

### **SARAF MEBT commissioning**

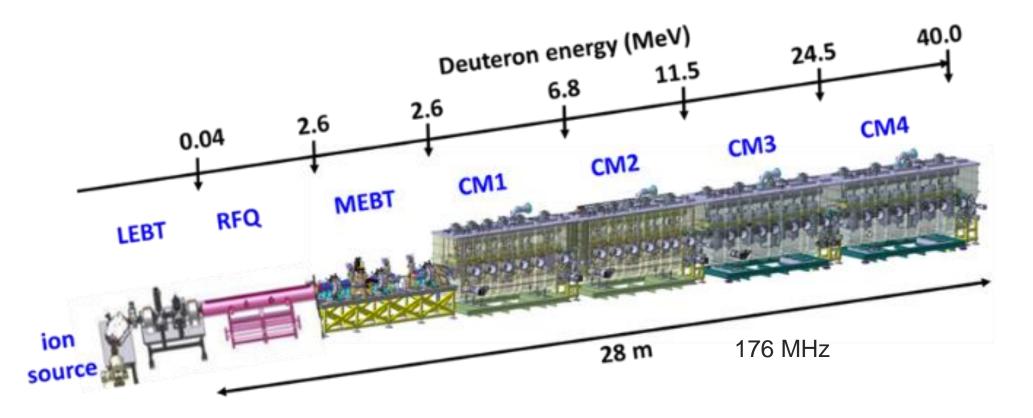
CEA-IRFU - J. Dumas, <u>N. Pichoff</u>, A. Chance, F. Gougnaud, F. Senée, D. Uriot SNRC - A. Kreisel, J. Luner, A. Perry, E. Reinfeld, L. Weissman





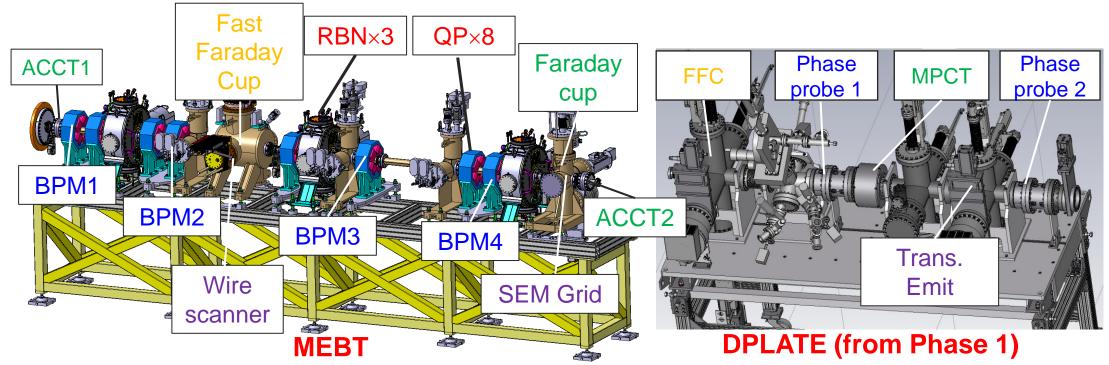
#### **The SARAF LINAC**

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





#### **The SARAF MEBT**



- 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...

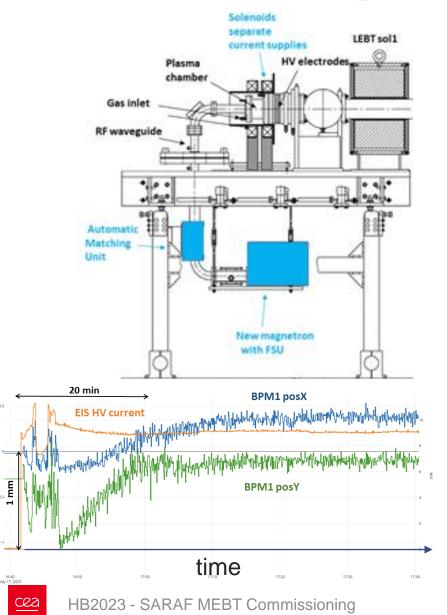


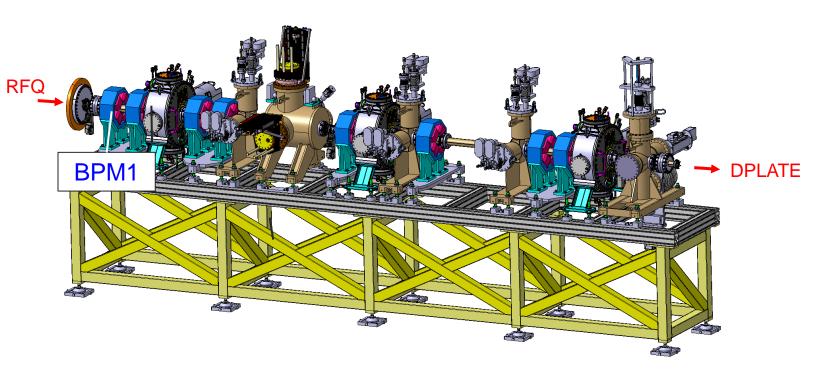


# Machine Tuning

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#### **EIS - Warm-up**

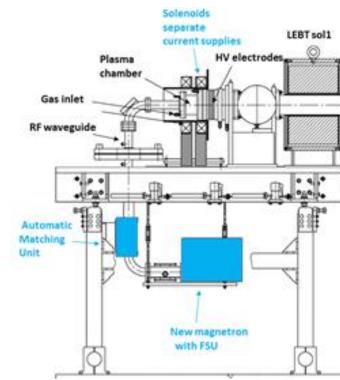


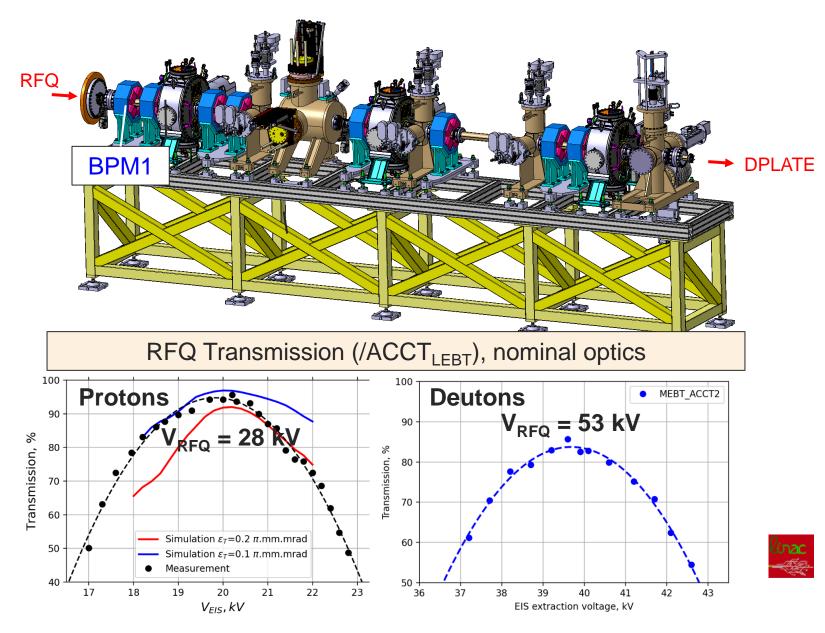


#### 20 minutes are needed after EIS switch ON for a stable beam out of the RFQ

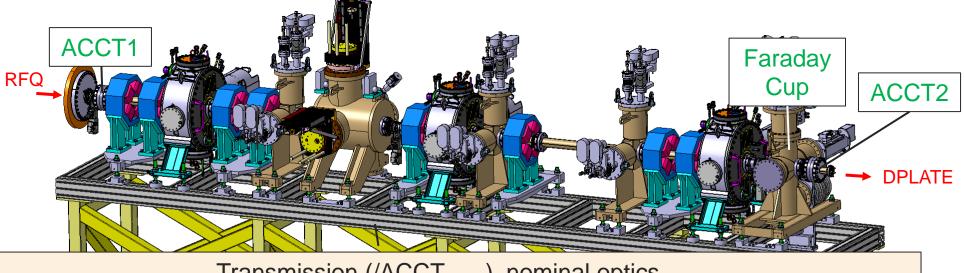


#### **EIS - Voltage tuning (to RFQ)**

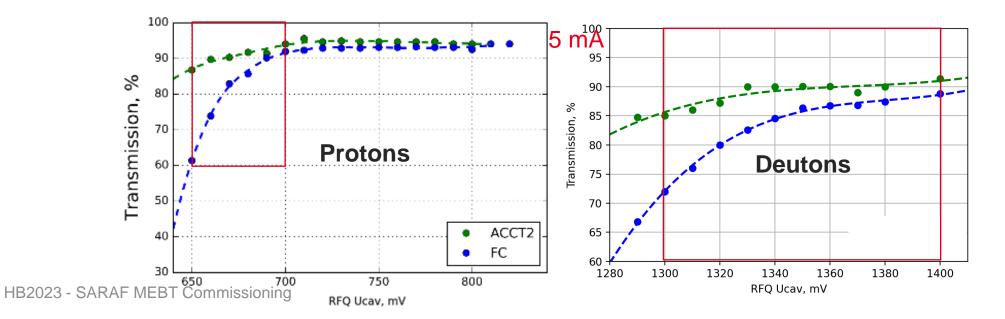




#### **RFQ and MEBT transmission measurements**

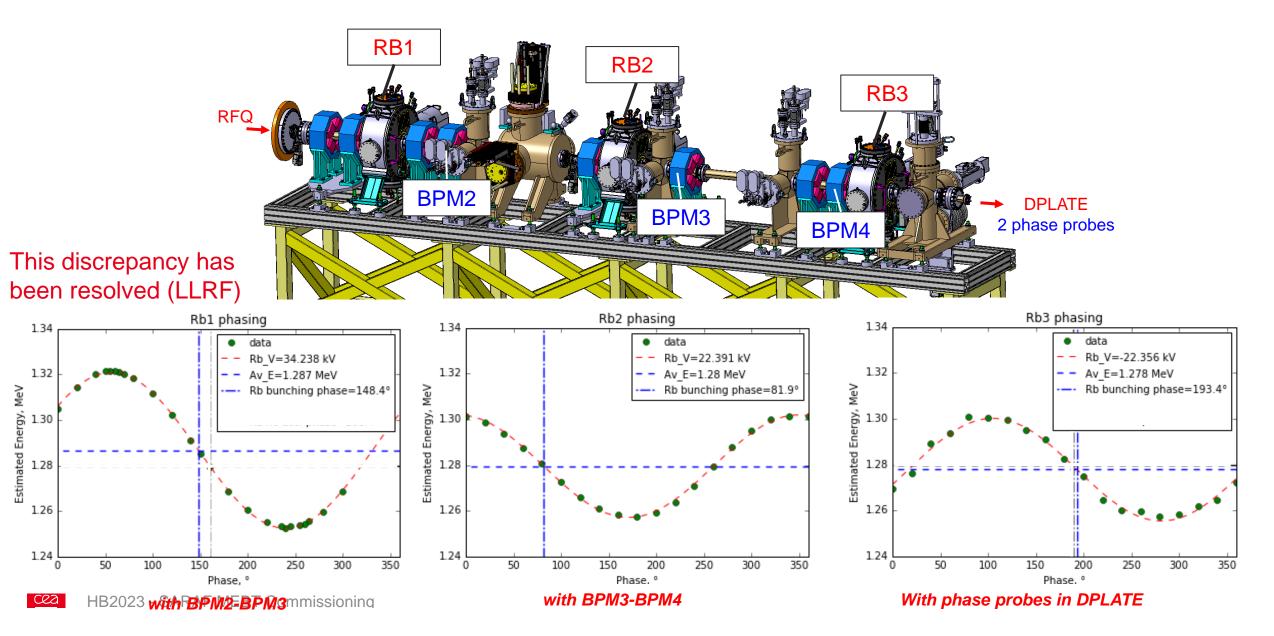


Transmission (/ACCT<sub>LEBT</sub>), nominal optics



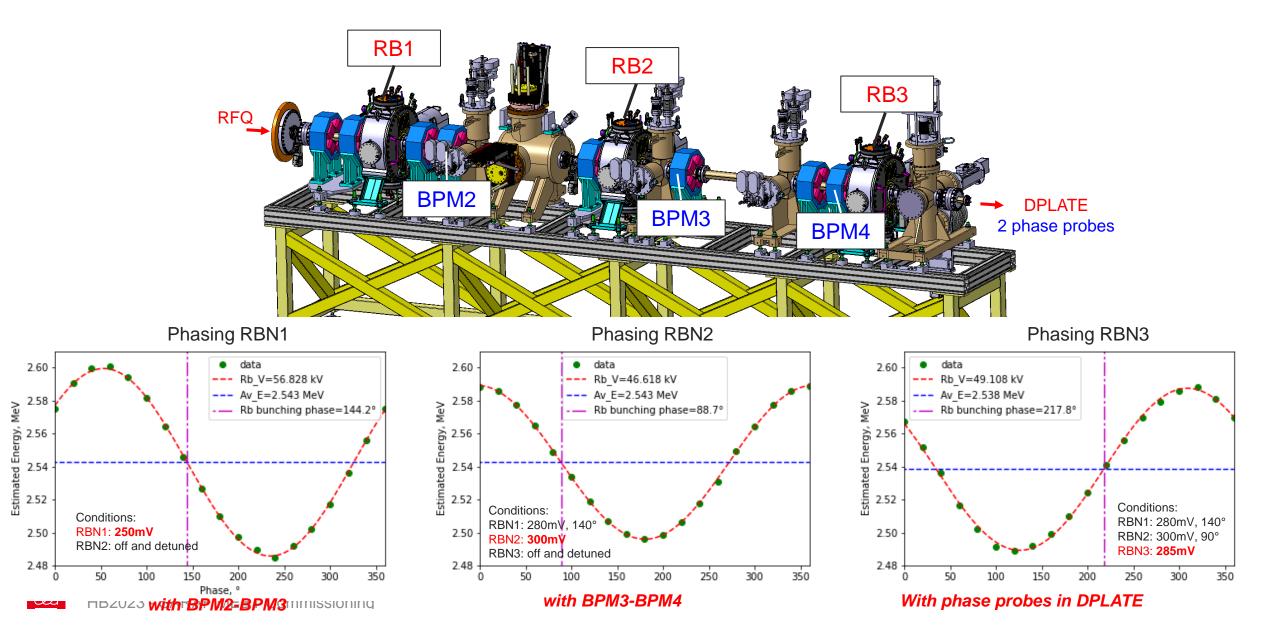


### **Rebuncher calibration (protons)**



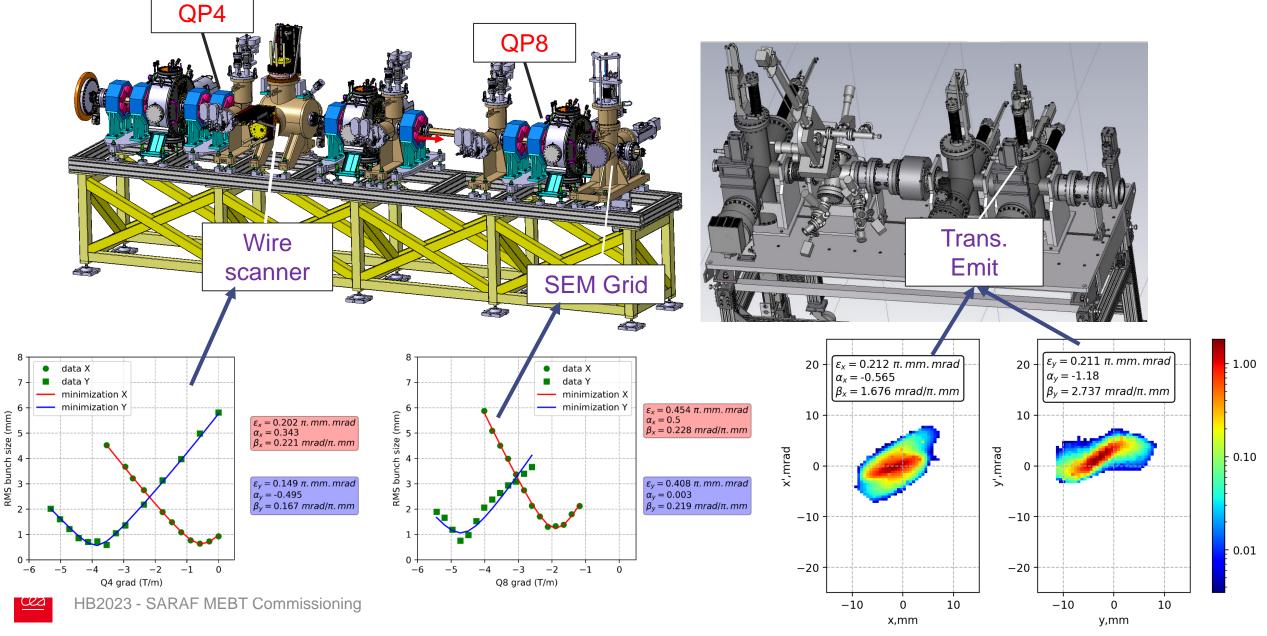
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#### **Rebuncher calibration (deutons)**

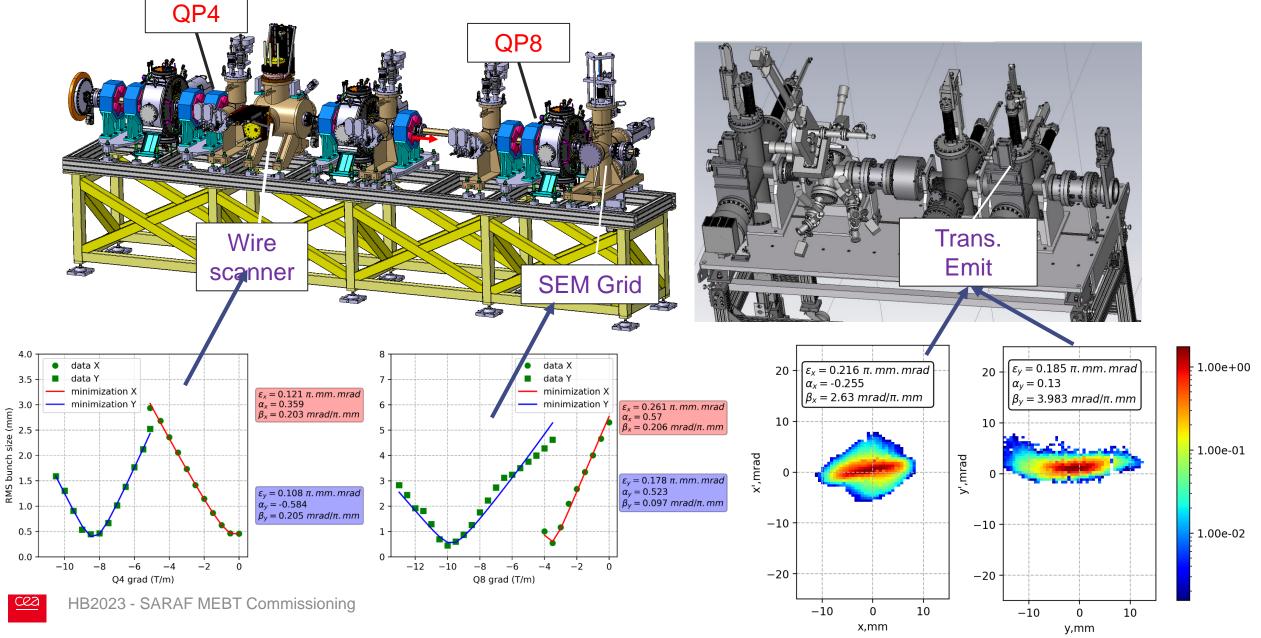




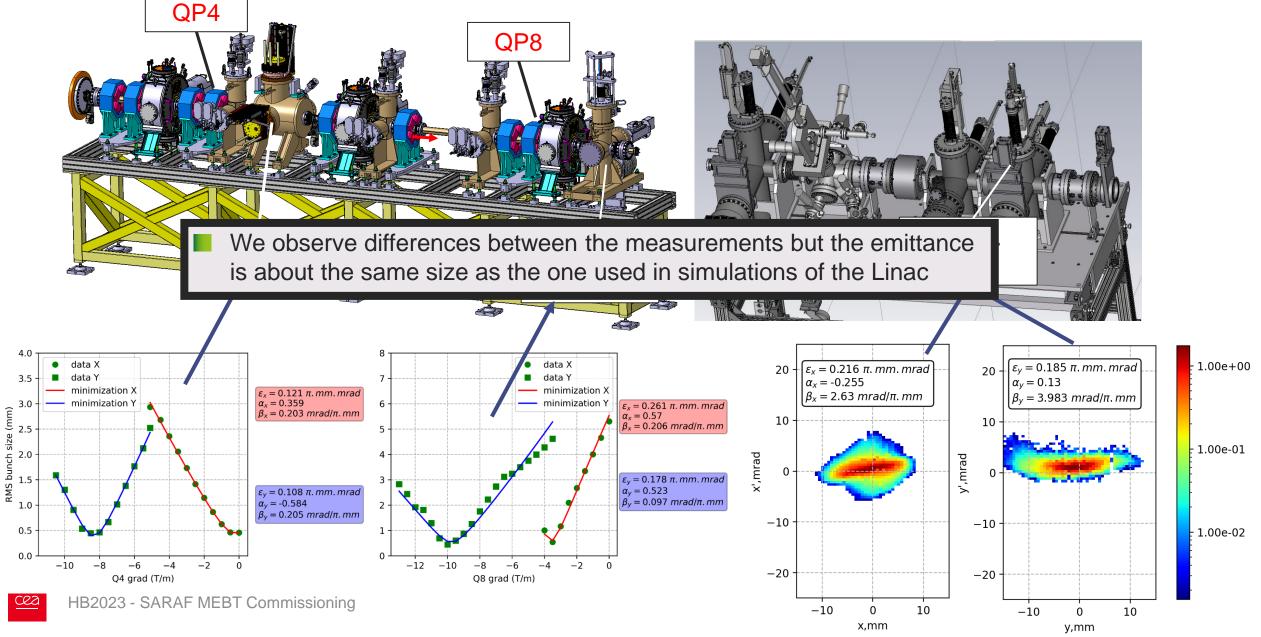
#### **Transversal characterization (protons)**



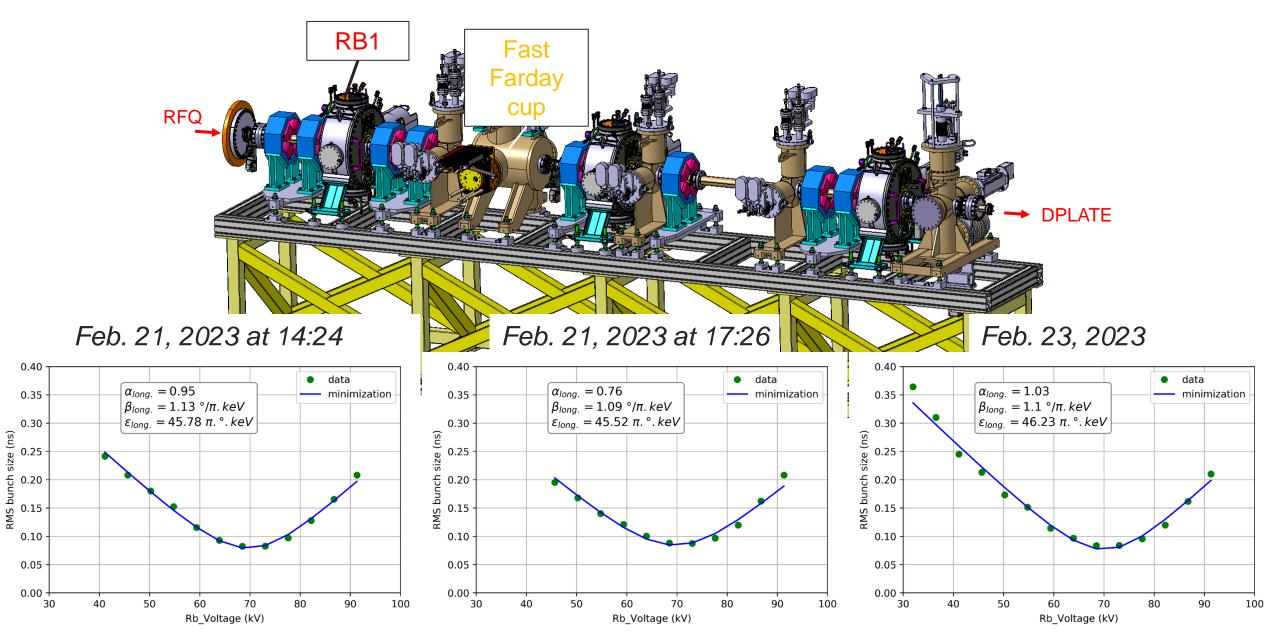
#### **Transversal characterization (deutons)**



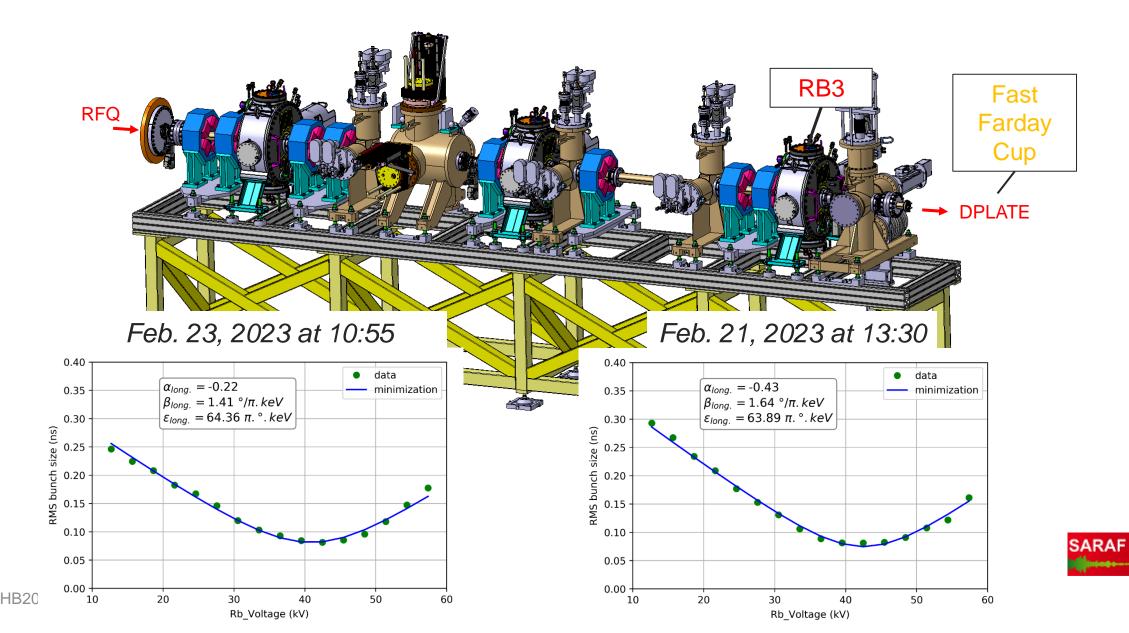
#### **Transversal characterization (deutons)**



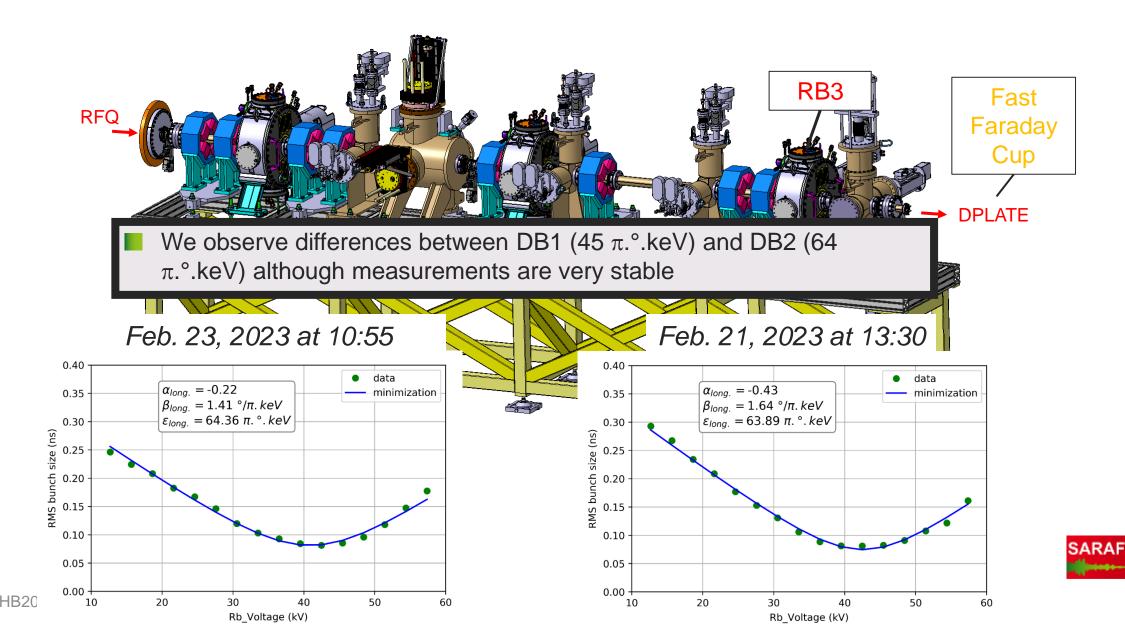
#### Longitudinal characterization in DB1 (protons)



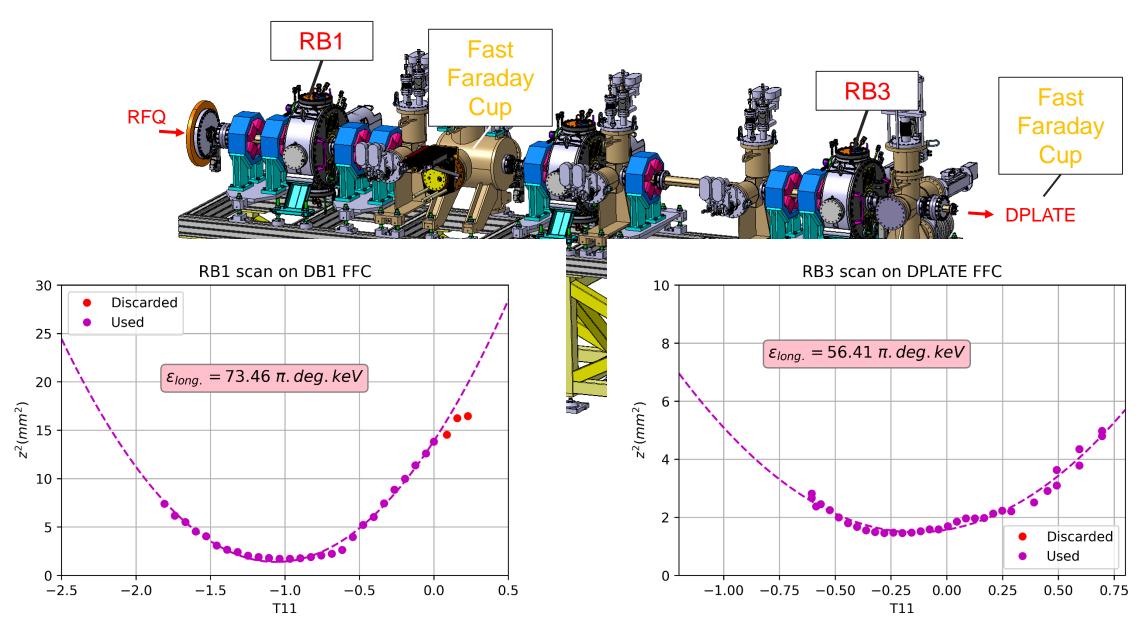
#### Longitudinal characterization in Dplate (protons)



#### Longitudinal characterization in DB2 (protons)

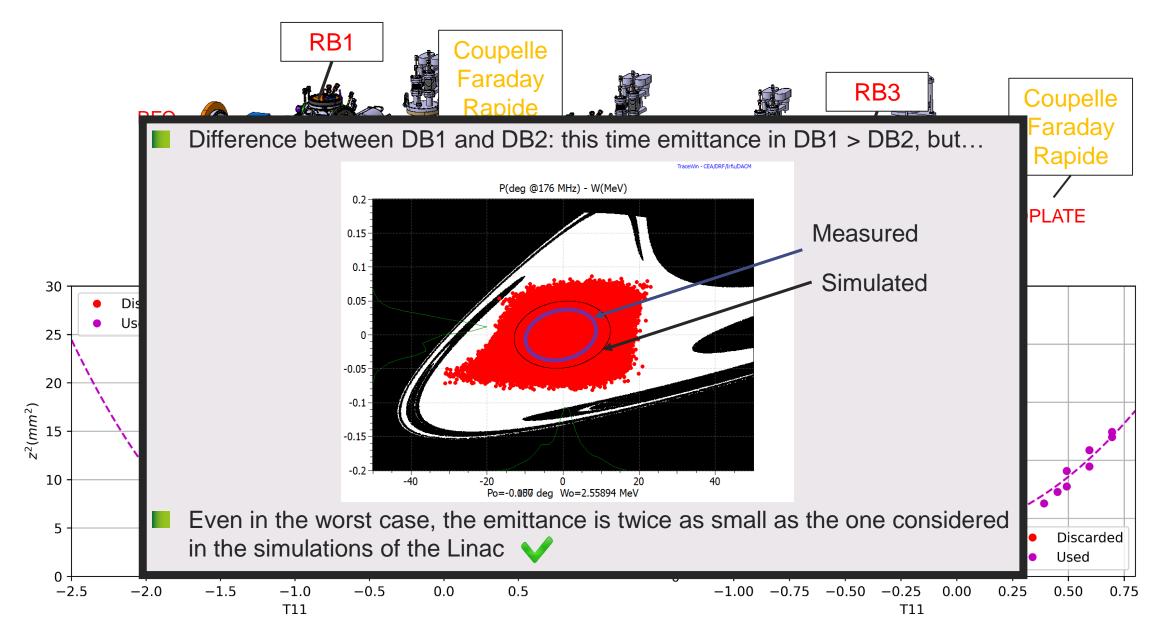


#### **Longitudinal characterization (deutons)**





#### **Caractérisation longitudinale (deutons)**



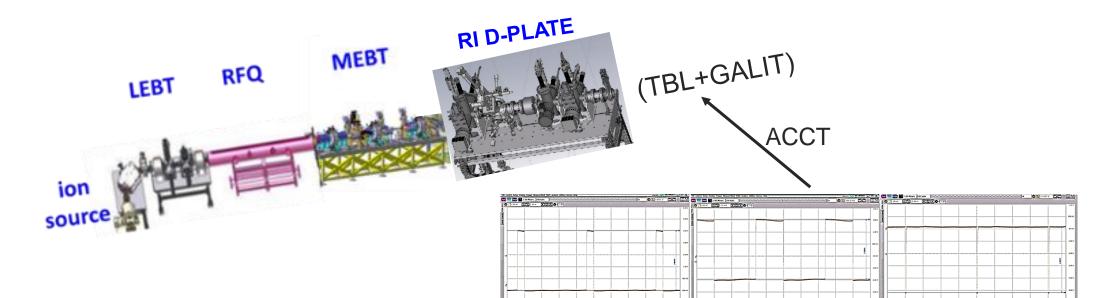


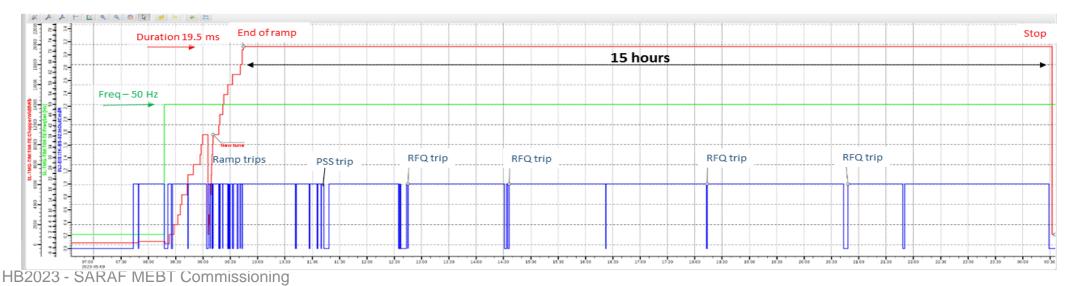


SARAF

linac

#### **Power ramp up (protons)**

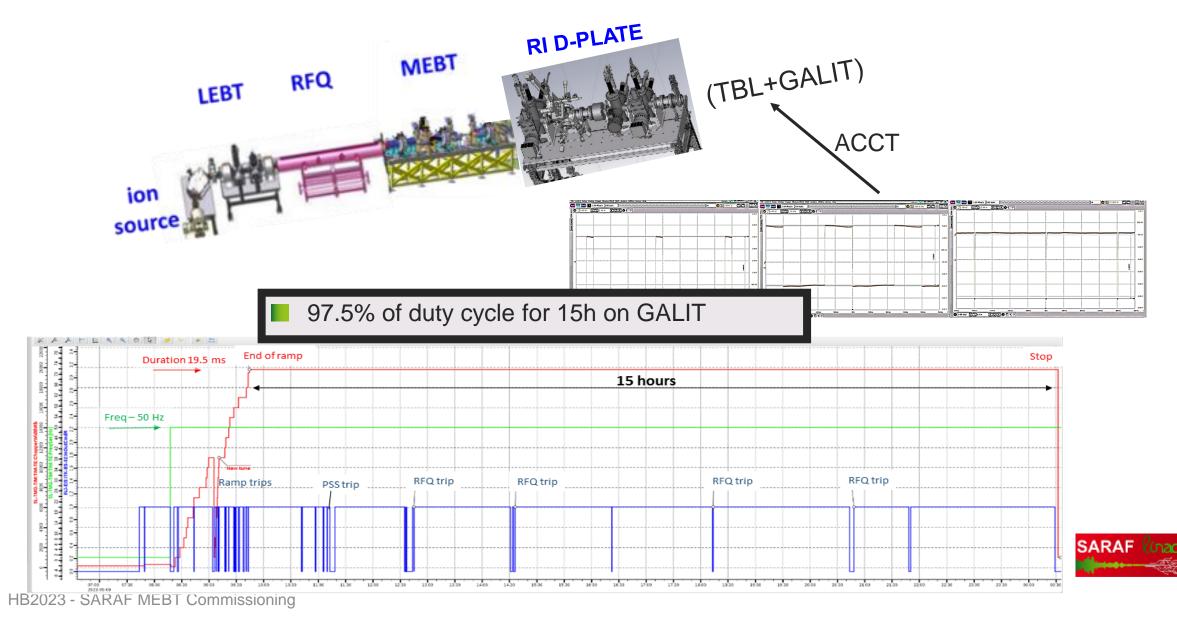




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#### **Power ramp up (protons)**





# Machine learning

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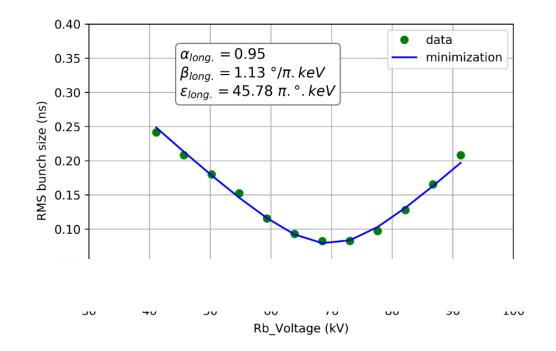
### **Usual data processing**

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

<u>Examples</u>: Bunch length...

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

<u>Examples</u>: 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).

<u>Examples</u>: 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).

<u>Examples</u>: 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.
   <u>Examples</u>: 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.

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<u>Example</u>: QP1_G = k0 [±dk] * QP1_I, ...
```

We propose to adjust gradually, <u>experiment after experiment</u>, the links (k...) in order to improve the <u>digital twin</u>, 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 <u>after</u> the experiment

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

The probability of the parameters <u>before</u> 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  $A_{n-1}$ )

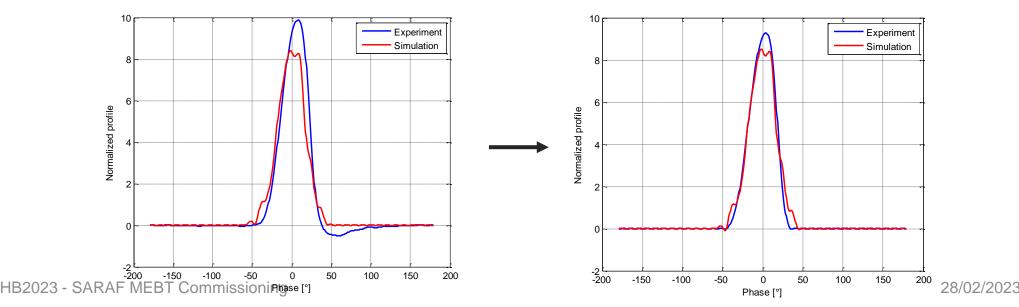
$$p(B/A_n) = \frac{p(A_n/B)}{p(A_n)} \times p(B/A_{n-1})$$

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

- 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)

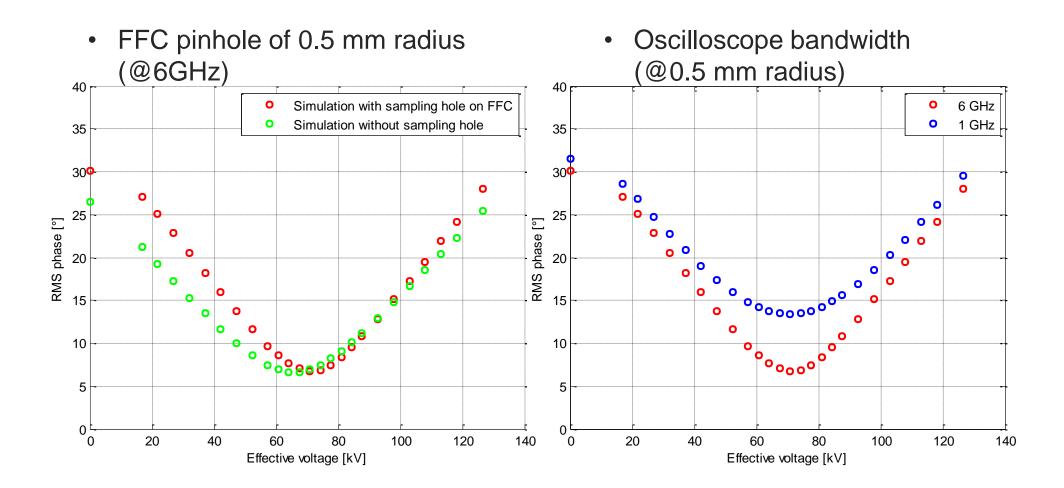
#### Longitudinal emittance : improving model

- FFC pinhole of 0.5 mm radius
  - $\rightarrow$  only a fraction of the beam is measured
- The profiles are noisy and experimental profiles have negative "bounce"
  - $\rightarrow$  This can be simulated or at least smoothed
- Scope Bandwidth of 6Ghz
  - $\rightarrow$  Possible resolution limitation  $\rightarrow$  can be simulated
- $\rightarrow$  A simulation of the measurement is applied to the simulated beam  $\rightarrow$  Experiment and simulated experiments can be compared



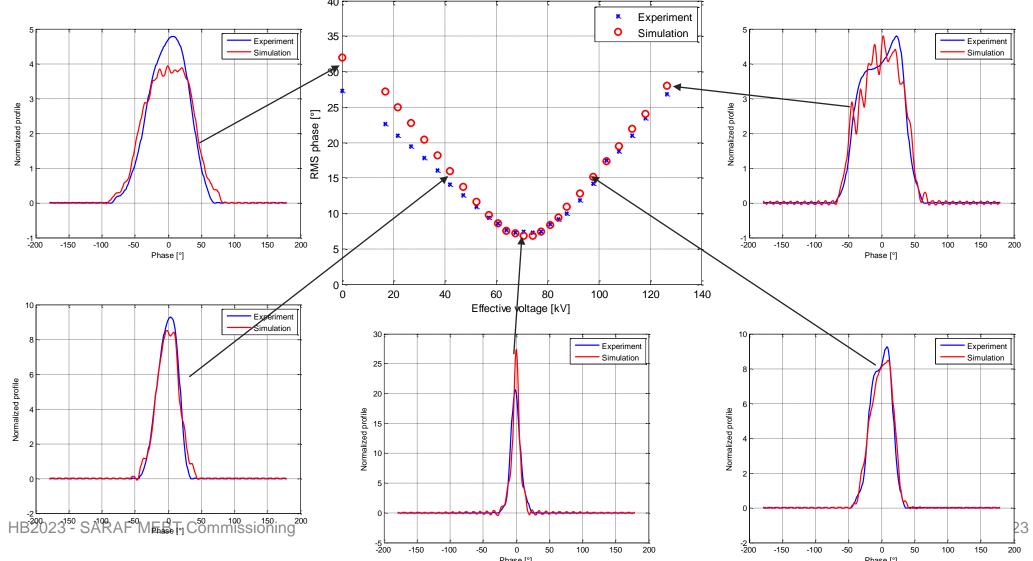


#### **Example of exp. conditions simulation**



### **Longitudinal emittance : Improving model**

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



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#### **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.

<u>Strategy 1</u>: 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.

<u>Strategy 2</u>: 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 <u>strategy 1</u>, 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.

