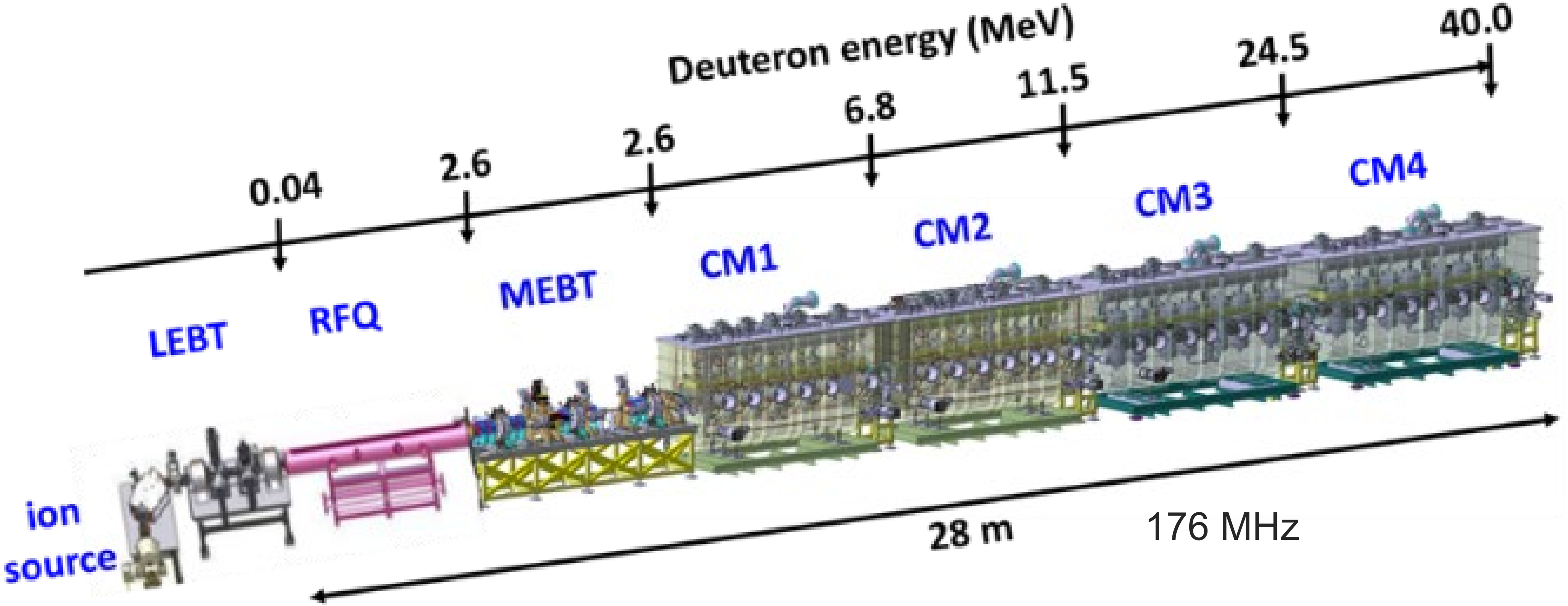
SARAF MEBT commissioning

CEA-IRFU - J. Dumas, N. Pichoff, A. Chance, F. Gougnaud, F. Senée, D. Uriot

SNRC - A. Kreisel, J. Luner, A. Perry, E. Reinfeld, L. Weissman

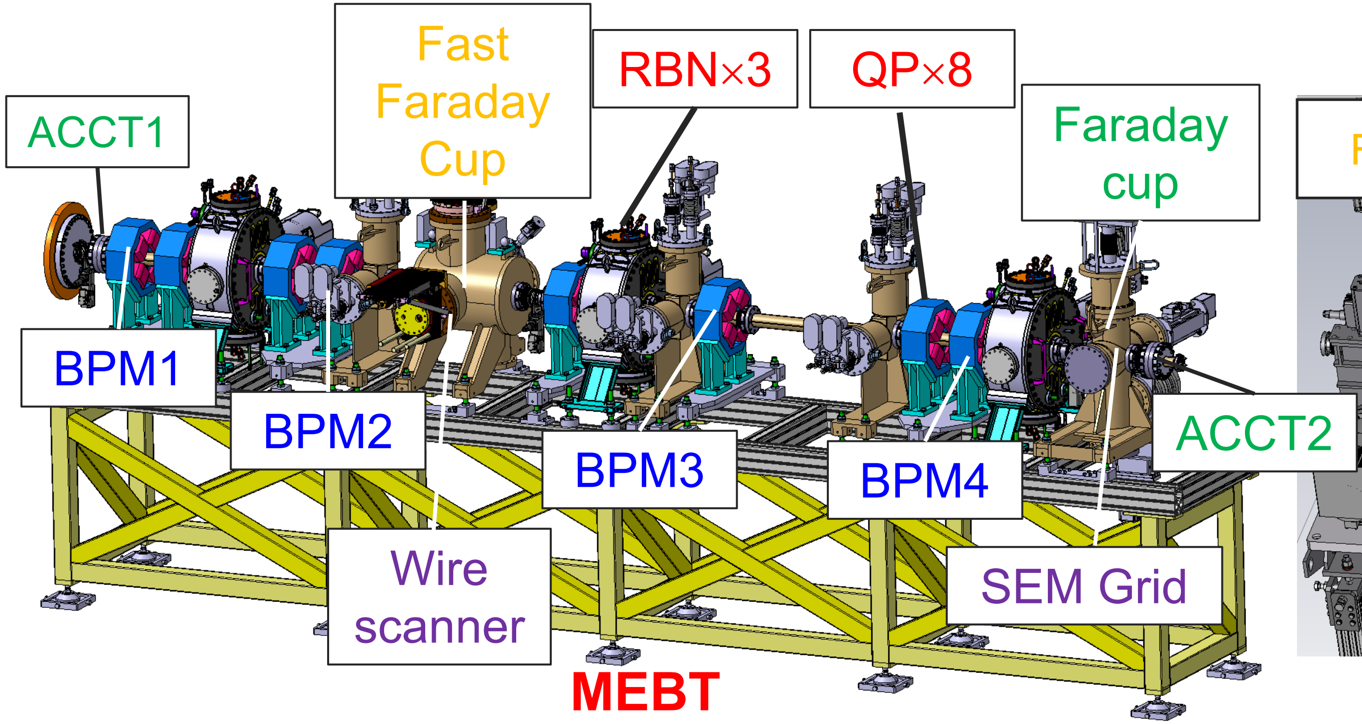
The SARAF LINAC

Ions	Protons/Deutons
Energy	1.3/2.6 – 35/40 MeV
Current	0.04 - 5 mA 100µs to CW

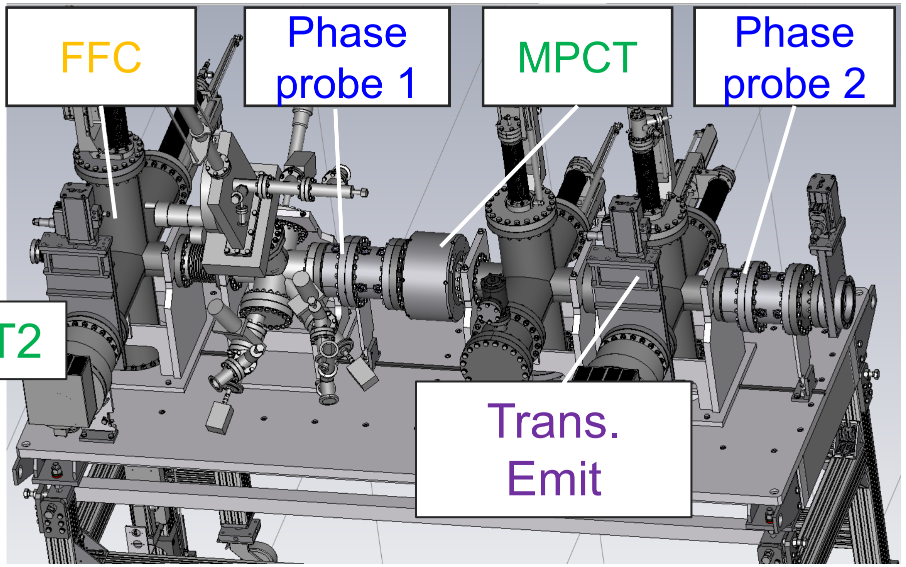


176 MHz

The SARAF MEBT



MEBT



DPLATE (from Phase 1)

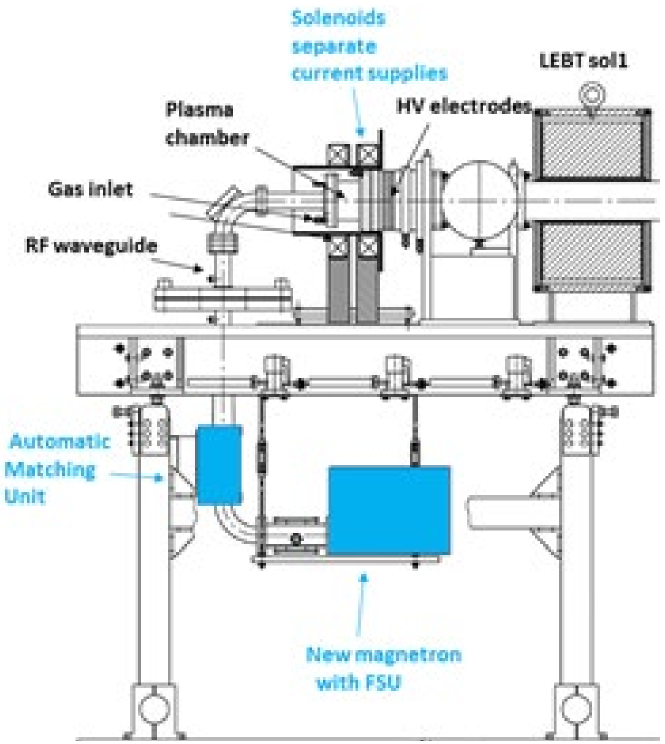
- ❑ Tests of Beam Diagnostics and Local Control System
- ❑ RFQ and MEBT transmission measurements
- ❑ Rebuncher calibration
- ❑ Longitudinal characterization (bunch length, emittance)
- ❑ Transverse characterization (bunch width, emittance)

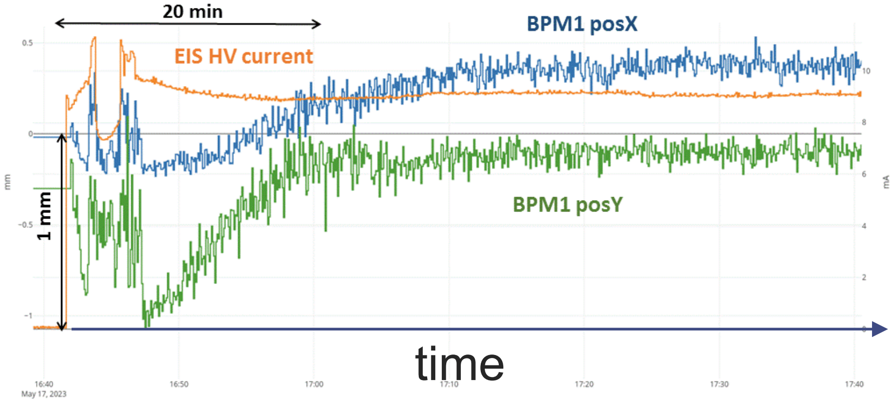
Contents

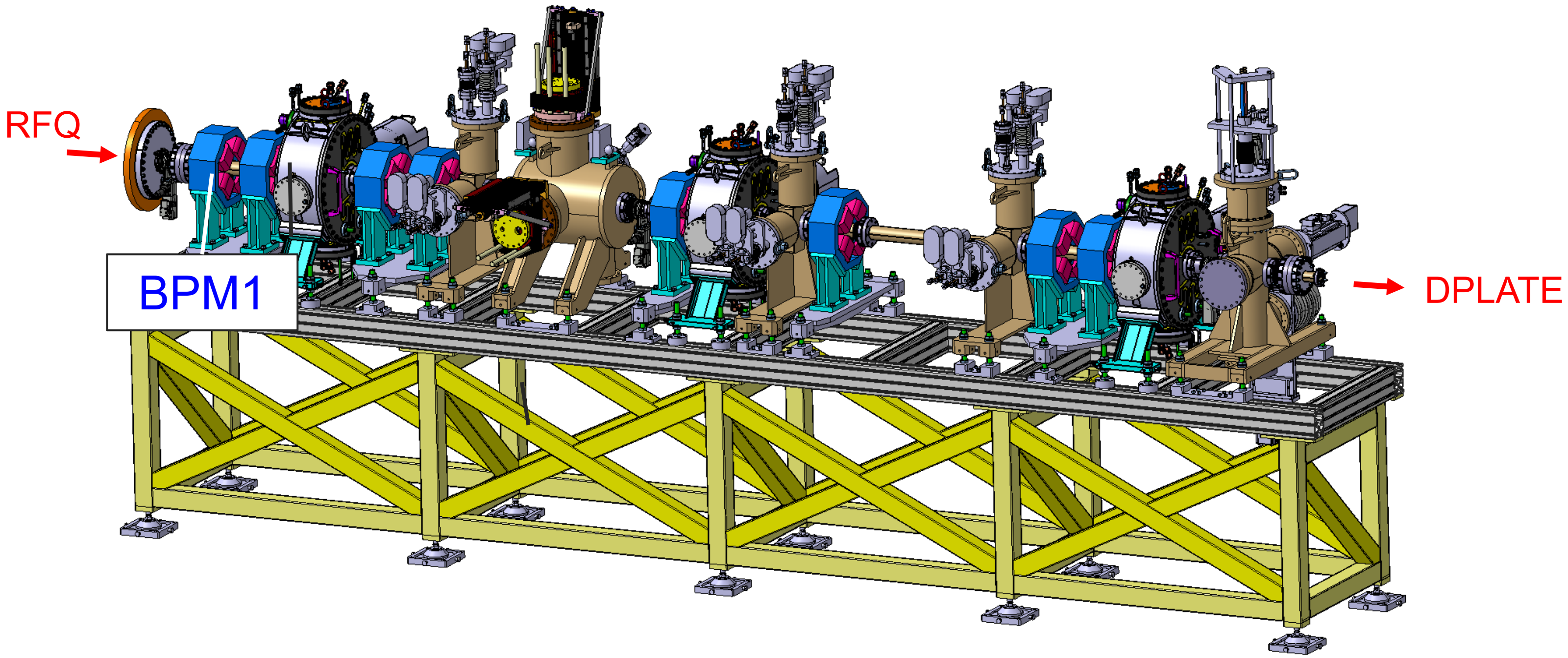
- The Machine tuning
- The Beam characterization in MEBT
- Machine learning philosophy…

■ Machine Tuning

EIS - Warm-up

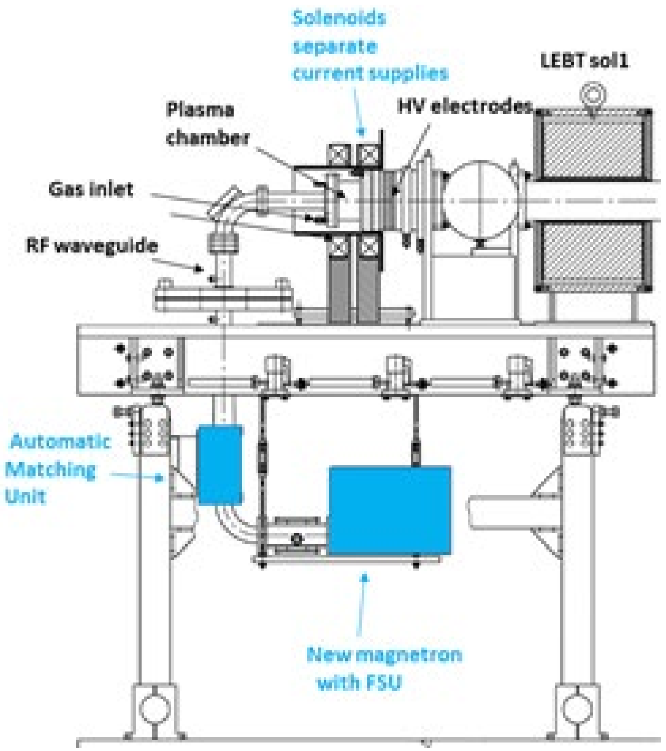


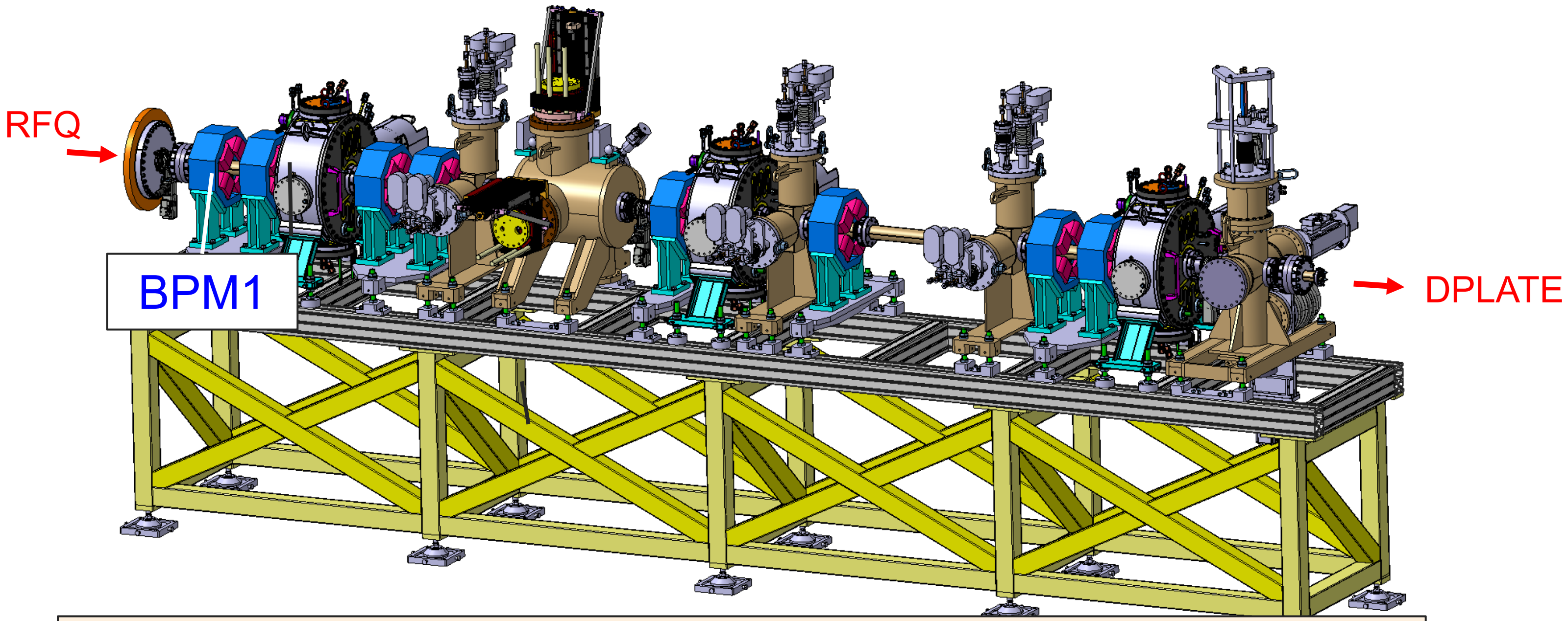




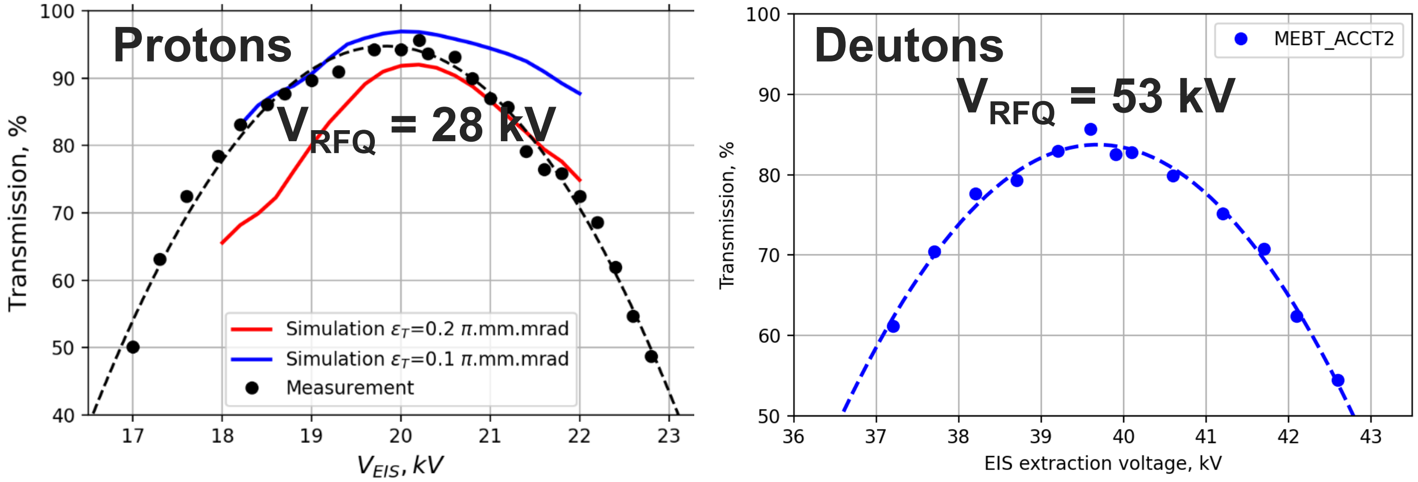
20 minutes are needed after EIS switch ON for a stable beam out of the RFQ

EIS - Voltage tuning (to RFQ)

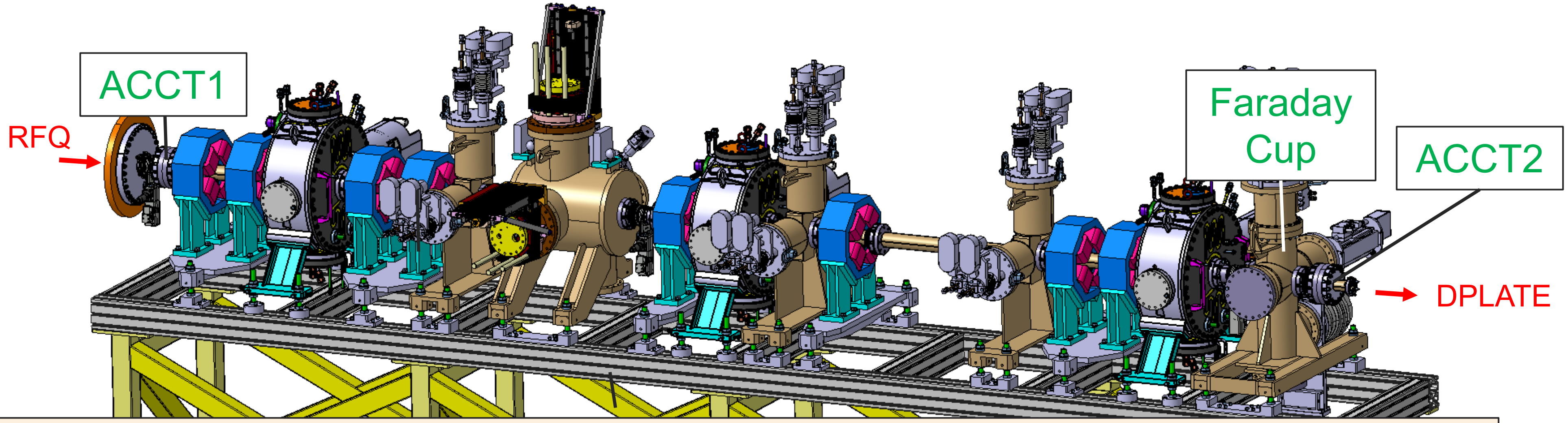




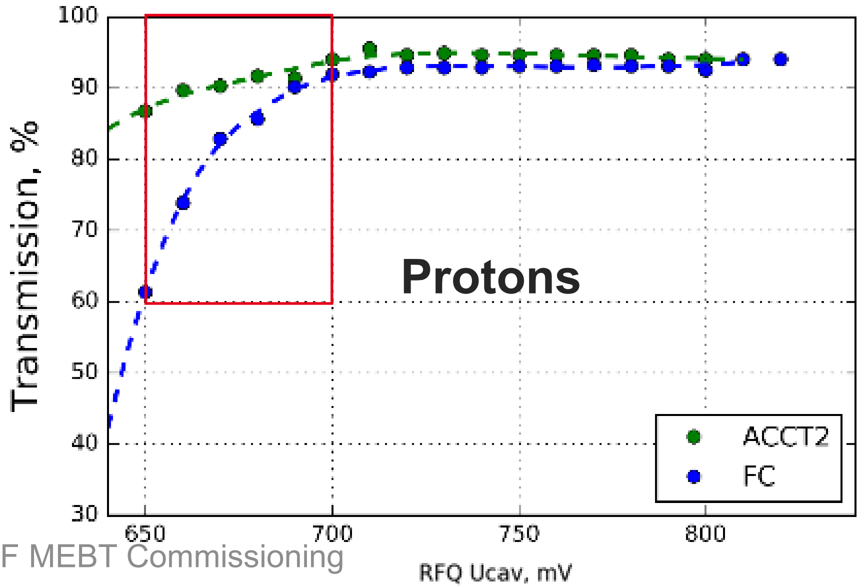
RFQ Transmission (/ACCT$_{LEBT}$), nominal optics

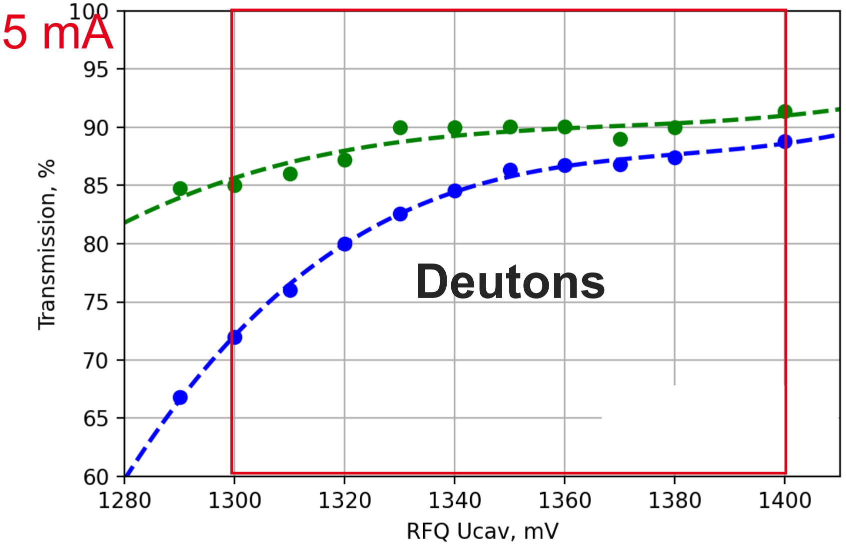


RFQ and MEBT transmission measurements

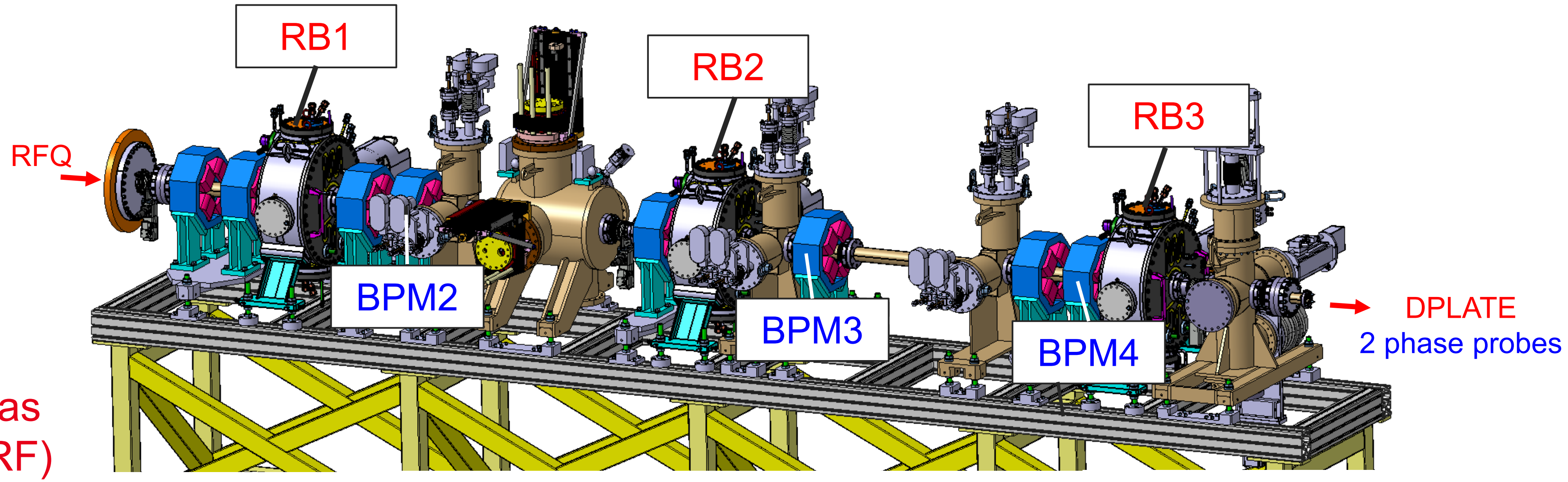


Transmission (/ACCT$_{LEBT}$), nominal optics

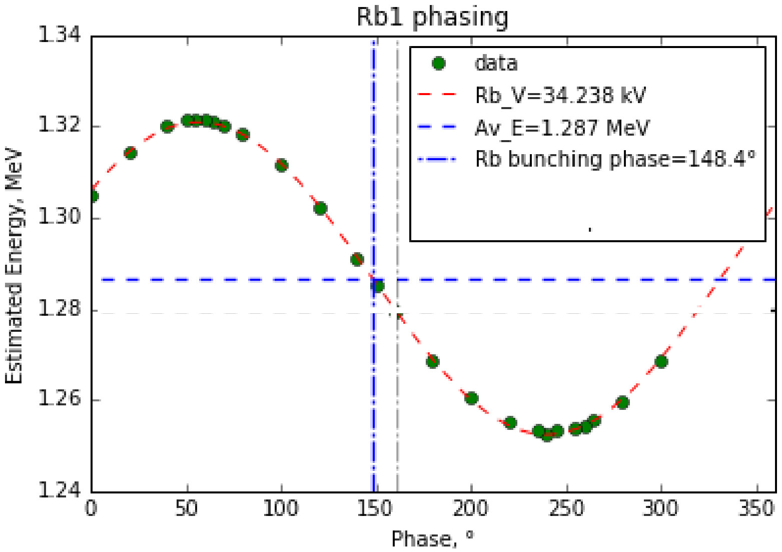




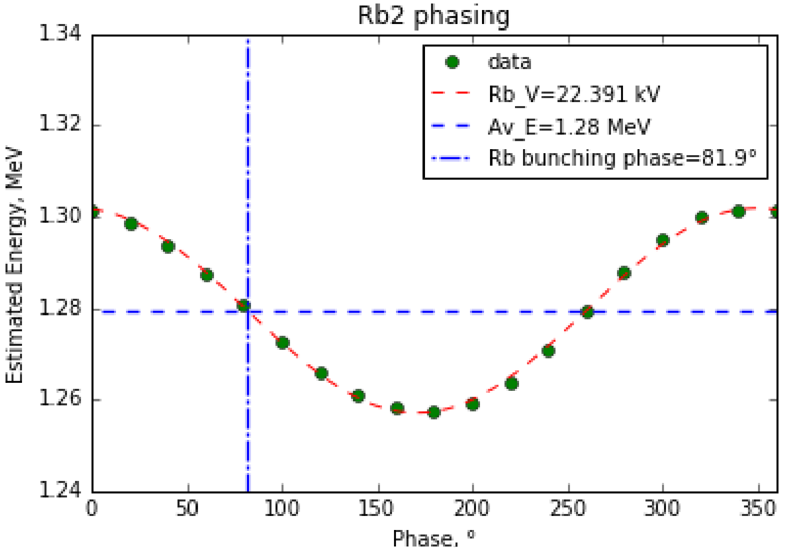
Rebuncher calibration (protons)



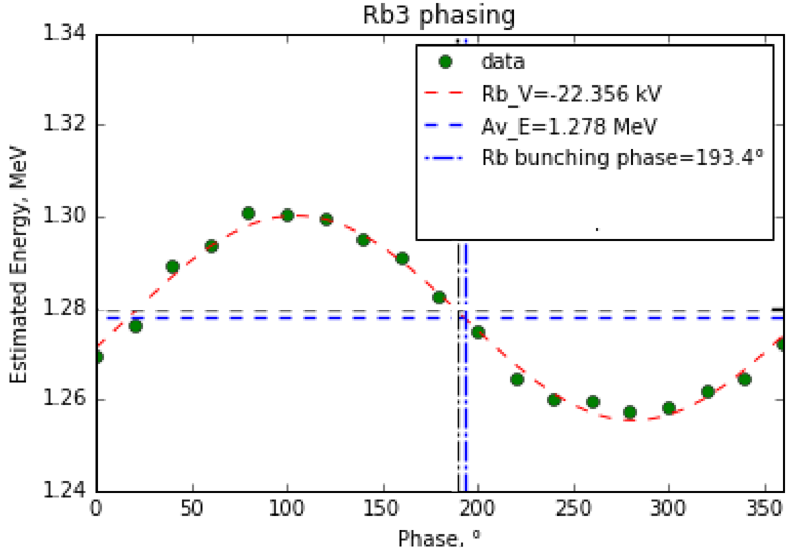
This discrepancy has been resolved (LLRF)



with BPM2-BPM3

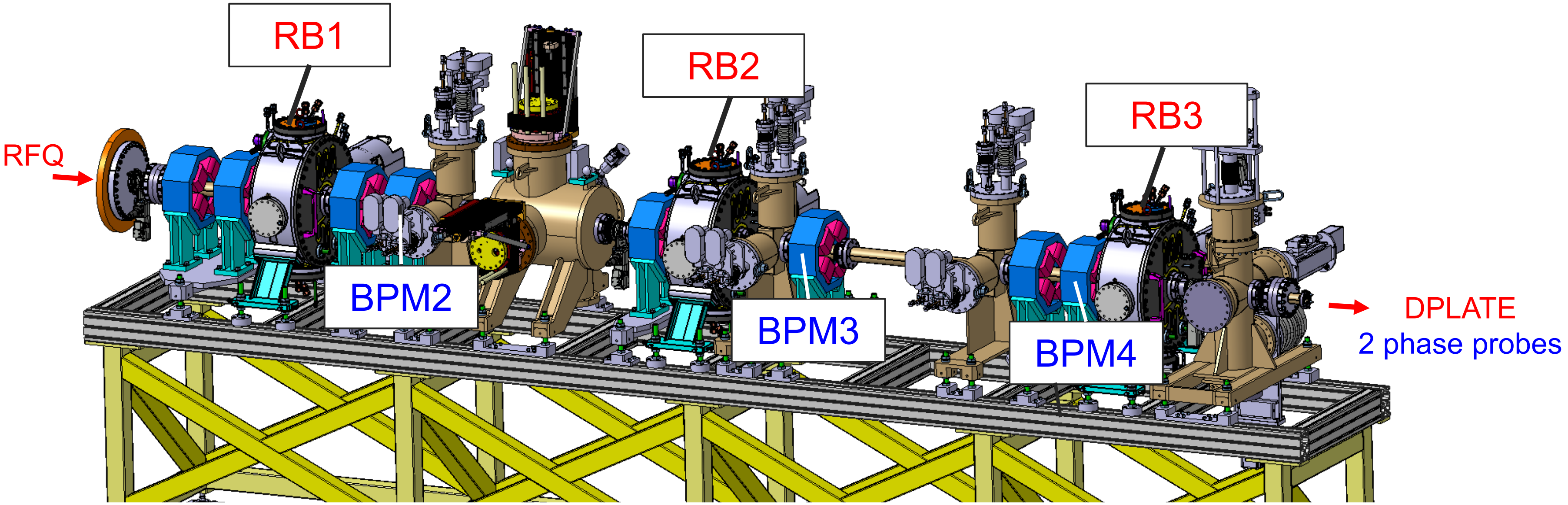


with BPM3-BPM4

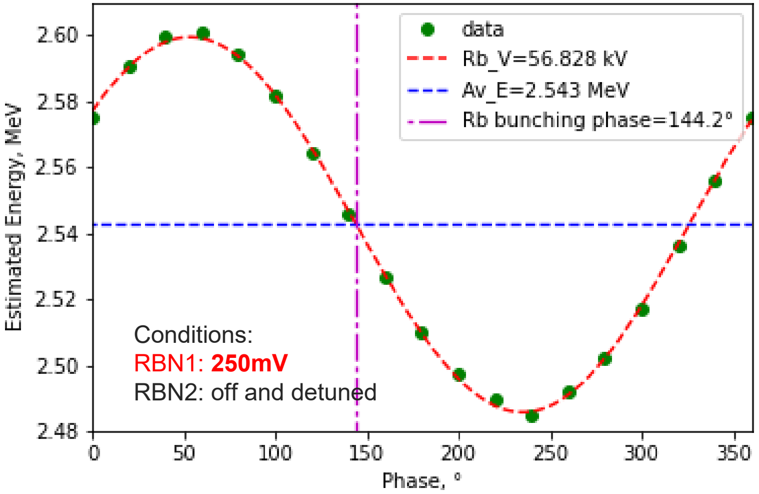


With phase probes in DPLATE

Rebuncher calibration (deutons)

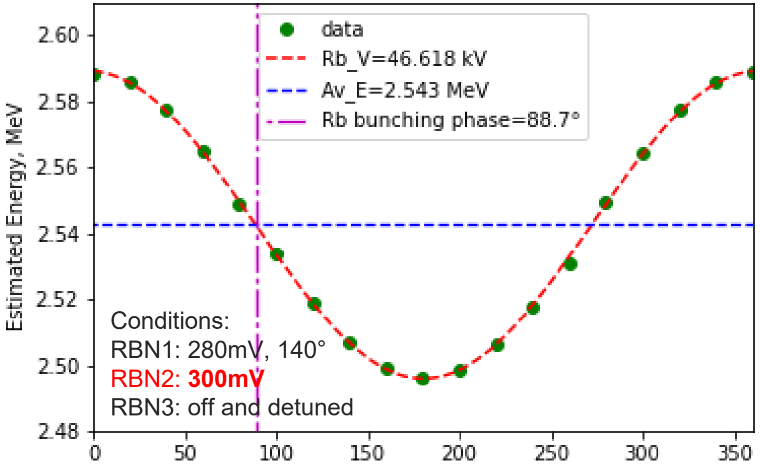


Phasing RBN1



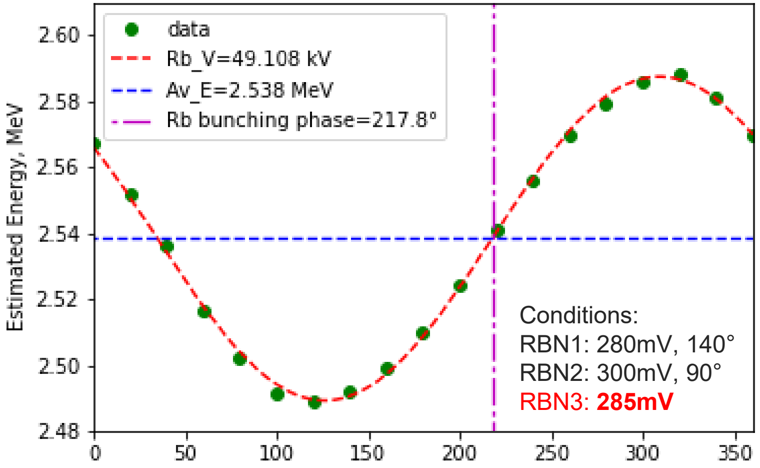
with BPM2-BPM3

Phasing RBN2



with BPM3-BPM4

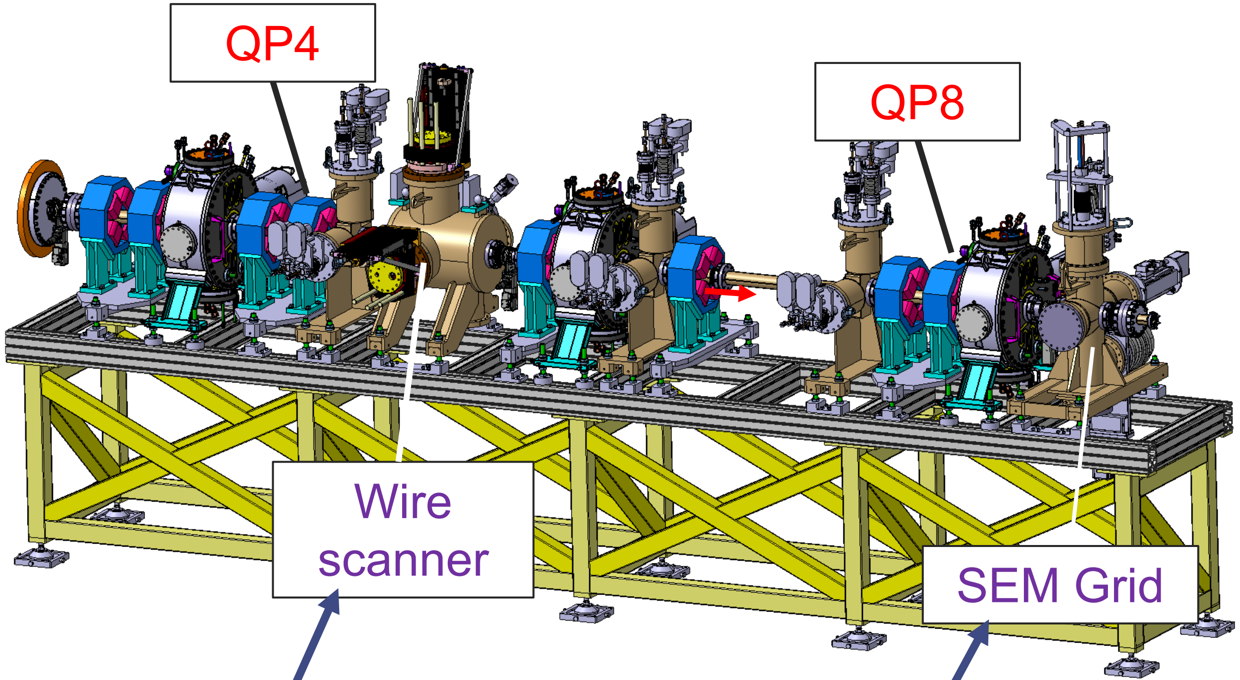
Phasing RBN3

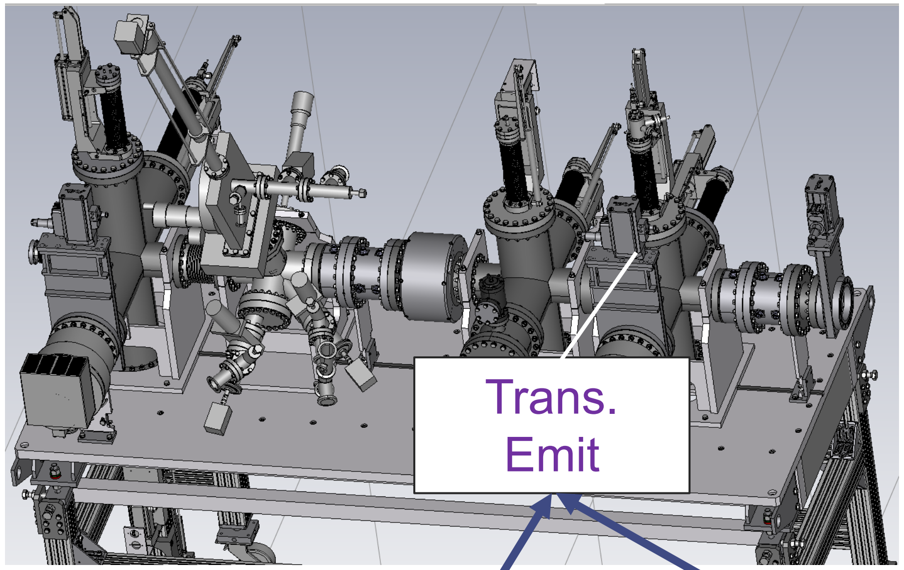


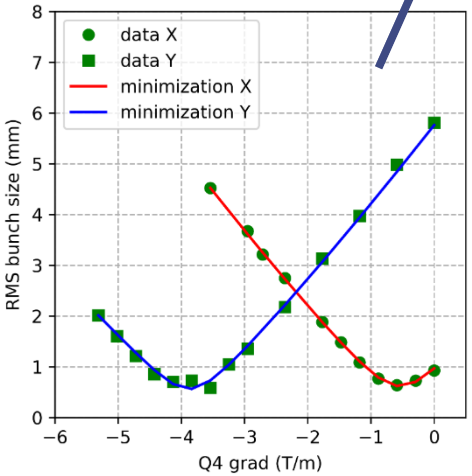
With phase probes in DPLATE

■ Beam characterization

Transversal characterization (protons)

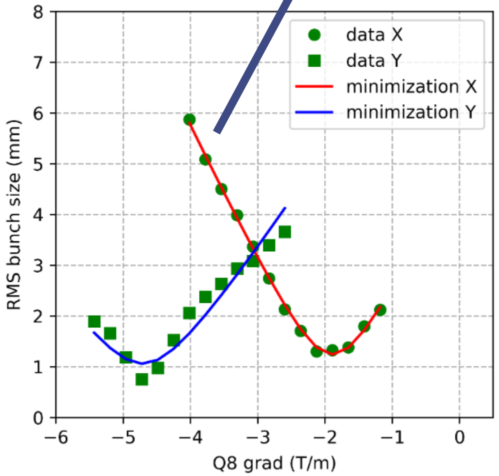






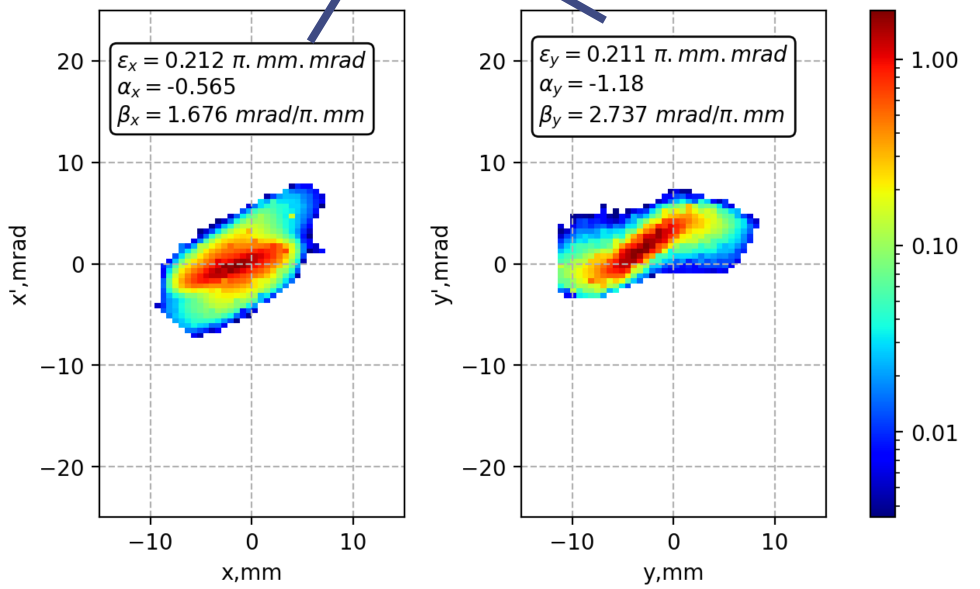
$\varepsilon_x = 0.202\ \pi.mm.mrad$
$\alpha_x = 0.343$
$\beta_x = 0.221\ mrad/\pi.mm$

$\varepsilon_y = 0.149\ \pi.mm.mrad$
$\alpha_y = -0.495$
$\beta_y = 0.167\ mrad/\pi.mm$



$\varepsilon_x = 0.454\ \pi.mm.mrad$
$\alpha_x = 0.5$
$\beta_x = 0.228\ mrad/\pi.mm$

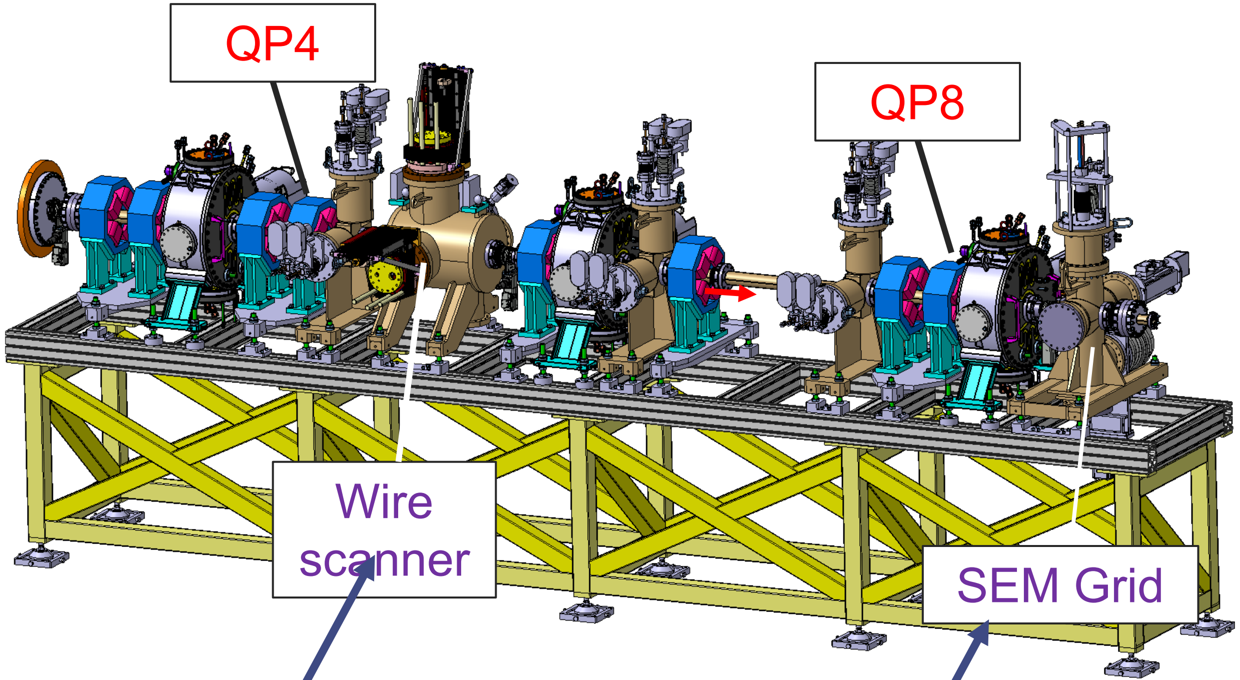
$\varepsilon_y = 0.408\ \pi.mm.mrad$
$\alpha_y = 0.003$
$\beta_y = 0.219\ mrad/\pi.mm$

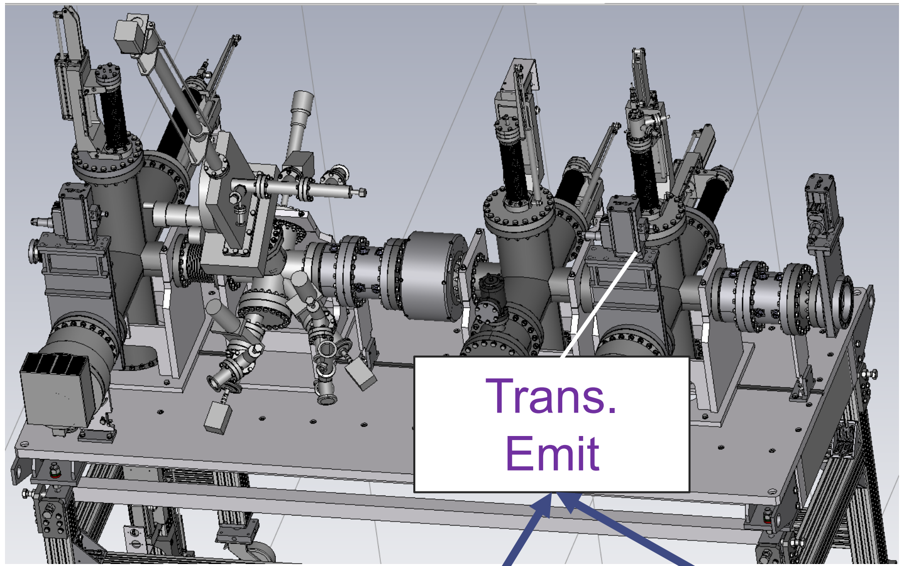


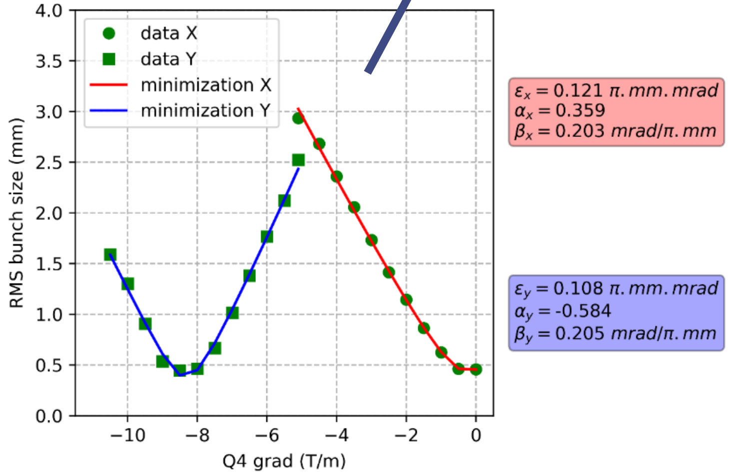
$\varepsilon_x = 0.212\ \pi.mm.mrad$
$\alpha_x = -0.565$
$\beta_x = 1.676\ mrad/\pi.mm$

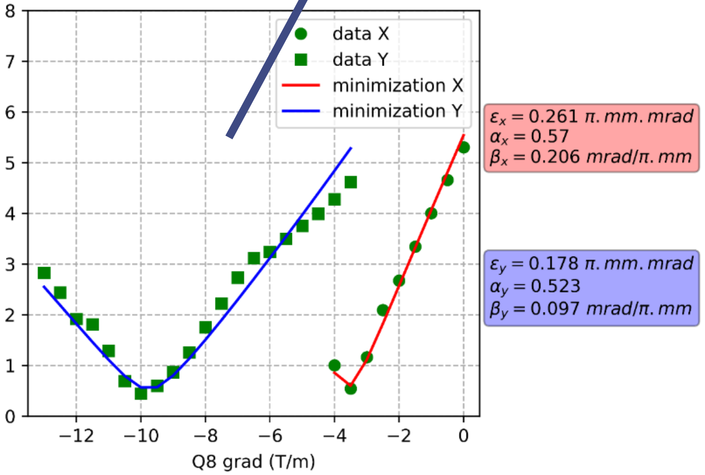
$\varepsilon_y = 0.211\ \pi.mm.mrad$
$\alpha_y = -1.18$
$\beta_y = 2.737\ mrad/\pi.mm$

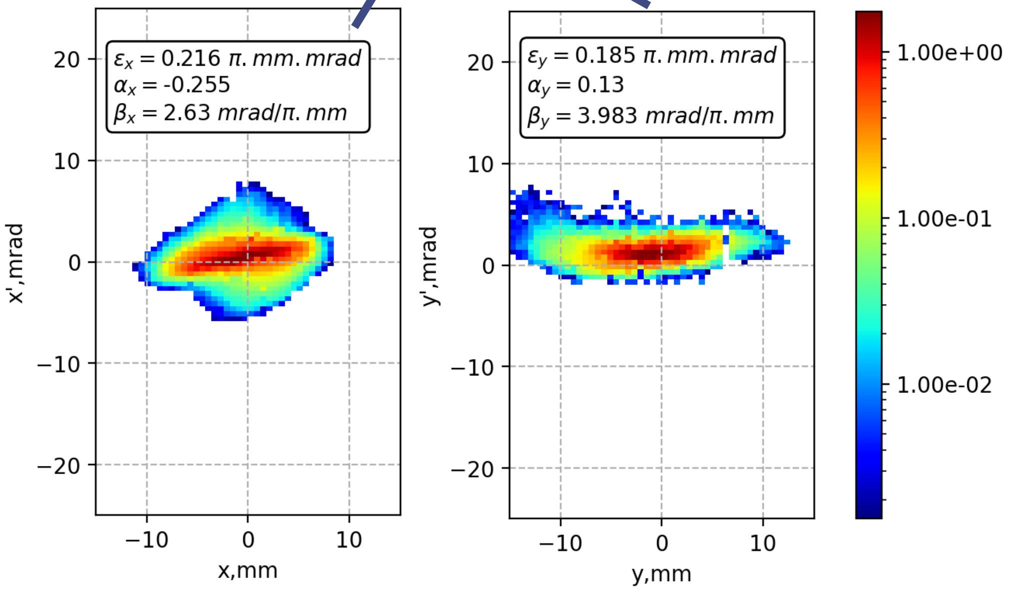
Transversal characterization (deutons)



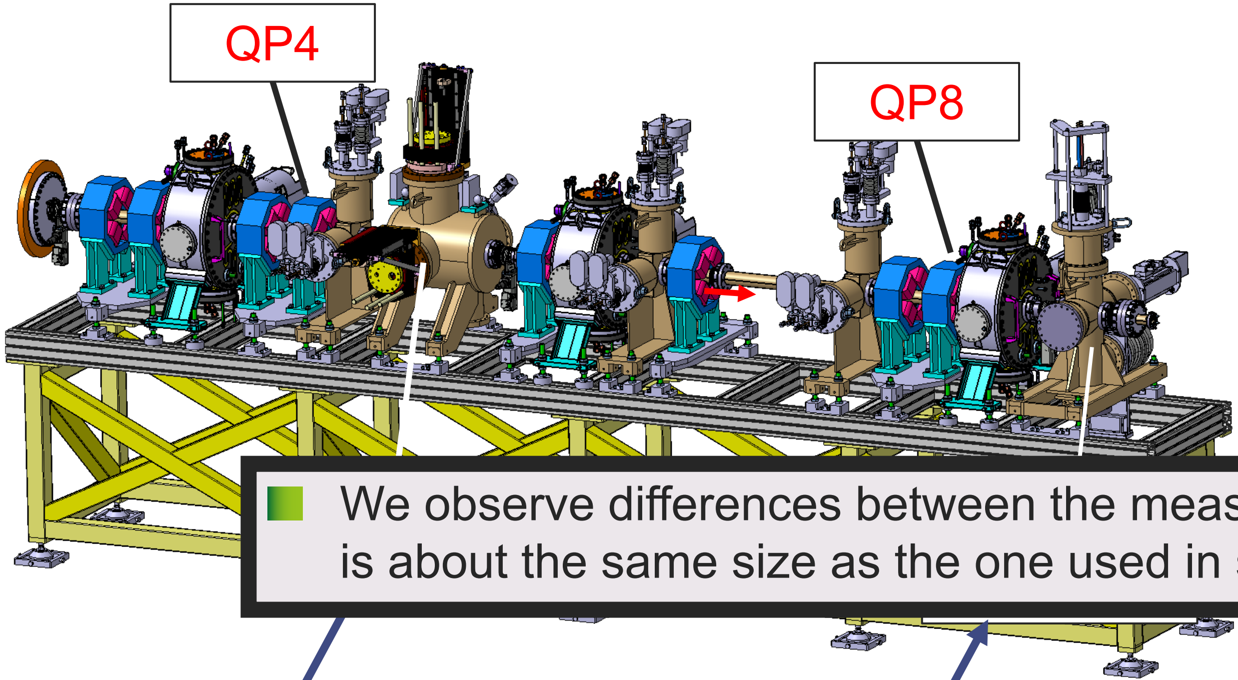


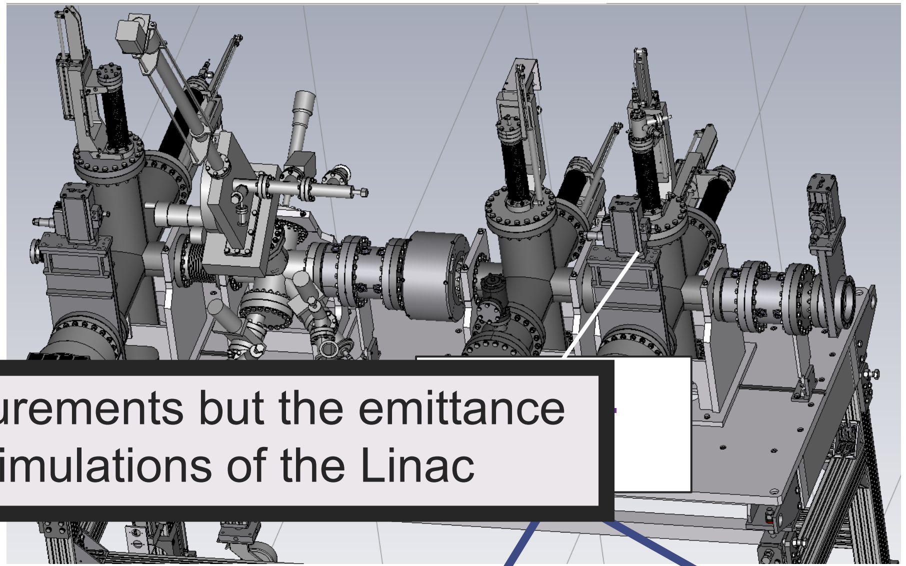




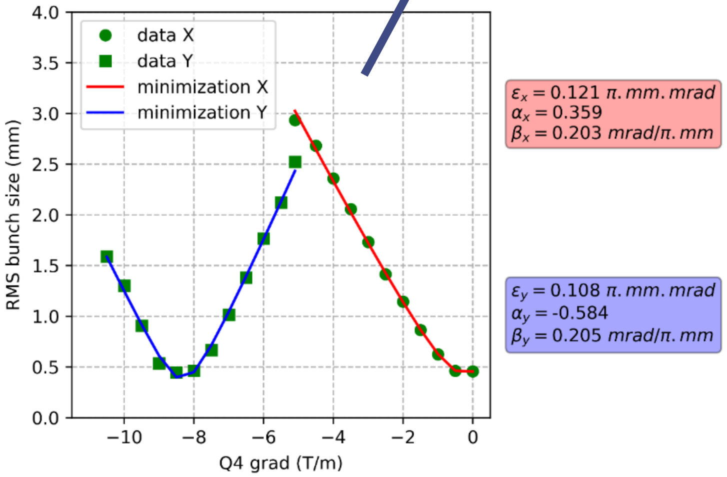


Transversal characterization (deutons)



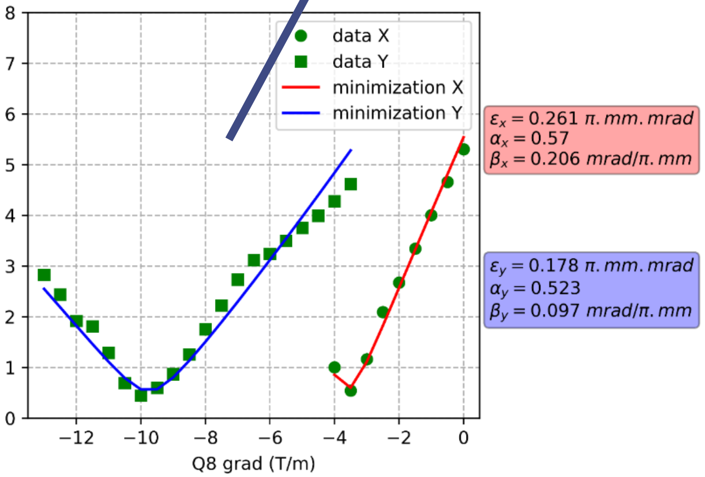


- We observe differences between the measurements but the emittance is about the same size as the one used in simulations of the Linac



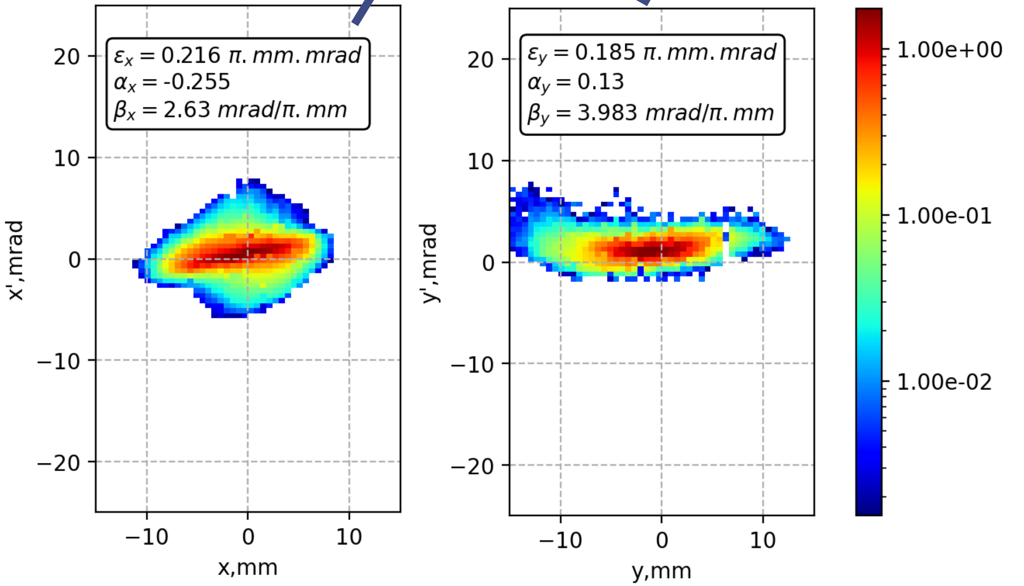
$\varepsilon_x = 0.121\ \pi.mm.mrad$
$\alpha_x = 0.359$
$\beta_x = 0.203\ mrad/\pi.mm$

$\varepsilon_y = 0.108\ \pi.mm.mrad$
$\alpha_y = -0.584$
$\beta_y = 0.205\ mrad/\pi.mm$



$\varepsilon_x = 0.261\ \pi.mm.mrad$
$\alpha_x = 0.57$
$\beta_x = 0.206\ mrad/\pi.mm$

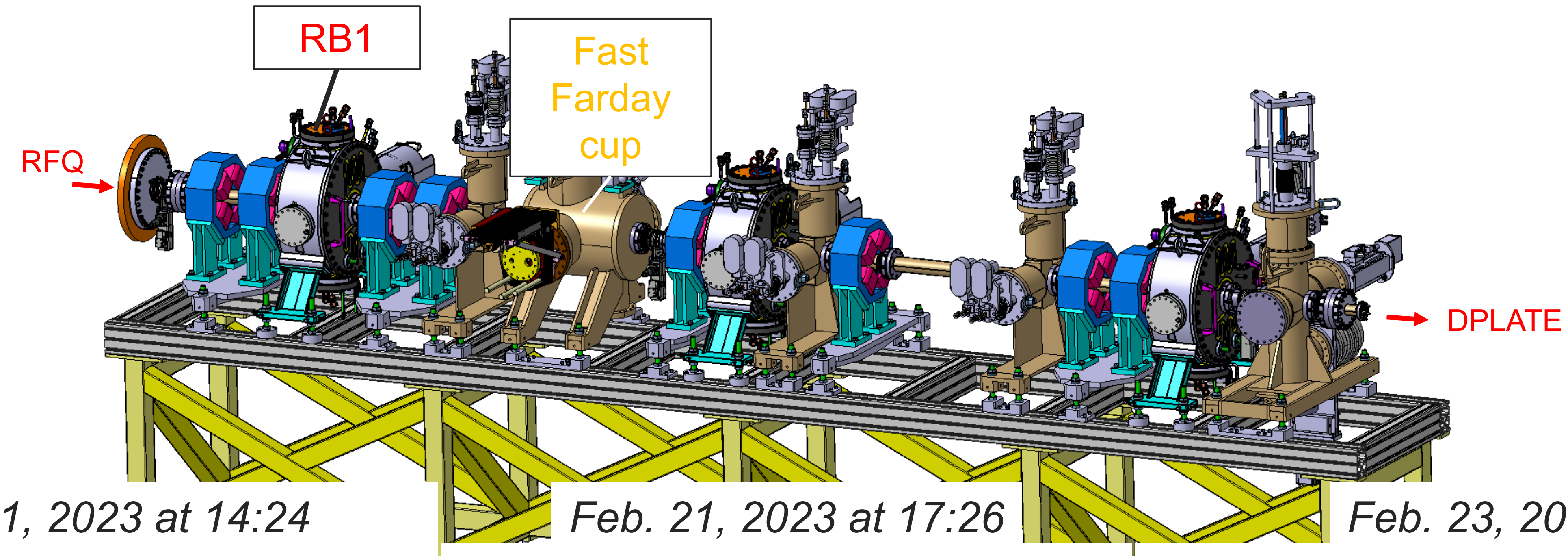
$\varepsilon_y = 0.178\ \pi.mm.mrad$
$\alpha_y = 0.523$
$\beta_y = 0.097\ mrad/\pi.mm$



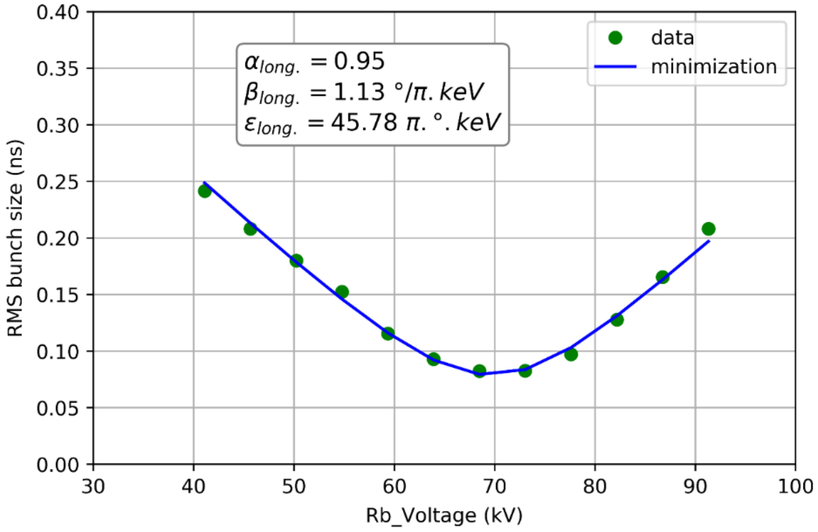
$\varepsilon_x = 0.216\ \pi.mm.mrad$
$\alpha_x = -0.255$
$\beta_x = 2.63\ mrad/\pi.mm$

$\varepsilon_y = 0.185\ \pi.mm.mrad$
$\alpha_y = 0.13$
$\beta_y = 3.983\ mrad/\pi.mm$

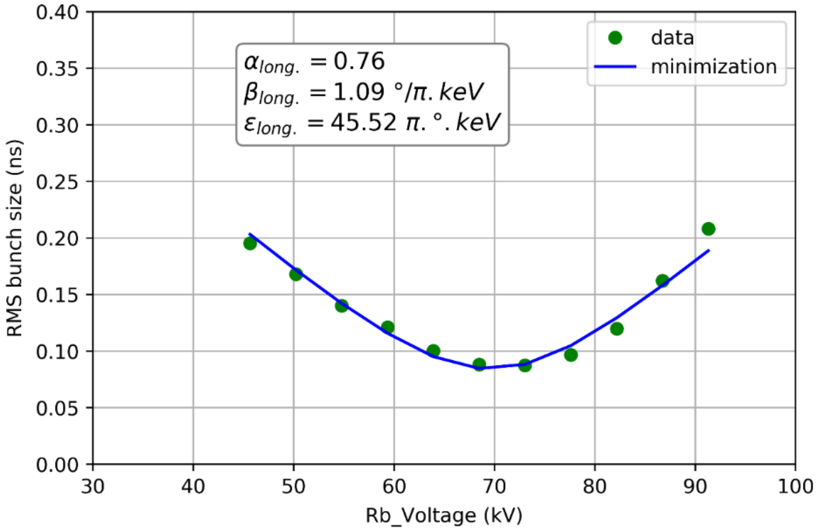
Longitudinal characterization in DB1 (protons)



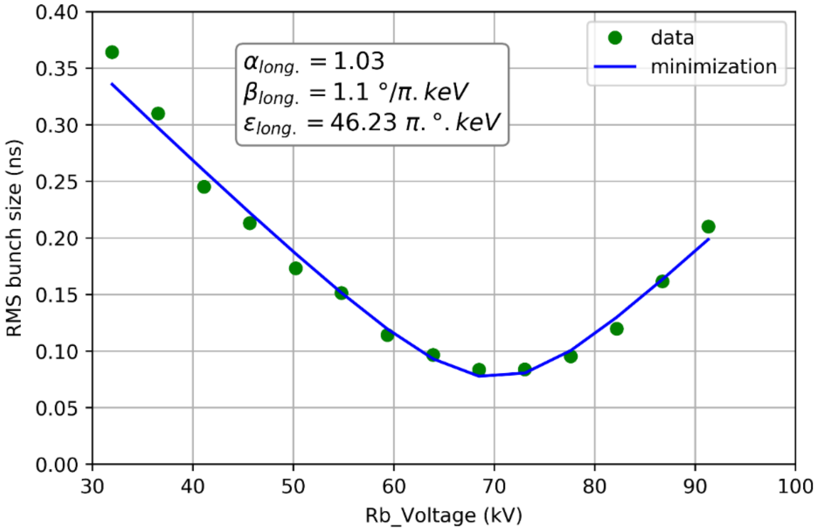
Feb. 21, 2023 at 14:24



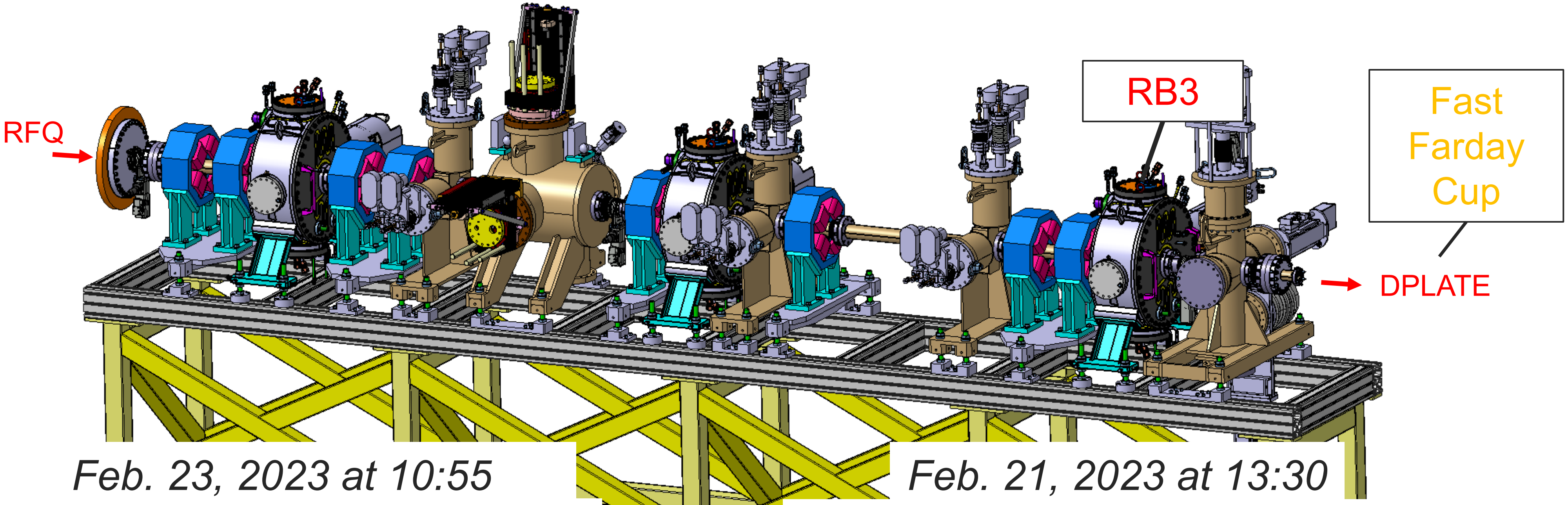
Feb. 21, 2023 at 17:26



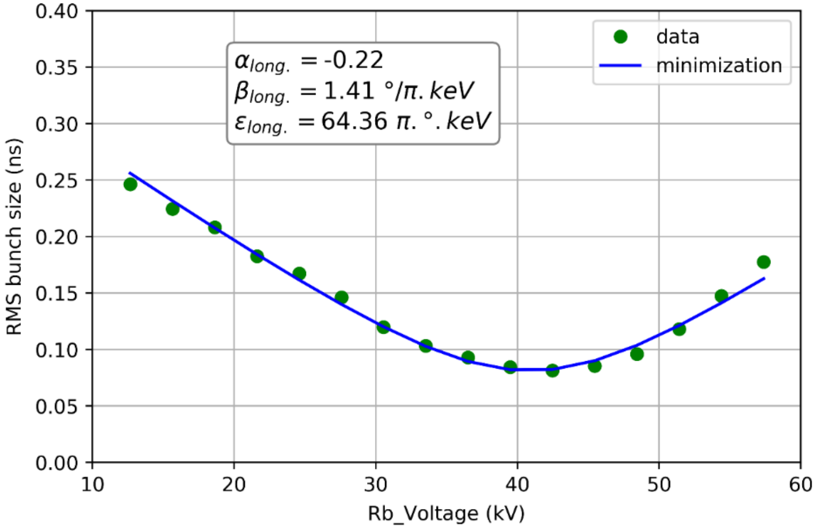
Feb. 23, 2023



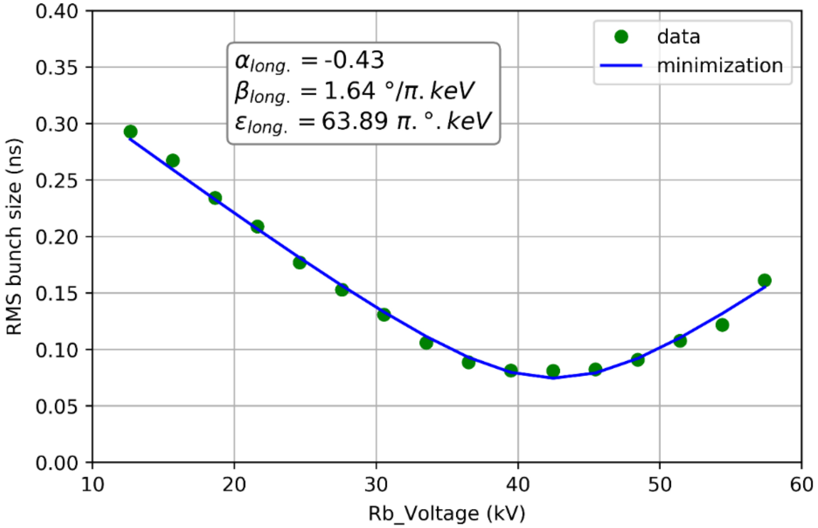
Longitudinal characterization in Dplate (protons)



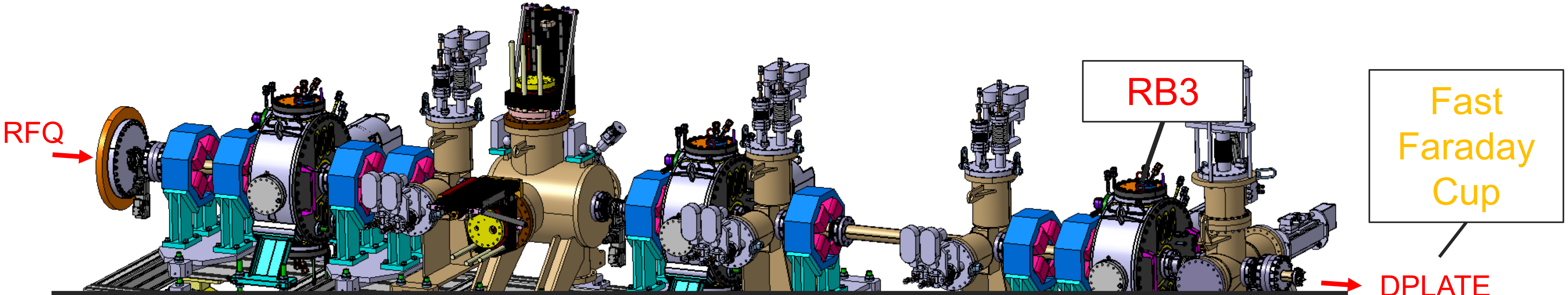
Feb. 23, 2023 at 10:55



Feb. 21, 2023 at 13:30

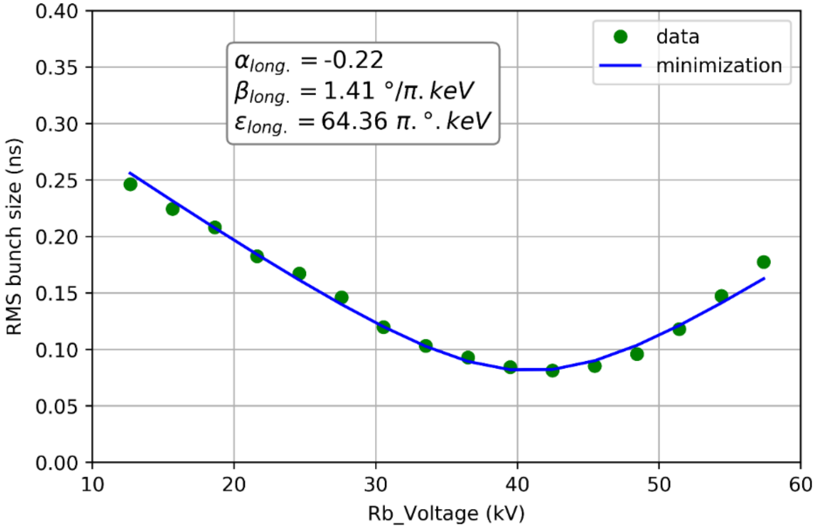


Longitudinal characterization in DB2 (protons)

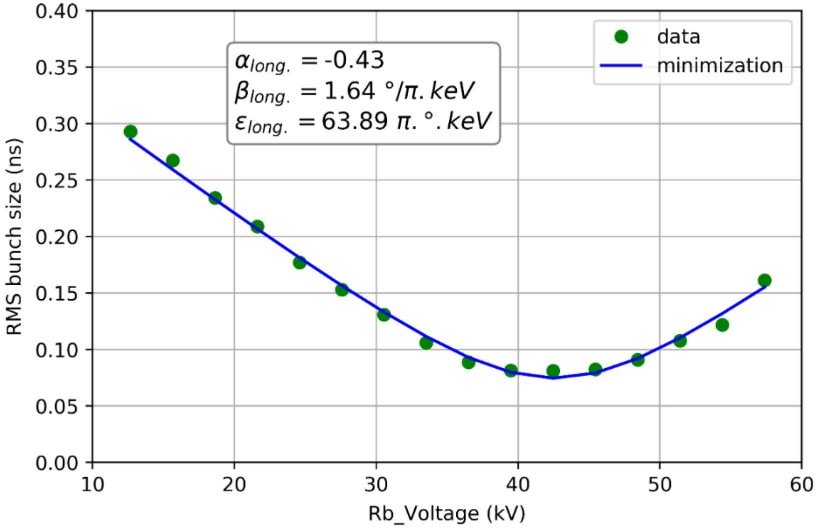


- We observe differences between DB1 (45 π.°.keV) and DB2 (64 π.°.keV) although measurements are very stable

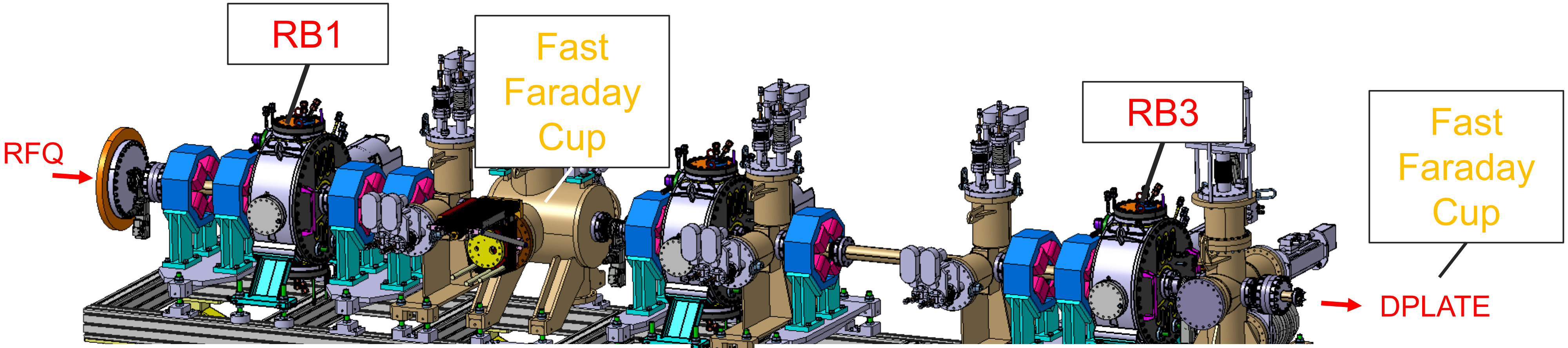
Feb. 23, 2023 at 10:55

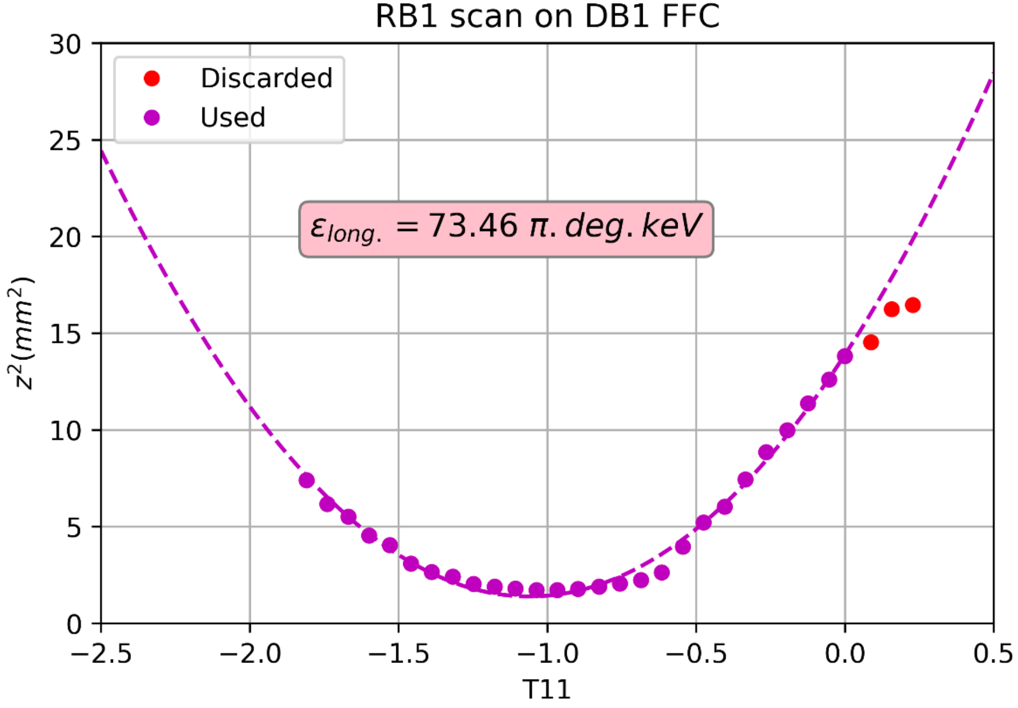


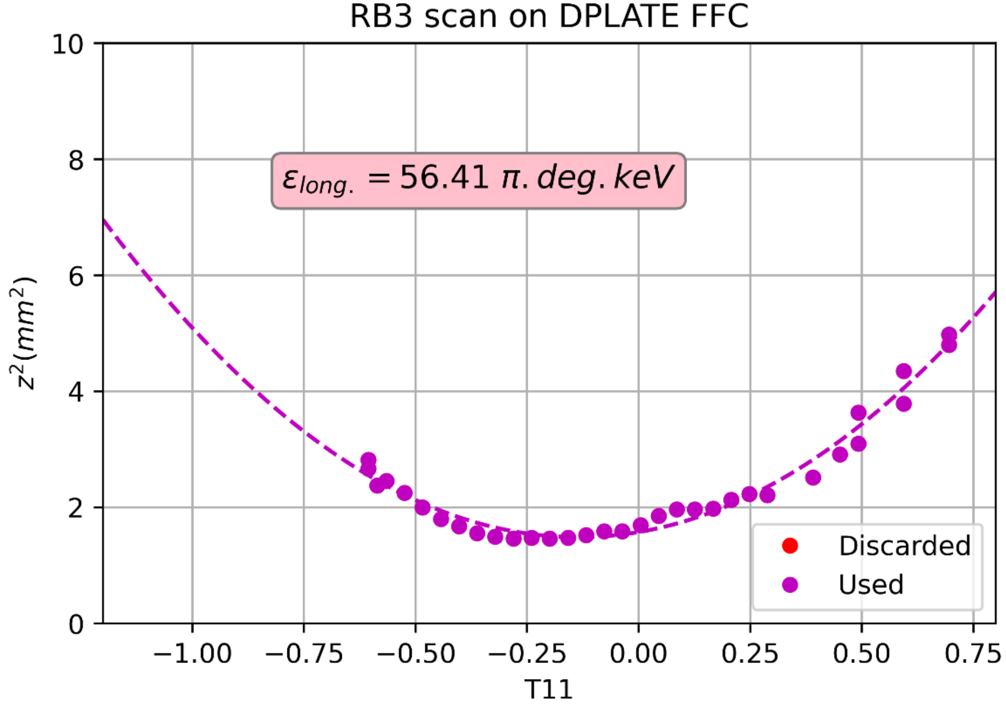
Feb. 21, 2023 at 13:30



Longitudinal characterization (deutons)

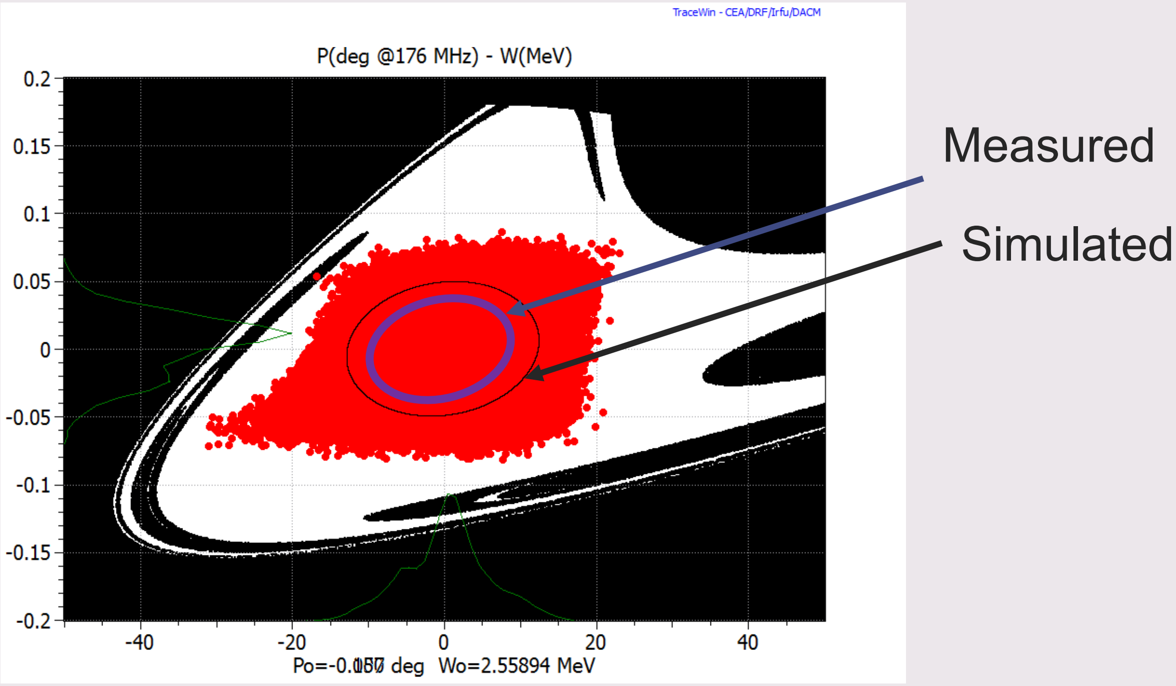




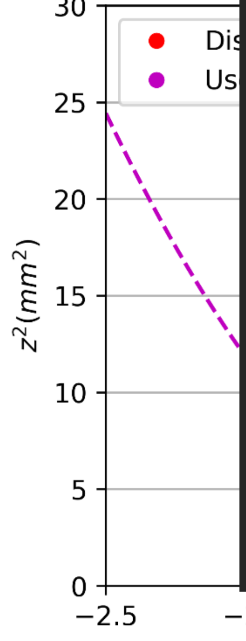


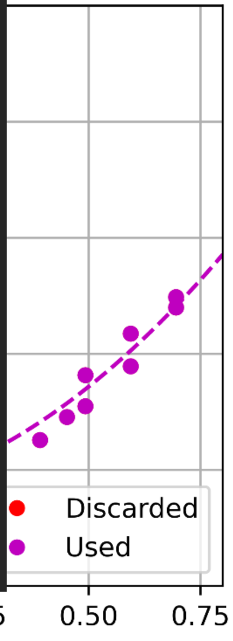
Caractérisation longitudinale (deutons)

- Difference between DB1 and DB2: this time emittance in DB1 > DB2, but…

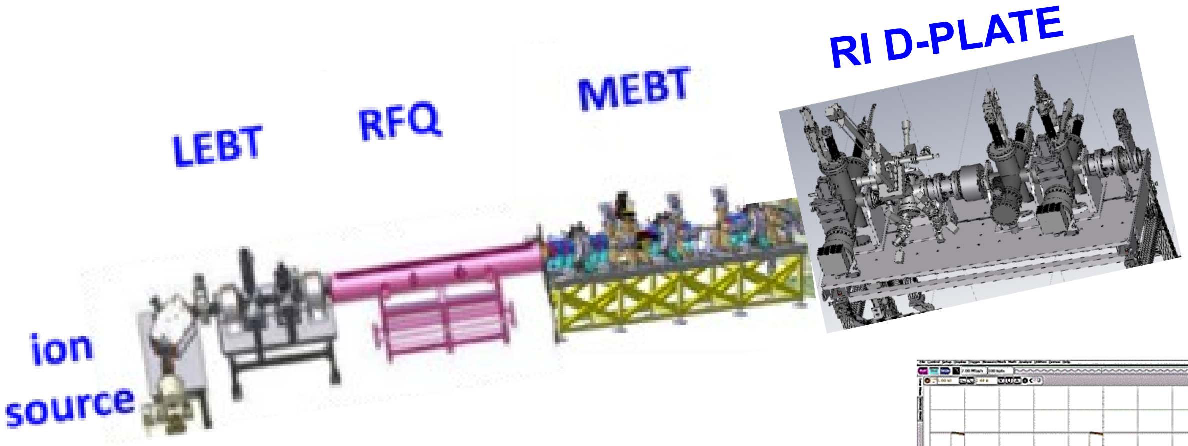


- Even in the worst case, the emittance is twice as small as the one considered in the simulations of the Linac ✓



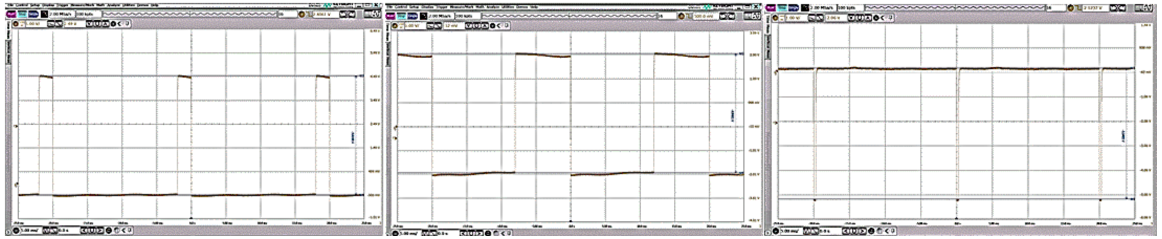


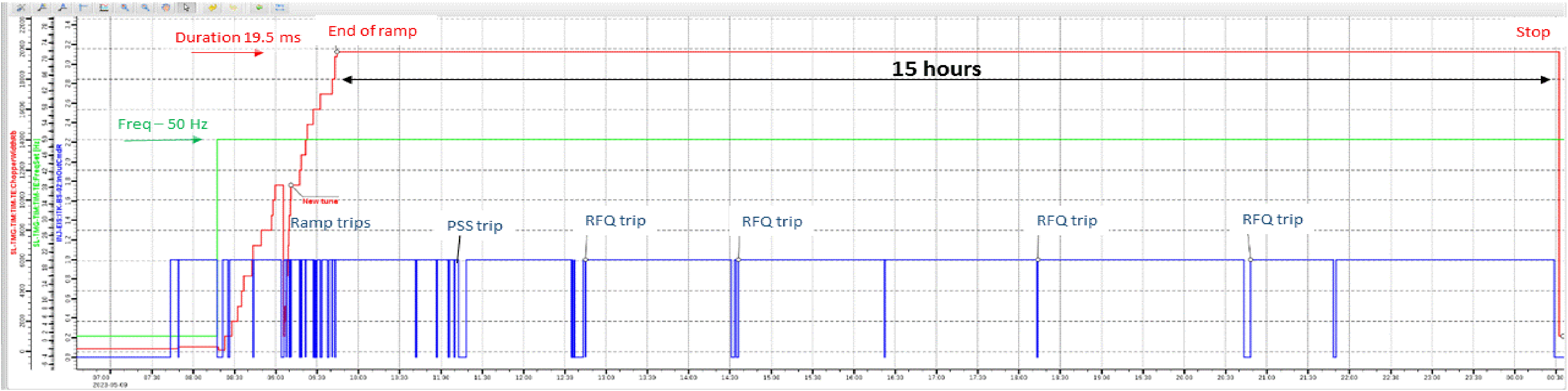
Power ramp up (protons)



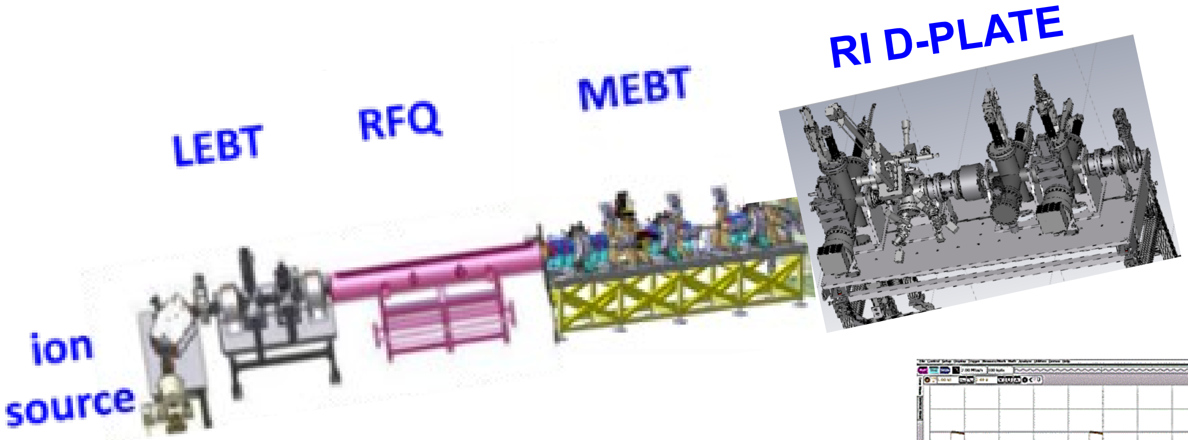
(TBL+GALIT)

ACCT



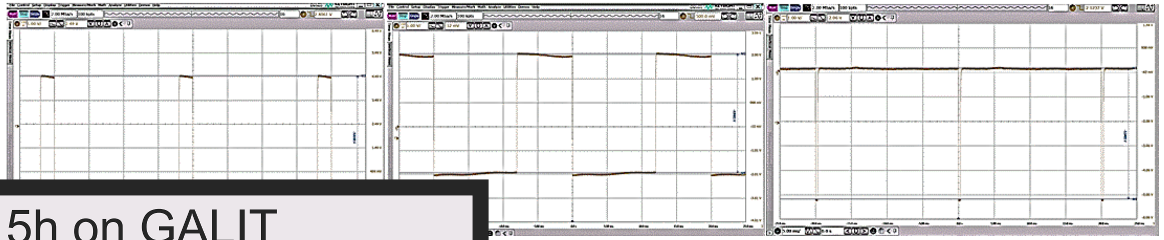


Power ramp up (protons)

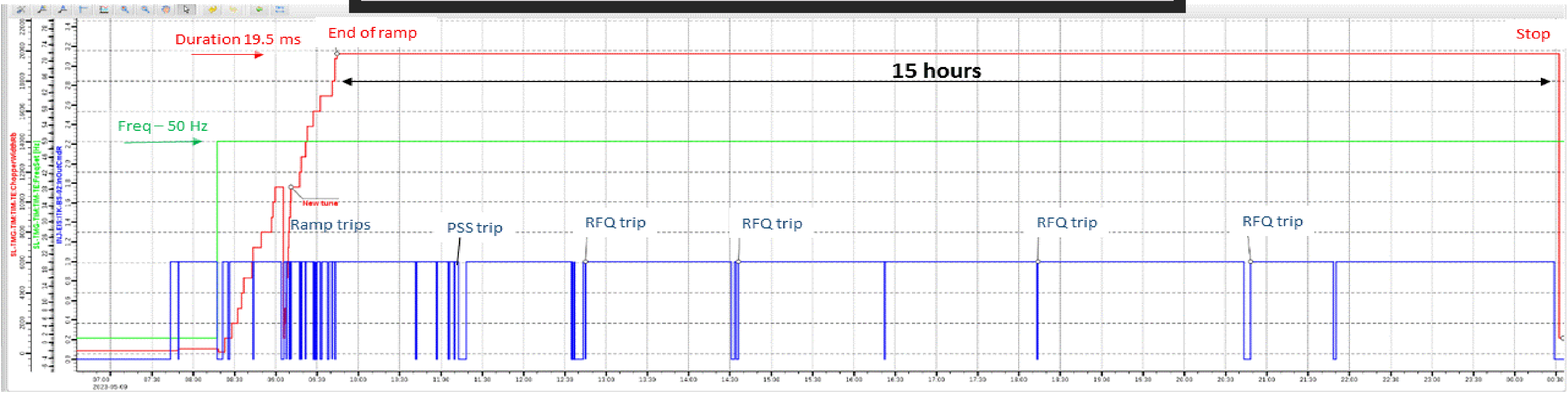


(TBL+GALIT)

ACCT



- 97.5% of duty cycle for 15h on GALIT



■ Machine learning

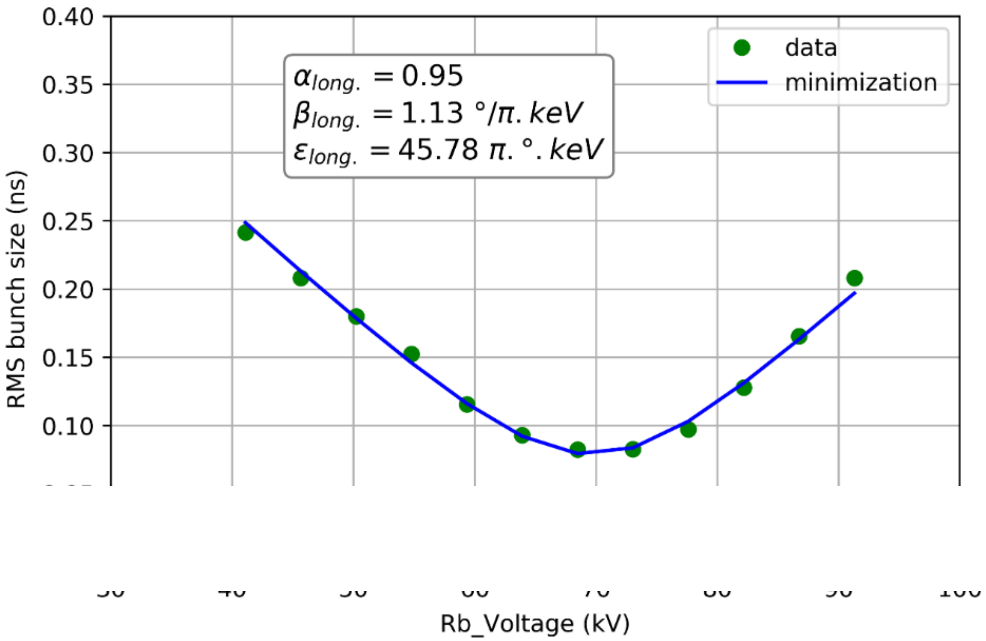
Usual data processing

The usual way to process the experimental data, is to consider “perfect” (possibly after device transfer function deconvolution) beam **measured properties**

Examples: Bunch length…

From these measured properties, one tries to access to other **deduced properties**

Examples: Longitudinal emittance…



Nevertheless :

- The final deduced properties (emittance) are **not exactly those of the beam** (measurement uncertainties)
- They are usually **uncompleted** (dimensions are missing, no correlation…)
- **How to use** the deduced properties to make predictions and associated uncertainties ?

Digital twin

Real world: The linac is operated according to:

- a set of **physical parameters**,
- a set of **control parameters** (IN/OUT Control-System variables).

Examples: Distances, Source voltage, RFQ-peak-up, Power supply currents…

Virtual world: A linac has been designed and is modeled with a **digital twin** made of:

- a **simulation tool** (TraceWIN),
- a set of **model parameters** (SARAF file description).

Examples: Input beam energy, RFQ-Voltage, MEBT-QP1 gradient…

Links between real and virtual worlds:

- The simulation tool models the physics (with possible bugs),
- Each model parameter is linked to one or more control parameters.

Examples: Qpole gradient ↔ PS current…

Adjusting digital twin

During the design and at the start of the machine, links are “estimated” as measured individually on each components, with uncertainties.

*Example: QP1_G = k0 [±dk] * QP1_I, …*

We propose to adjust gradually, experiment after experiment, the links *(k…)* in order to improve the digital twin, using **Bayesian inference** technics (machine learning).

In order to do it, one should be able to:

- Store in a **database** each experimental result and associated machine configuration (installed devices+control parameters),
- **Simulate** the best as possible the results of the experiments,
- Calculate a “**distance**” between experimental and simulated measurements,
- **Adjusting** the best digital twin parameters minimizing the average weighted distance of all experiments and associated uncertainties.

Bayesian method

A : a set of experimental measurements

B : a theory or a set of parameters in the numerical Twin

Simulation of the experimental results

The probability of the parameters after the experiment

$$p(B/A) = \frac{p(A/B)}{p(A)} \times p(B)$$

The probability of the parameters before the experiment

The uncertainties of the experimental measurements

Leading to:

- The best set of parameter set B_{opt} (maximizing $p(B/A)$ or $B_{opt} = \frac{\int p(B/A) \times B \cdot dB}{\int p(B/A) \cdot dB}$)
- The uncertainties on the parameters : $V_B = \frac{\int p(B/A) \times B \times B^* \cdot dB}{\int p(B/A) \cdot dB}$

Bayesian method - incremental

A_n: a new set of experimental measurements (after A_{n-1})

$$p(B/A_n) = \frac{p(A_n/B)}{p(A_n)} \times p(B/A_{n-1})$$

$$\rightarrow \qquad p(B/A_n) = \prod_{i=1}^{n} \frac{p(A_i/B)}{p(A_i)} \times p_0(B)$$

- The numerical twin can then be « adjusted » experiment after experiment.

- If needed, all the experiments can be processed again.

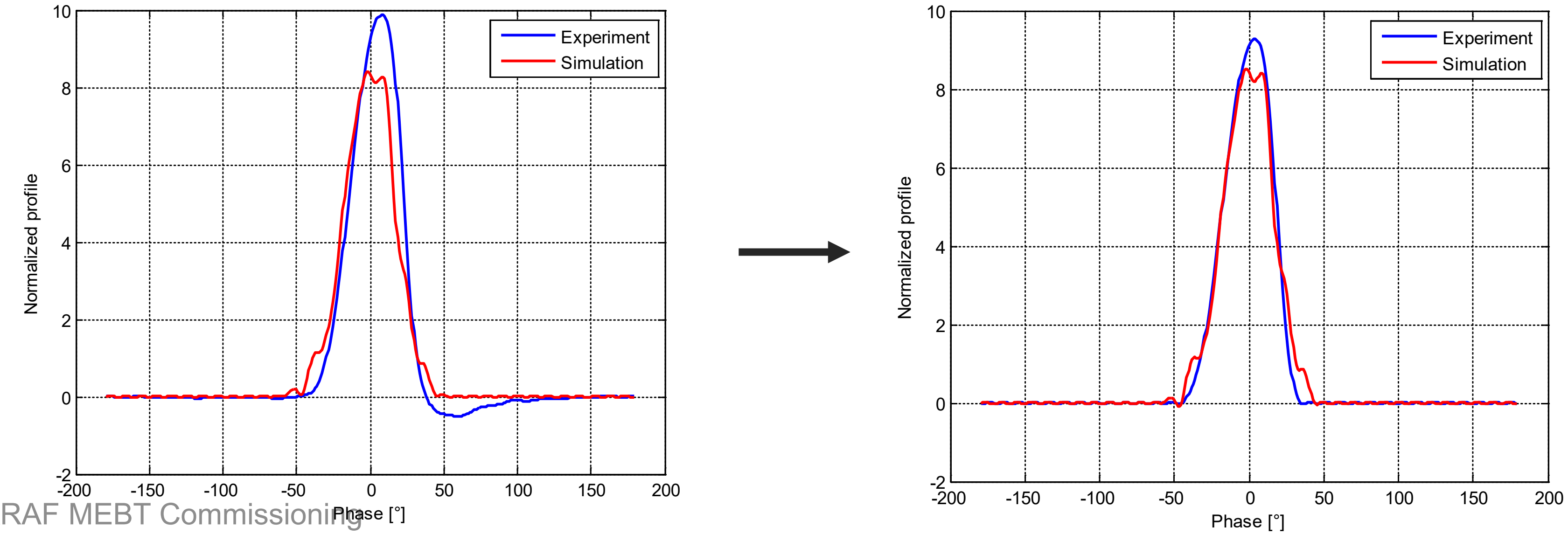
- New parameters can be added without losing what has been learned on other parameters.

- Analysing deviant experimental results, one can:
  - Either improve measurement understanding (badly simulated)
  - Or improve linac model (missing parameters)
  - …

Longitudinal emittance : improving model

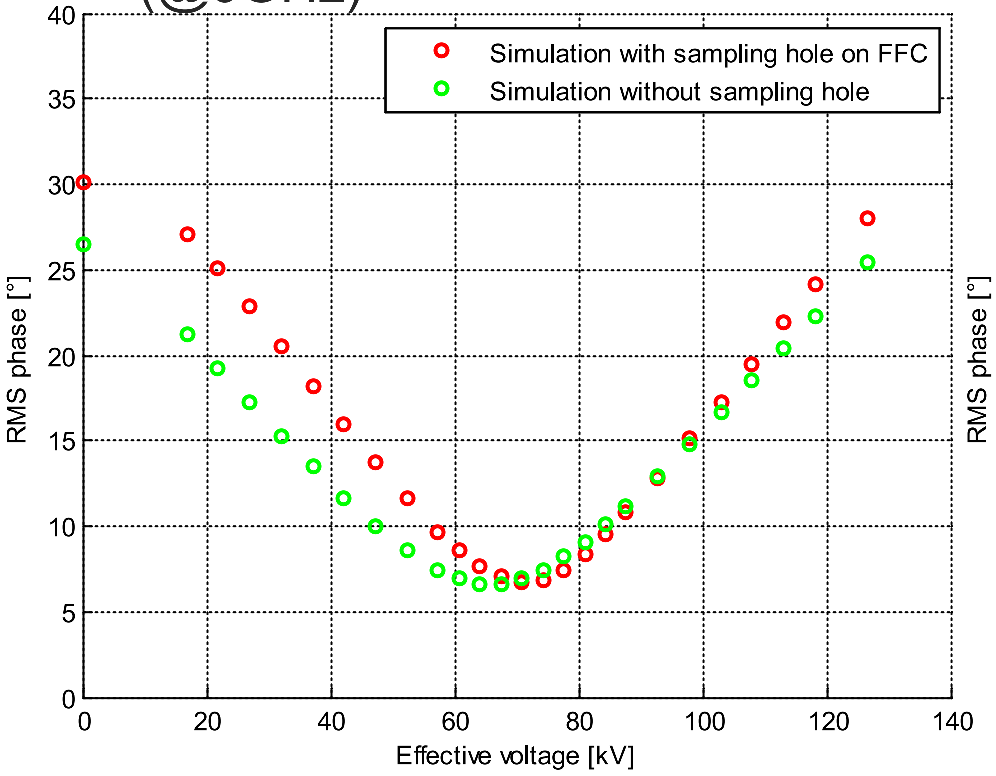
- FFC **pinhole** of 0.5 mm radius
  - → only a fraction of the beam is measured
- The profiles are noisy and experimental profiles have **negative “bounce”**
  - → This can be simulated or at least smoothed
- **Scope Bandwidth** of 6Ghz
  - → Possible resolution limitation → can be simulated

→ A simulation of the measurement is applied to the simulated beam
→ Experiment and simulated experiments can be compared

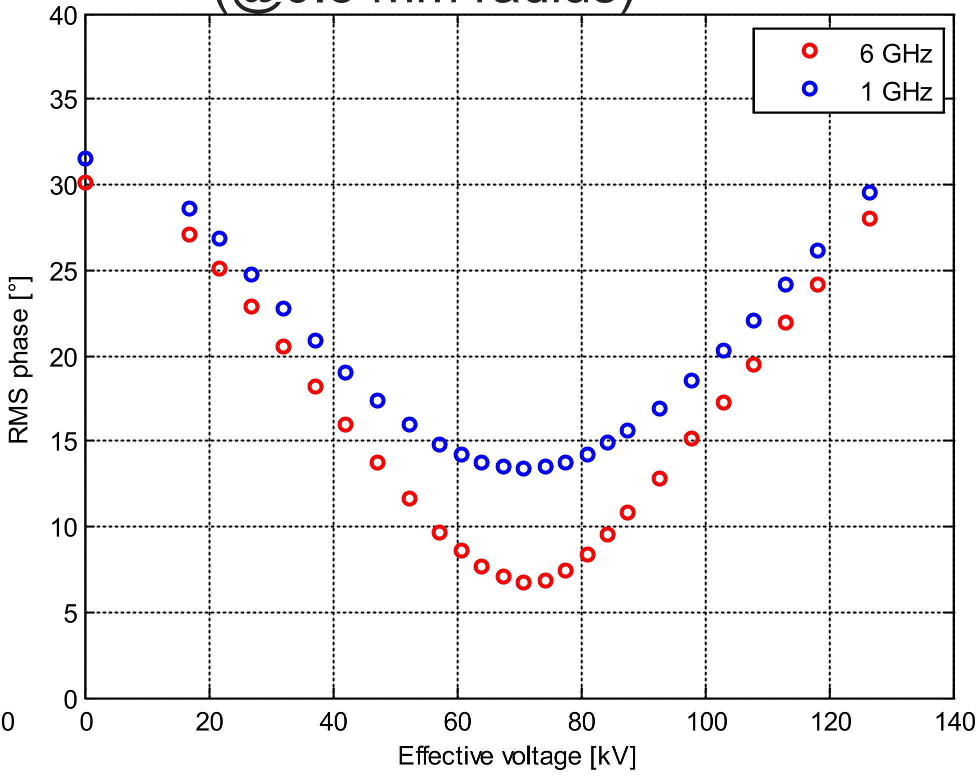


Example of exp. conditions simulation

- FFC pinhole of 0.5 mm radius (@6GHz)

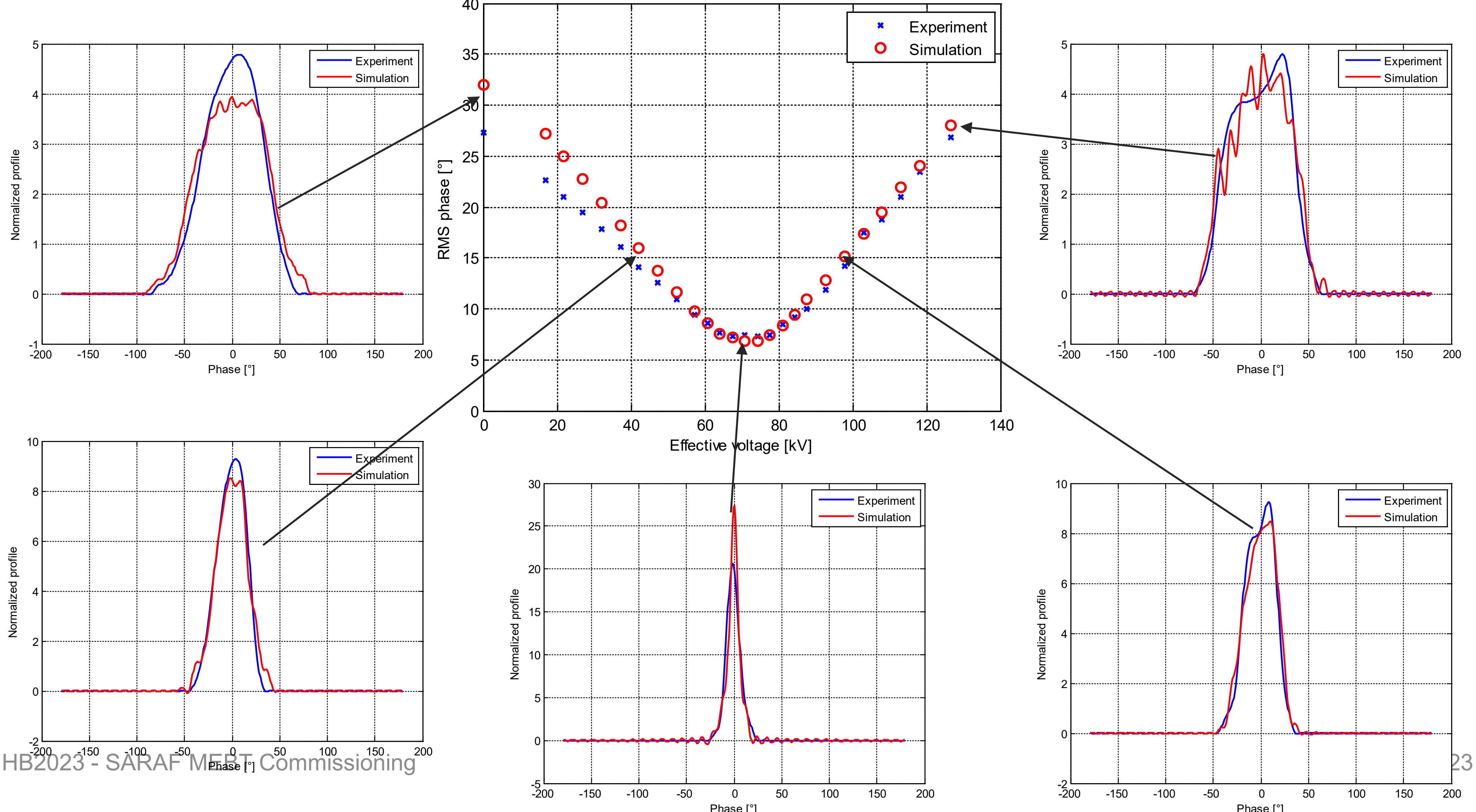


- Oscilloscope bandwidth (@0.5 mm radius)



Longitudinal emittance : Improving model

- Remarkable agreement between simulations (TraceWin) and experiments (no parameter change)
- Iterative process with new beam/beamline characterization (RFQ, transverse emittance…)



Little story

When doing **the transverse emittance measurements** (Quad scan) of the 5 mA proton beam, one remarked that the experiment results were **very different** from the numerical twin predictions.

Strategy 1: We could have kept the experiment result “as reality” and have considered that the beam transverse parameters were not “as expected”, trying to implement them in the code.

Strategy 2: Nevertheless, using this “machine learning” philosophy, we observed that the experimental results were much better reproduced by considering an increasing of the focusing force by about +20% (much more that estimated initial uncertainties of a few %).

→ Finally, checking the Control-System, one founds out that **there was a mistake on the G_QP/I_QP parameter by +18%** (wrong magnetic length was used) !

By using strategy 1, one could have **resolved the incoherence** between code and measurement by compensating two errors (one on the initial distribution, one in Qpole gradients). Nevertheless, this would have produced **new incoherence with other MEBT configurations (**deuterons, current…)

Using strategy 2 allowed us to improve our machine knowledge **for all configurations**.