



Training of a neural network to model the MYRRHA LEBT for reliability improvements

Presented by Mathieu Debongnie

PhD Student ACS/LPSC

Introduction

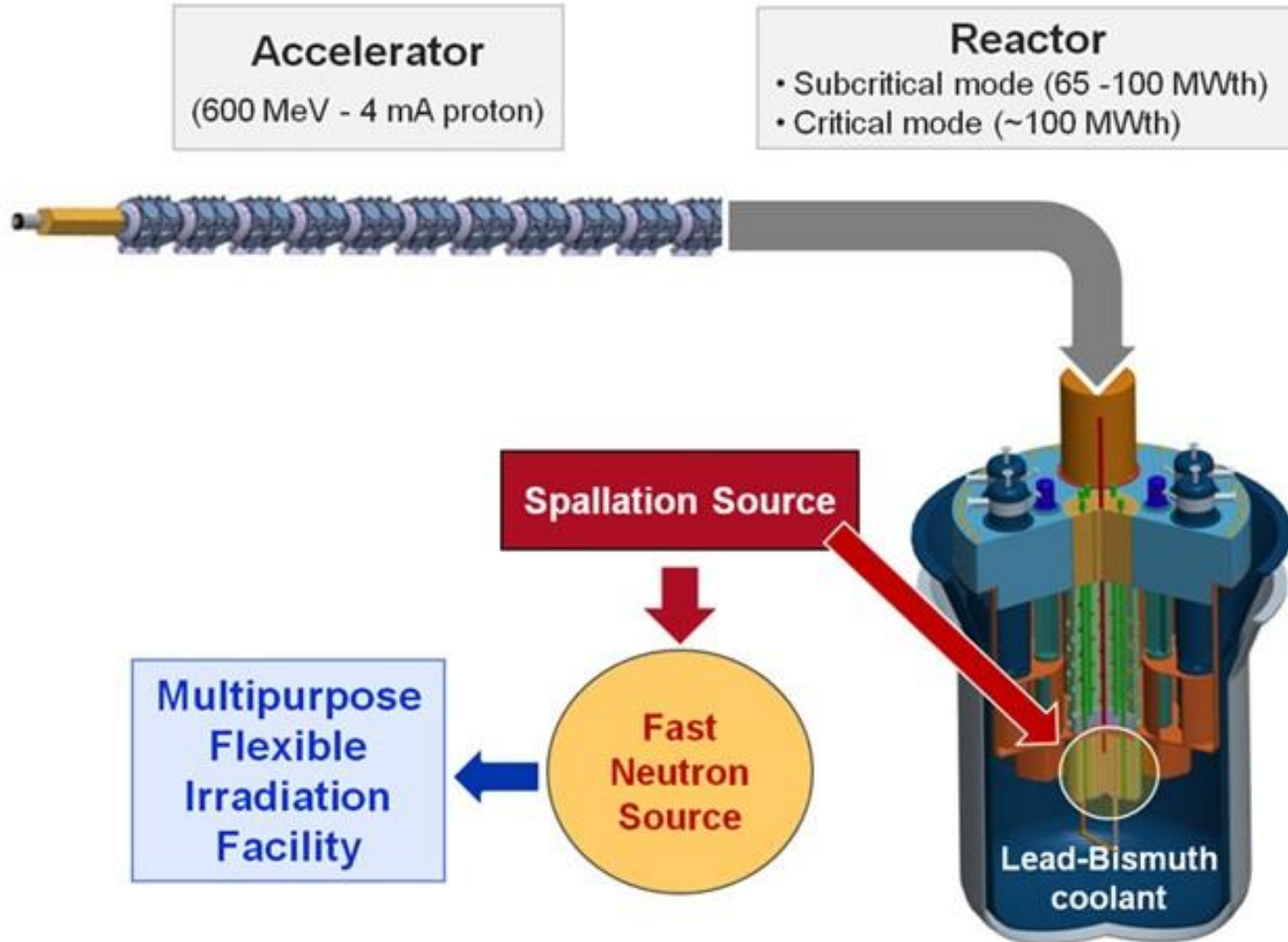
- The MYRRHA project
- Low energy beam transport line

Machine learning

- Training databases
- Network performances
- Transferability

Conclusion & Prospects

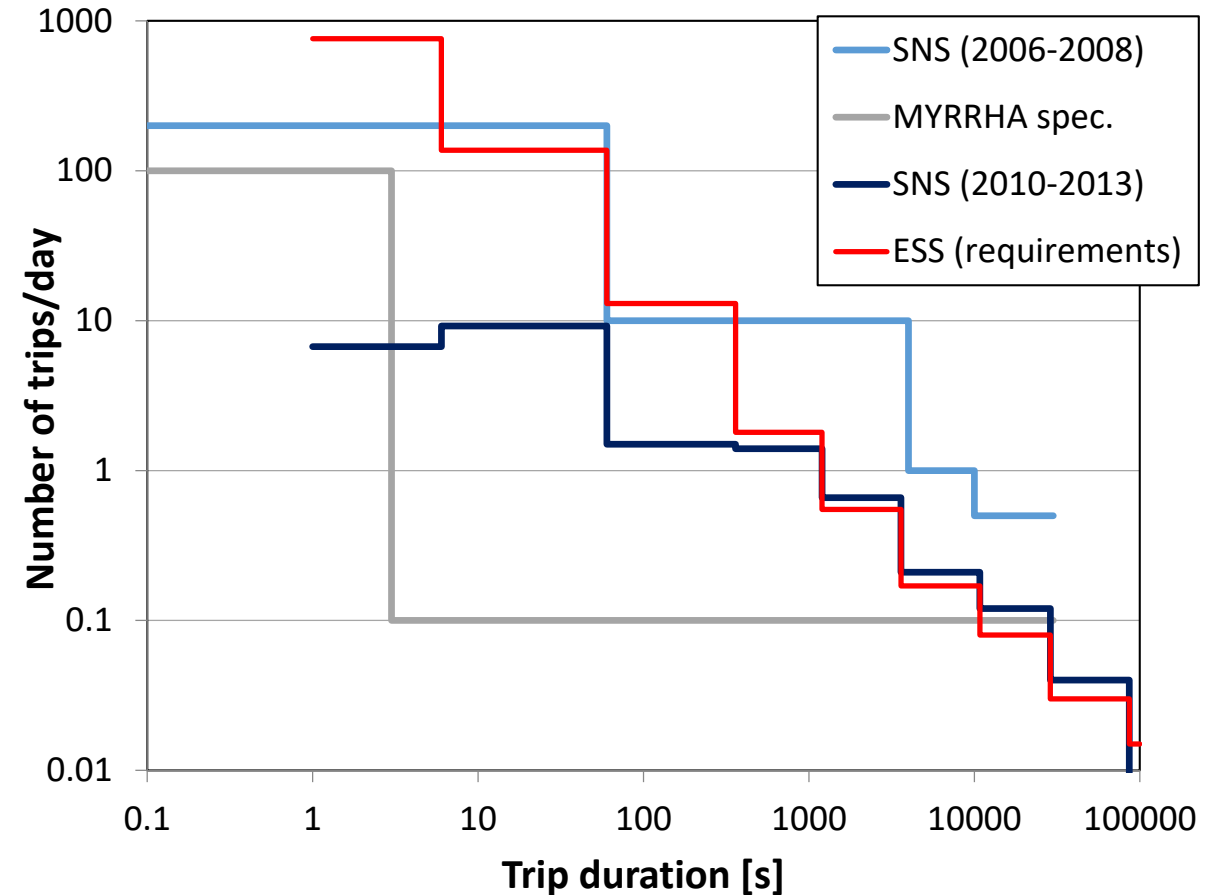
Multi-purpose hYbrid Research Reactor for High-tech Applications



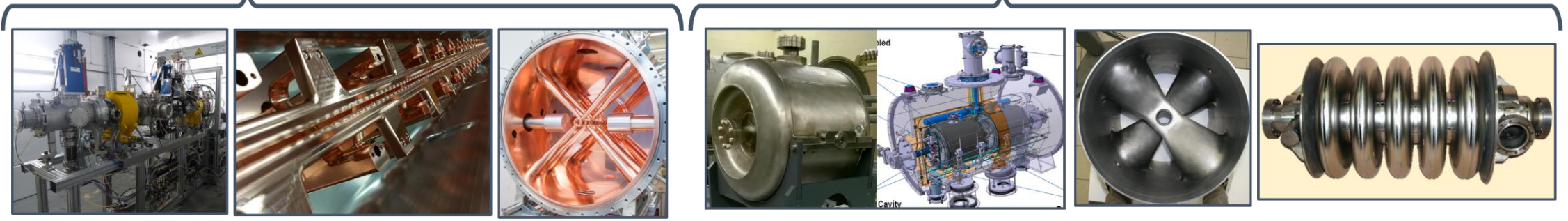
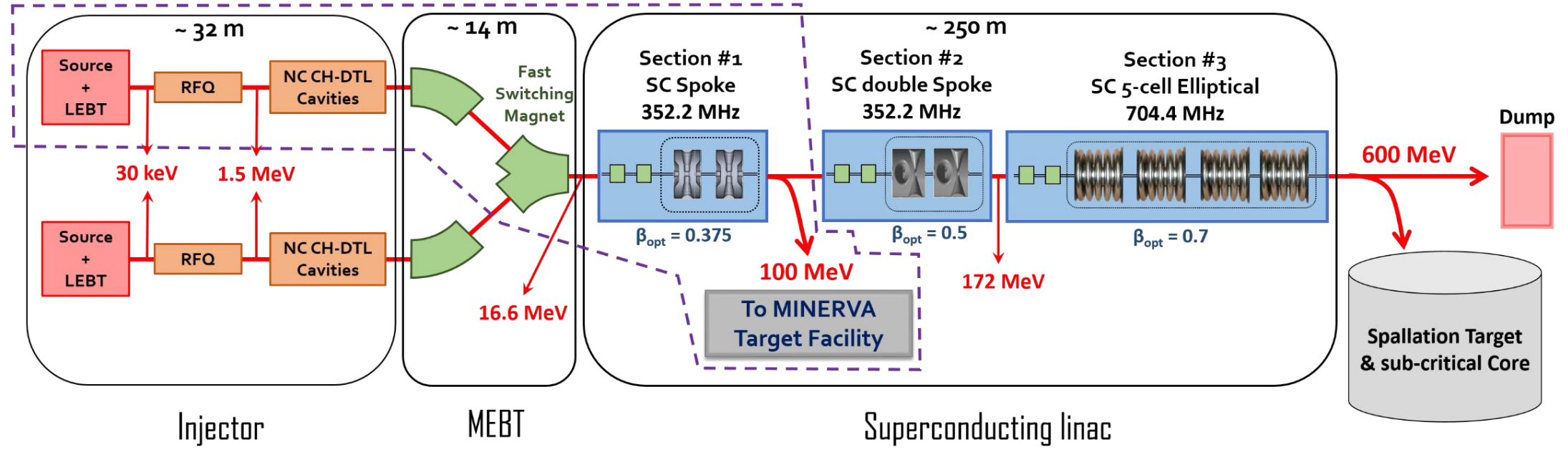
High power proton beam (up to 2.4 MW)

Proton energy	600 MeV
Peak beam current	0.1 to 4.0 mA
Repetition rate	1 to 250 Hz
Beam duty cycle	10^{-4} to 1
Beam power stability	$< \pm 2\%$ on a time scale of 100ms
Beam footprint on reactor window	Circular $\varnothing 85\text{mm}$
Beam footprint stability	$< \pm 10\%$ on a time scale of 1s
# of allowed beam trips on reactor longer than 3 sec	10 maximum per 3-month operation period
# of allowed beam trips on reactor longer than 0.1 sec	100 maximum per day
# of allowed beam trips on reactor shorter than 0.1 sec	unlimited

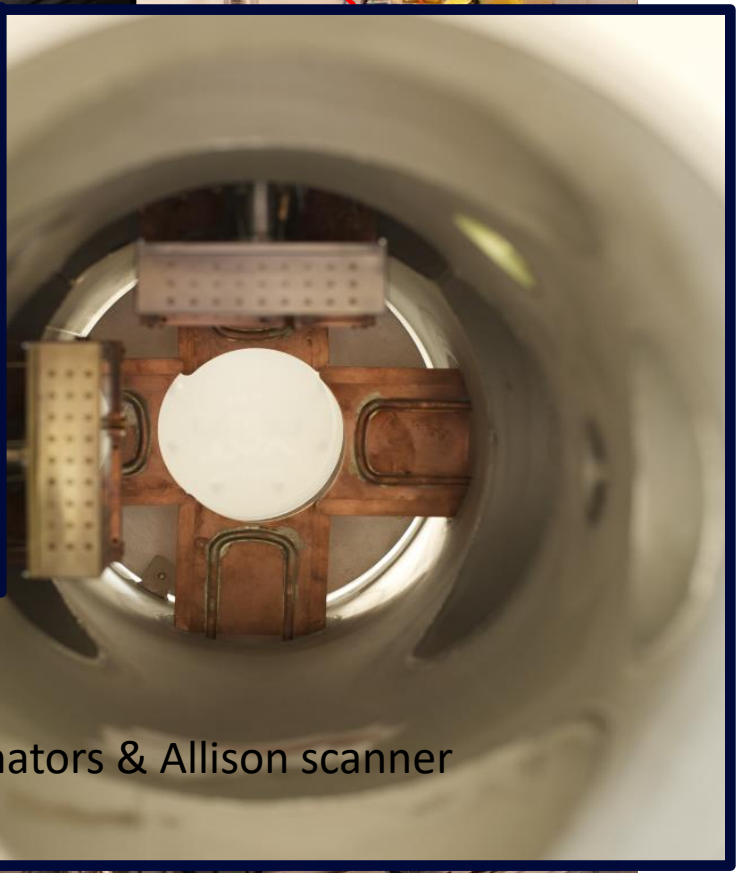
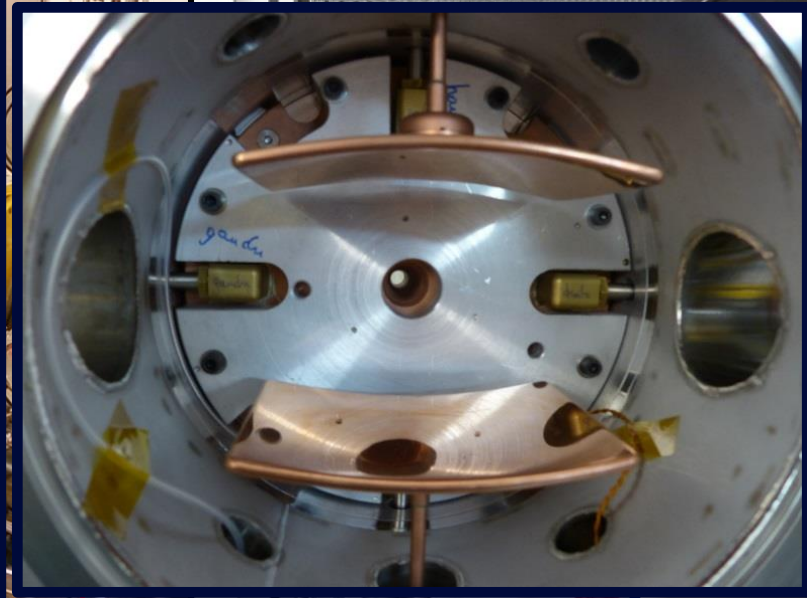
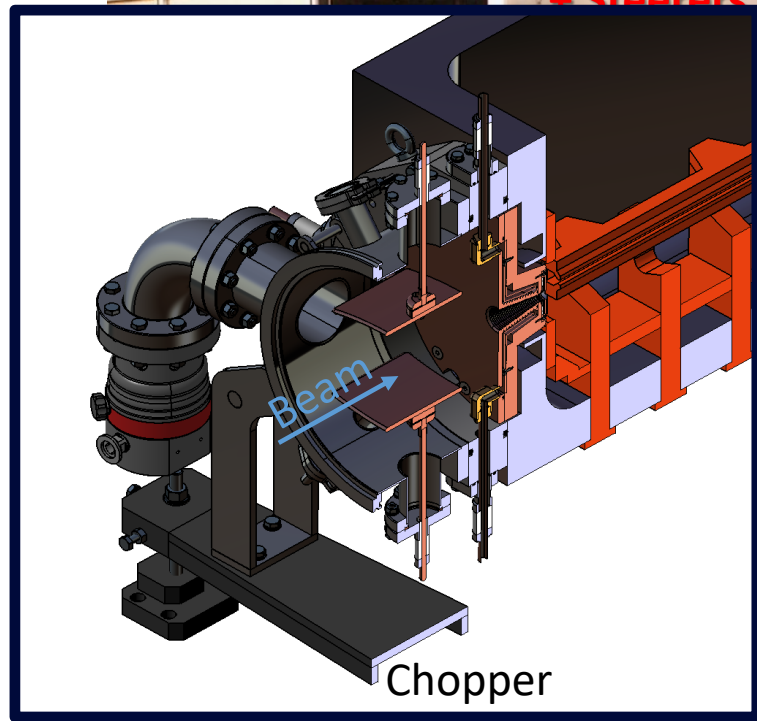
Extreme reliability



MYRRHA Phase 1 : MINERVA



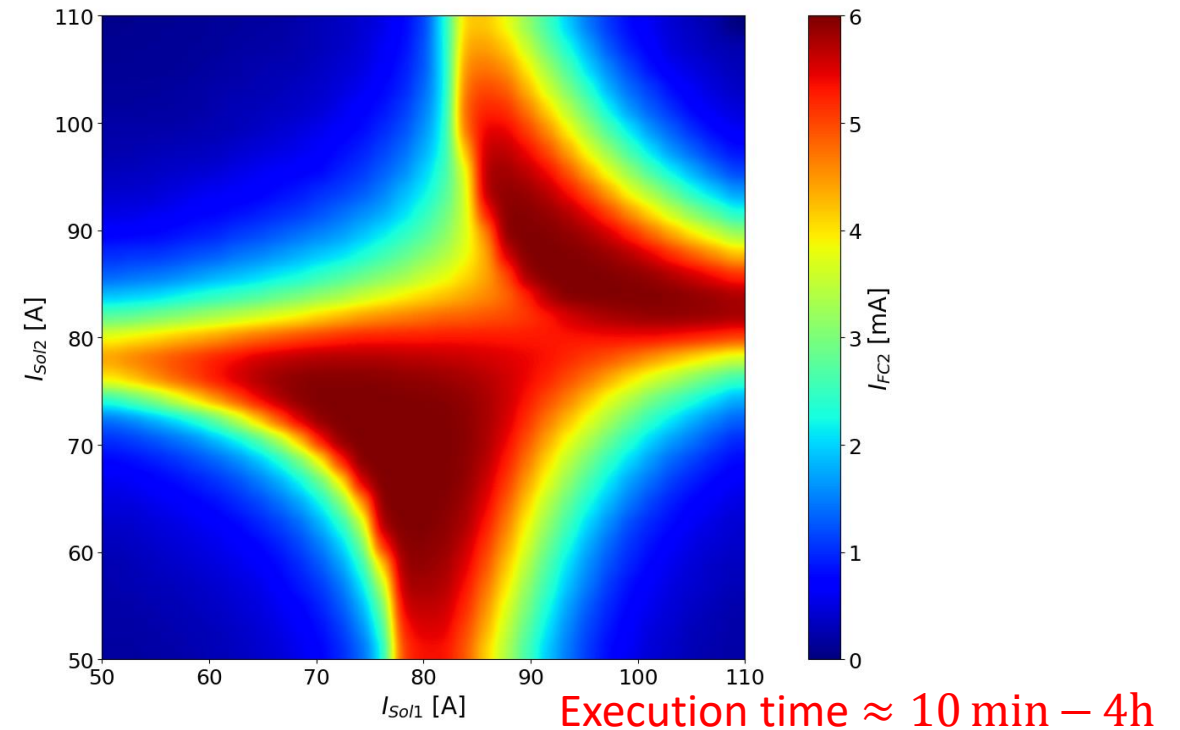
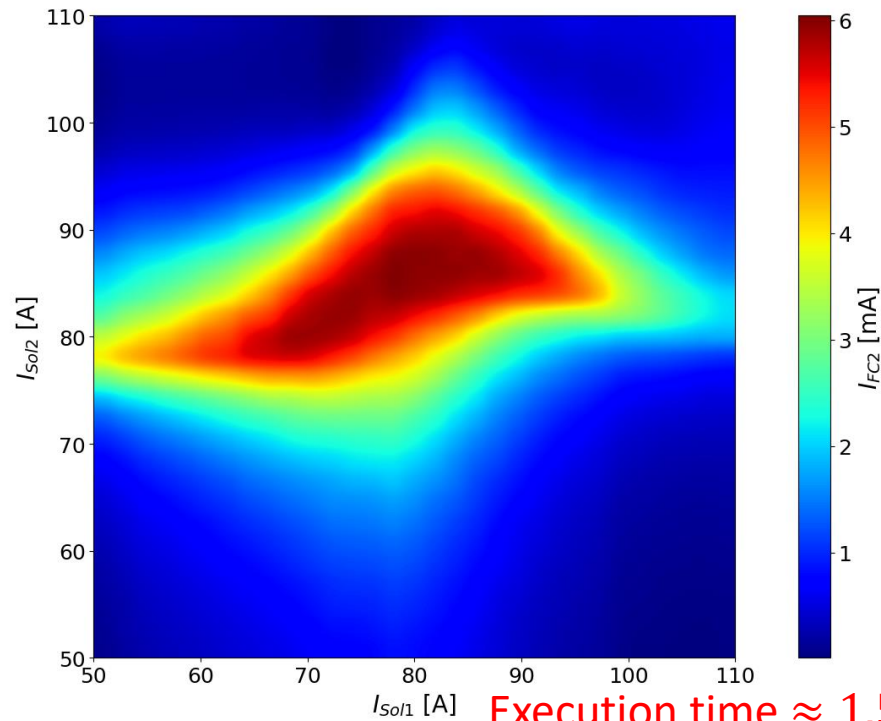
R. BOUT (LPSC/IN2P3) - January 2019



Beam current transmitted through the LEBT as a function of the solenoids focusing or the steering strength (current applied in the coils)

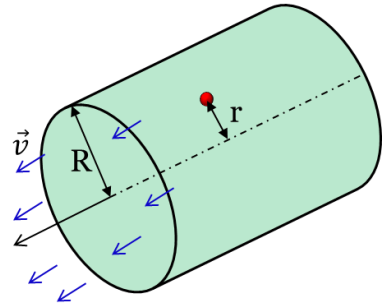
- $I_{Sol1}, I_{Sol2} \in [50, 110] \text{ A}, \text{stepsize} = 2 \text{ A}$
- $I_{source} = 8 \text{ mA}$
- $P = 2 \times 10^{-5} \text{ mbar}$
- $I_{St3} = 1 \text{ A}, I_{St4} = -0.5 \text{ A}$

- $I_{Sol1}, I_{Sol2} \in [50, 110] \text{ A}, \text{stepsize} = 2 \text{ A}$
- $I_{source} = 6 \text{ mA}$
- *Space charge compensation = 99%*
- $I_{St3} = 0 \text{ A}, I_{St4} = 0 \text{ A}$



- Defocusing effect : Coulomb repulsion of charged particles inside the beam

- 2 contributions (Lorentz):
 - ◆ Electrostatic : repelling Force
 - ◆ Magnetic : attractive Force (charged particles in movement)

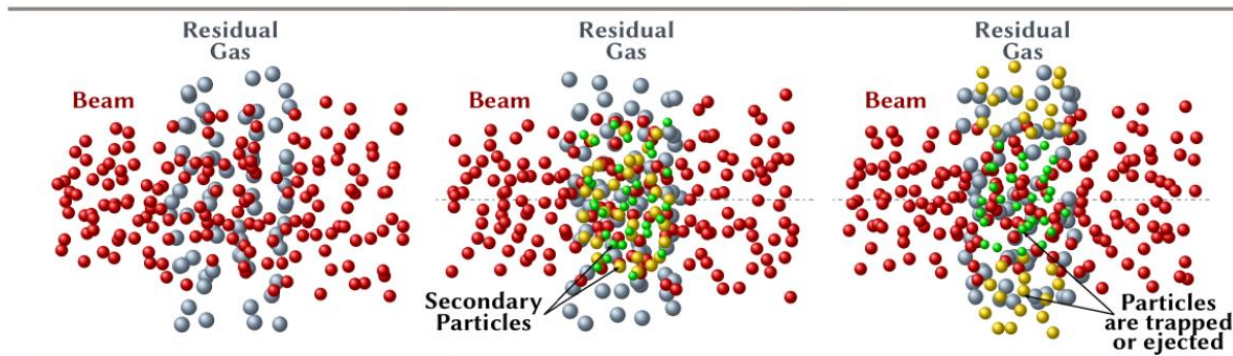


Radial force seen by one particle of a continuous (DC) cylindrical and homogenous beam

$$F_r = \frac{(1 - \beta_L^2)}{\beta_L} \frac{qI}{2\pi \epsilon_0 c} \cdot \frac{r}{R^2} \quad (r < R)$$

β_L : reduced speed
 ϵ_0 : vacuum permittivity
 q : charge
 I : beam current

- **Complex phenomena, difficult to model, depends on many parameters** : influence of the vacuum chamber walls, beam transverse and longitudinal distribution, different species/ions, **residual gas interaction**, etc.



Courtesy of N. Chauvin

- A solution to compensate the beam diverging effect in the LEPT :
 → Use the Ionisation of the residual gas in the vacuum chamber.

- Objectives

 - Fast control and tuning for different linac beam modes (peak current, duty cycle)

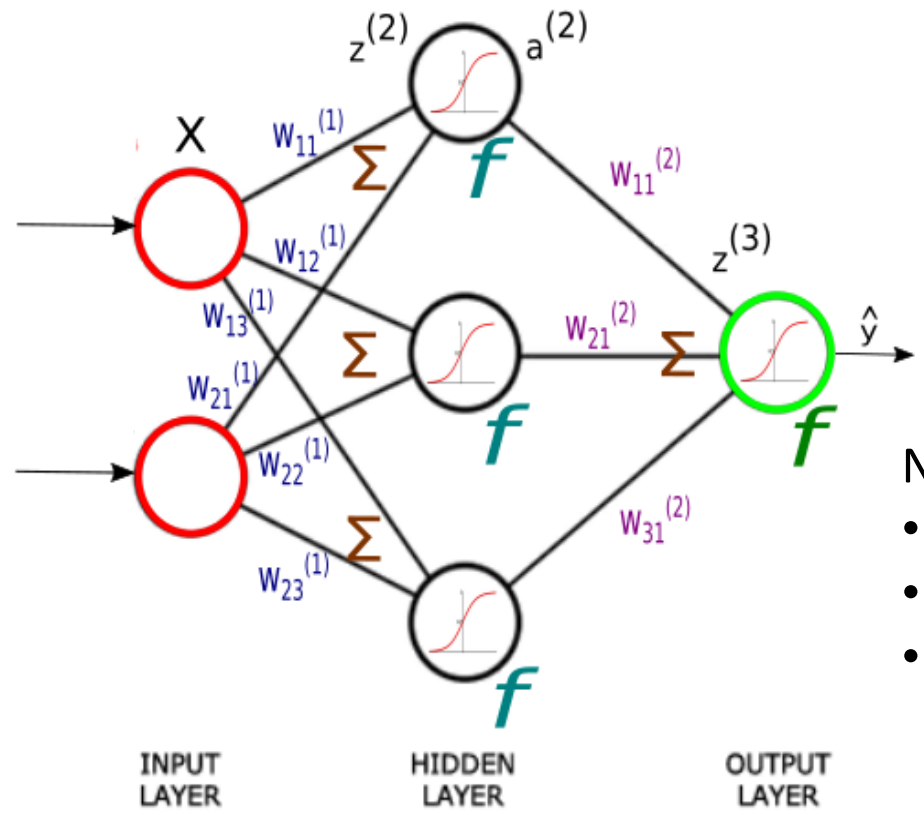
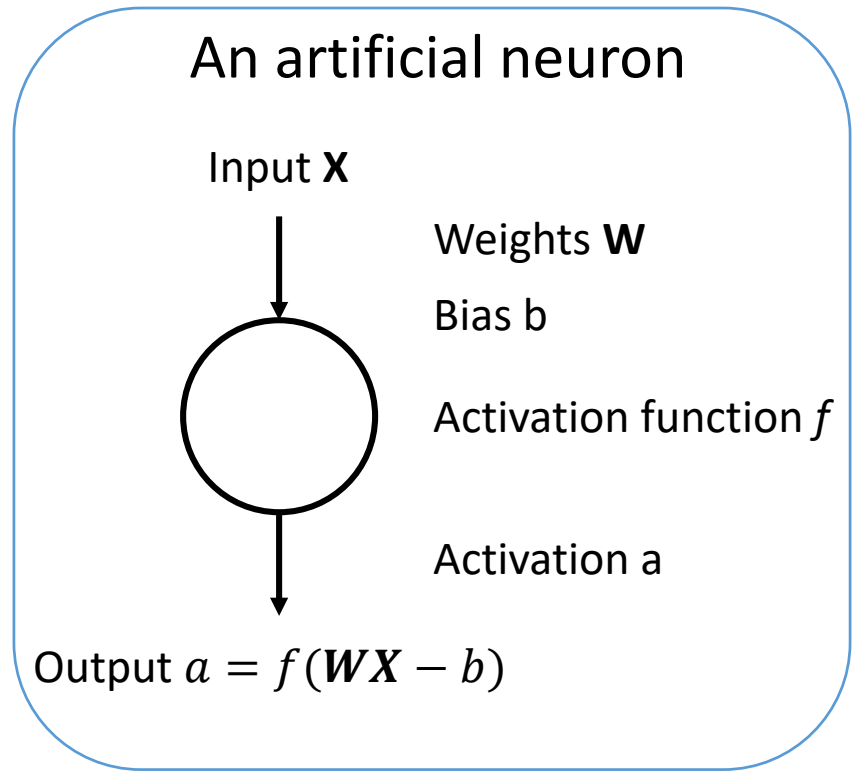
- Why?

 - Classic simulation are slow

 - Classic simulation don't reproduce experiments accurately

- How?

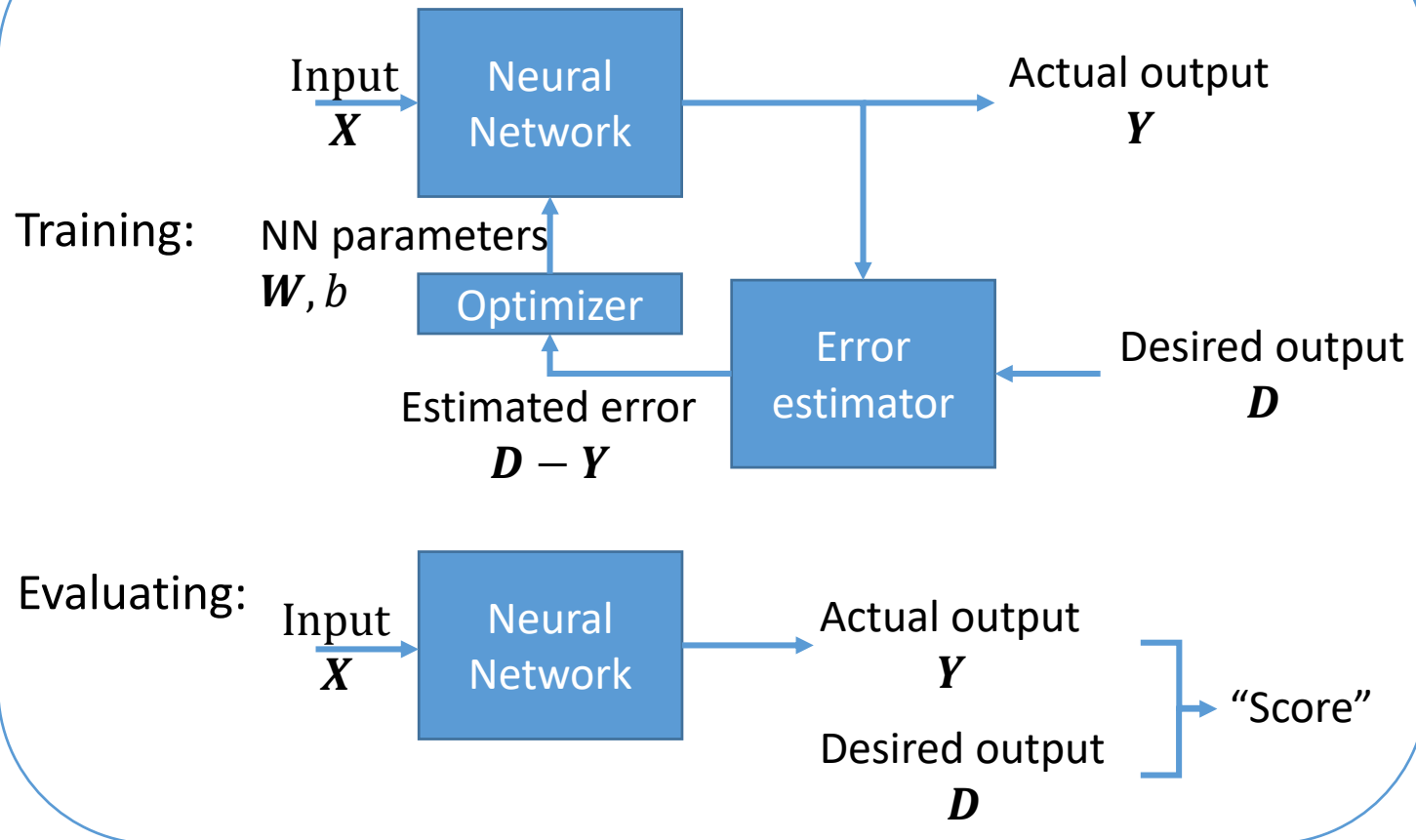
 - Training of an experimental model using supervised learning



- Network characteristics:
- Dense
 - ReLu (hidden layers)
 - Sigmoid (output layer)

Can fit any continuous function

Supervised learning of a neural network

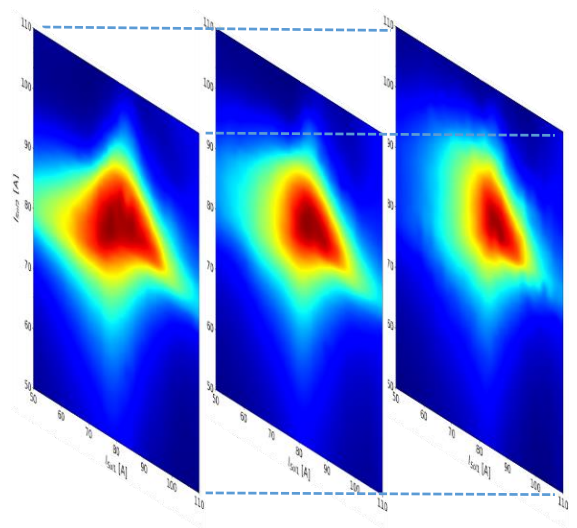


Parameters

- Learning rate: from 0.1 down to 0.001
- Error estimator: MSE
- Optimizer: SGD

MYRRHA (SCK*CEN, Belgium)

- ~20000 measurements

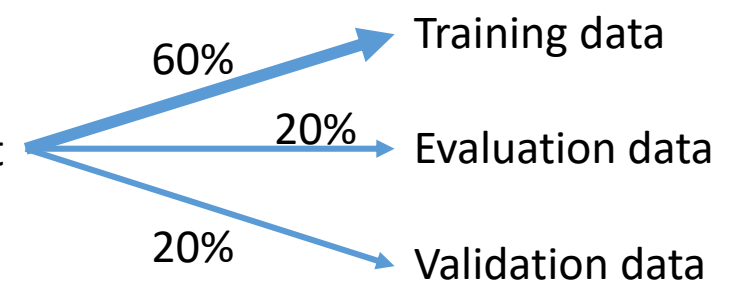


Slices at different slits extensions

19 "slices" with solenoids
6 "slices" with steerers



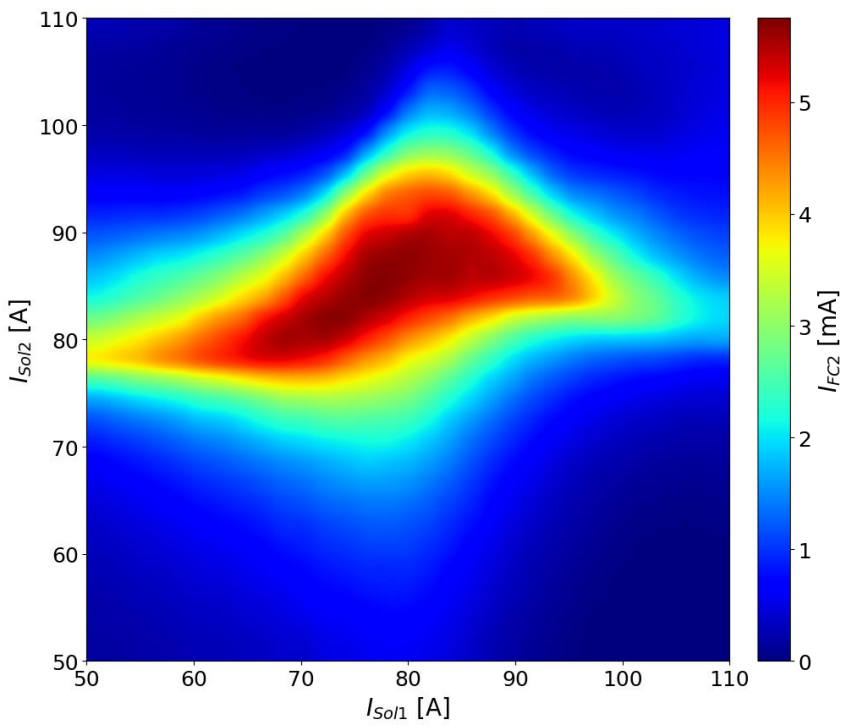
Dataset



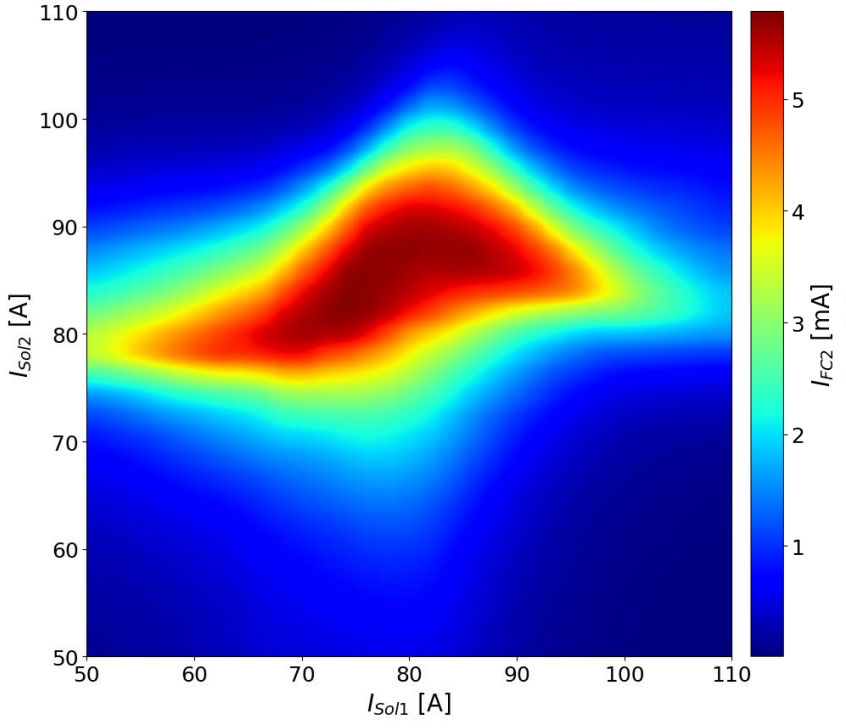
Input				Desired output
Current in steerer x4 [A]	Current in solenoid x2 [A]	Collimator opening x1 [m]	Pressure gauge x3 [bar]	Current in FC2 [A]

$$\rightarrow \text{model } f(I_{st1}, I_{st2}, I_{st3}, I_{st4}, I_{so1}, I_{so2}, r_{coll} | p_1, p_2, p_3) = I_{FC2}$$

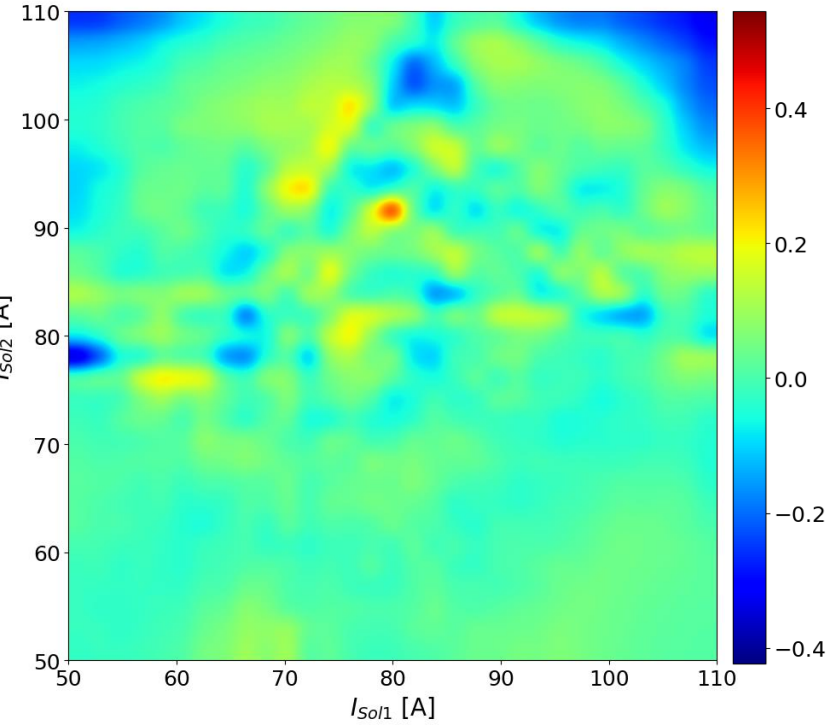
Experimental



Model

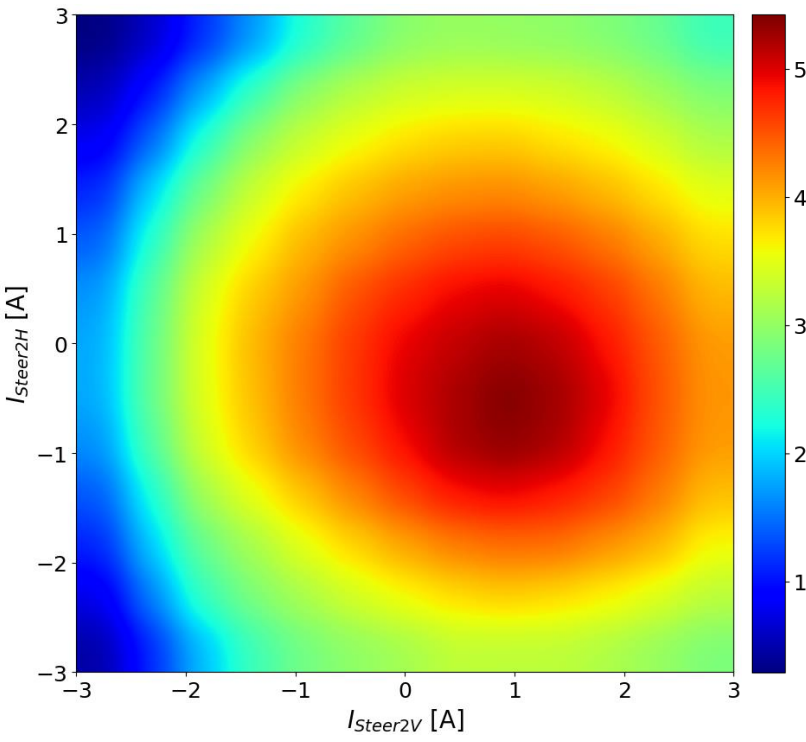


Error

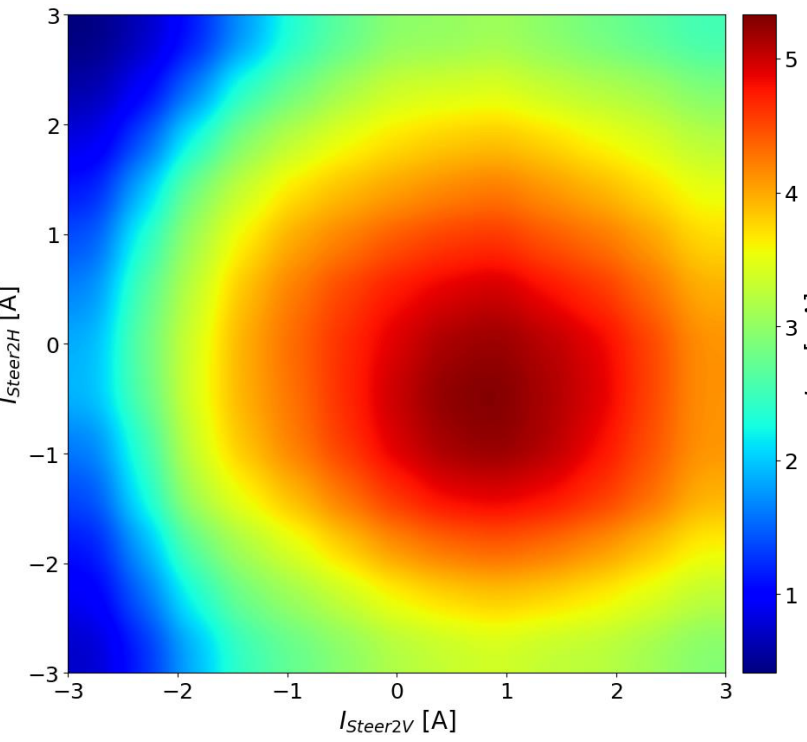


Execution time ≈ 1 ms

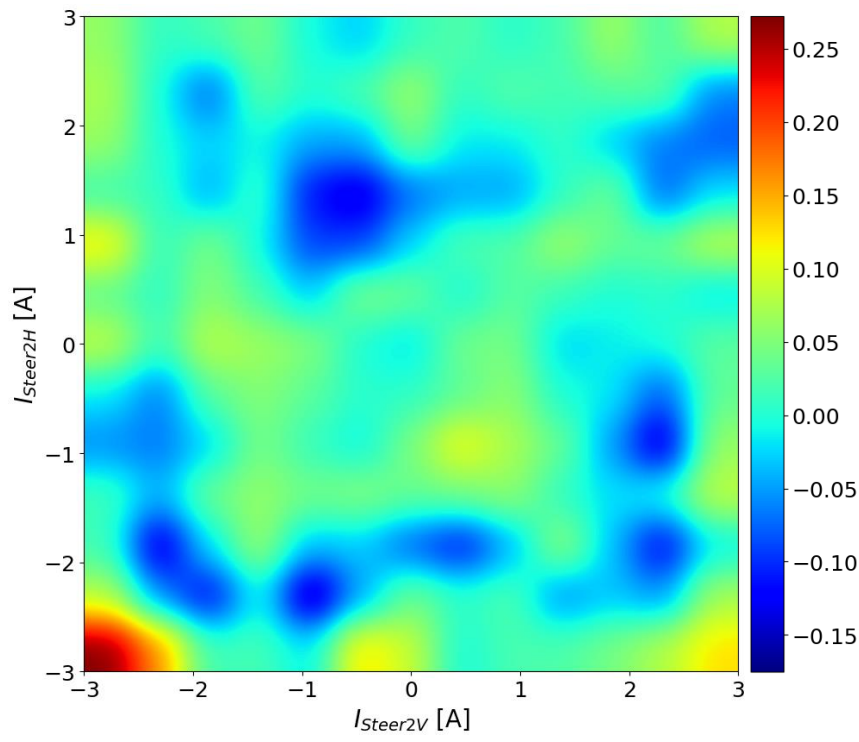
Experimental

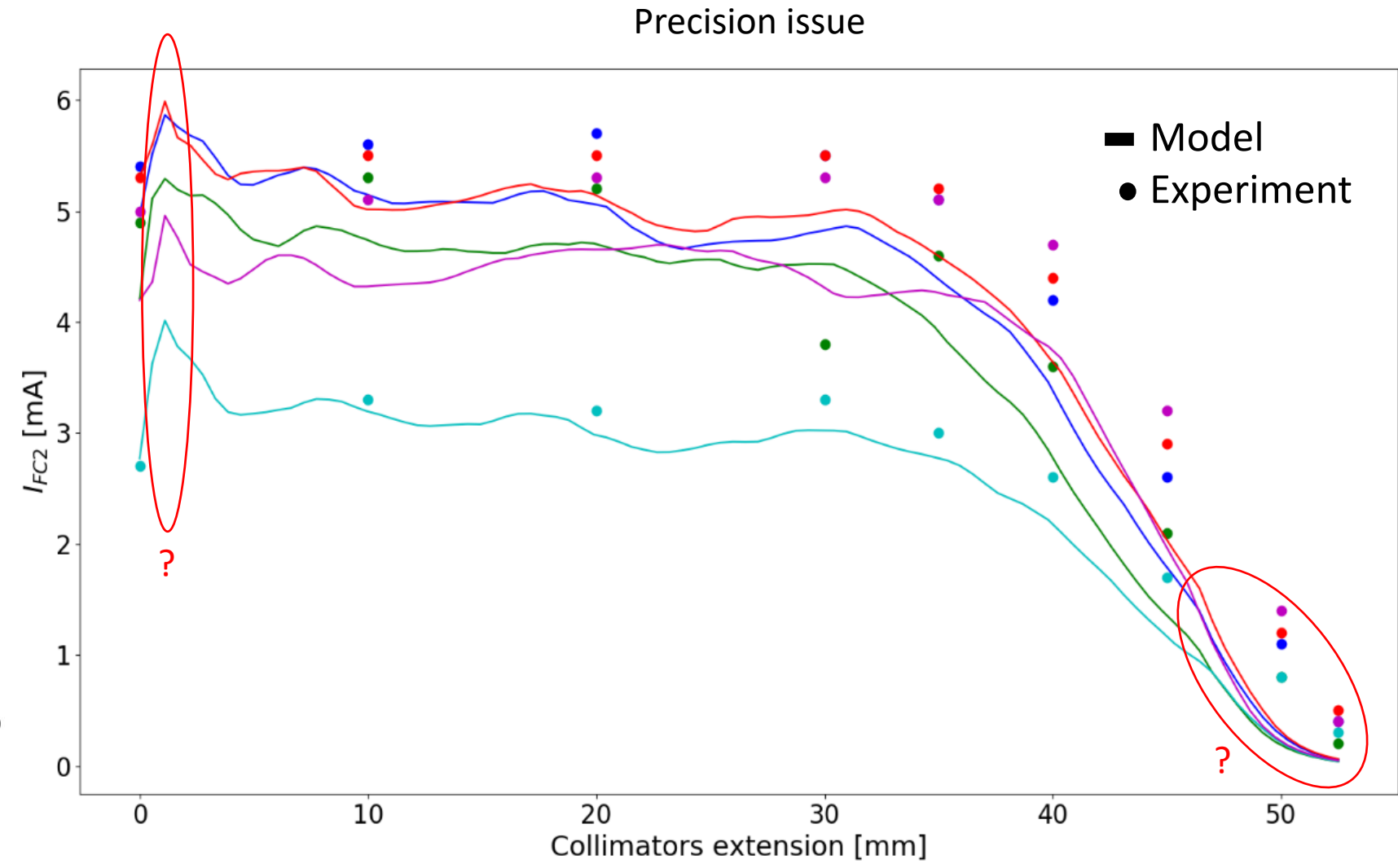
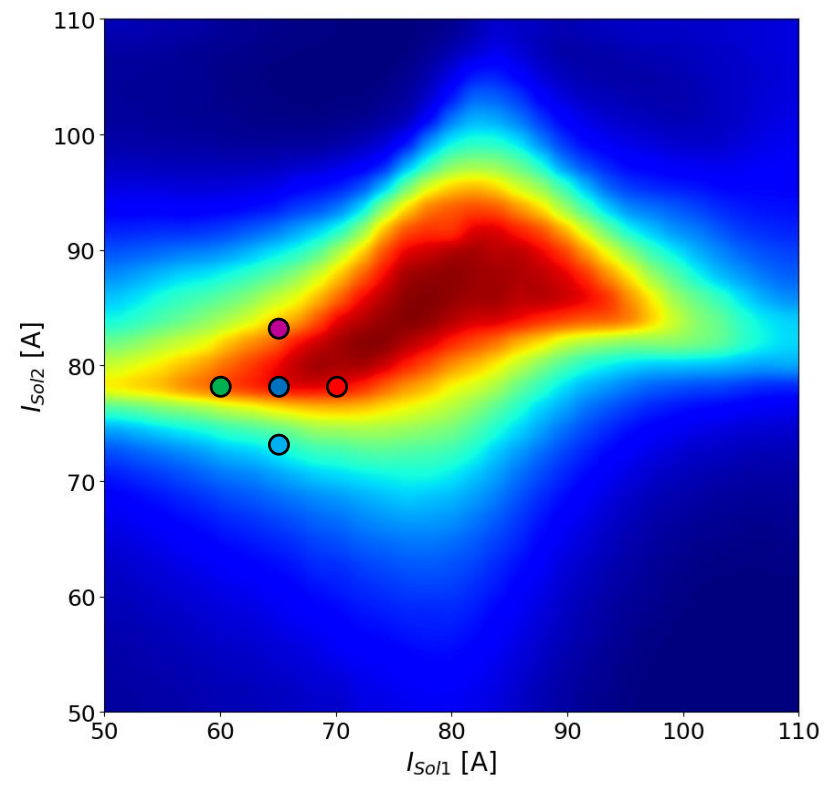


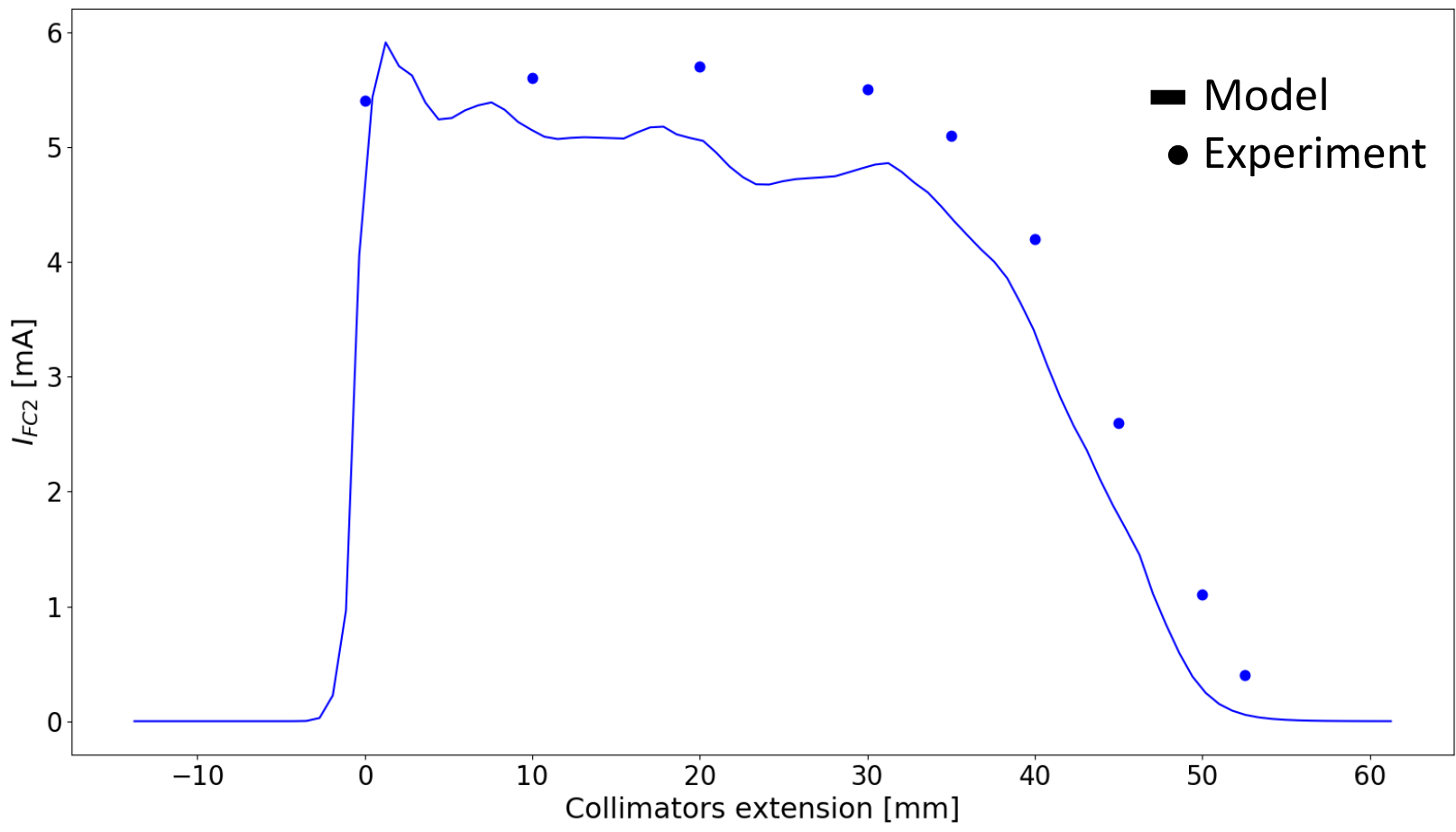
Model



Error







➔ Issue comes from continuity

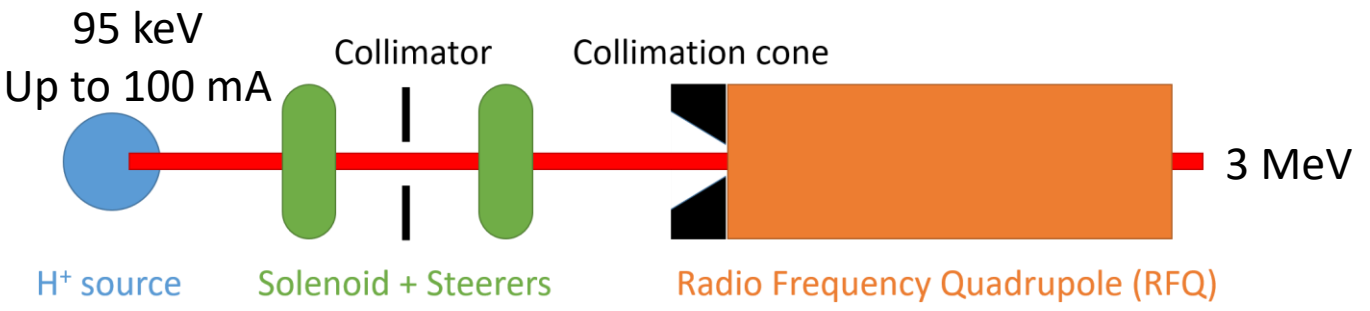
How to improve ?

More training data !

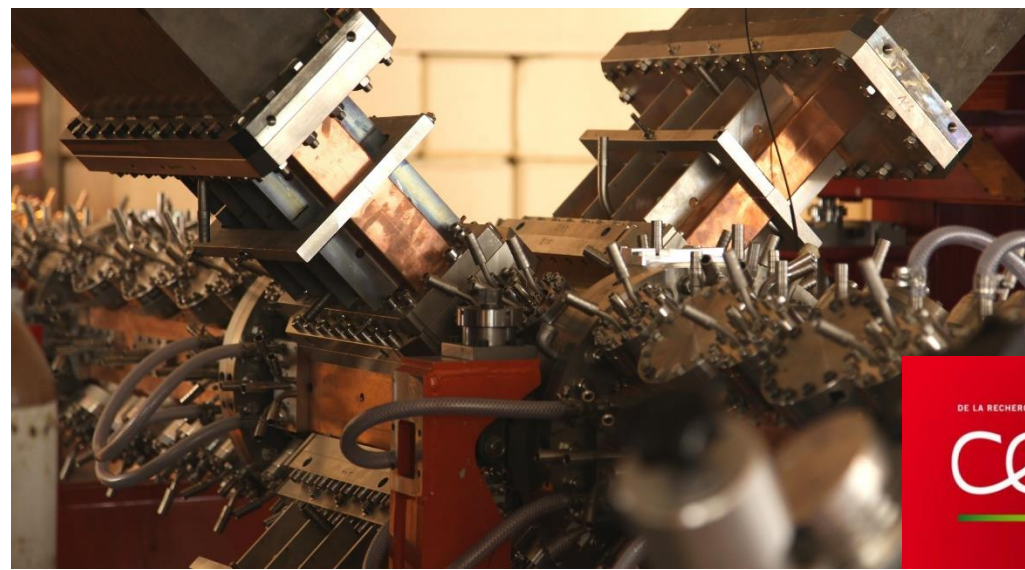
Simulation or Measurements

Cycle utile $\sim 0.4\% \times 50 \text{ mA} \times 3 \text{ MeV} \cong 600 \text{ W}$

Same configuration as MYRRHA (LEBT + RFQ)

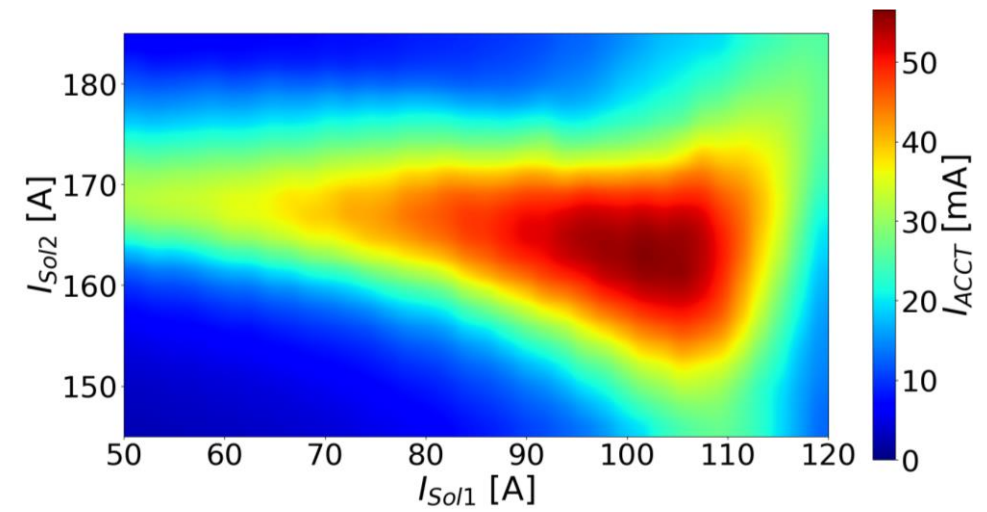


IPHI @ CEA Saclay

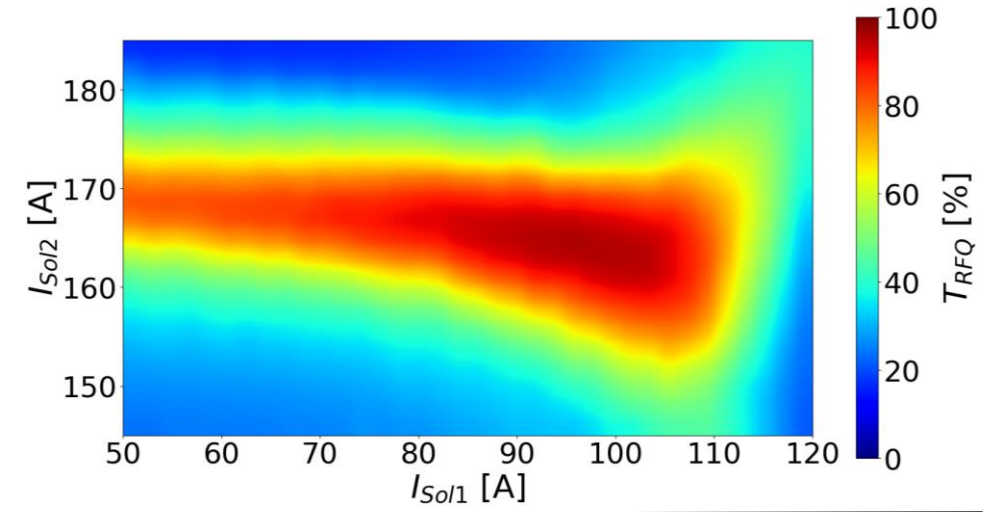


Experimental

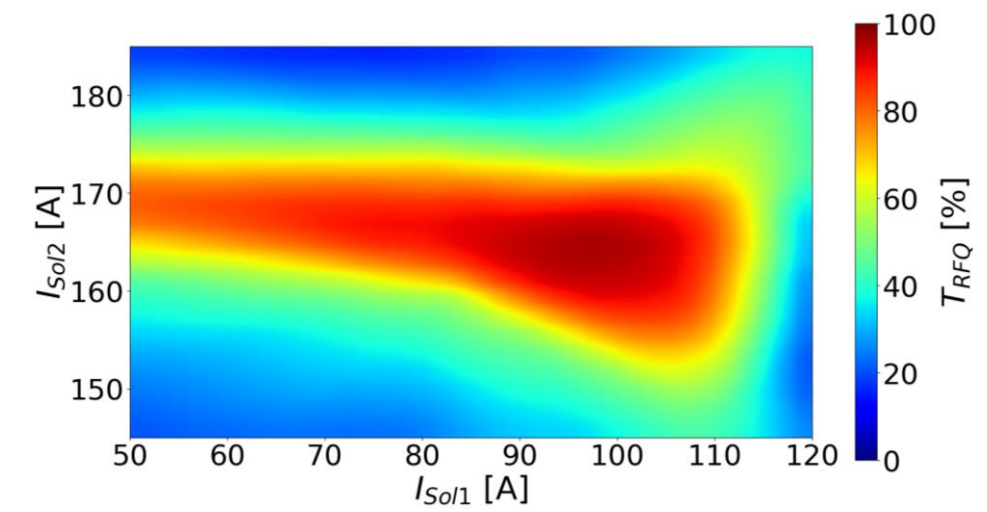
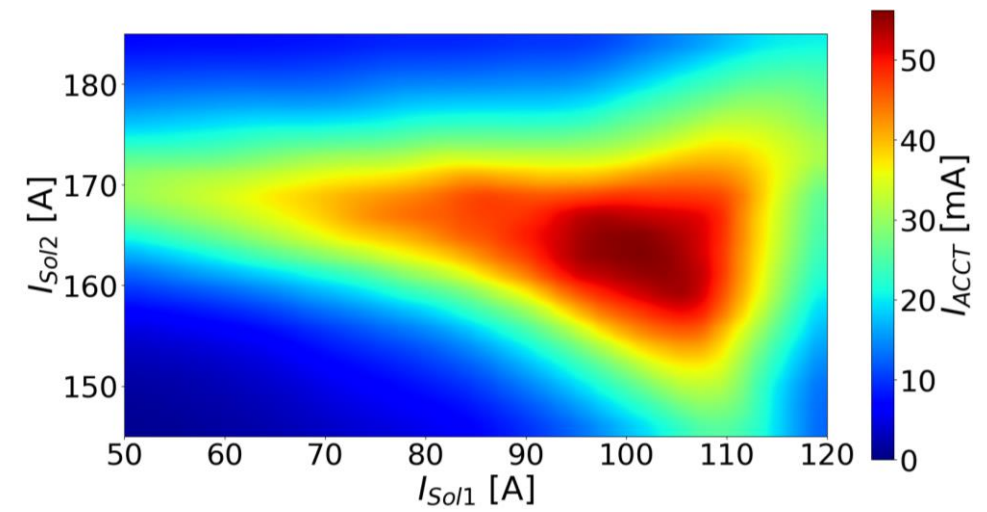
RFQ output current



RFQ transmission



Model



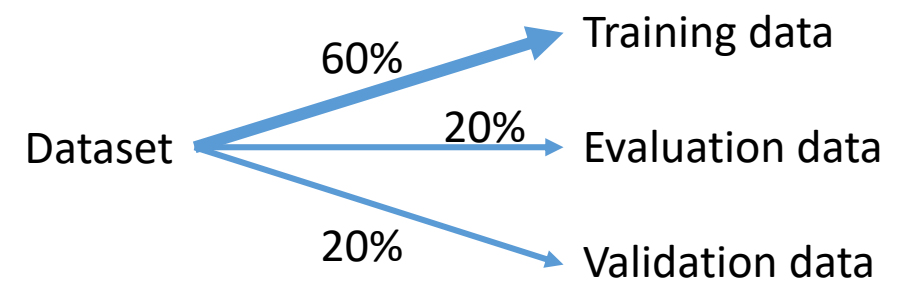
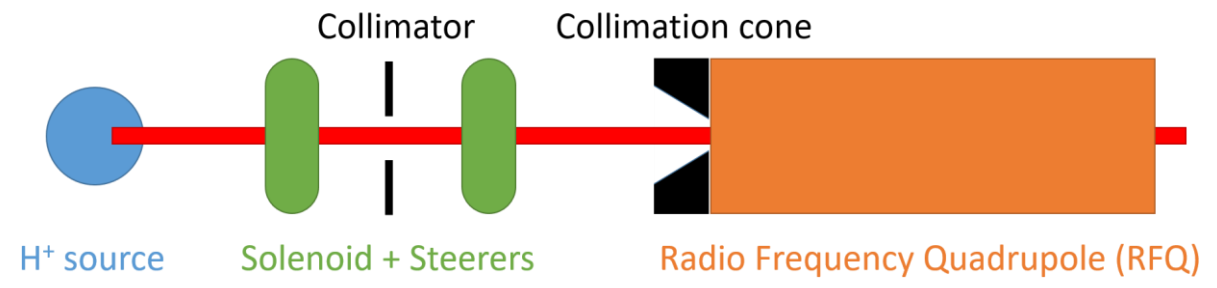
- Machine Learning model
 - Training of an experimental model is possible
 - Improvement to be made
 - Optimize training: solve over fit issues
 - Optimize neural network (minimize training/execution time): #neurons, #layers, ...
- Alternative
 - Particle Swarm Optimization
- Prospects
 - Training of a neural network controller
 - From desired current and RFQ transmission → solenoid settings
 - Applications to SC cavities fast fault-recovery

- Execution time $\sim 10 \mu\text{s}$

$$RMSE = \sqrt{\frac{\sum_{y_i} (y_i^{true} - y_i^{model})^2}{N_{y_i}}}$$

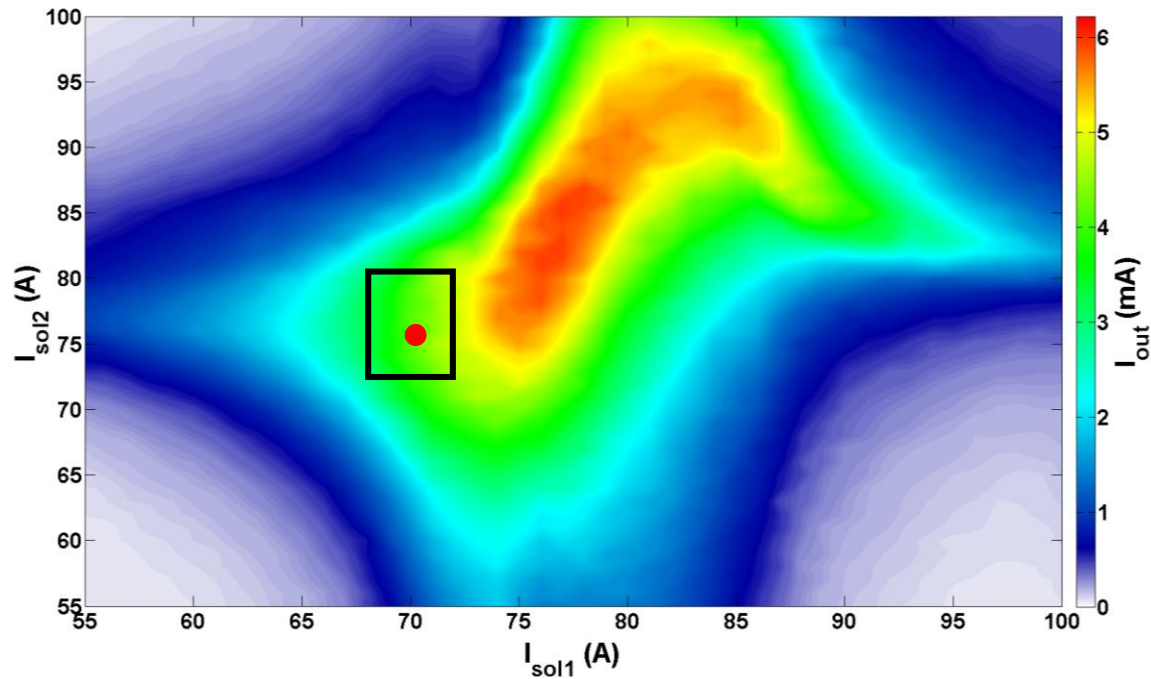
- Quality evaluation: RMS error

	MYRRHA	IPHI	
Outputs	Beam current [mA]	Beam current [mA]	RFQ transmission [%]
RMSE on training dataset	0.09	0.66	1.25
RMSE on validation dataset	0.10	0.79	1.62
RMSE on test dataset	0.10	0.81	1.65
RMSE on whole dataset	0.09	0.72	1.42

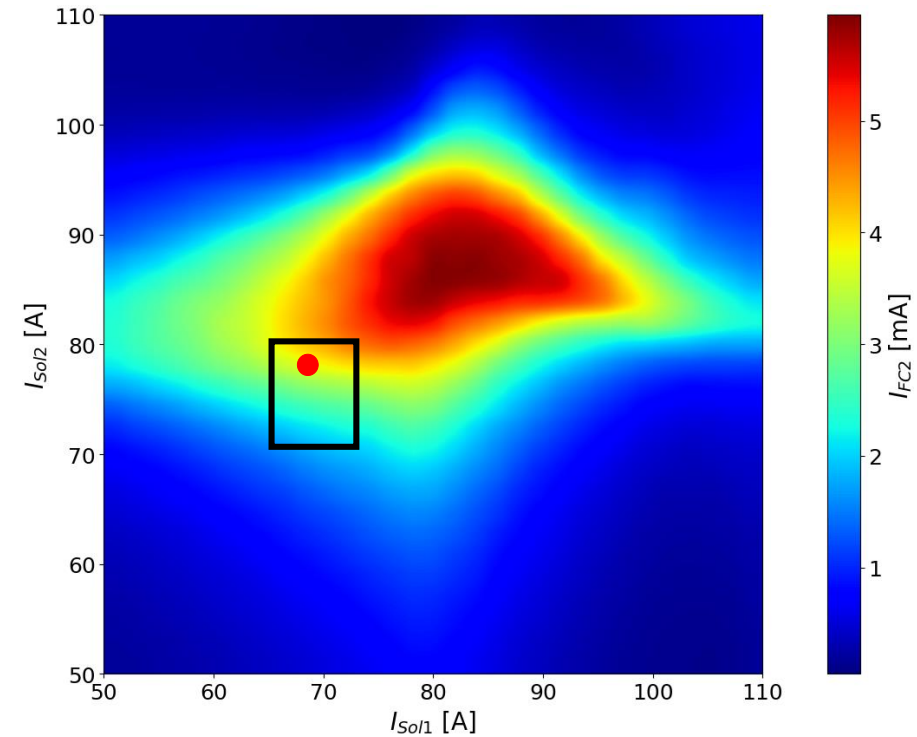


IPHI (CEA Saclay, France)
• ~8000 measurements

Input		Desired output	
Current in solenoids [A]	Collimator opening [m]	Beam current output [mA]	Transmission [I]
I_{sol1}	I_{sol2}	r_{coll}	$I_{Beam,out}$
			T_{RFQ}

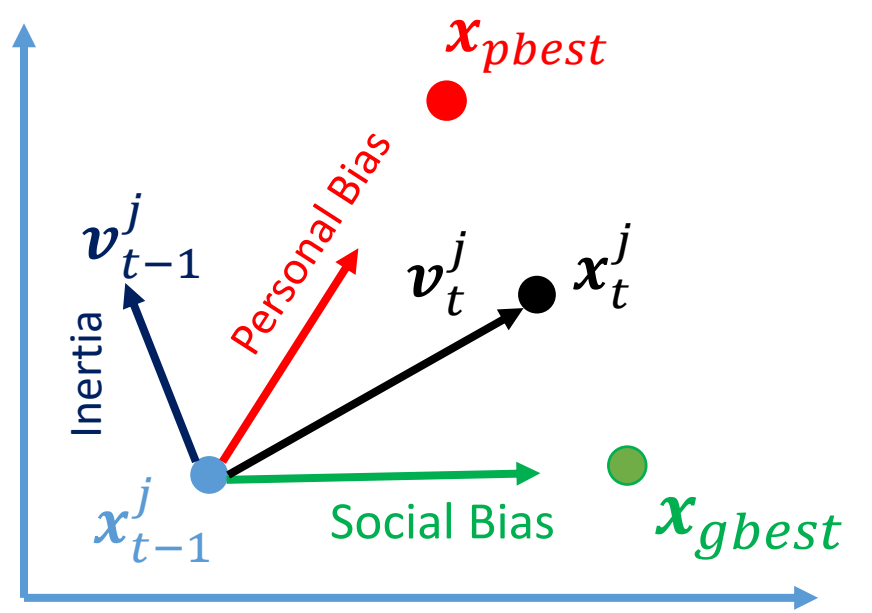


- $I_{source} = 9 \text{ mA}$
- $P = 2.4 \cdot 10^{-5} \text{ mbar}$
- Collimator aperture : 37 mm
- Steerers settings inside solenoid 2 :
 - $I_{steererH} = 0.5 \text{ A}$
 - $I_{steererV} = -2 \text{ A}$



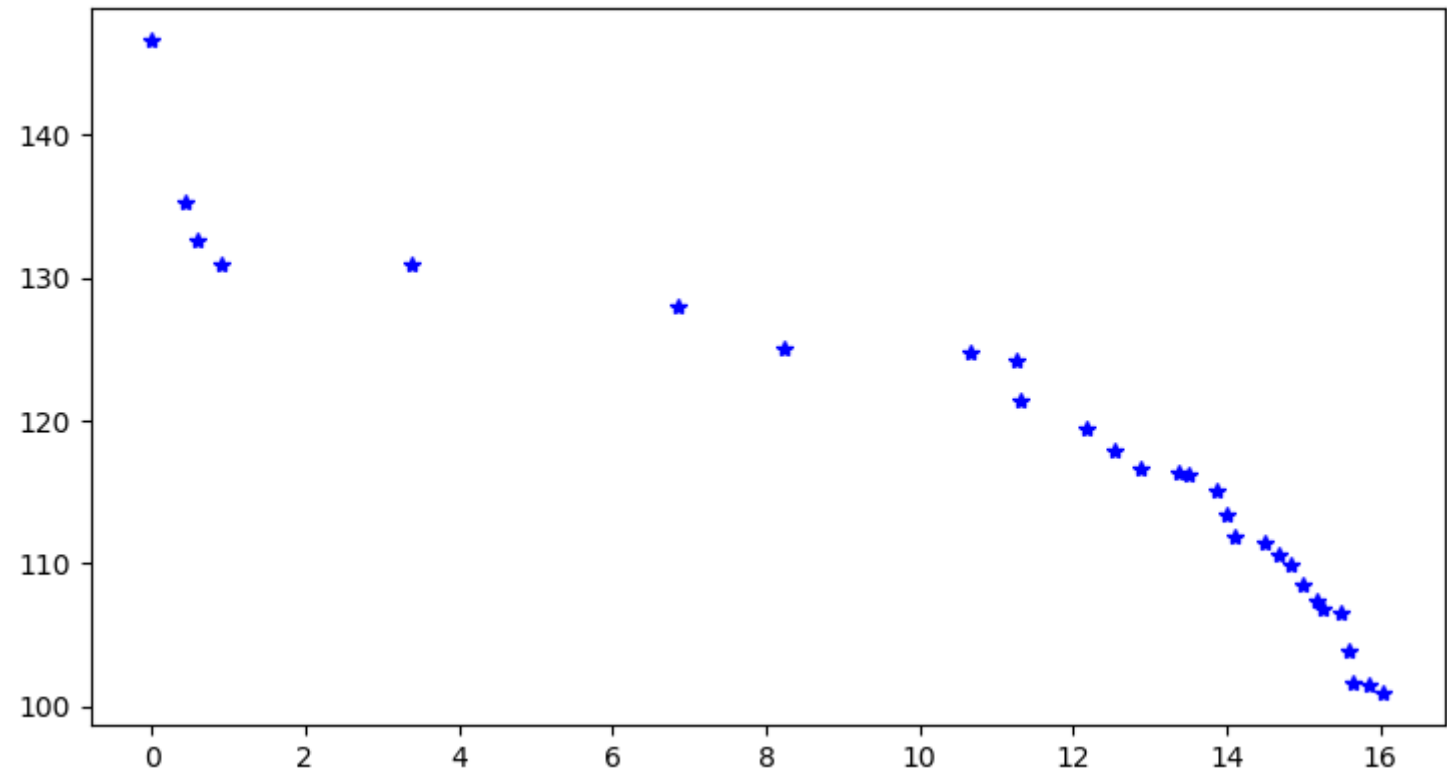
- $I_{source} = 8 \text{ mA}$
- $P = 1.9 \times 10^{-5} \text{ mbar}$
- $I_{Steer2H} = -0.5 \text{ A}, I_{Steer2V} = 0.75 \text{ A}$
- Collimator extension = 40 mm

- Metaheuristic algorithm



$$S_2 = I_{sol_1} + I_{sol_2} + |I_{steer_{2,V}}| + |I_{steer_{2,H}}|$$

Slits extension manually set to 40 mm



Score 1 = $(I - I^{target})^2$ with $I^{target} = 4.2 \text{ mA}$

First test !

Improvements to be made...



Particles are potential solutions of the optimization problem (\neq particles in physics)