Machine Learning Applications in the Radio-Frequency group at CERN

K. Iliakis, A. Lasheen, H. Timko
CERN, SY-RF group

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CERN AI/ML initiative

Initiative for Artificial Intelligence (AI) and Machine Learning (ML) started across the Accelerators & Technology Sector (ATS) at CERN

- The aim is to define an ATS-AI strategy for the coming 5-10 years
  - Acknowledging that it is a major new field arising in our domain
  - For efficient manpower use and ensuring support
- AI/ML are important for accelerator design, control, and operation

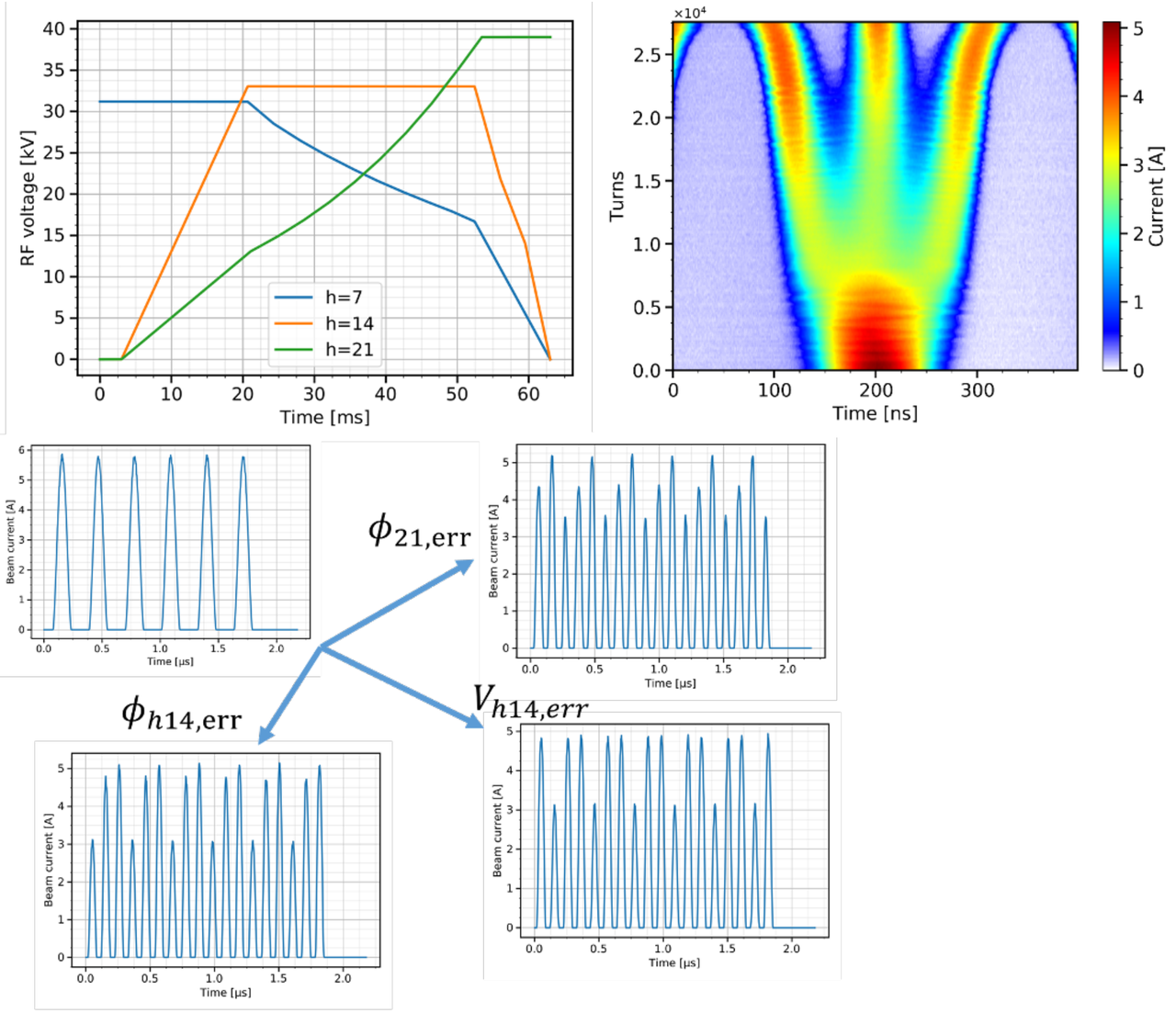
Once the strategy will be defined, it should determine…

- What applications could it be used for?
  - Automatised optimisation of parameters in operation?
  - Preventive maintenance?
  - Design of new accelerators such as the Future Circular collider?

The problem: even bunch splitting

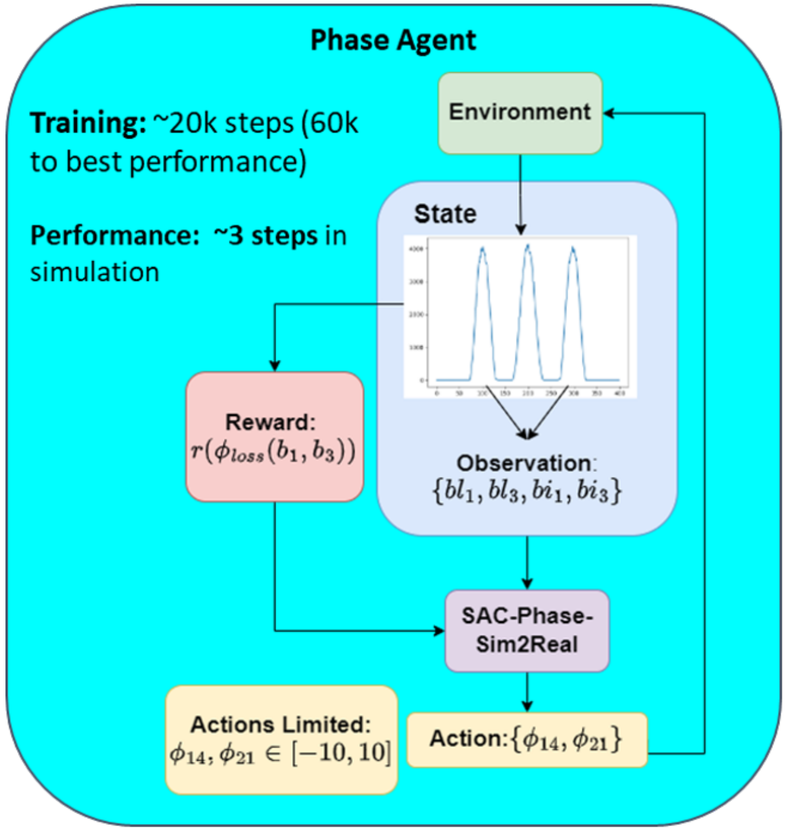
Objective: adjusting the RF phases and voltages to ensure identical bunches

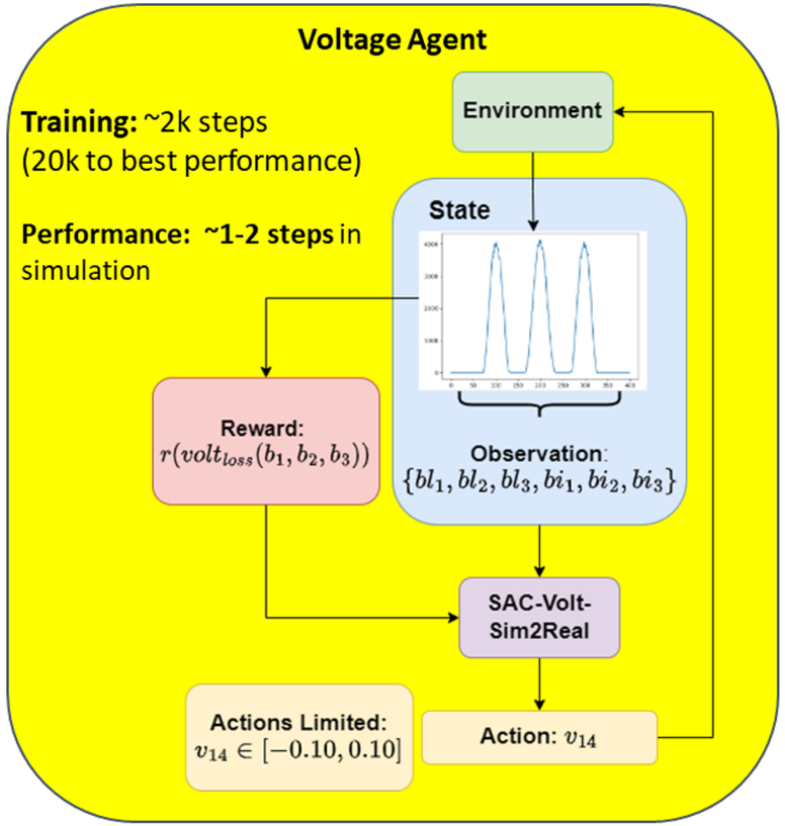
- Optimal parameters vary with beam intensity & transient beam loading
  - Process non-linear with interdependent parameters
- Reinforcement learning used for fast daily optimisation and while varying beam intensity



The approach: segmenting the problem

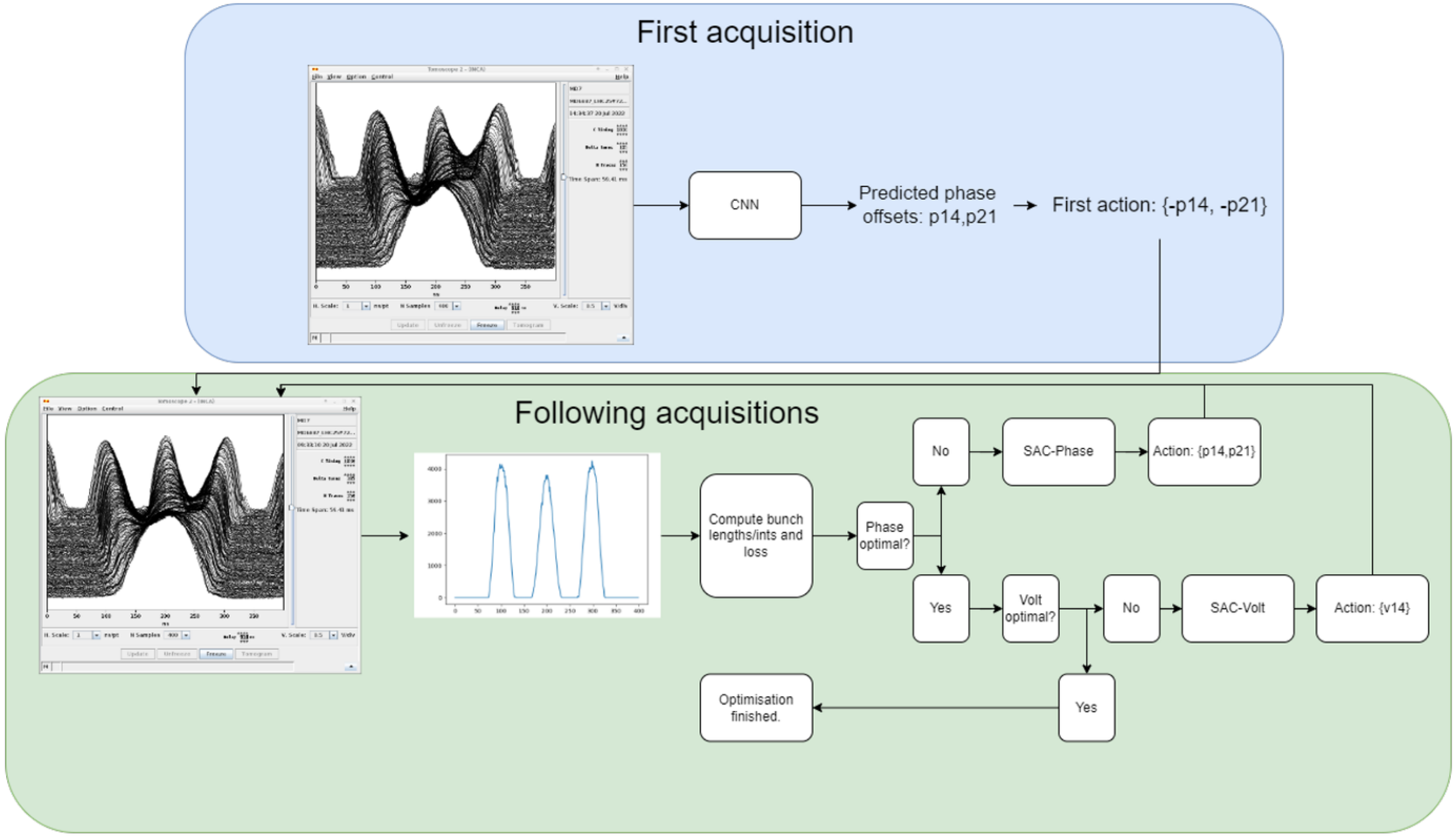
- Two Reinforcement Learning (RL) agents with “simpler” problems
  - One to adjust phase, one to adjust RF voltage
- Require tens of thousands of iterations for training, important limitation to train on the real accelerator
  - Training on simulations instead, aiming for generalisation!





The solution: combine 2 RL agents & 1 CNN

- In addition to the two RL agents, one Convolutional Neural Network (CNN) trained on simulations to do a first step closer to the optimum, avoid the agents to be stuck on local minima

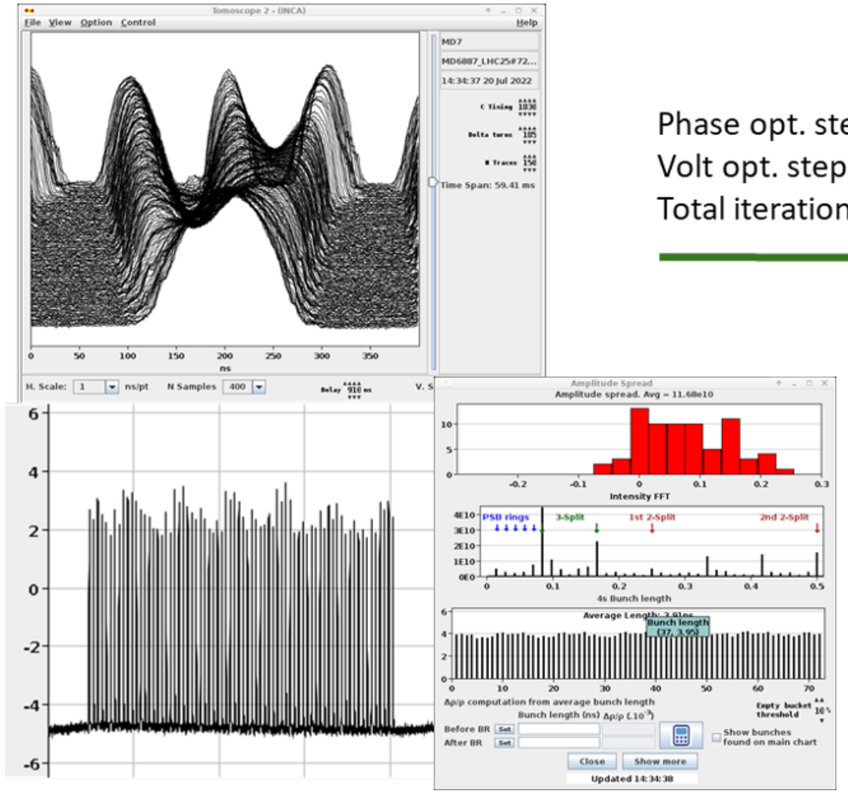


The results: first applications in operation

- Implemented as test in operation since 2022, with **over 95% success rate with performance comparable or better than experienced operator and experts** (2-3 iterations for standard adjustments)
- Further development ongoing for completely autonomous (and safe) operation

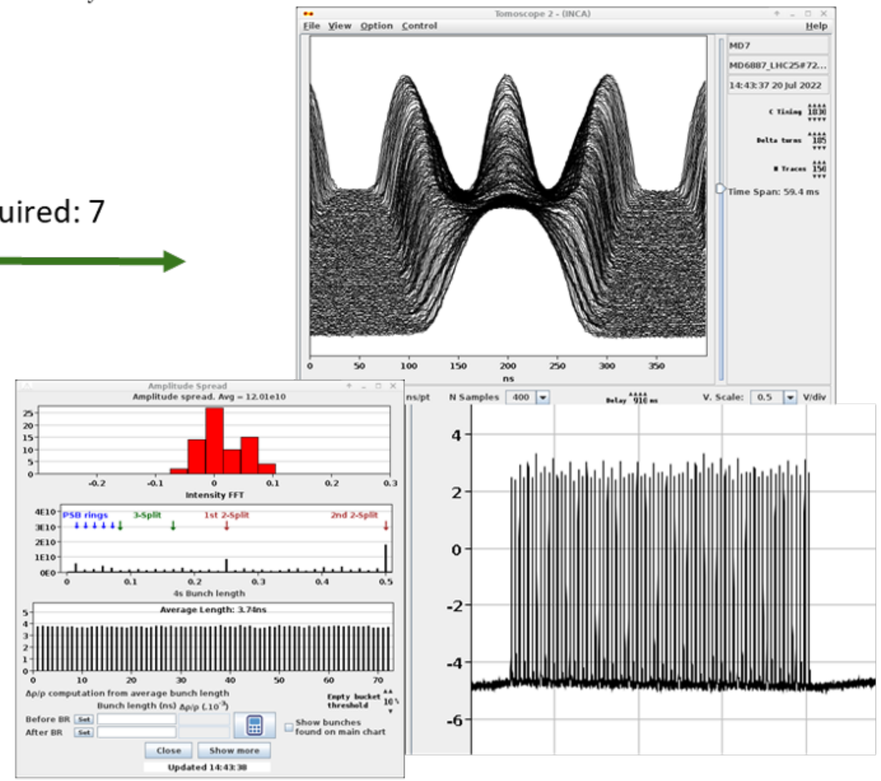
Example episode:
Approx. initial offset: $\phi_{14} = 10$, $\phi_{21} = -20$, $V_f = 1.08$

Init



Phase opt. steps: 3
Volt opt. steps: 4
Total iterations required: 7

Final

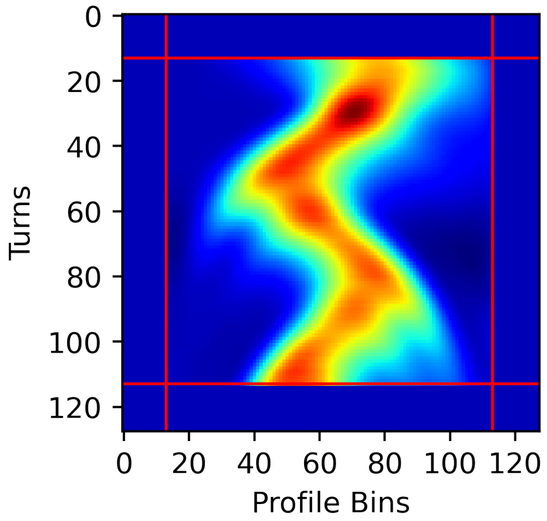


Machine-learning tomography: motivation

At injection: can now determine & log longitudinal beam parameters (e.g. injection errors, bunch length) and reconstruct the longitudinal phase space batch by batch, fill by fill [1,2]

- Tracking-based methods are too time consuming for online use, limited to single bunch
- Develop the ML model to:
  - Extract the desired beam parameters & 2D longitudinal beam distribution
  - Fast enough to allow for online use with multi-bunch beams

Encoder input



Encoder

➤ Extract beam parameters from beam profiles

➤ One model per parameter, seven in total

➤ First convolutional then fully connected layers

➤ ~22M parameters in total

Encoder output/ Decoder input

Beam Parameters
Phase Error
Energy Error
Bunch Length
Intensity
LHC VRF
μ
SPS VRF

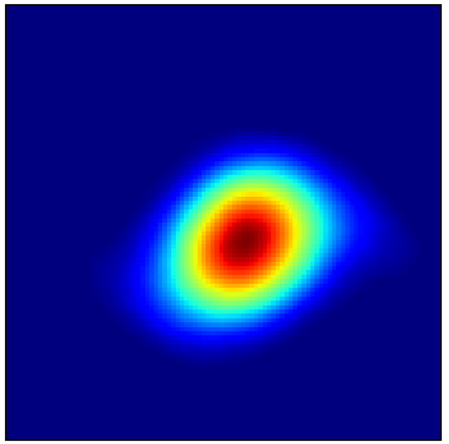
Decoder

➤ Re-construct phase-space from beam parameters

➤ Mirror encoder: first fully connected layers, then transpose convolutional

➤ ~8M parameters

Decoder output



[1] T. Argyropoulos and G. Trad, 'Machine-learning tomography and longitudinal beam parameters at LHC injection', Talk at CERN, Geneva, Switzerland, 2022.
[2] K. Iliakis, T. Argyropoulos, and G. Trad, 'Longitudinal tomography in the LHC', Talk at CERN, Geneva, Switzerland, 2023.

Machine-learning tomography: evaluation

Encoder evaluation (simulation data)

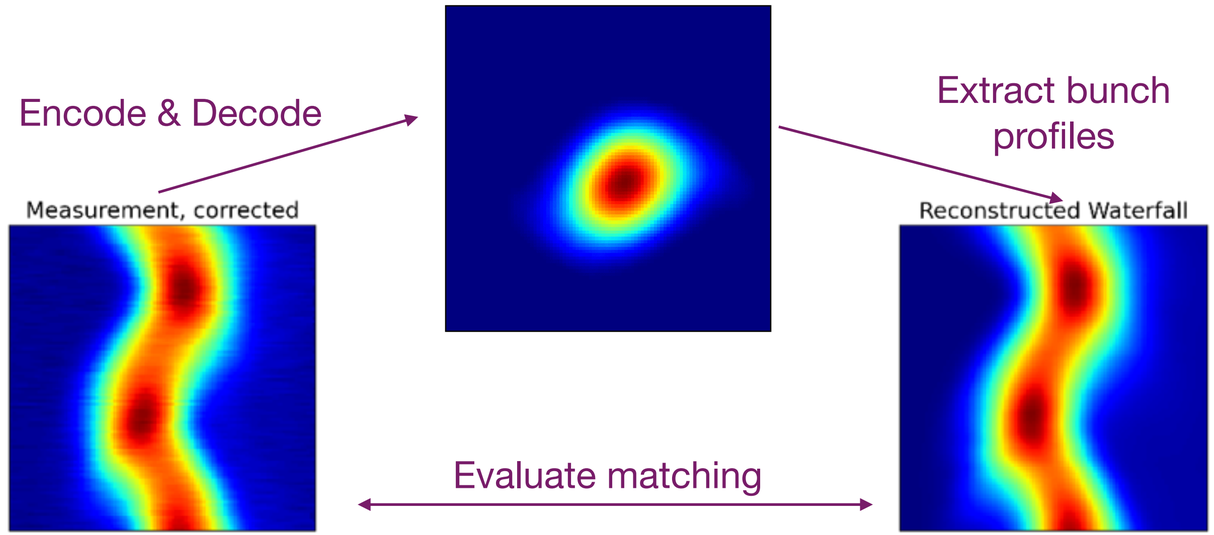
- Ground truth available only in simulations

	95 percentile
Phase Error	0.3 deg
Energy Error	1.56 MeV
Bunch Length	13.2 ps
Intensity	1.2e9 p
LHC VRF	0.05 MV
μ	0.2 a.u.
SPS VRF	0.16 MV

= max error of 95 % of the samples

Decoder evaluation (measurement data)

- Visually indistinguishable
- Takes ~50 sec for a full tomography reconstruction
  - For 48 bunches over 300 turns



Conclusion: excellent agreement in simulation data, good agreement in measurements

On-going

- Deploy operationally, apply model online at every injection, store beam parameters in NXCALS
- Refine based on observations from real measurements