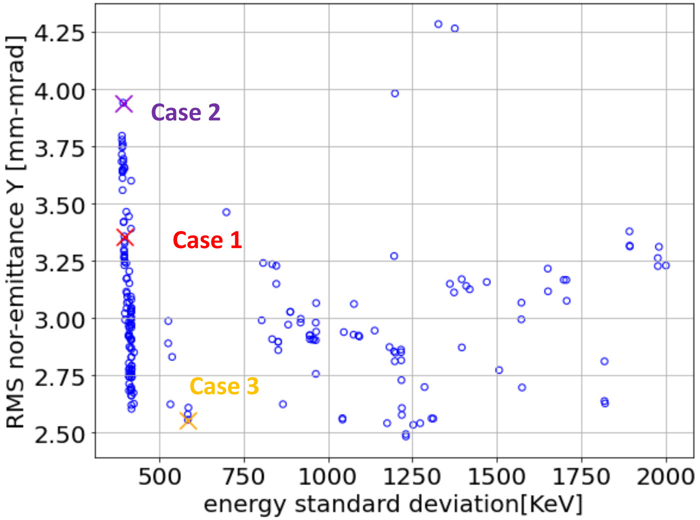


Parameters	Requirements	Optimized	Units
Beam Energy	> 200	201	MeV
Bunch Length	< 7	6.35	ps
Transverse RMS Emittance	< 10	9.69	nm
RMS Beam Size	< 0.2	0.1997	mm
RMS Energy Spread	< 0.2	0.165	%

Weights on Optimization Results

Object Spaces

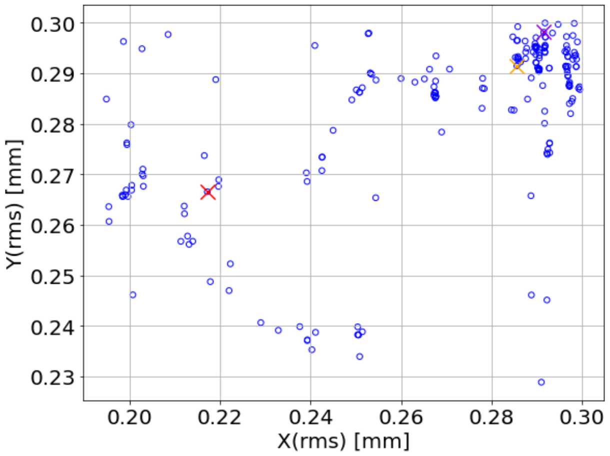


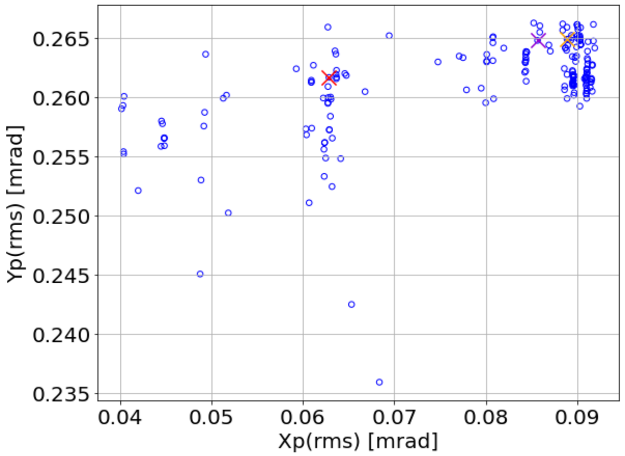


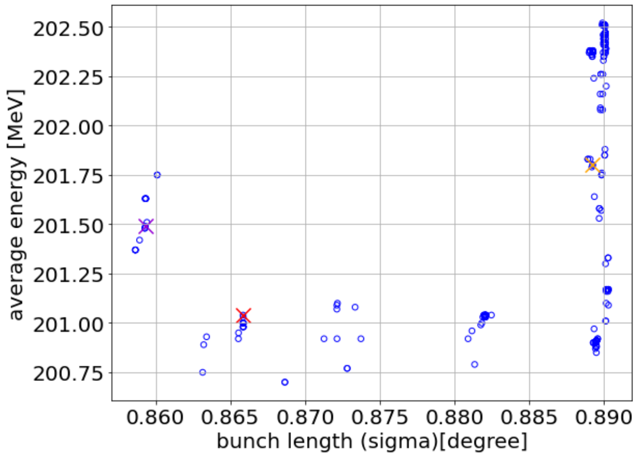
Weights

	Energy Spread	Emittance X	Emittance Y
Case 1	0.5	0.25	0.25
Case 2	0.8	0.1	0.1
Case 3	0.3	0.35	0.35

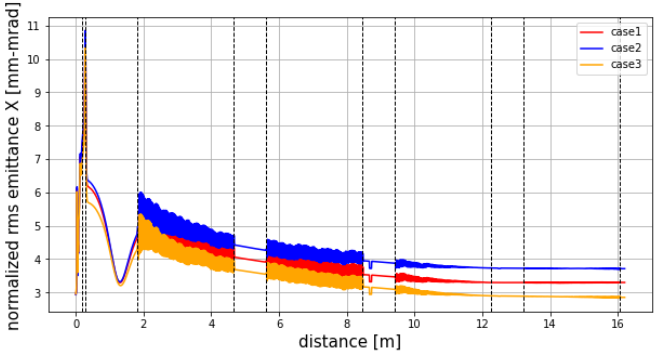
Constraint Spaces

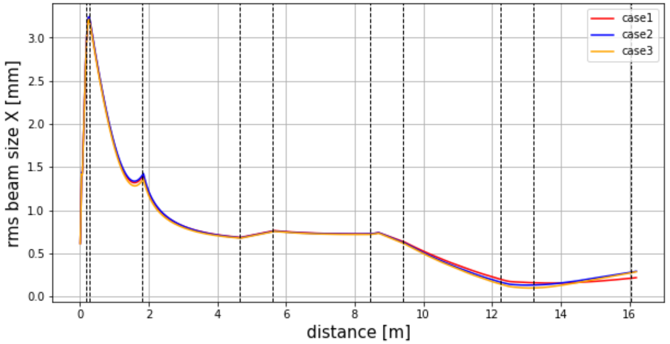


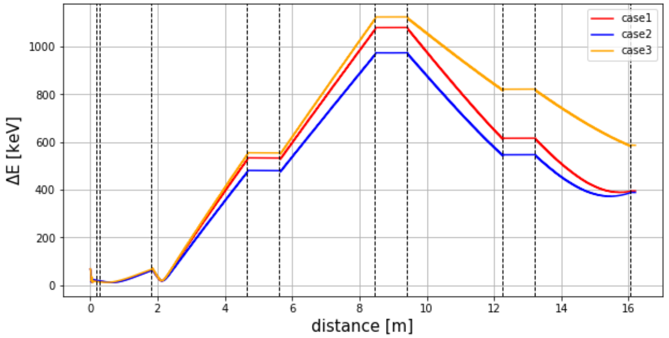


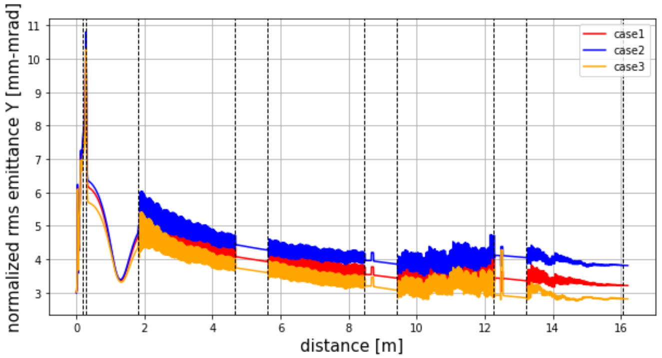


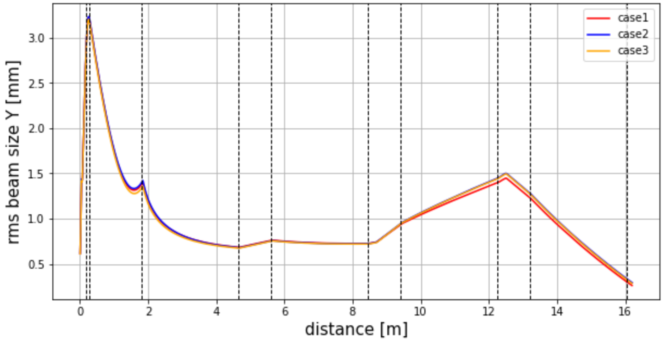
Beam Dynamics Simulations of Selected Cases

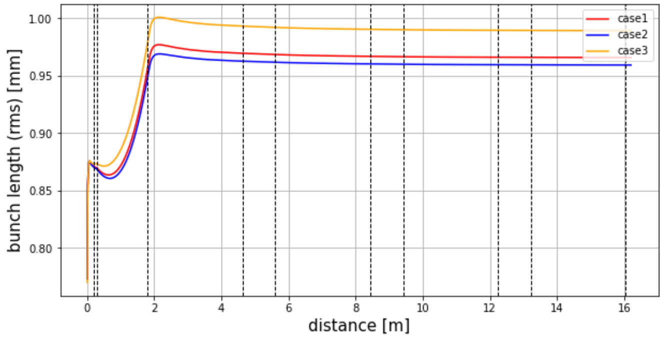






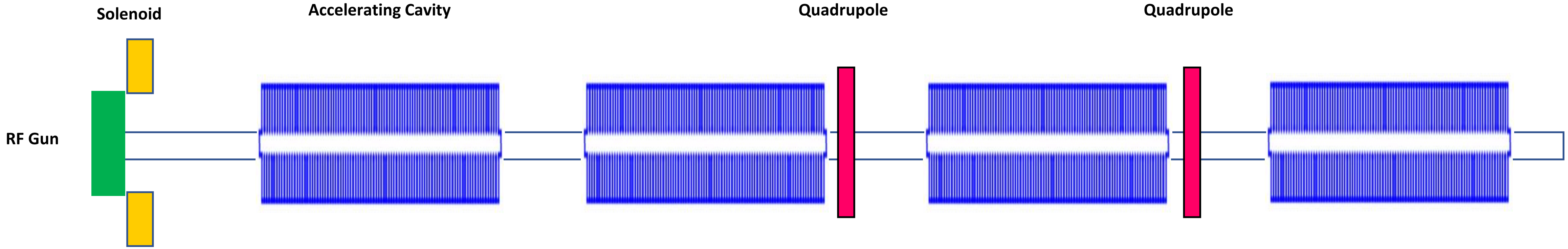






	<E>	σ_E	ε_x^N	ε_x	ε_y^N	ε_y	σ_x	σ_y	L_{bunch}
Units	MeV	keV	mm-mrad	nm	mm-mrad	nm	mm	mm	mm
Case 1	200.16	381.50	3.2990	8.44	3.2145	8.18	0.21760	0.26149	0.96584
Case 2	200.61	372.17	3.7122	9.52	3.8144	9.71	0.29162	0.29447	0.95932
Case 3	200.92	411.98	2.8520	7.37	2.8147	7.21	0.28593	0.28566	0.98924

Error Study

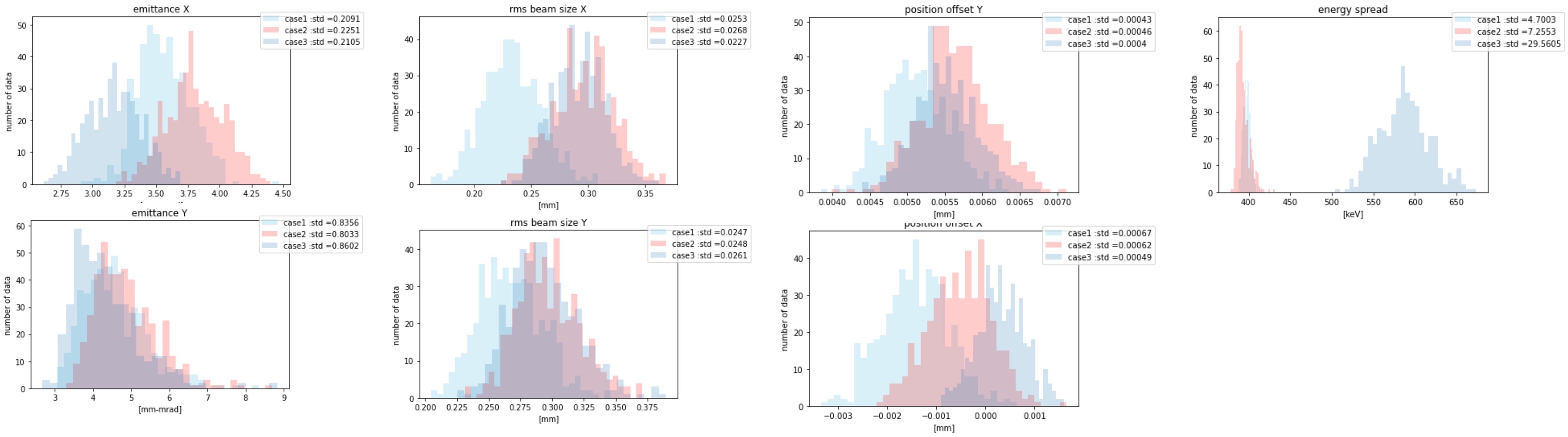


Parameters		Sigma	Units
RF Gun Cavity	Gradient	0.2	%
	Input Phase	0.2	Degree
Accelerating Cavity	Gradient	0.2	%
	Input Phase	0.2	Degree
Solenoid	Strength	0.1	%
Quadrupole	Strength	0.1	%

Target		
Energy Spread	< 0.5	%
Average Energy	< 0.2	%
Position Offset in X & Y	< 10	%

- Error Cut-Off: 2 Sigma (Gaussian)
- Random Numbers: 1,000

Error Study Results



	<E>	σ_E	ε_x^N	ε_y^N	σ_x	σ_y	X Offset	Y Offset	L_{bunch}
Units	MeV	keV	mm-mrad	mm-mrad	mm	mm	mm	mm	mm
Case 1	0.1762	4.7003	0.2091	0.8356	0.0253	0.0247	0.00067	0.00043	0.0044
Case 2	0.1749	7.2553	0.2251	0.8033	0.0268	0.0248	0.00062	0.00046	0.0043
Case 3	0.1756	29.5605	0.2105	0.8602	0.0227	0.0261	0.00049	0.0004	0.0045

Summary

- Complex optimization problems in design of accelerator systems with multi-objective goals, are solvable through methods like Genetic Algorithms and Machine Learning models.
- Optimized design parameters for RF Gun and Accelerating Cavities achieved desired performance levels.
- The injector system met or exceeded performance benchmarks: beam energy of 200 MeV, transverse RMS emittance below 10 nm, and bunch length under 7 ps.
- Simulations confirm that constraints were met with high accuracy.
- The injector system exhibits resilience to small errors, with minimal impact on critical parameters like energy spread and beam size.
- Further optimization using advanced algorithms, potentially involving reinforcement learning and Bayesian optimization, etc., can yield even better system performance.
- Application to other accelerator systems can lead to broader advancements in accelerator technology.