AI for autonomous particle accelerator operations

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SINGULARITY

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Outline

SINGULARITY

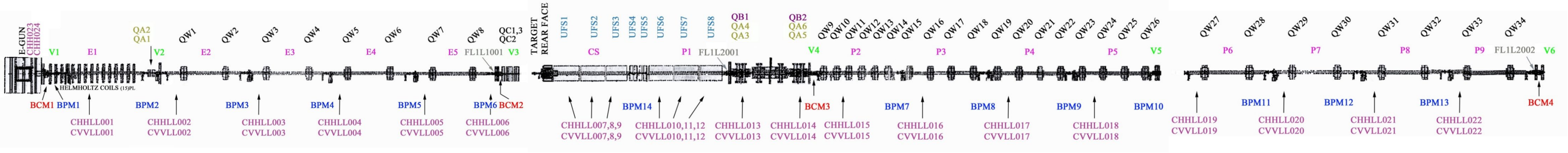
Singularity project aim to develop automated middle-layer to control accelerator operation through machine learning (ML) algorithms.

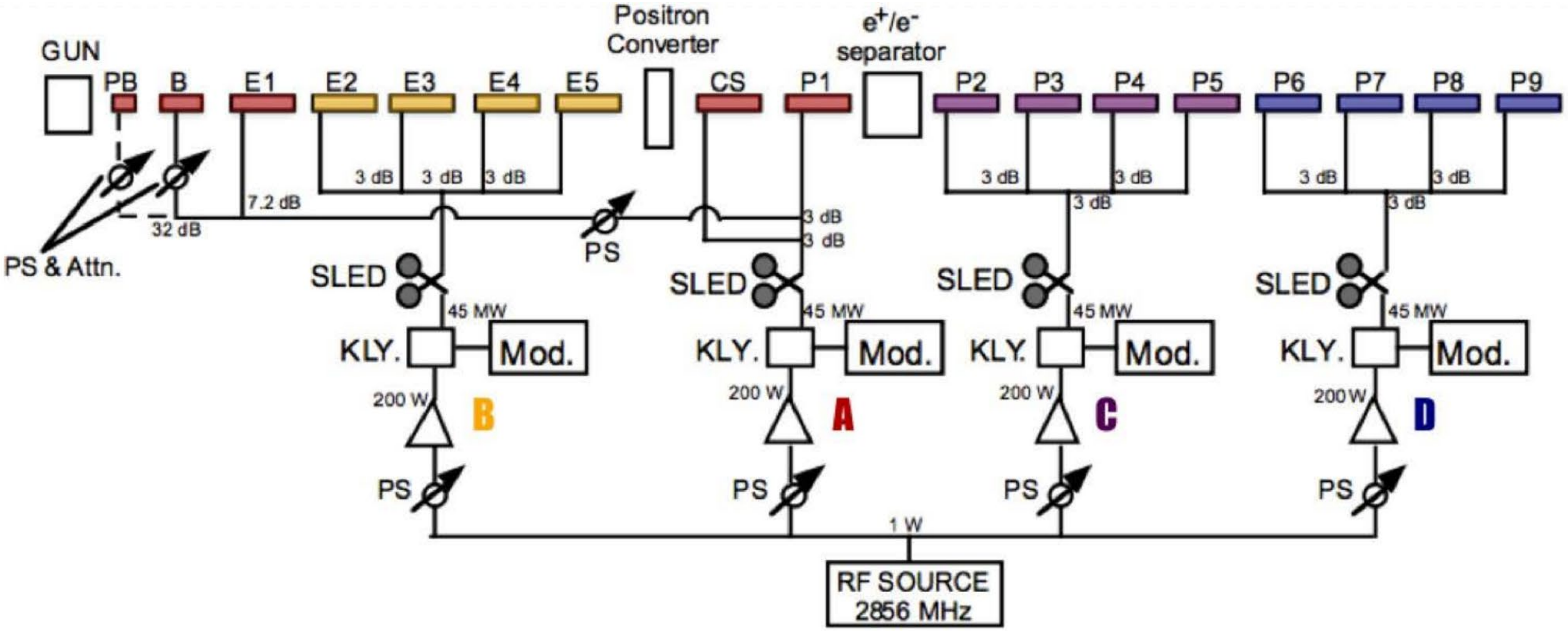
Main topic:

- **Autonomous operation, tuning and commissioning**
- Sub-systems anomaly detection
- Virtualized beam diagnostics

Project founded by CSN5 and Rome Technopole (PNRR)

Dafne LINAC

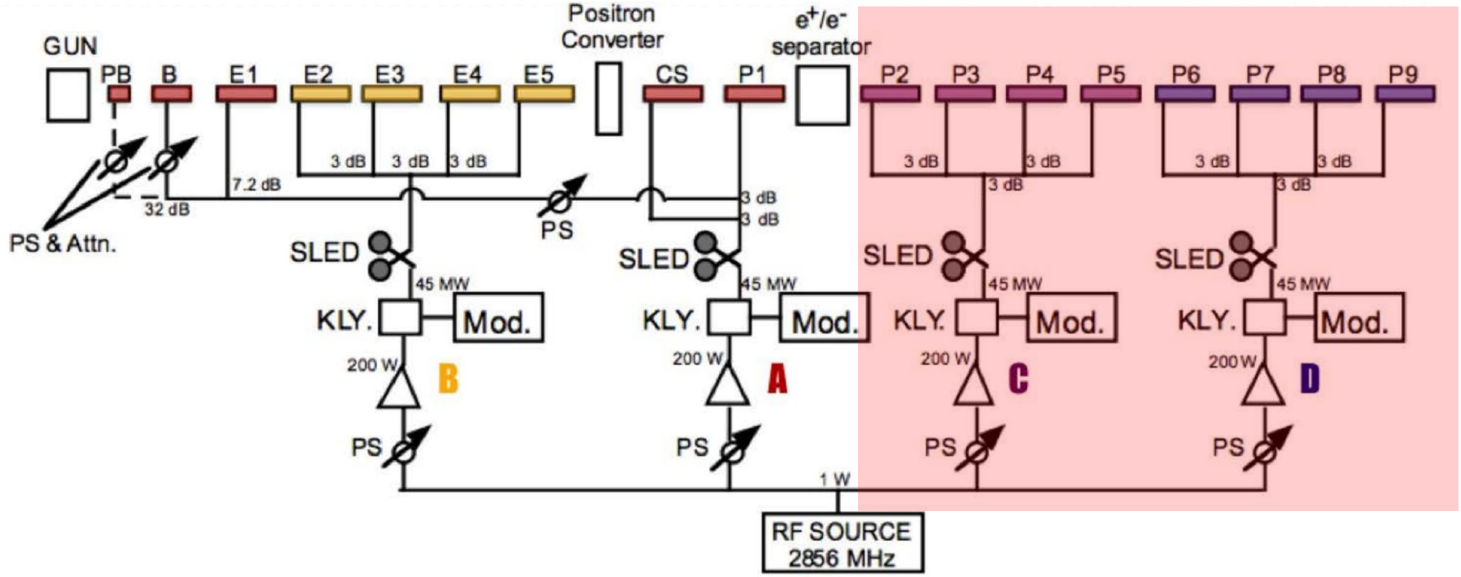




	Design	Operational
Electron beam final energy	800 MeV	510 MeV
Positron beam final energy	550 MeV	510 MeV
RF frequency	2856 MHz	
Positron conversion energy	250 MeV	220 MeV
Beam pulse rep. rate	1 to 50 Hz	1 to 50 Hz
Beam macropulse length	10 nsec	1.4 to 300 nsec
Gun current	8 A	8 A
Beam spot on positron converter	1 mm	1 mm
norm. Emittance (mm. mrad)	1 (electron) 10 (positron)	< 1.5
rms Energy spread	0.5% (electron) 1.0% (positron)	0.5% (electron) 1.0% (positron)
electron current on positron converter	5 A	5.2 A
Max output electron current	>150 mA	500 mA
Max output positron current	36 mA	85 mA
Trasport efficiency from capture section to linac end	90%	90%
Accelerating structure	SLAC-type, CG, 2π/3	
RF source	4 x 45 MWp sledded klystrons TH2128C	

Dafne LINAC beam energy tuning tool

Automate accelerator beam energy tuning.



Environment:

- 2 RF Sources:

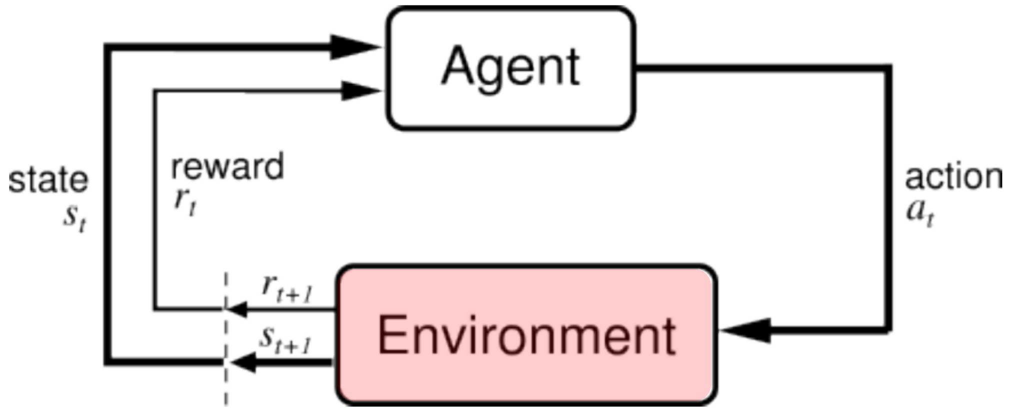
  Phase-C SetPoint [20, 70] deg +/- 0.1 deg

  Phase-D SetPoint [150, 245] deg +/- 0.1 deg

  Power-C SetPoint [0, 35] MW +/- 1 MW

  Power-D SetPoint [0, 55] MW +/- 1 MW

- 1 Odoscope [400, 650] MeV +/- 3 MeV



Markov Decision Process (MDP)

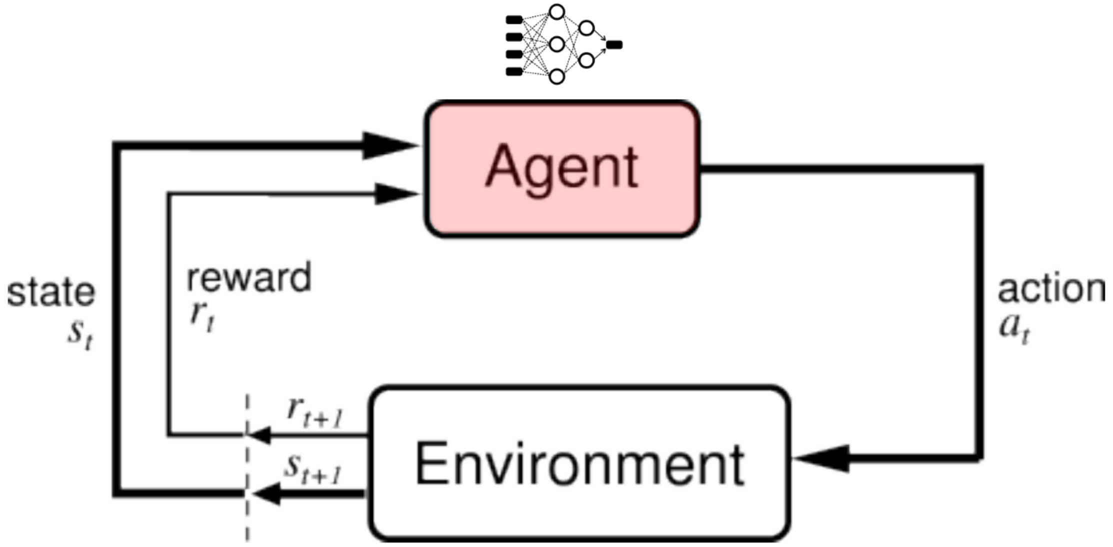
Dafne LINAC beam energy tuning tool

Agent:

- Deep Q-learning (DQN) to estimate optimal policy Q* to maximize scoring:

$$max(energy_{target} - energy)$$

- Exploration vs Exploitation balancing through decaying ε-greedy strategy.



Markov Decision Process (MDP)

Q* (State, Action)	ph-c,Pot-c, ph-d,Pot-d, …	ph-c,Pot-c, ph-d,Pot-d, …	ph-c,Pot-c, ph-d,Pot-d, …
energy			
…			
Energy working point			goal

Bellman transition function:

$$\boldsymbol{Q^{new}(s_t, a_t)} \leftarrow (1-\alpha) \cdot Q(s,a) + \alpha\big(r + \gamma \cdot max_a Q(s_{t+1}, a)\big)$$

$$\alpha = learning\ rate$$

$$\gamma = discount\ factor$$

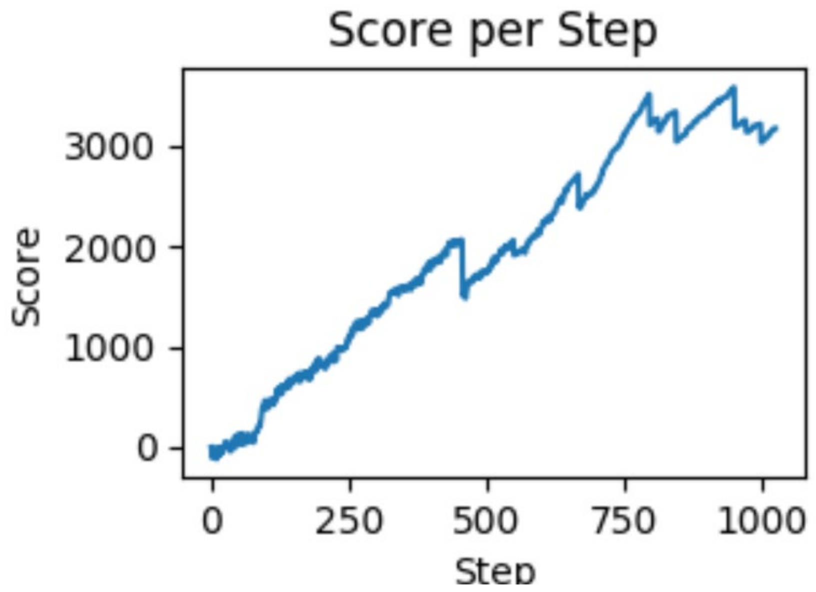
Dafne LINAC beam energy tuning tool

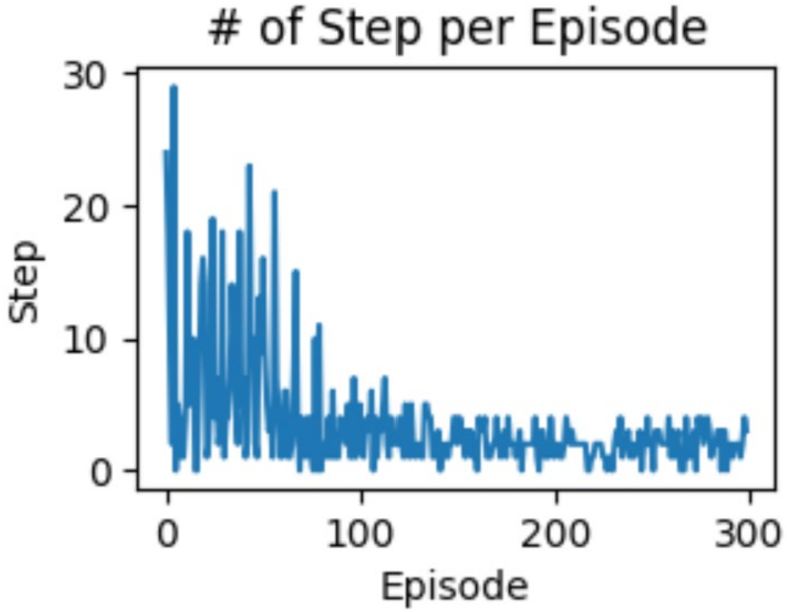
Training on 300 simulated episodes:

- Instance linac lattice

1. generate random [phase, power] setpoint
2. Move RF sources updating $Q(s,a) \rightarrow Q^*$
3. Final Goal:

   $energy_{target} - energy < energy_{tollerance}$

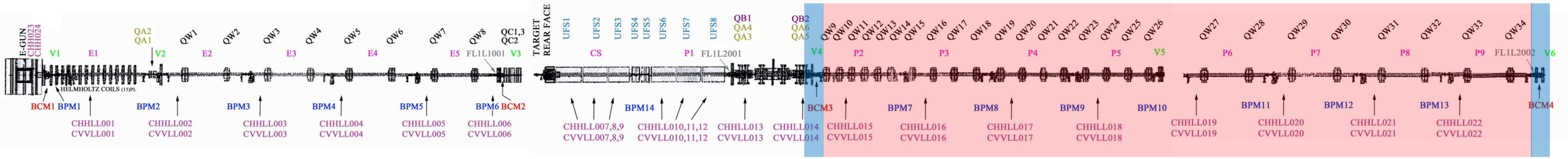


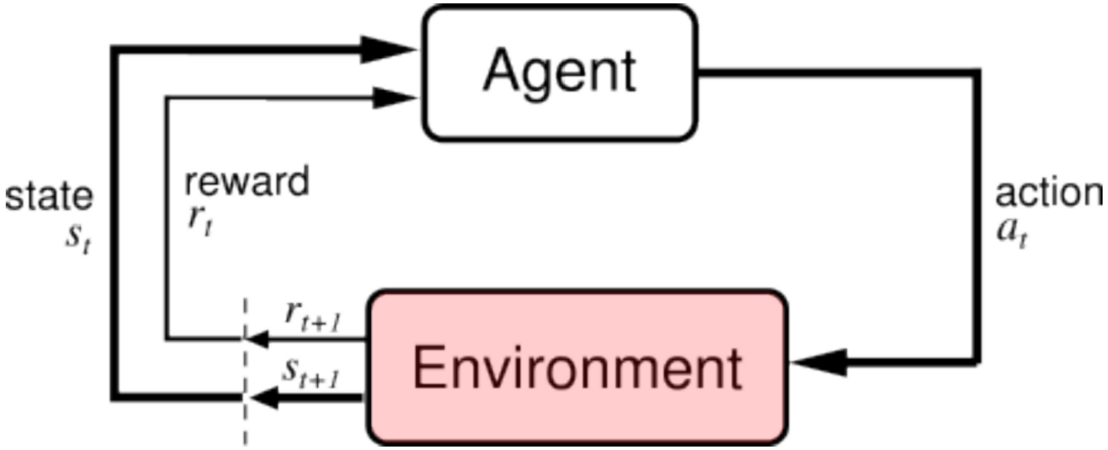


Results:

- RL algorithm tested with simulated data:
  - AI trained in 1ksteps (expected 1 week of beam shift).
  - Capable of training on multiple working point in parallel.
  - Machine, misalignment and performance drift indipendent.

Dafne LINAC beam charge optimization tool





Markov Decision Process (MDP)

Automate accelerator beam charge optimization.

Environment:

- 8 Quadrupole Magnets

  Current PSU SetPoint [0, 10] A +/- 0.1 A

- 2 BCMs [0, 1.2] mA +/- 1 uA

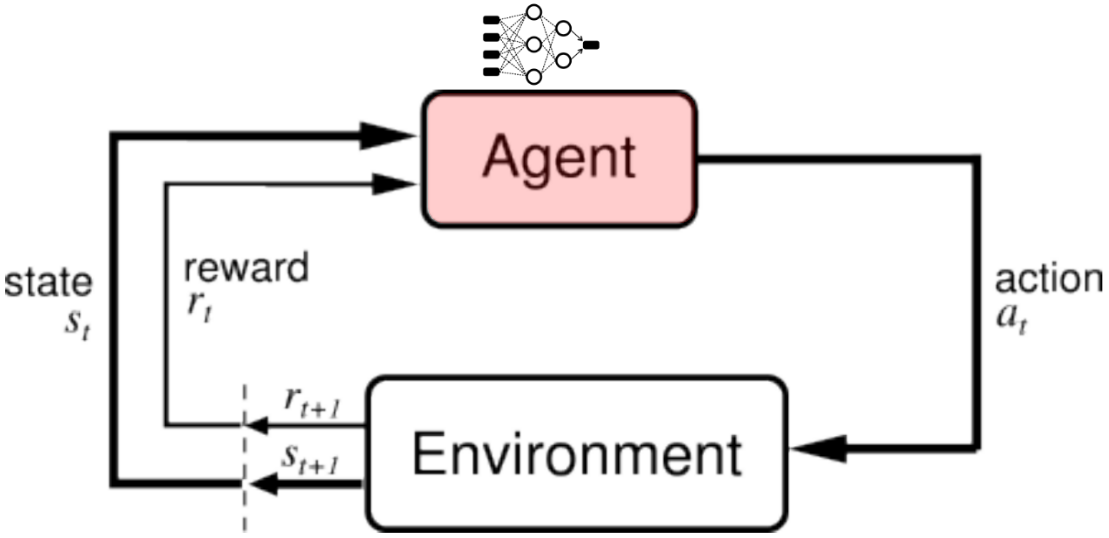
Dafne LINAC beam charge optimization tool

Agent:

- Deep Q-learning (DQN) to estimate optimal policy Q* to maximize scoring:

$$max\left(charge\ ratio_{target} - charge\ ratio\right)$$

- Exploration vs Exploitation balancing through decaying ε-greedy strategy.



Markov Decision Process (MDP)

Q* (State, Action)	Q1,Q2,Q3…	Q1,Q2,Q3…	Q1,Q2,Q3…
Charge ratio			
…			
Optimal charge ratio			goal

Bellman transition function:

$$\boldsymbol{Q}^{new}(\boldsymbol{s}_t, \boldsymbol{a}_t) \leftarrow (1-\alpha) \cdot Q(s,a) + \alpha\left(r + \gamma \cdot max_a Q(s_{t+1}, a)\right)$$

$$\alpha = learning\ rate$$

$$\gamma = discount\ factor$$

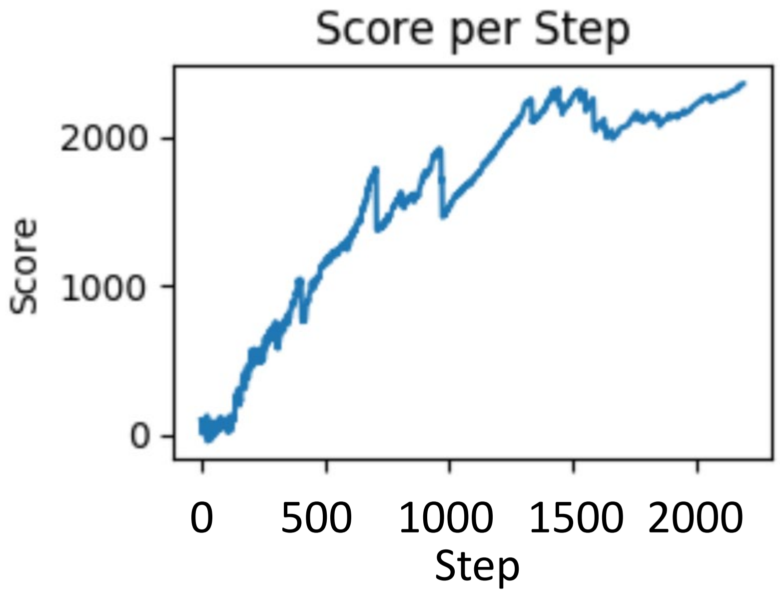
Dafne LINAC beam charge optimization tool

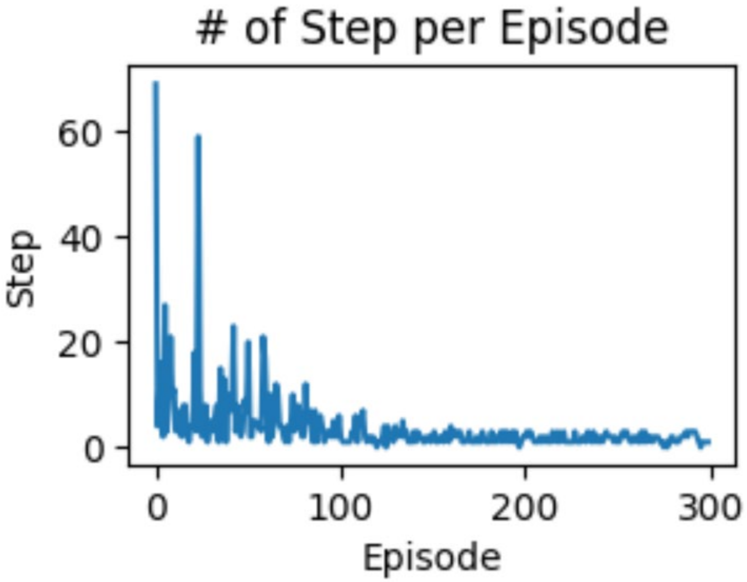
Training on 300 simulated episodes:

- Instance linac lattice

1. generate random quads setpoint
2. Move quads updating $Q(s, a) \rightarrow Q^*$
3. Final Goal:

   $charge\ ratio_{target} - charge\ ratio < \ charge\ ratio_{tollerance}$



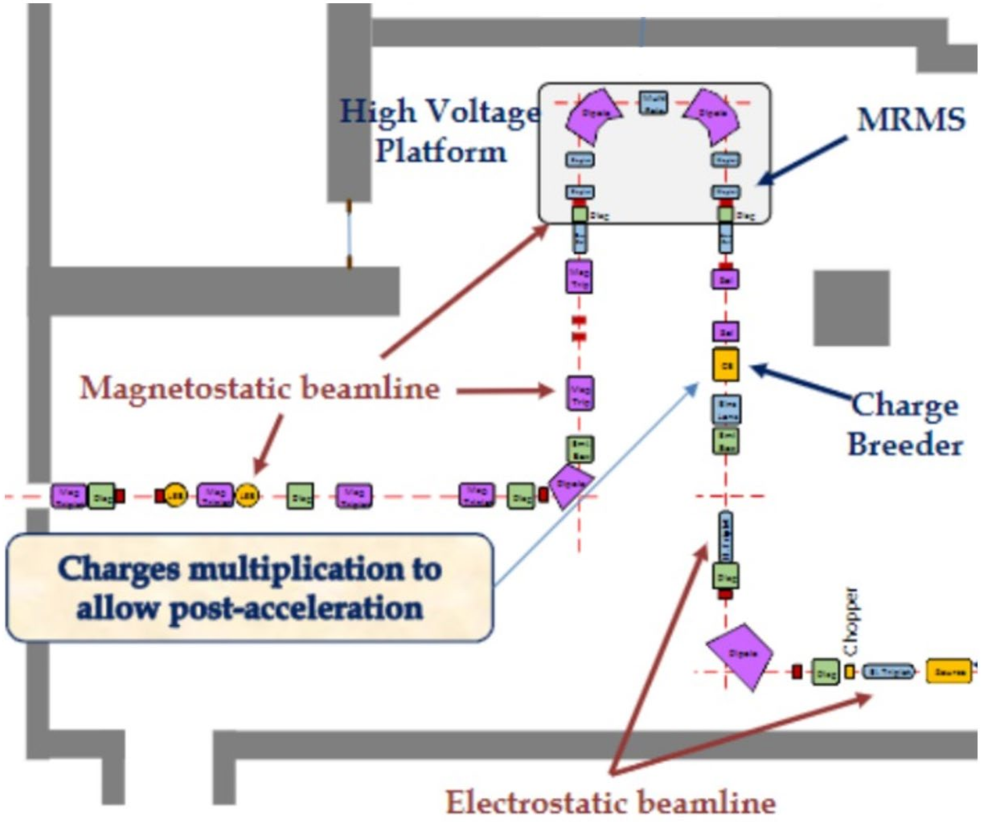


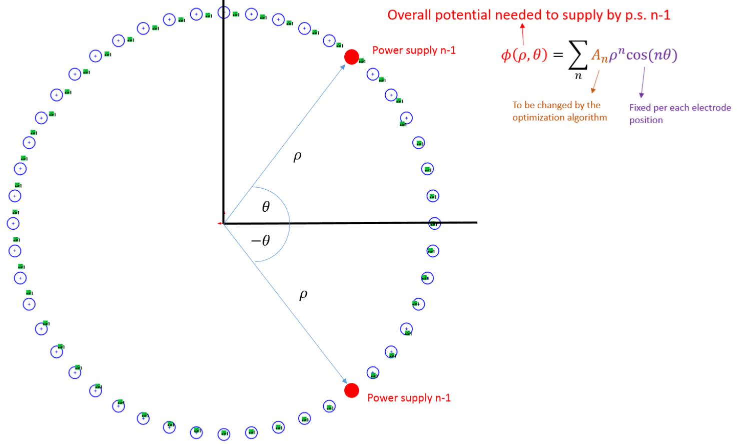
Results:

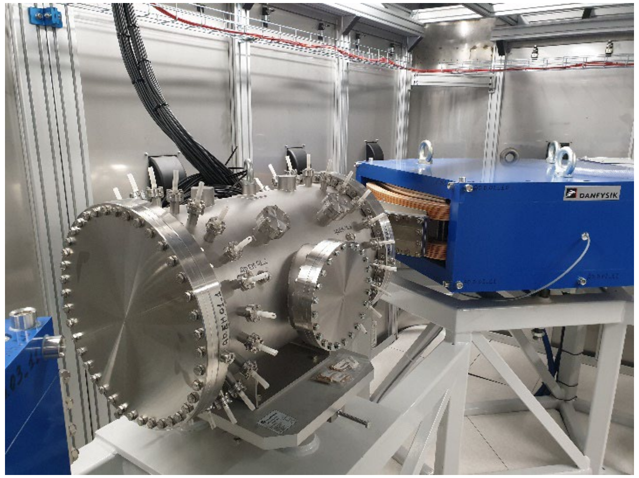
- RL algorithm tested with simulated data:
  - AI trained in 2ksteps (expected 2 weeks of beam shift).
  - Machine, misalignment and performance drift indipendent.

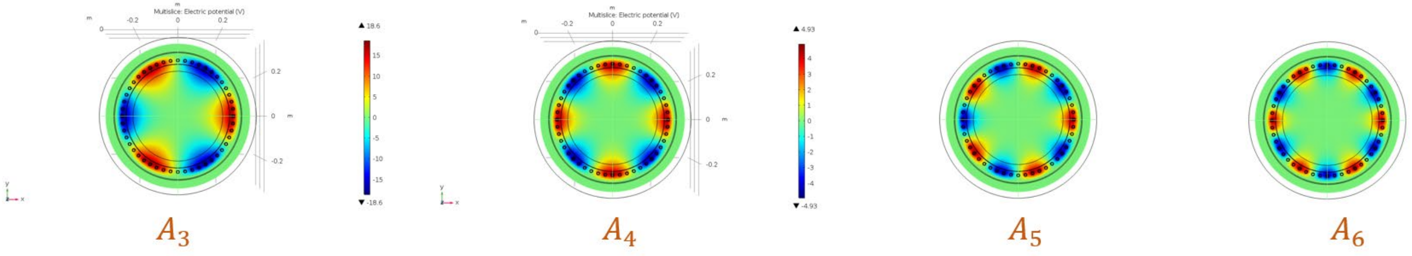
SPES Mass Separator

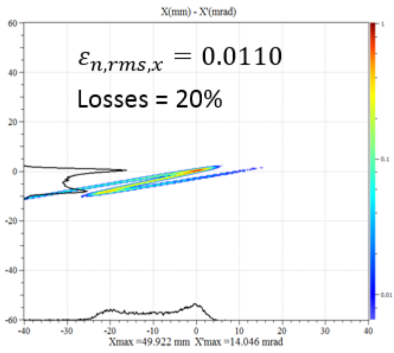
Multi-pole for emittance optimization

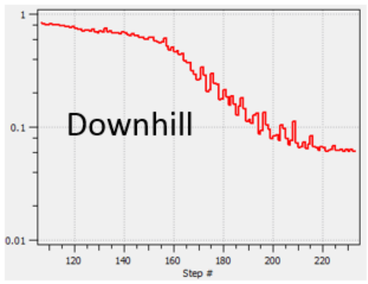


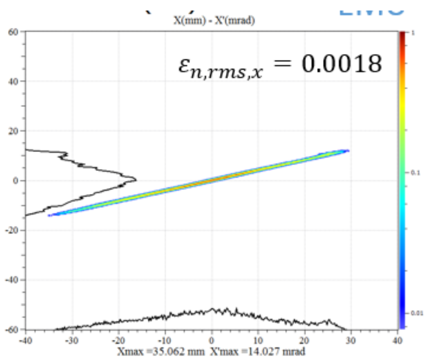








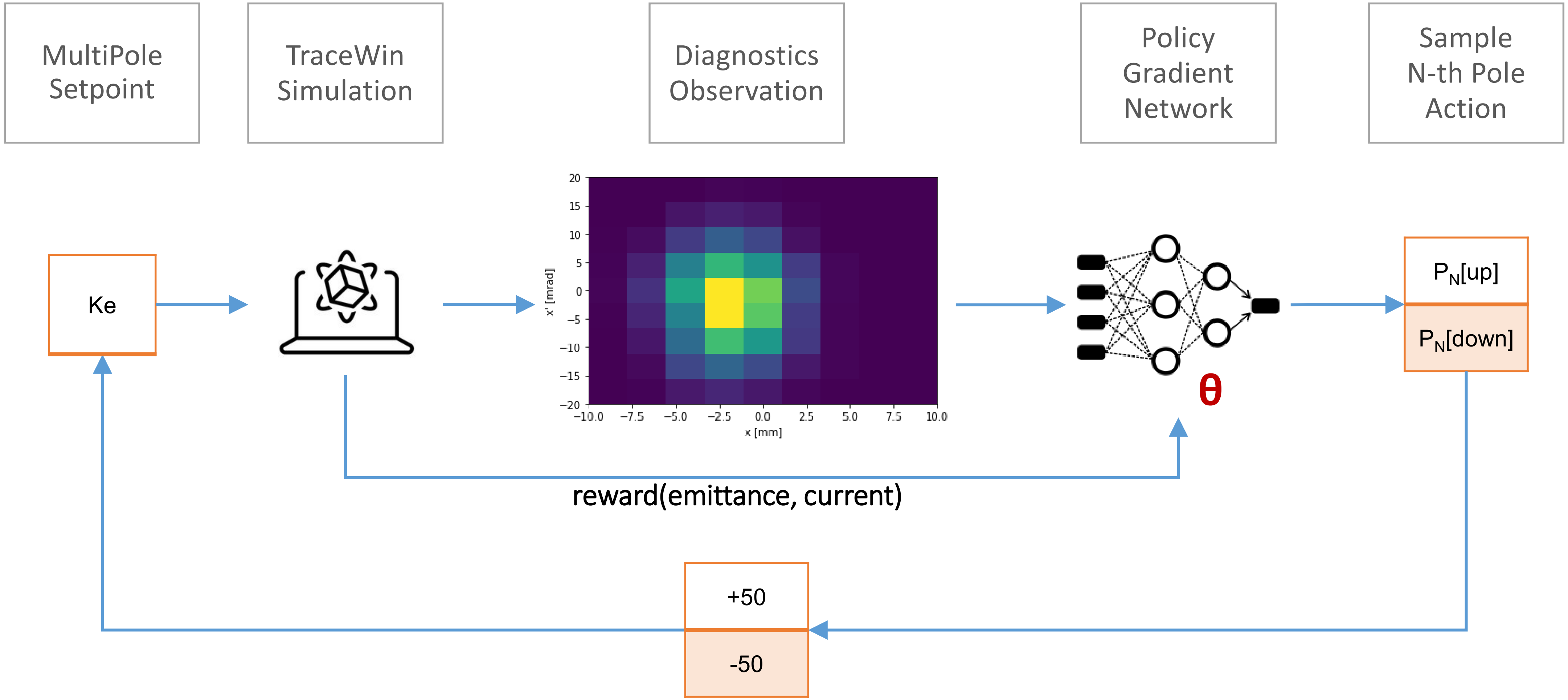




Simplex method optimization

SPES Mass Separator emittance optimization tool

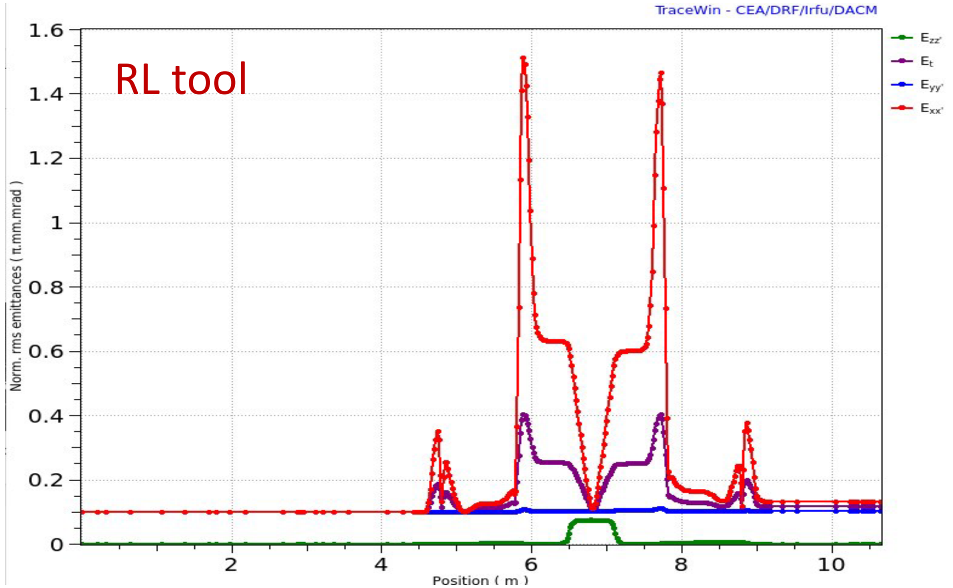
Automate fine emittance optimization

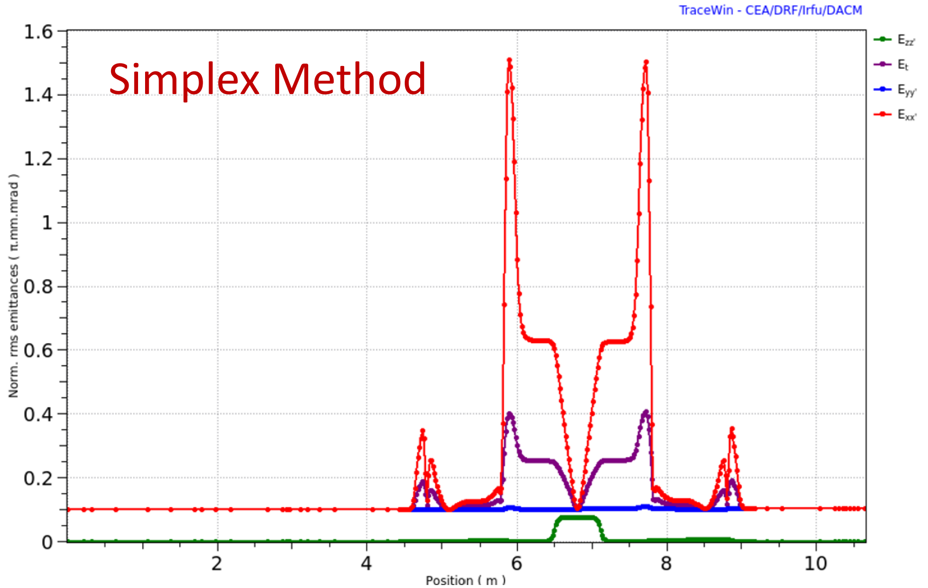


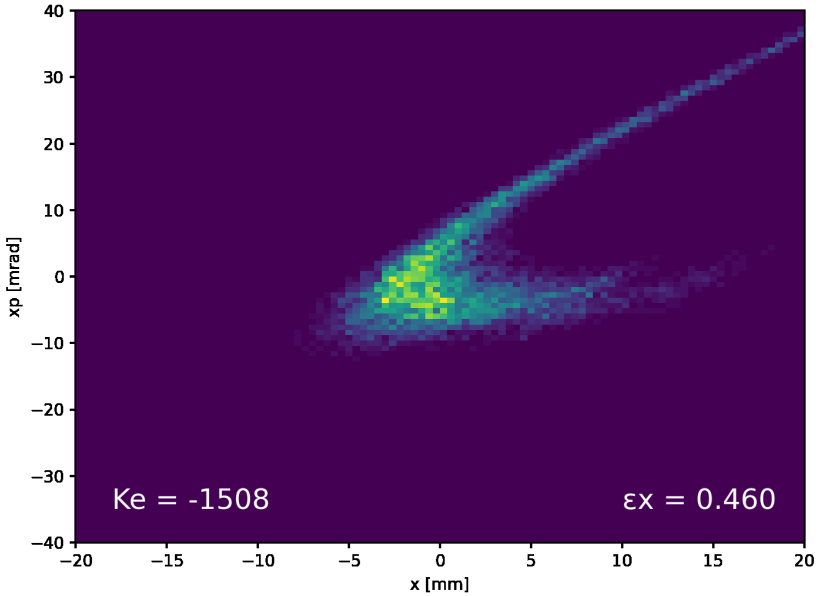
SPES Mass Separator emittance optimization tool

Training:

- 60 hours
- 4500 episodes
- 33200 simulations







Run-time emittance optimization results:
200 steps Simplex method, emittance 0,103 mm mrad
10 steps with RL tool, emittance 0,130 mm mrad

Conclusions and next steps

- Reinforcement Learning tools validated as suitable for autonomous operation on accelerator facilities in operation, in commissioning or in old complex.
- RL tools developed to be easily configured on different lattice with safe operation limit.
- Training period reasonable to schedule dedicated beamn shift.
- Run-time operation will increase particle accelerator uptime and efficiency.

Thank you for the attention