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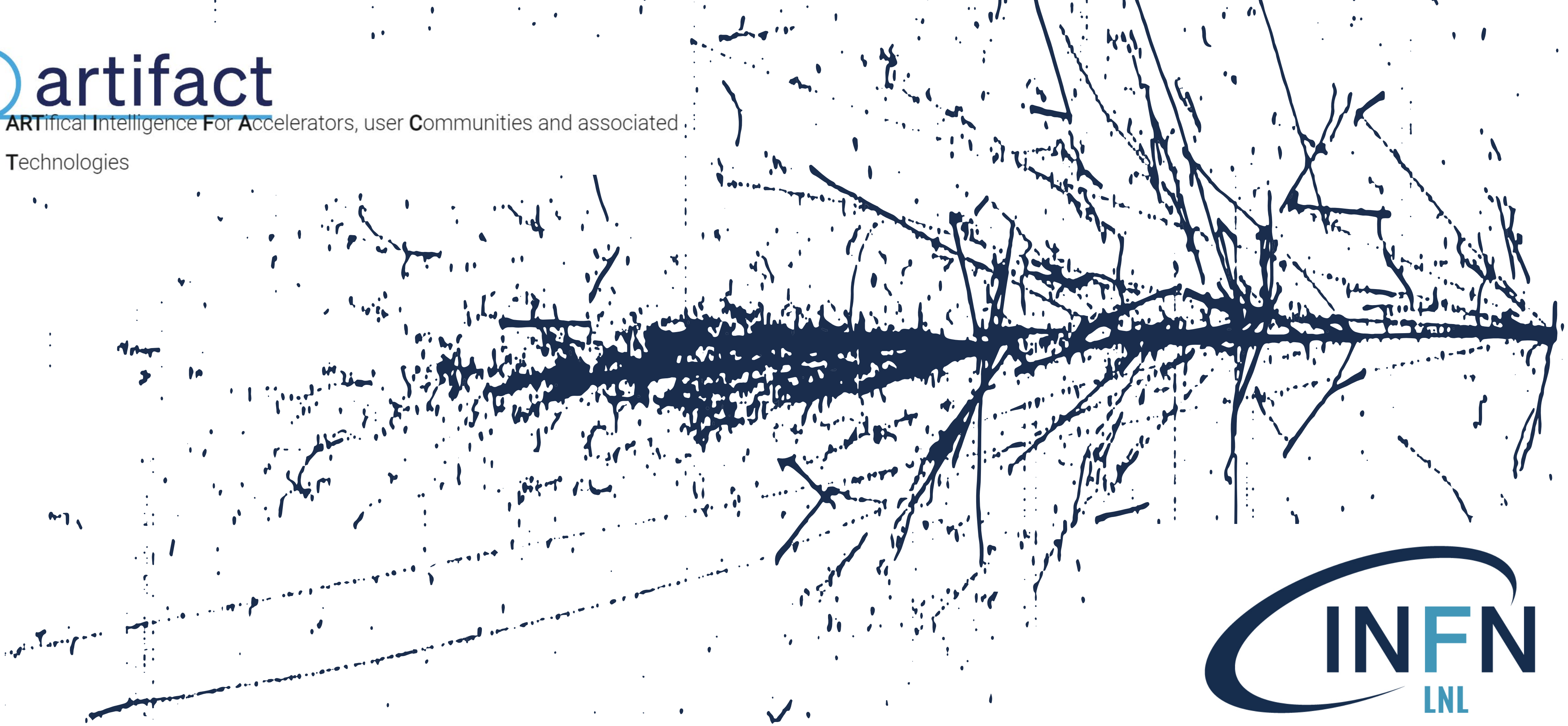
ARTifical **I**ntelligence **F**or **A**ccelerators, user **C**ommunities and associated **T**echnologies



INFN
LNL
Istituto Nazionale di Fisica Nucleare
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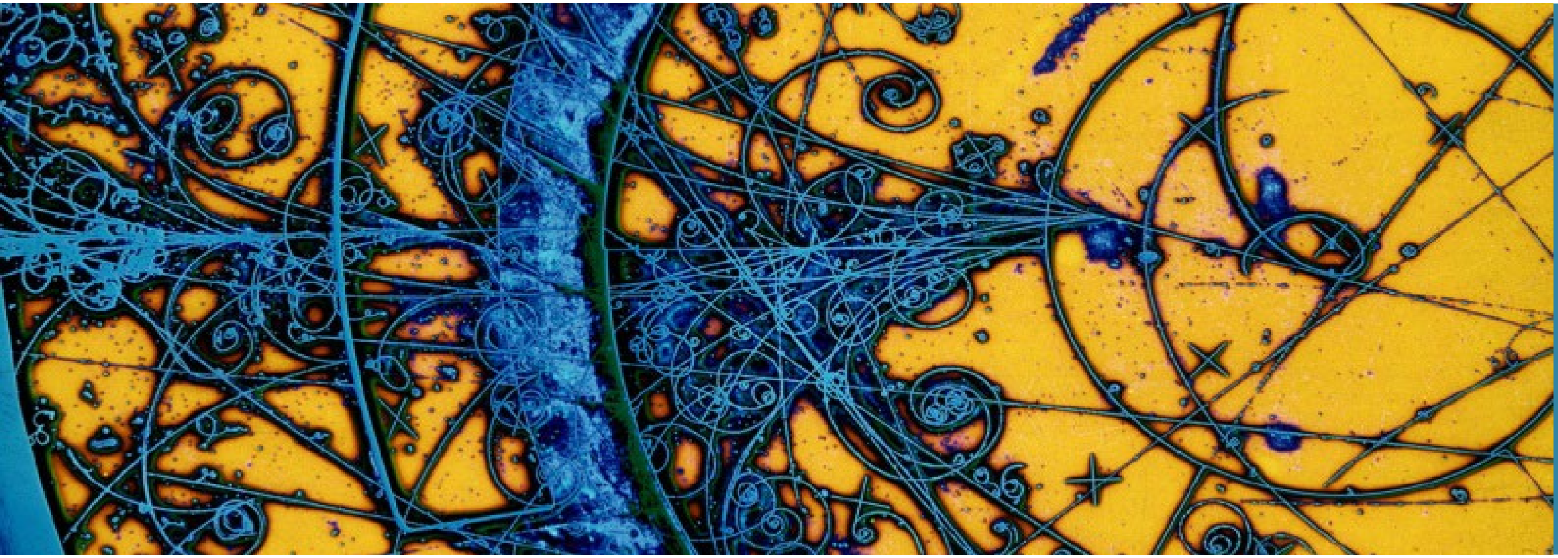
New techniques method for improving the performance of low beta ion linacs

New techniques method for improving the performance of low beta ion linacs

November, 28th 2023



Istituto Nazionale di Fisica Nucleare

The Italian National Institute for Nuclear Physics

Maurizio Montis
on behalf of INFN-LNL team for ARTIFACT

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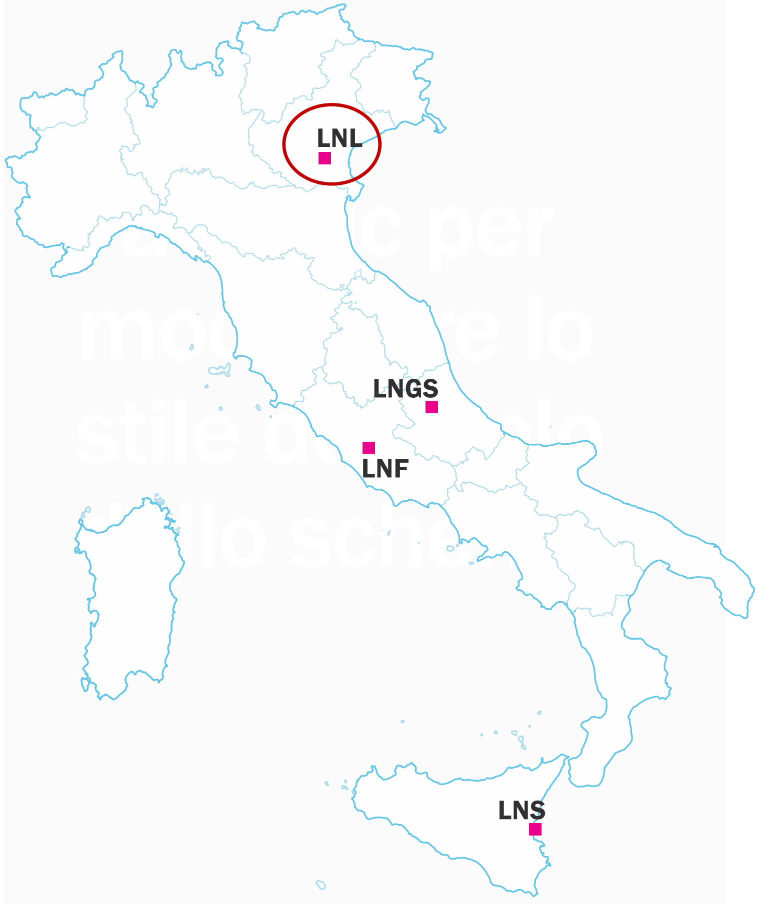
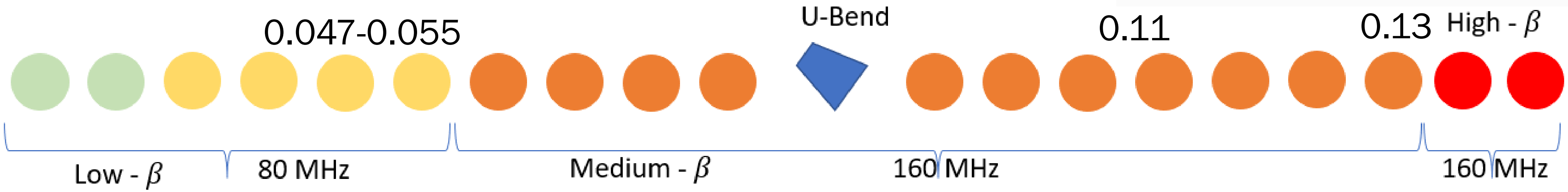
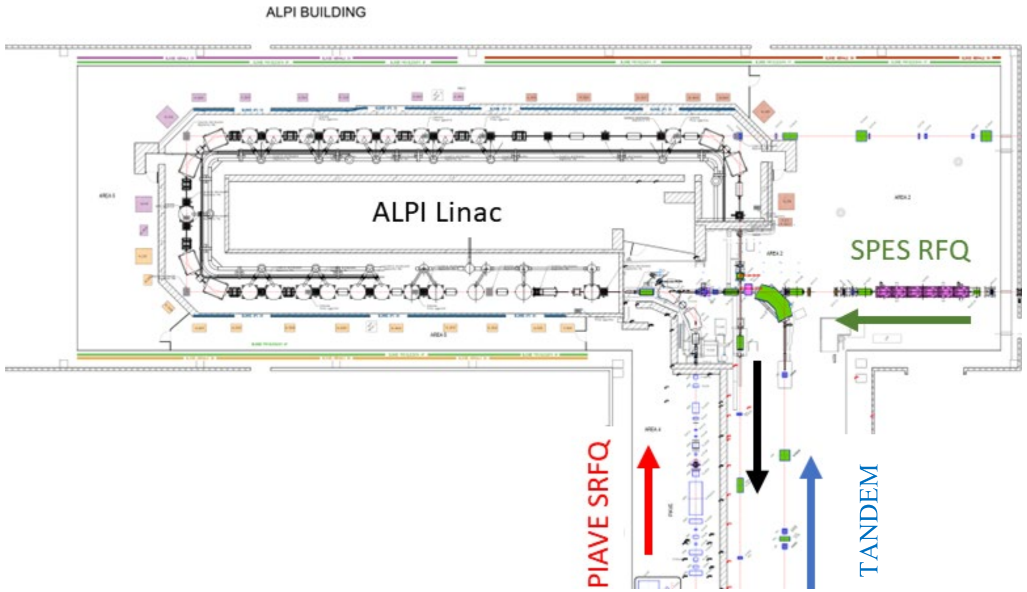


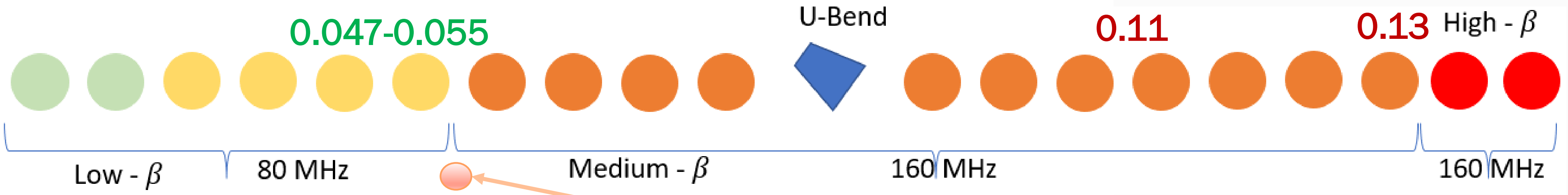
Tandem-ALPI-PIAVE facility at LNL





- Heavy ion CW folded independent superconductive cavity LINAc.
- Design and built 80’-90’ (One of the first prototypes in Europe)
- Three injectors: tandem, Super conductive RFQ, normal conductive RFQ (*in the next future*)
- 82 Quarter Waves cavities at 4 K (80-160 MHz).
- 10 MeV/u energy output, from C to U

Tandem-ALPI-PIAVE facility: Challenges

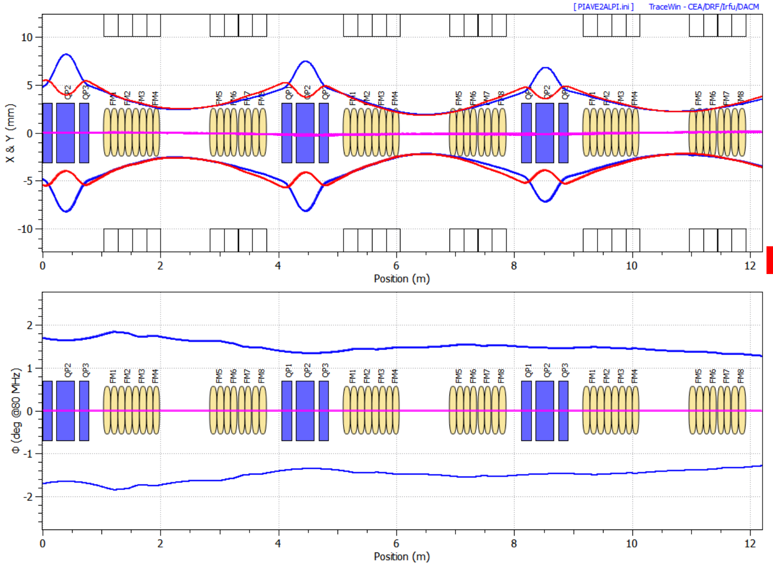


Heavy step in frequency and transit time factor

- <u>Beam Dynamics:</u>
  - Applied field problem (no space charge)
  - E_0 **(5 MV/m) increased 4 times from the design** → **high longitudinal phase advance**
  - **20 mm diameter aperture** of the QW (very small)
  - **Very long period (8 QW cavities per triplet)** → **transverse longitudinal optics problems**
  - Aggressive 0-current transverse phase advance (**120 deg**) makes the dynamics **sensible to the misalignments**, further enhanced by low beta
  - **Transition between 0.055 and 0.11 cavities (with a frequency change) happens quite early in the LINAc**
  - Small transverse acceptance
  - Difficult benchmark with simulations

- <u>Controls and Operations:</u>
  - Linear Accelerator Setup:
    - Errors between simulation and final setup
    - Difficulties for optimize transmission
    - Operation setting time

Optimization Techniques for Simulations



Alternate Phase Focusing ± 20 deg → Small acceptance → Let's try population-based algorithm, **PSO**

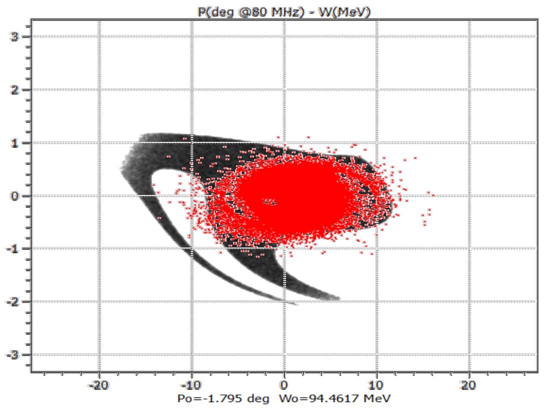
(tried by CEA-Saclay for DONES superconductive linac design)

$$k_{l,0}^2 = \frac{2\pi q E_0(s) TTF sin[-\phi_s(s)]}{mc^2 \beta_s^2 \gamma_s^2 \lambda}$$

$$K_{RF} = \pi \frac{eE_a \sin\phi_0}{\beta^3 \gamma^3 mc^2 \lambda}$$

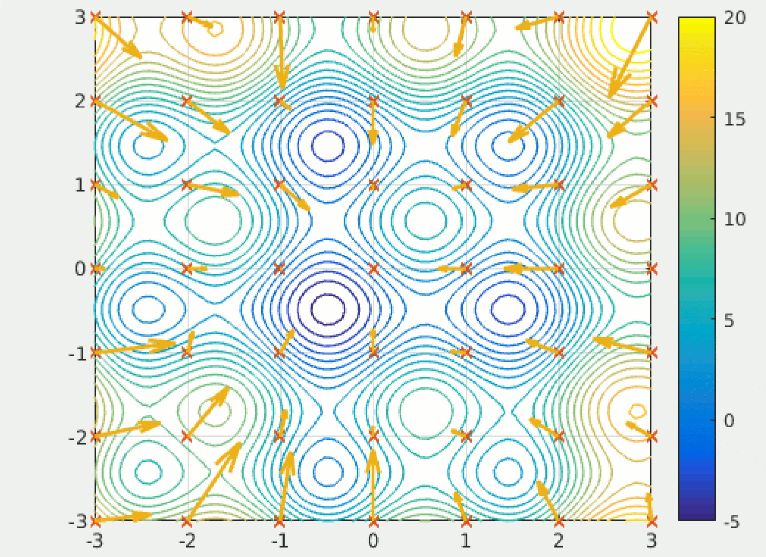
$$\Delta y' \sim \frac{2qeg \sin\phi}{\beta^2 \gamma A m_0 c^2} TTF \left[\beta c B_x \sin\left(\frac{\pi d}{\beta\lambda}\right) - E_y \cos\left(\frac{\pi d}{\beta\lambda}\right)\right]$$

Note: *Tipical behavior in QWRs*



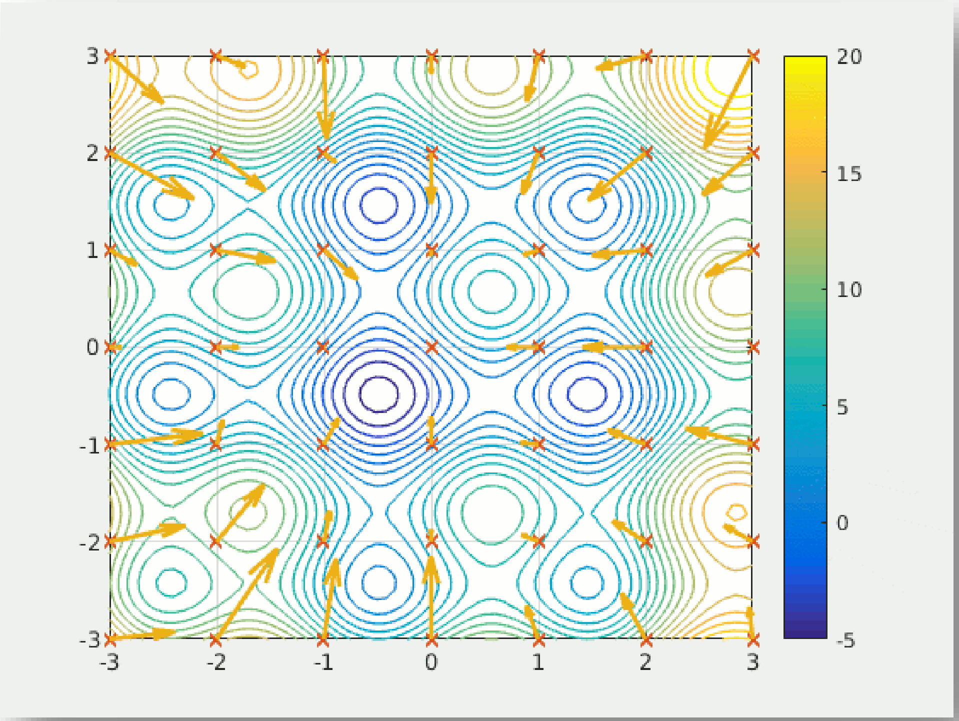
APF

PSO – Particle Swarm Optimization



PSO – Particle Swarm Optimization

- Algorithm based on information sharing between the swarm components
- Direction of each particle depends on best maximum found along its path and the best maximum found by the whole ensemble of particles
- Able to avoid local minima
- Fast search for minima in multidimensional scalar field



"Particle swarm optimization", Wikipedia, 2023

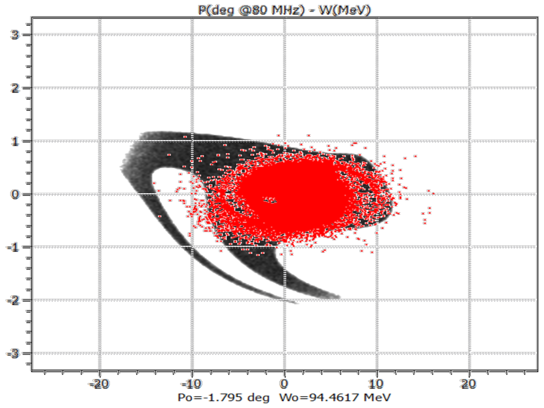
Optimization Techniques for Simulations – part 1

Increment studies of the longitudinal acceptance with PSO

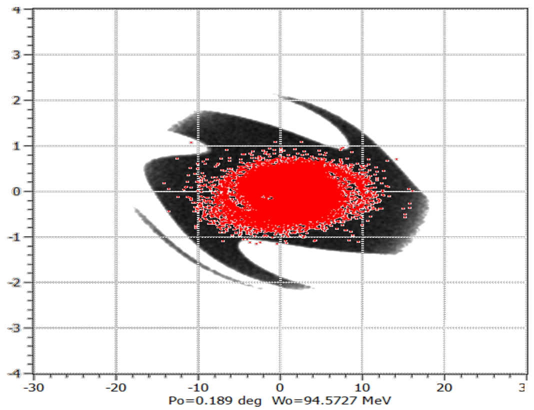
- Applied to 82 cavity phases (± 90 deg range) to find new synchronous phases
- Tested with input beam from normal conductive RFQ.

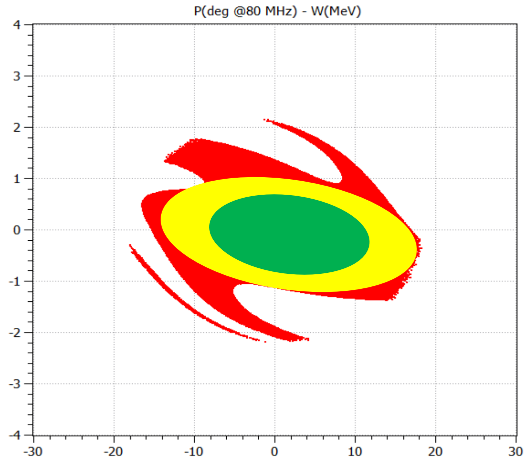
Steering in y: $\Delta y' \sim \frac{2qeg\sin\phi}{\beta^2\gamma A m_0 c^2} TTF \left[\beta c B_x \sin\left(\frac{\pi d}{\beta\lambda}\right) - E_y \cos\left(\frac{\pi d}{\beta\lambda}\right)\right]$

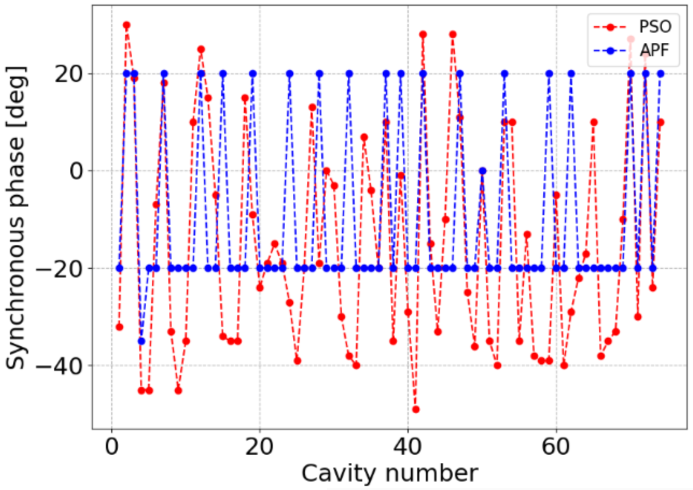
APF



PSO







- Normal conductive longitudinal phase space is not well contained in the ALPI acceptance
- Increased usable acceptance (yellow)
- APF usable acceptance (green)
- Due to a larger average negative synchronous phase w.r. to APF, expected that the solution is more sensible to steering

(*) L. Bellan *et al.*, " New Techniques For The LNL Superconductive Linac Alpi Beam Dynamics Simulations And Commissioning", *IPAC'23*, Italy, Venice. doi: 10.18429/JACoW-IPAC2023-TUODA3

Optimization Techniques for Simulations – part 2

Pairing of an artificial neural network with heuristic optimization methods

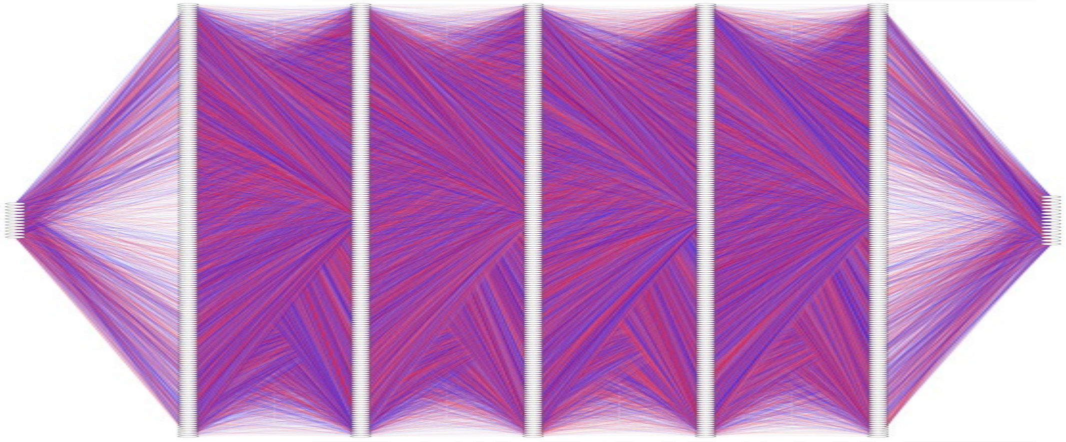
- Optimization Algorithm used:
    - Particle Swarm Optimization (PSO)
    - Genetic Algorithm (GA)
- Tested with input beam from normal conductive RFQ

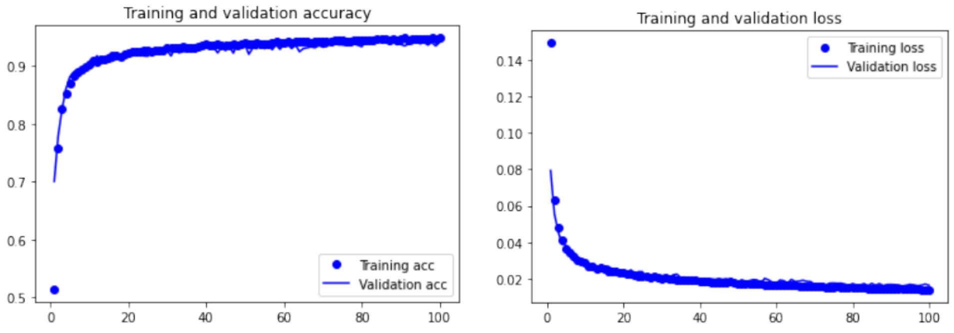
Neural Network + Optimization Algorithm

- Requirement:
  build and train the neural network to predict beam parameters (emittance, halo, size, etc.)

Note: important step is tuning the *hyperparemeters* such as the optimizers, hidden layers, and neurons, according to the data

Neural Network built





(a) Training and validation accuracy (b) Training and validation loss

Optimal Hyperparemeters → Neural Network Training → Accelerator System Model

artifact
ARTificial Intelligence For Accelerators, user Communities and associated Technologies

(*) Y. K. Ong, "Beam transfer lines design study for high-intensity proton beam (30 and 50 mA) for Boron Neutron Capture Therapy facility", *Università degli Studi di Catania*, Italy, MS Thesis.

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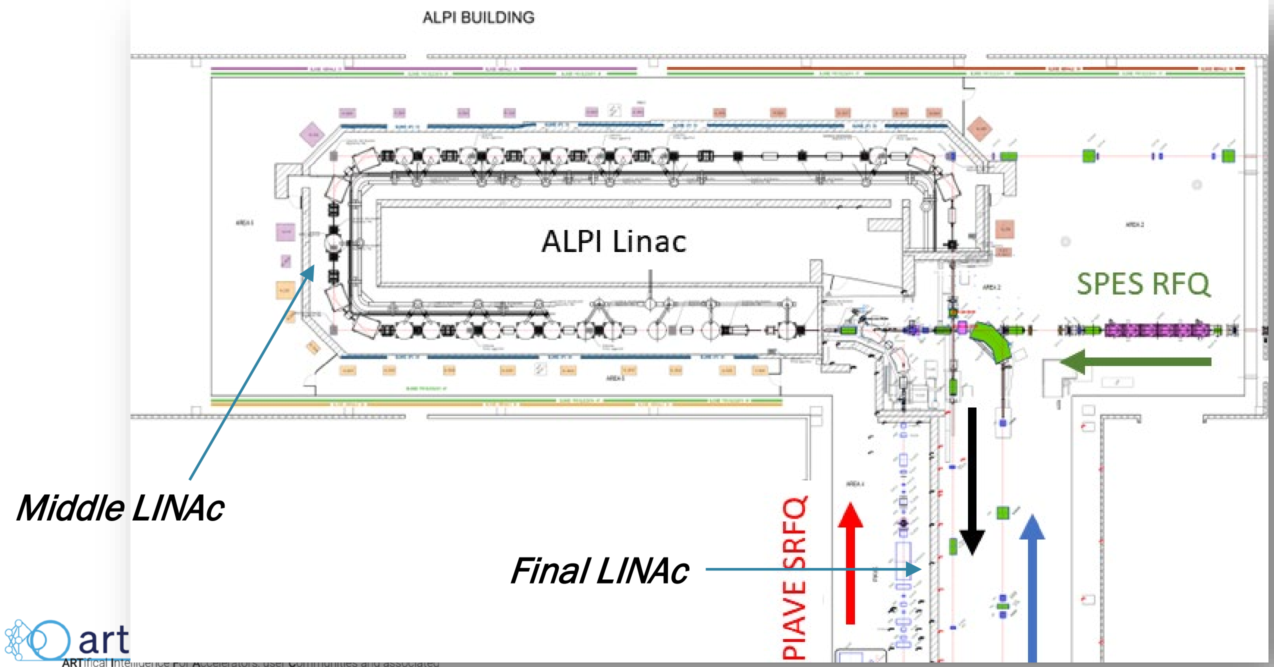
From Simulation to Real Accelerator

In the last years, several improvements on the linac increased (dramatically) its reliability

- **Organizational Improvements:**
  - Possibility to allocate several days for accelerator experiments and machine studies
- **Technical Improvements:**
  - Control System migration to the EPICS framework has been a revolution in the LINACs controls



- **Goal**: fast routine which can fit in the small amount of time given (2 h) to optimize beam transport, adaptable to multiple beam input parameters
- **Challenge**:
  - enormous number of cases
    - different A/q
    - different production mode
    - different input conditions
    - different cavity configurations (not scaled beta)
    - different instabilities
    - etc.
  - controls limitations
    - slow feedbacks
    - HW faults reset
    - etc.

Solution Selected for Tests:
PSO

From Simulation to Real Accelerator

Why PSO?

- **Population-based approach**: This approach enables the exploration of multiple areas at once, improving the likelihood of identifying global optimal solutions.
- **Social interaction**: Each particle adjusts its position based on its own best solution (personal best) and the best solution found by any particle in the population (global best). This cooperation helps explore promising areas of the search space, considering correlations between devices.
- **Simplicity and ease of implementation**: it requires fewer parameters compared to other optimization algorithms like Genetic Algorithms or Simulated Annealing. This simplicity makes it easier to implement and tune for different problem domains.
- **Convergence speed**: PSO tends to converge quickly towards optimal solutions due to its ability to exploit good regions in the search space efficiently while exploring new areas as well, especially for single objective function.
- **Lack of gradient information**: PSO does not require any derivative information, which is difficult data to define in a complex system like a particle accelerator.
- **No need for algorithm training**: while neural network algorithms require several datasets for training, with an important impact in the operational time, the training is not required with PSO.

From Simulation to Real Accelerator

Tests and Results

- First tests (Dec. 2022 - Jan. 2023): optimization times estimation test performed only with corrector system

PSO problem: $\mathbb{R}^6 \rightarrow \mathbb{R}$ $(middle\ LINAc\ FC)$ and $\mathbb{R}^{10} \rightarrow \mathbb{R}$ $(final\ LINAc\ FC)$

Target Element (Faraday Cup)	PSO Execution Time (PSO main params)	Transmission		
		No corrector	Manual Optimization (operators)	Automatic Optimization (PSO)
middle LINAc Faraday Cup	30 min pop size: 20 iterations: 10	15%	41%	56.2%
final LINAc Faraday Cup	1 h pop size: 30 iterations: 15	1% - 2%	24.5%	35%

From Simulation to Real Accelerator

Tests and Results

- Second tests (Jul. 2023): algorithm optimization test performed with corrector system and lens system (dipoles and quadrupoles)

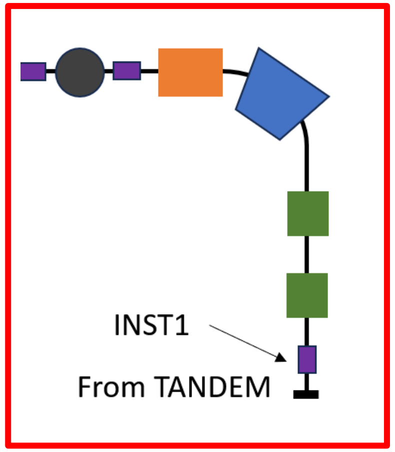
PSO problem: $\mathbb{R}^{37} \rightarrow \mathbb{R}$ $(middle\ LINAc\ FC)$

Params	Execution Time	Current	
		Manual Optimization	Automatic Optimization
pop size: 25 iterations: - (*)	45 min	43 nA	54 nA
pop size: 25 iterations: 20	1h 30 min	25 - 23 nA	29 - 28 nA
pop size: 25 iterations: 35	2h 30 min	37 - 30 nA	60.7 - 49 nA

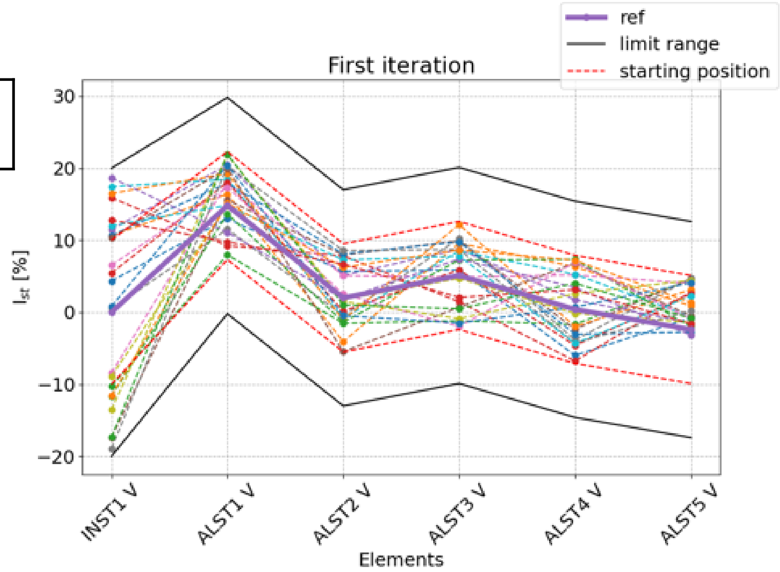
From Simulation to Real Accelerator

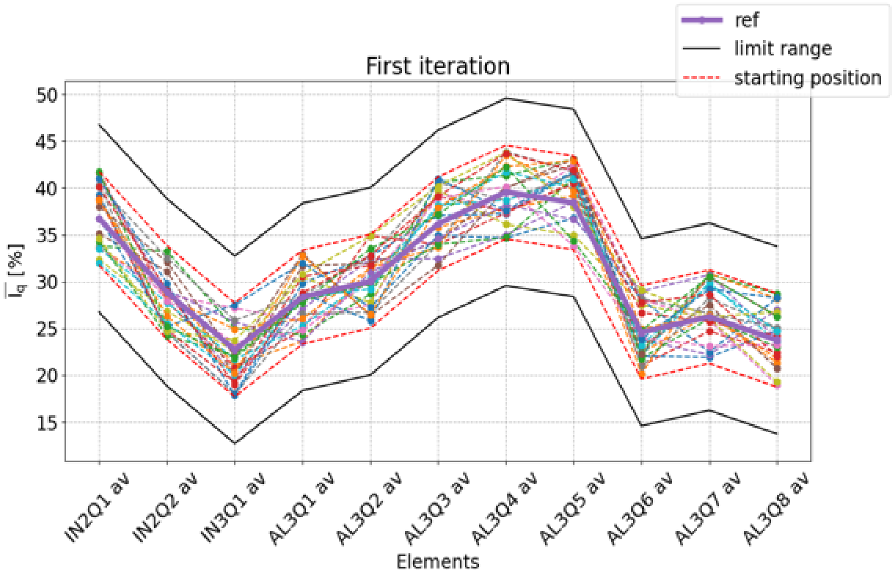
More Details:

pop size: 25 iter: 20	1.5h	25 - 23 nA	29 - 28 nA

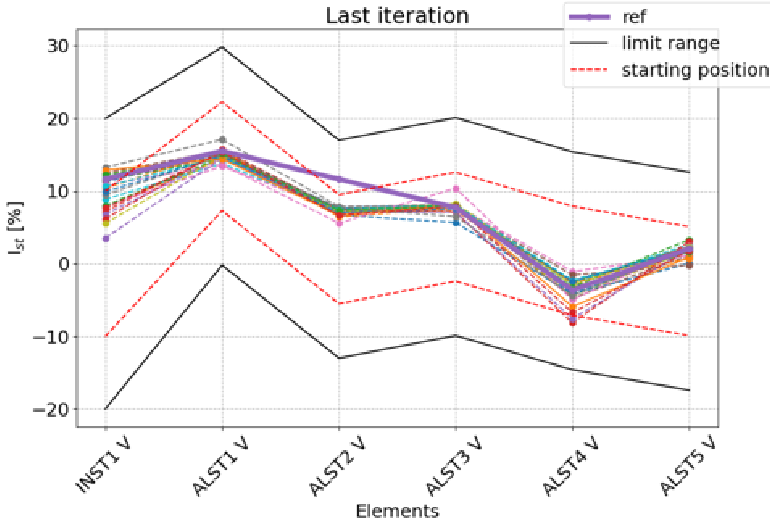


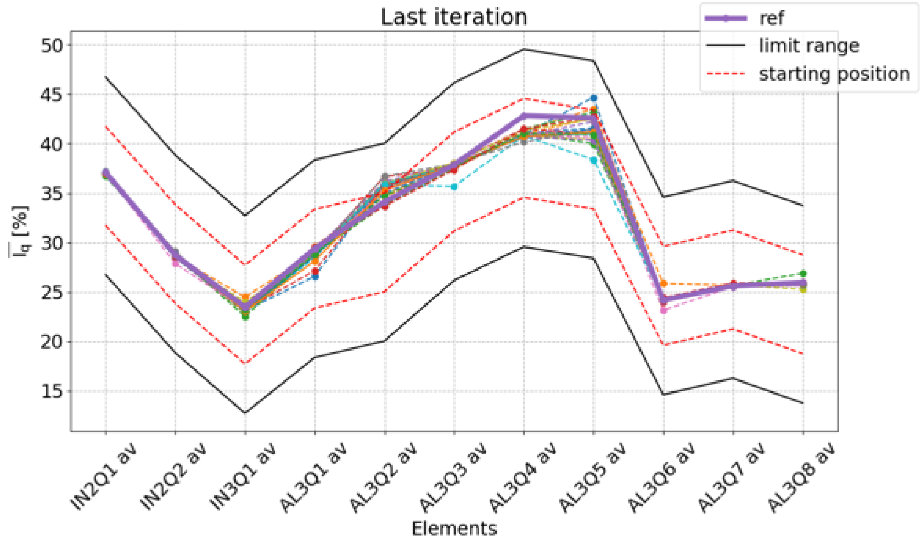
START





END





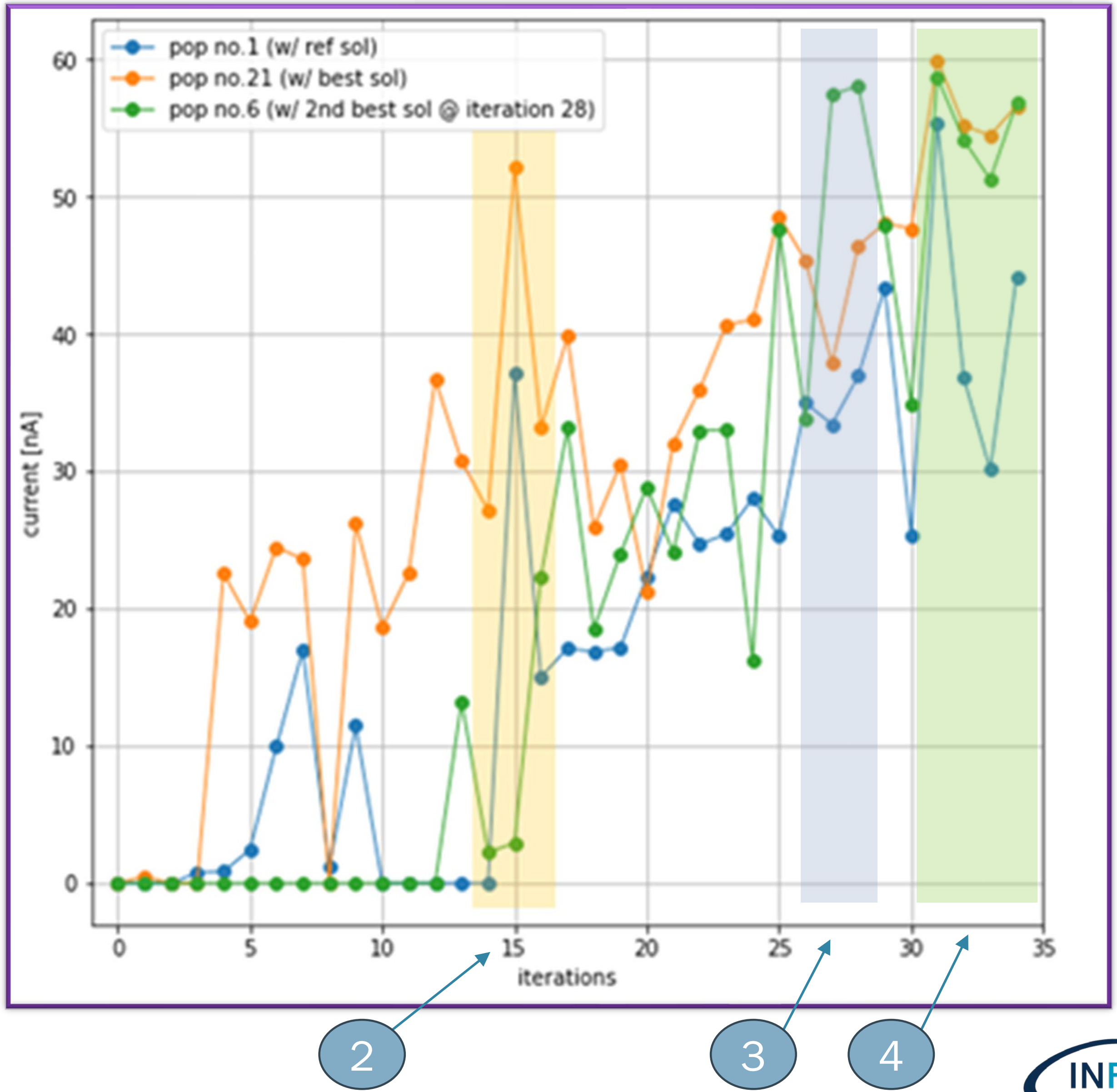
From Simulation to Real Accelerator

More Details:

pop size: 25 iterations: 35	**2h 30 min**	**37 - 30 nA**	**60.7 - 49 nA**

TSO's ability to adapt to changes in machine conditions

1. trends of three components of the swarm related to steering devices as the iterations and current change (current at the Faraday Cup).
2. around iteration 15, the system was nearing a maximum, but changes occurred after iteration 16.
3. The control component started using higher current values, reaching a new maximum around iterations 26-27.
4. It then shared these new parameters with the group, leading to improved performance.



From Simulation to Real Accelerator

Tests and Results

- Second tests (Jul. 2023): algorithm optimization test performed with corrector system and lens system (dipoles and quadrupoles)

PSO problem: $\mathbb{R}^{\mathbf{37}} \rightarrow \mathbb{R}$ $(middle\ LINAc\ FC)$

Parameter	Previous value	Manual	Automatic
Transmission in middle LINAc FC	0%	50%	55% (upper limit due to injector setting)
Time required	-	3 h	1.5 h (considering the instability)

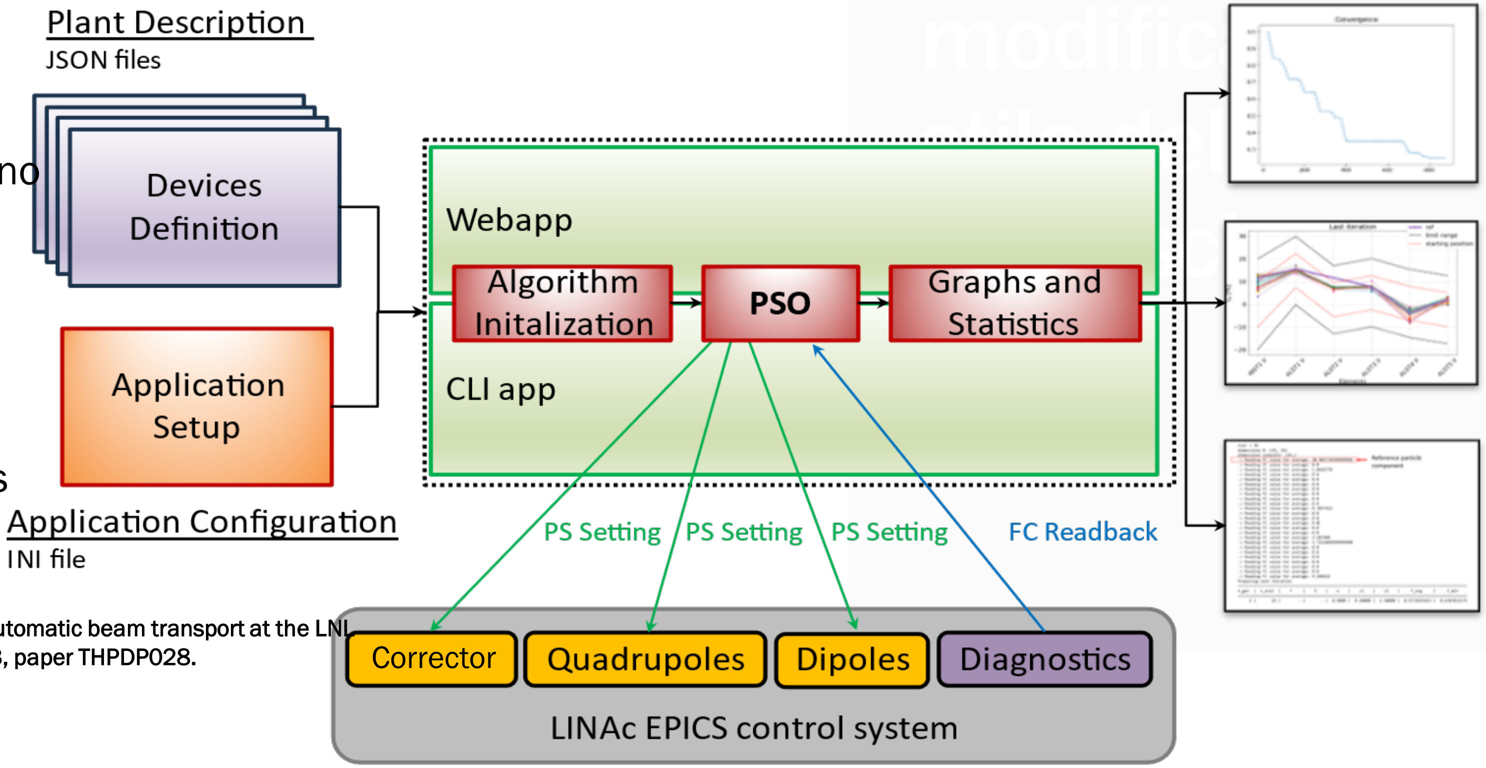
PSO for ALPI Accelerator - TSO

- Tests performed using dedicated Python scripts
  - Programs customized for the particular line and for the set of tests executed

⬇

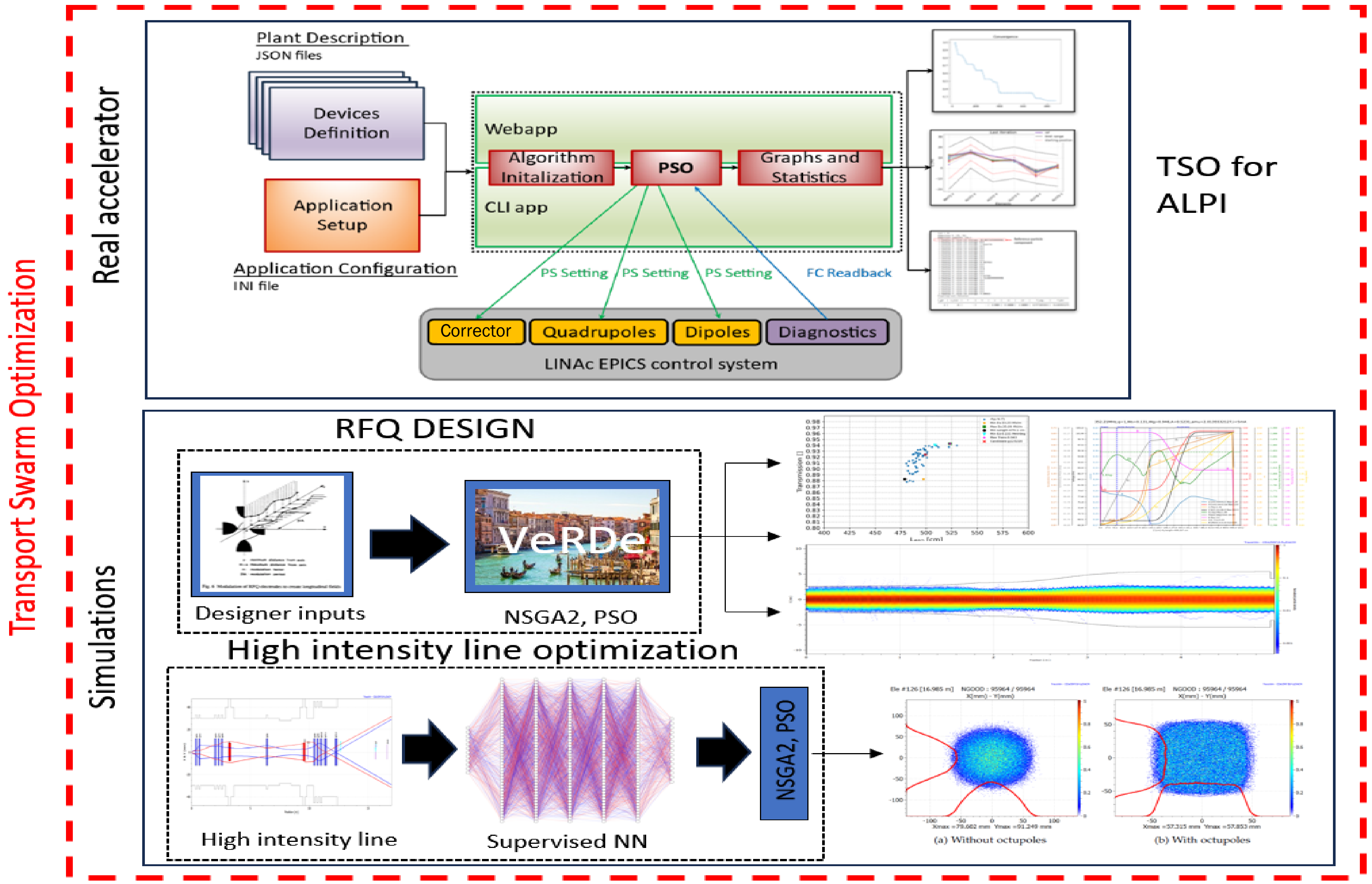
- [Idea: define a software framework for using PSO in different accelerators]
  TSO - ***Transport Swarm Optimization*** – is a dedicated Python application based on Particle Swarm Optimization algorithm *(already under development)*

  - Webapp and CLI app
  - Plant Description & Application setup (no modification to the code)
  - Possibility to extend the optimization methods to other algorithms
  - Possibility to extend the kind of devices under control



(*) M. Montis and L. Bellan, "Particle swarm optimization techniques for automatic beam transport at the LNL superconducting linac", ICALEPCS'23, Cape Town, South Africa, Oct. 2023, paper THPDP028.

Long Term Development for TSO



Prospectives and Contribution

the contribution we would like to give in the collaboration can be summarized in the following points:

- Continue the study and develop optimization applications in low beta ion LINACs
    - New methods and algorithms (GA, Bayesian, etc.)
    - Standardize TSO application for generic LINACs

- Supply experimental runs for the collaboration, with our LINACs, for someone interested in testing the environment through EPICS framework

- Create further connections with the other high intensity light ions projects in which we are already involved, such as ESS and IFMIF-DONES.

- *(desire 1)* Upgrade our toolkit with machine learning techniques, in particular with a deep reinforcement learning method, depending on the feedback of the collaboration.

- *(desire 2)* link to other existing Linac facilities (ESS, GSI, Ganil, maybe IFMIF and DONES) in order to test with specific beam runs the generality of our approach to be extended to different accelerator setup.

Thank you for your attention