THPAB191

Physics-Enhanced Reinforcement Learning for Optimal Control

12th International Particle Accelerator conference

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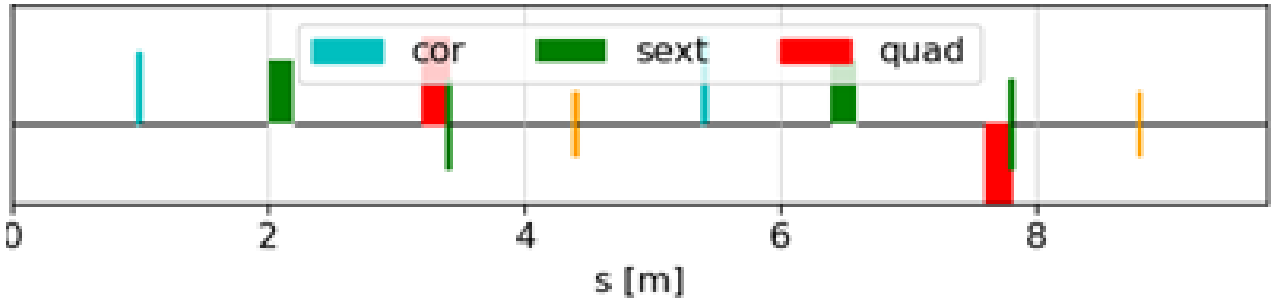
27.05.2021

HELMHOLTZ RESEARCH FOR GRAND CHALLENGES

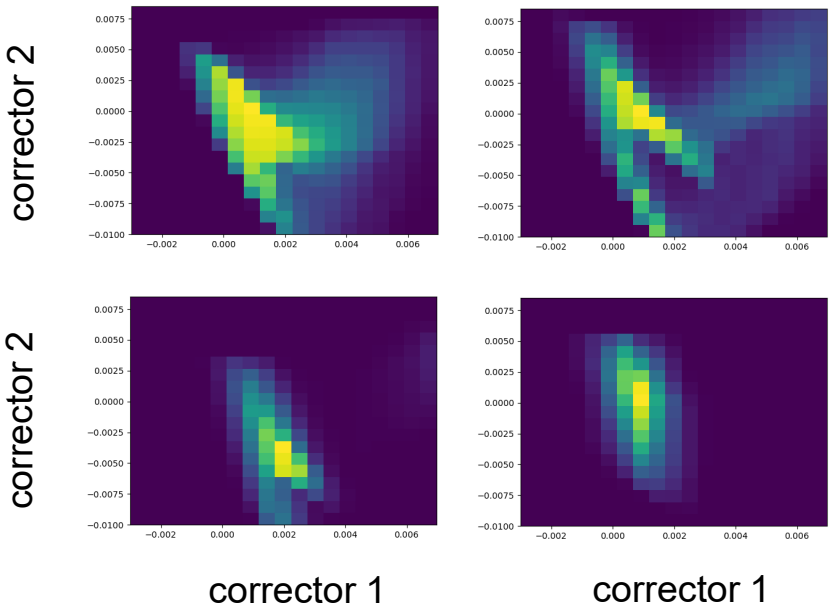
DESY.

Problem formulation

beam transmission: 2 actuators (correctors), 1 objective, sextupoles and apertures

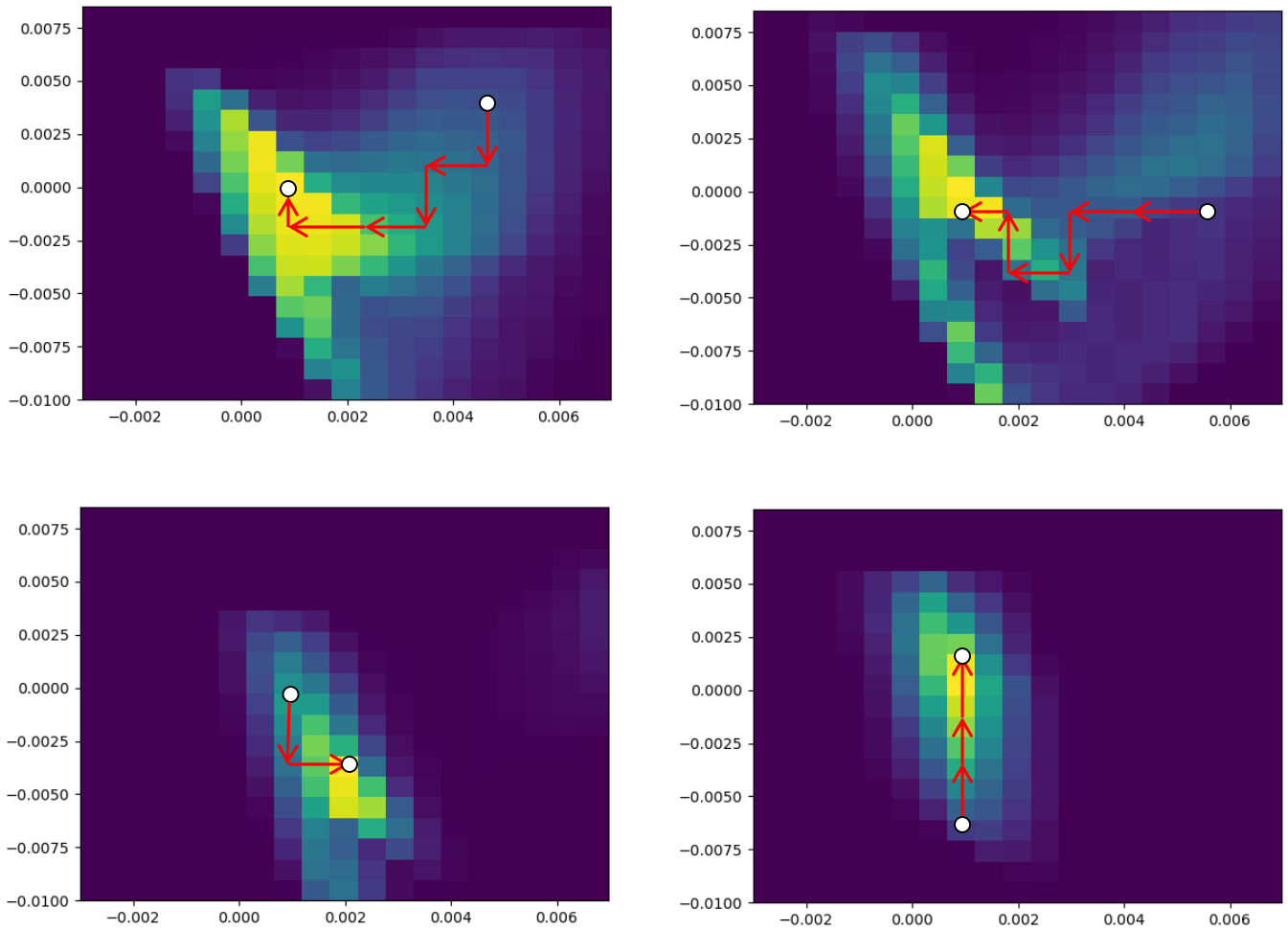


nonlinear response concerning the random misalignments of magnets



Numerical optimization

using traditional optimizers one can iteratively find out optimal corrector's values



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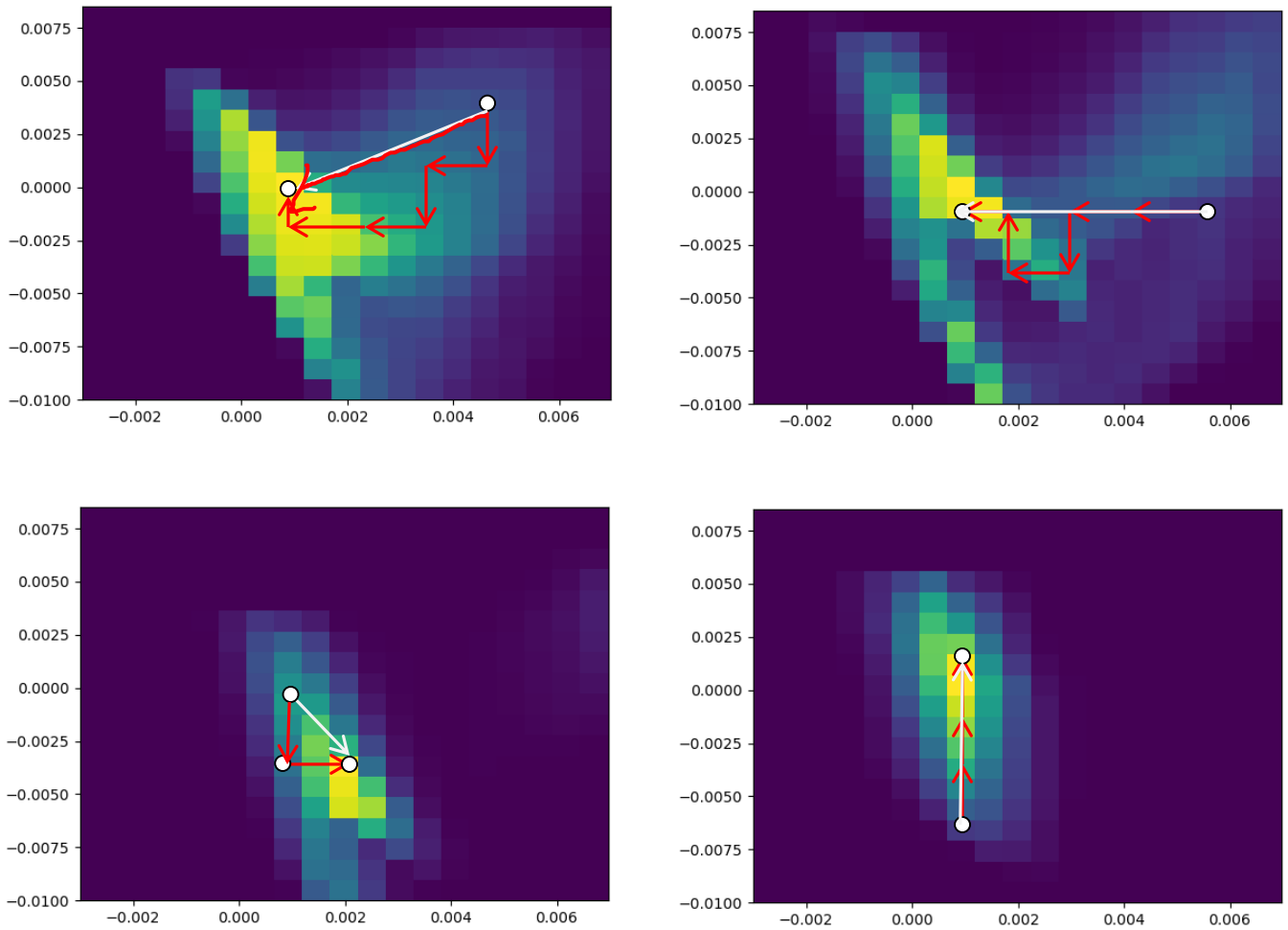
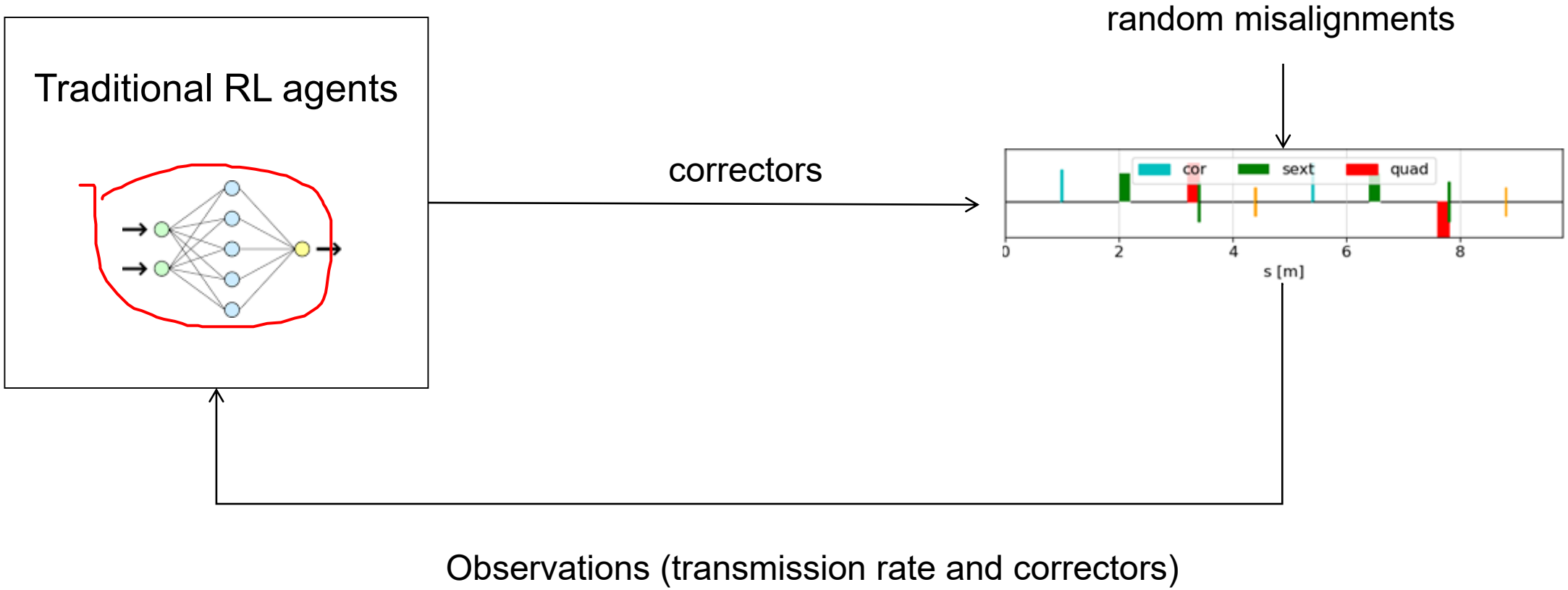


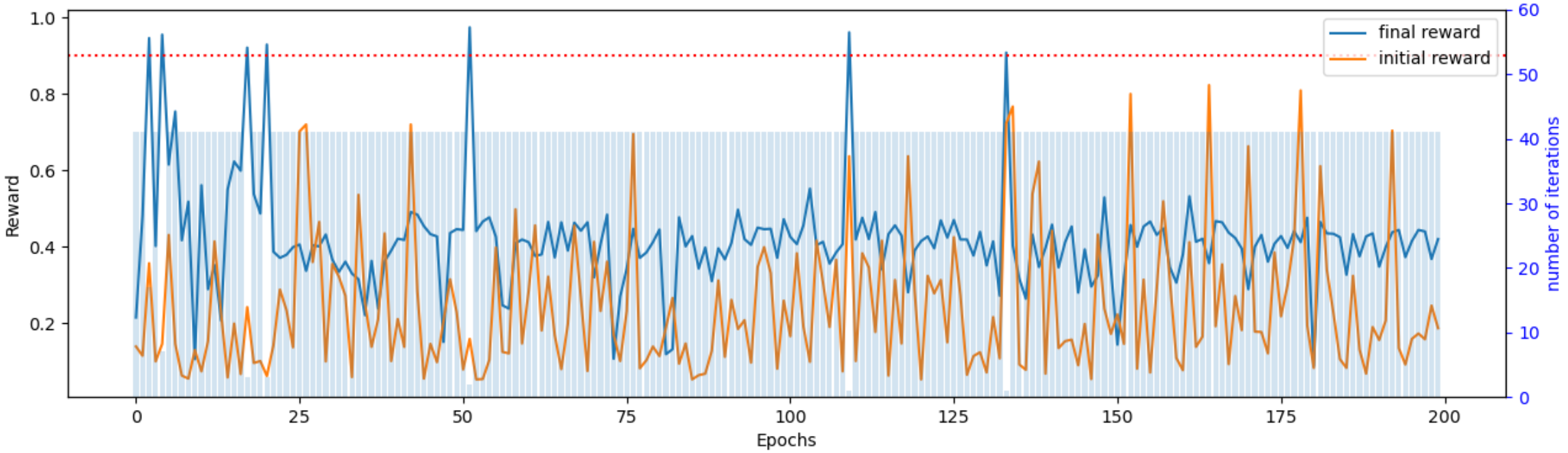
RL for control

NN is trained with historical data and learns an optimal policy



RL for control

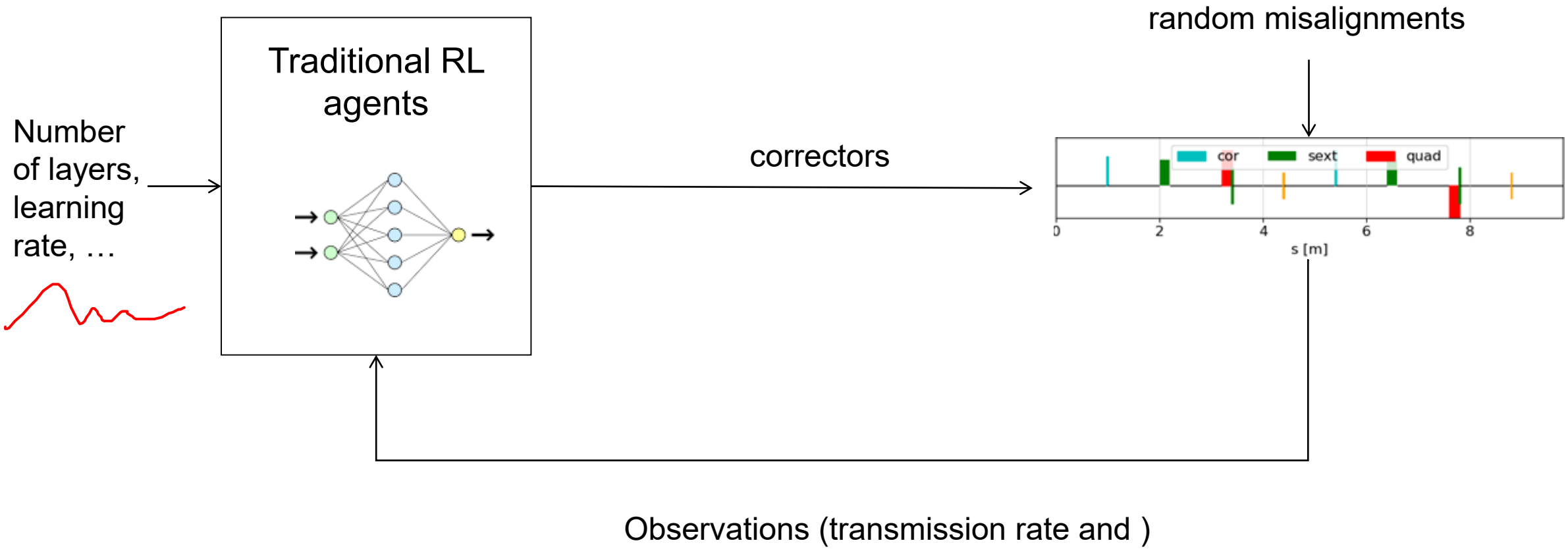
It is hard to achieve meaningful results with black-box models



During each epoch NN is trained with simulated data for the given random misalignments and tries to maximize initial state (orange line). After max. 40 iterations the procedure begins again for new random misalignments.

RL for control

To fix this issue ML methods provide possibility to tune hyper parameters of the NN



RL for control

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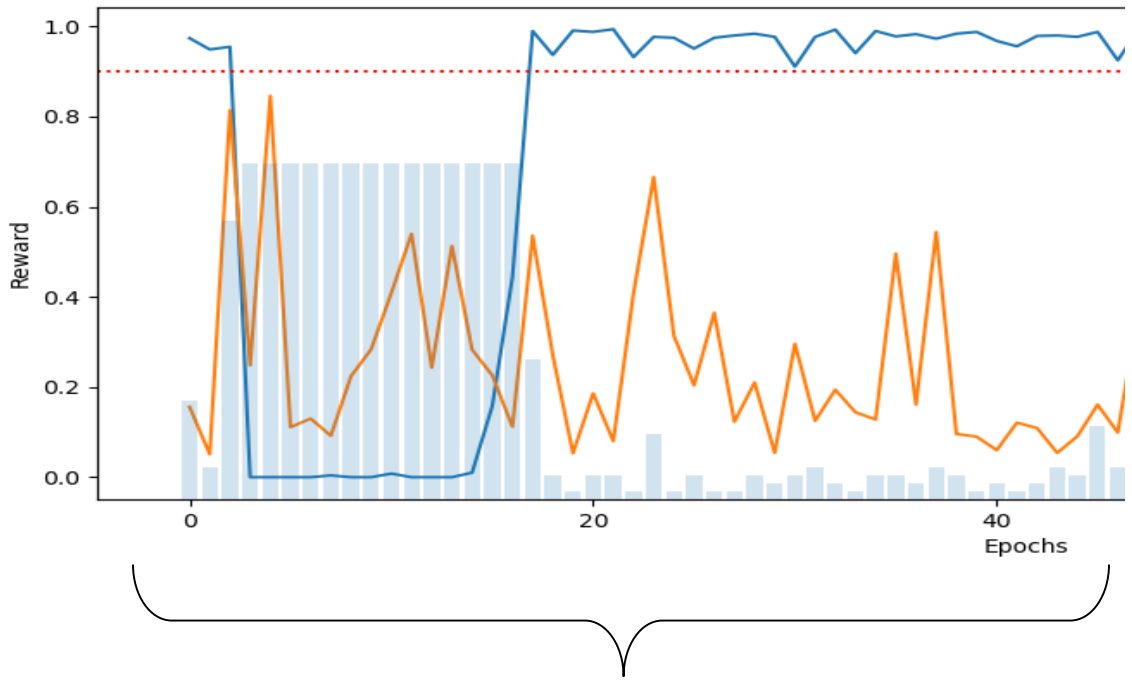

looks like a convergence

RL for control

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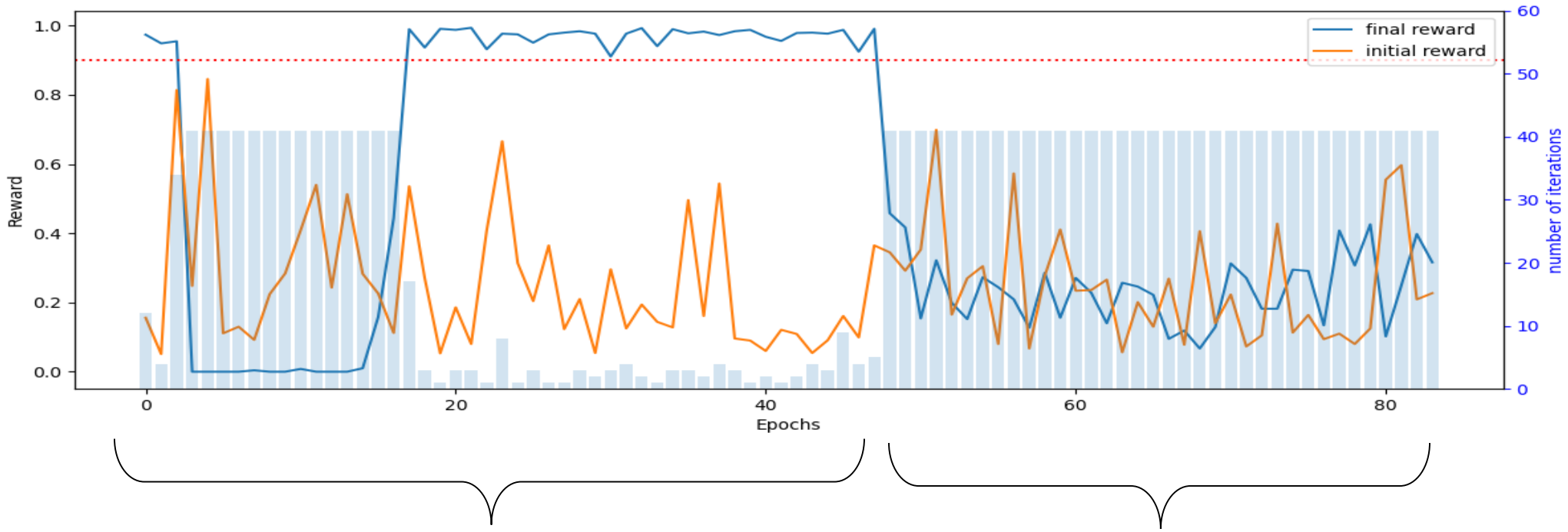
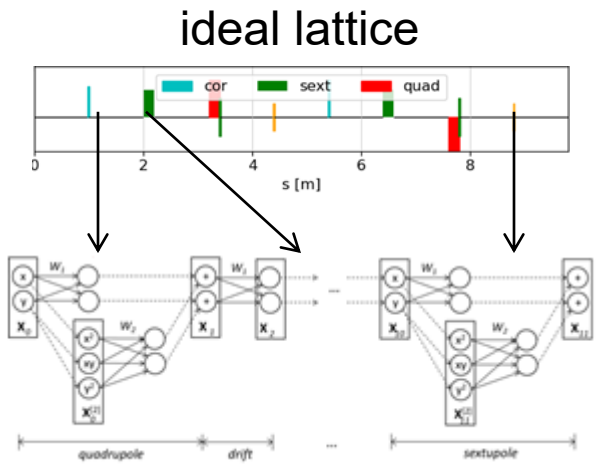


looks like a convergence

no guarantee that NN worsk for new parameters

RL for control enhanced by physics-based NN

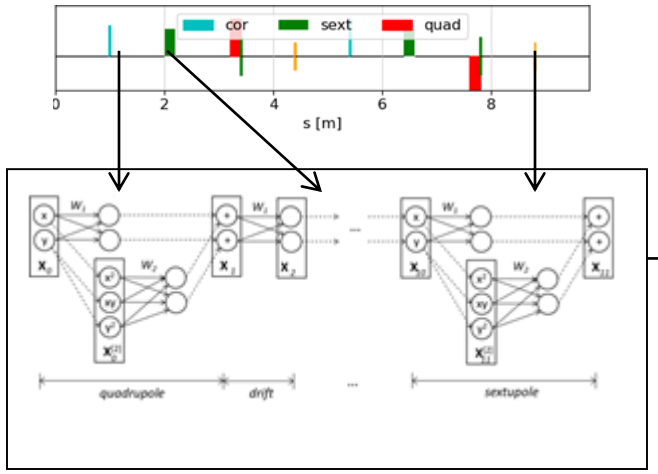
Incorporate a priory knowledge in form of a trainable NN



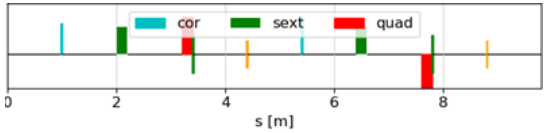
RL for control enhanced by physics-based NN

Incorporate a priory knowledge in form of a trainable NN

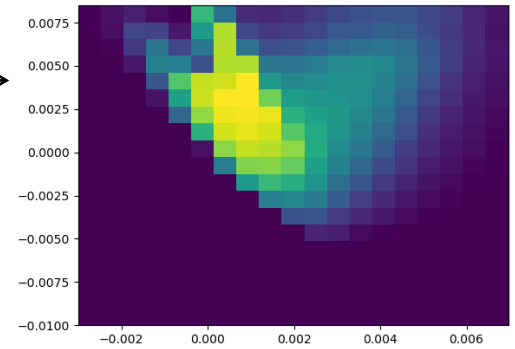
ideal lattice

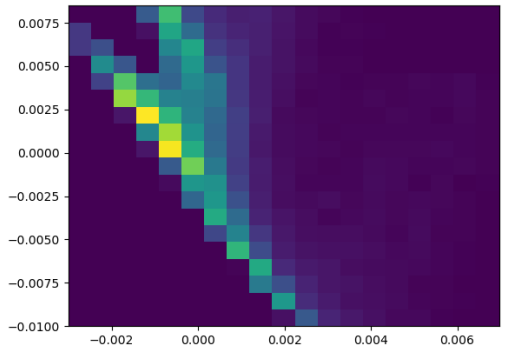


real lattice with random misalignments



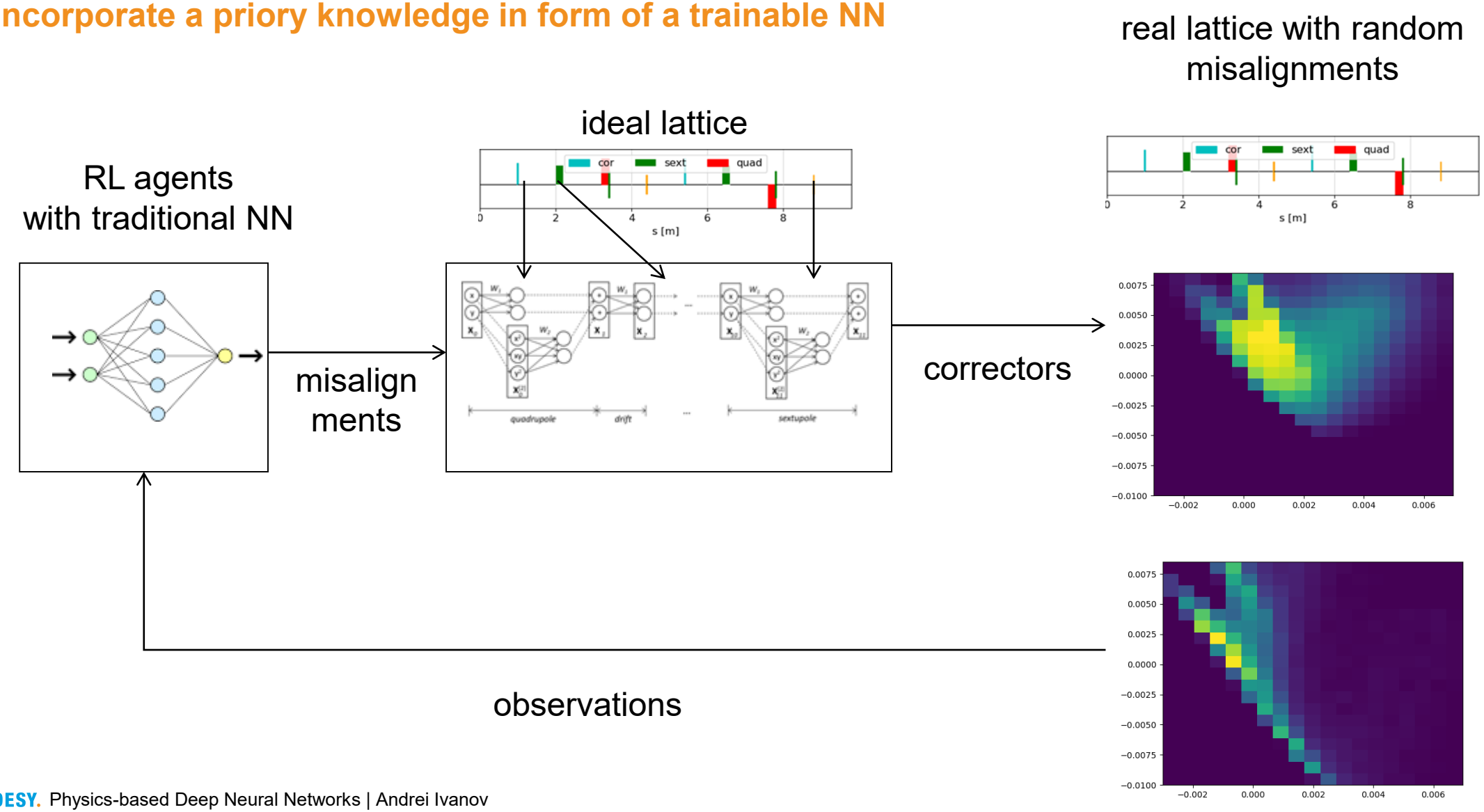
correctors





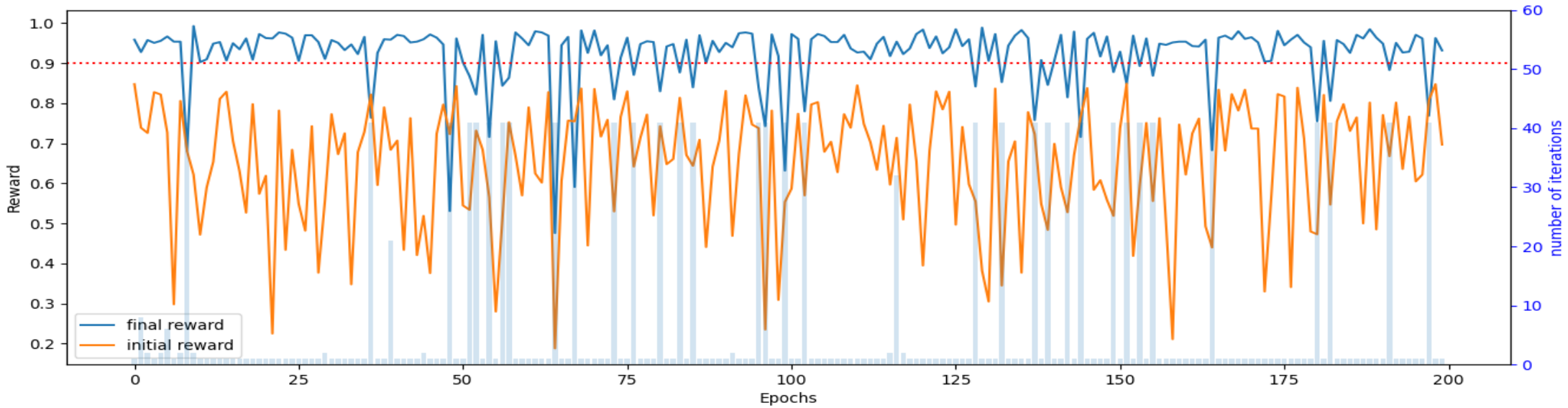
RL for control enhanced by physics-based NN

Incorporate a priory knowledge in form of a trainable NN



RL agent recovers misalignments distribution from data and provides an optimal strategy

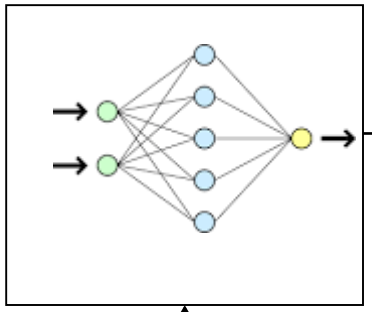
Similar to a traditional optimizer that utilizes knowledge from historical data and uses adaptive steps during objective maximization



RL for control enhanced by physics-based NN

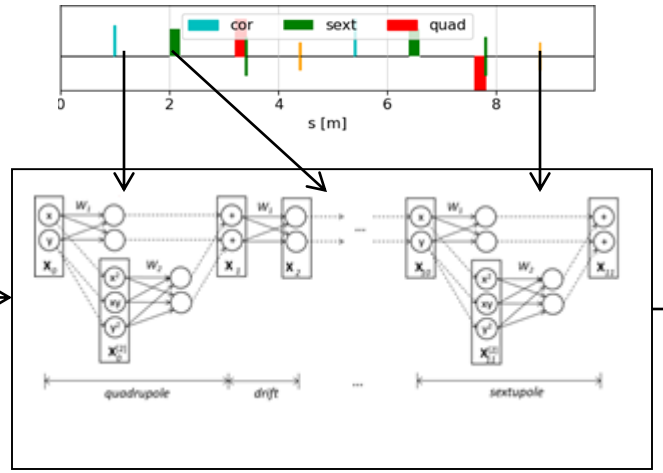
Incorporate a priory knowledge in form of trainable NN

RL agents
with traditional NN



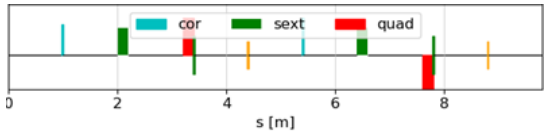
hidden
variables

ideal lattice



correctors

real lattice with random
misalignments
+
wrong magnet
strengths



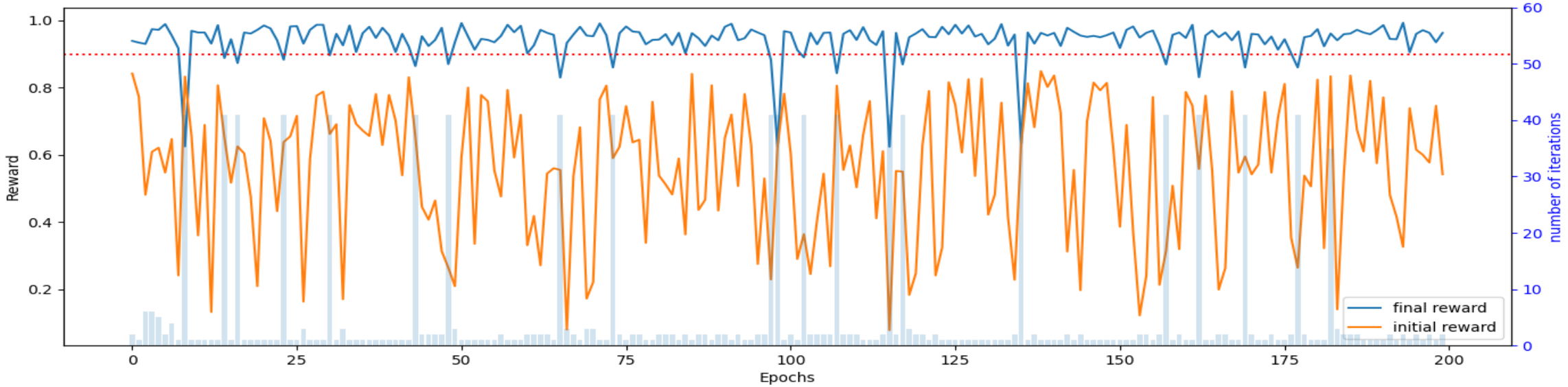
observations

uncertainties

known model variations

RL agent + Taylor map-based NN approximates true system

Taylor maps are calculated for the ideal lattice, but true lattice consists of magnets with strengths reduced by 20%



Thank you