Optimization of Dynamic Aperture for the Electron-Ion Collider

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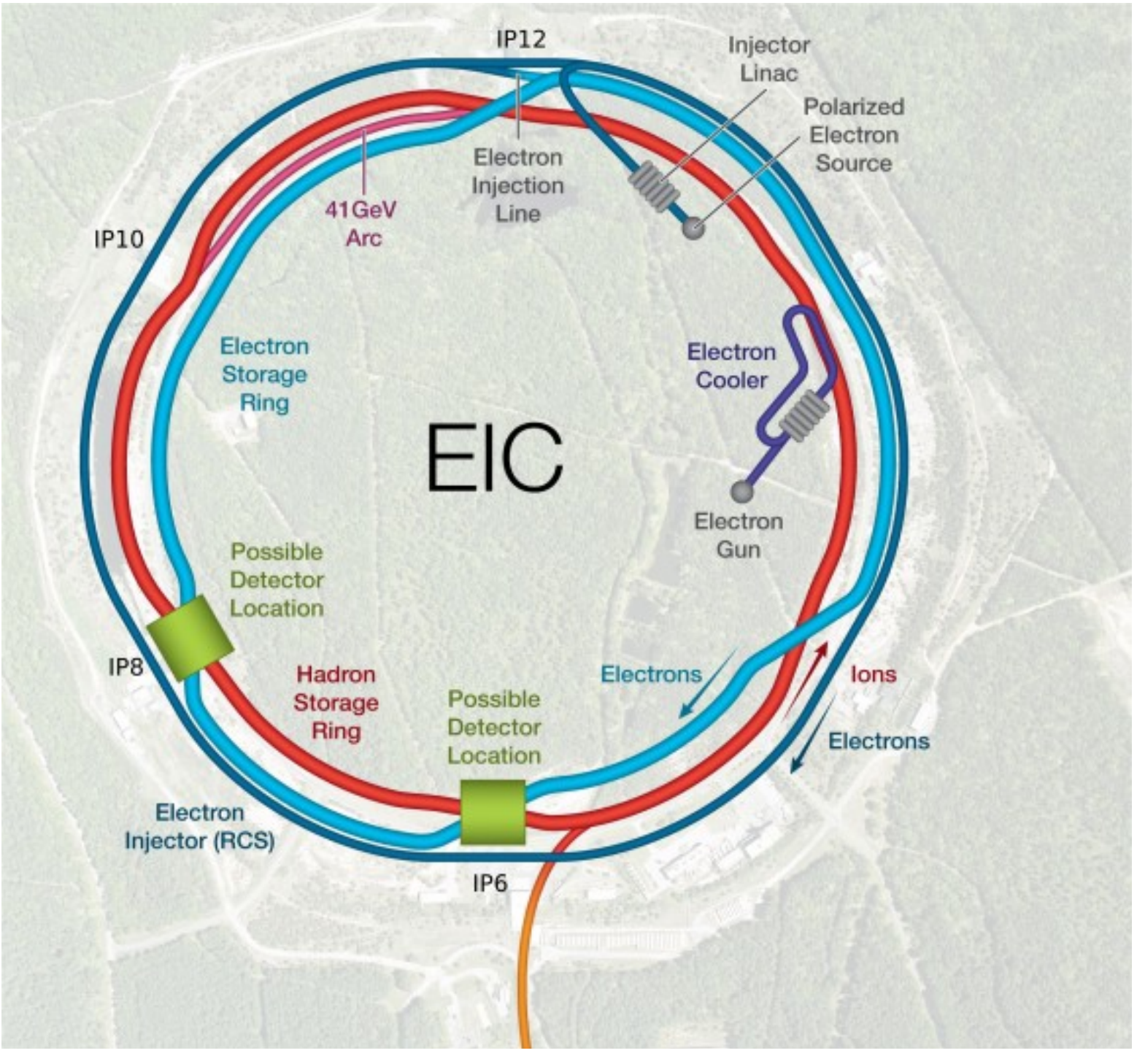
The Electron-Ion Collider (EIC)

- The EIC [1] will collide polarized electrons with polarized hadrons to investigate the structure and properties of nucleons
- The EIC will be built in RHIC tunnel by upgrading existing hadron rings and constructing brand-new electron accelerators: a Rapid Cycling Synchrotron (**RCS**) and an Electron Storage Ring (**ESR**)
- Luminosities up to 10^{34} cm^{-2} s^{-1}
- Collision CoM energies: 29 to 140 GeV
- Electron energies: 5-6, 10 & 18 GeV
- Hadron energies: 41, 100-275 GeV



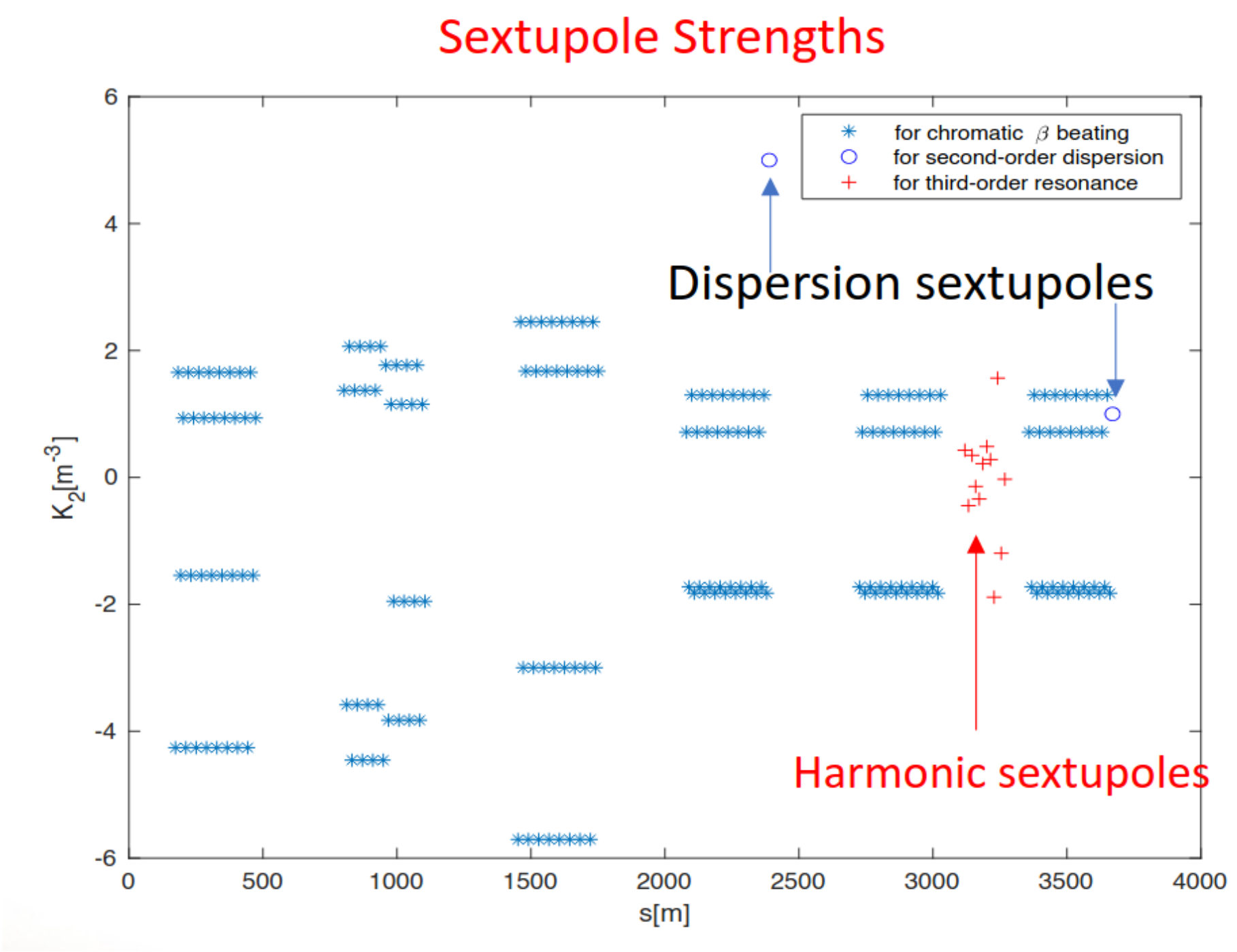
EIC Parameters

Species	proton	electron	proton	electron	proton	electron	proton	electron	proton	electron
Energy [GeV]	275	18	275	10	100	10	100	5	41	5
CM energy [GeV]	140.7		104.9		63.2		44.7		28.6	
Bunch intensity [10^{10}]	19.1	6.2	6.9	17.2	6.9	17.2	4.8	17.2	2.6	13.3
No. of bunches	290		1160		1160		1160		1160	
Beam current [A]	0.69	0.227	1	2.5	1	2.5	0.69	2.5	0.38	1.93
RMS norm. emit., h/v [μm]	5.2/0.47	845/71	3.3/0.3	391/26	3.2/0.29	391/26	2.7/0.25	196/18	1.9/0.45	196/34
RMS emittance, h/v [nm]	18/1.6	24/2.0	11.3/1.0	20/1.3	30/2.7	20/1.3	26/2.3	20/1.8	44/10	20/3.5
β^*, h/v [cm]]	80/7.1	59/5.7	80/7.2	45/5.6	63/5.7	96/12	61/5.5	78/7.1	90/7.1	196/21.0
IP RMS beam size, h/v [μm]	119/11		95/8.5		138/12		125/11		198/27	
K_x	11.1		11.1		11.1		11.1		7.3	
RMS $\Delta\theta$, h/v [μrad]	150/150	202/187	119/119	211/152	220/220	145/105	206/206	160/160	220/380	101/129
BB parameter, h/v [10^{-3}]	3/3	93/100	12/12	72/100	12/12	72/100	14/14	100/100	15/9	53/42
RMS long. emittance [10^{-3}, eV·s]	36		36		21		21		11	
RMS bunch length [cm]	6	0.9	6	0.7	7	0.7	7	0.7	7.5	0.7
RMS $\Delta p/p$ [10^{-4}]	6.8	10.9	6.8	5.8	9.7	5.8	9.7	6.8	10.3	6.8
Max. space charge	0.007	neglig.	0.004	neglig.	0.026	neglig.	0.021	neglig.	0.05	neglig.
Piwinski angle [rad]	6.3	2.1	7.9	2.4	6.3	1.8	7.0	2.0	4.2	1.1
Long. IBS time [h]	2.0		2.9		2.5		3.1		3.8	
Transv. IBS time [h]	2.0		2		2.0/4.0		2.0/4.0		3.4/2.1	
Hourglass factor H	0.91		0.94		0.90		0.88		0.93	
Luminosity [10^{33}cm^{-2}s^{-1}]	1.54		10.00		4.48		3.68		0.44	

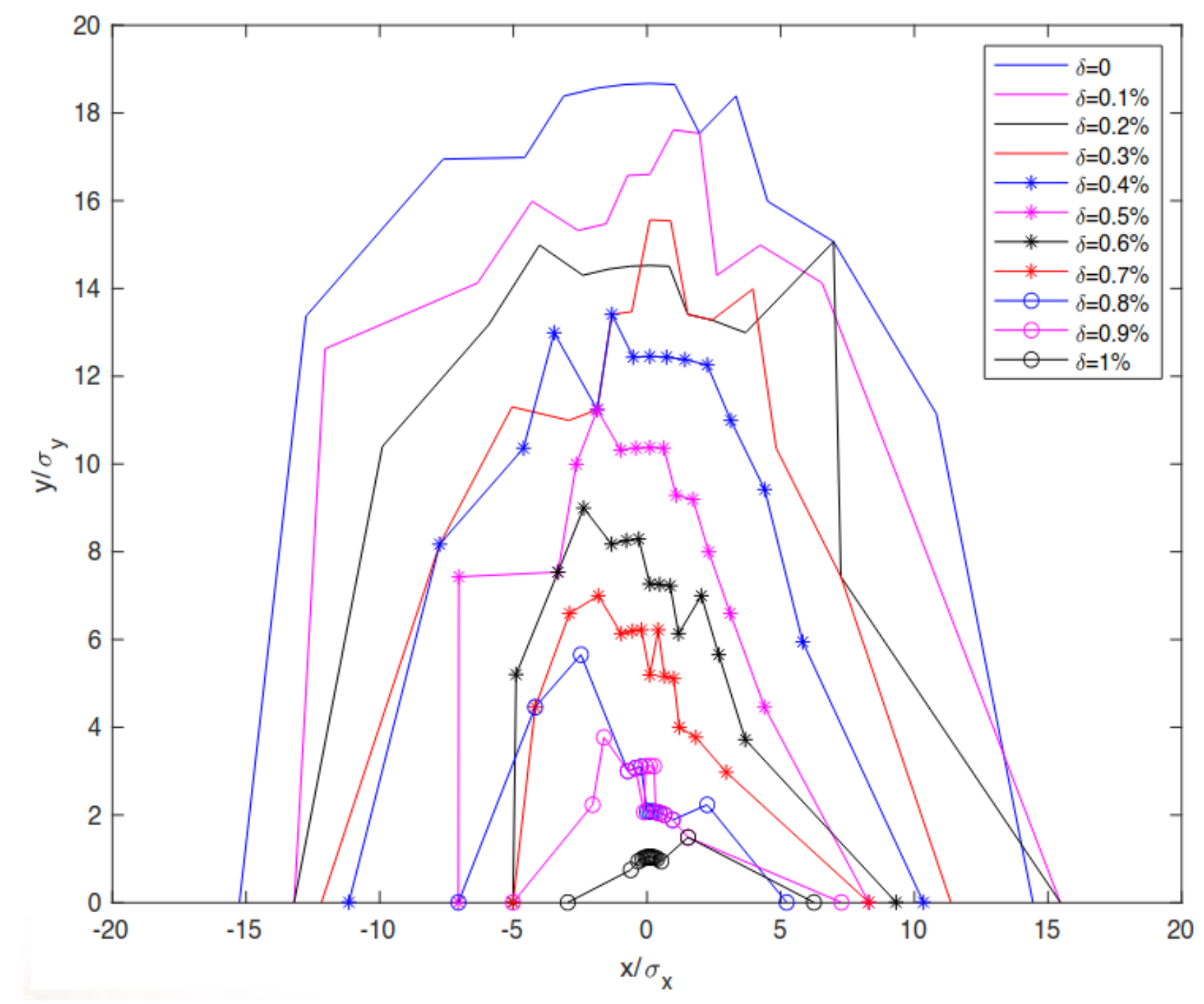
Dynamic aperture

Overall work required

1) Optimize dynamic aperture for baseline, ideal lattice using sextupoles and phase advances
2) Evaluate dynamic aperture with errors—misalignments, strength errors, multipole components—and determine tolerances and error-correction scheme
3) Evaluate dynamic aperture in the presence of beam-beam effects
4) Rerun simulations with updated lattice and errors as new information, e.g. magnetic measurements, becomes available
5) Develop online model of accelerator, and correct chromaticity and optimize dynamic aperture or lifetime



Sextupole strengths for the ESR 18 GeV, 2-IP lattice [2]
- 20 chromatic families of sextupoles
- 8 phase trombones
- 2 sextupoles for 2nd order dispersion
- 12 harmonic sextupoles for 3rd order resonances



Optimized ESR 18 GeV, 2-IP lattice [2]
- Tracking for >1000 turns
- For each momentum value, track points radially from origin at 15 different angles to determine boundary of stability

Possible machine-learning applications

Why are dynamic-aperture studies challenging?

- No simple analytical formula—looking at chromaticity terms at different orders and resonant driving terms can help, but in the end tracking is the only reliable way to compute dynamic aperture
- Computing dynamic aperture is computationally expensive
- Tracking must be done for a large number of turns (electrons > 1000; hadrons > 1m)
- Error correction must be done step-by-step to avoid optical instability

Can ML help speed up simulations?

- Various approaches have been proposed to speed up dynamic-aperture calculations, but all are in their infancy
- Simplest approach proposed by Jinyu Wan and Yi Jiao [3]
  - Track just a few particles (<10%) for many turns and use their first-turn trajectories and survival data to train the ML model
  - Track all other particles for just one or a few turn(s), and use their trajectories as input to the model to predict their survival after many turns
- More complex approaches possible in principle, e.g. mapping statistical seed of magnet misalignment to dynamic aperture (proposed by I. Agapov, 2018 workshop [4])

Can we apply such approaches to the EIC?

- Speeding up simulations would be helpful, but...
- Development and testing time would likely be long—not clear if investment is worth it
- Results would need to be cross-checked anyway with full simulations

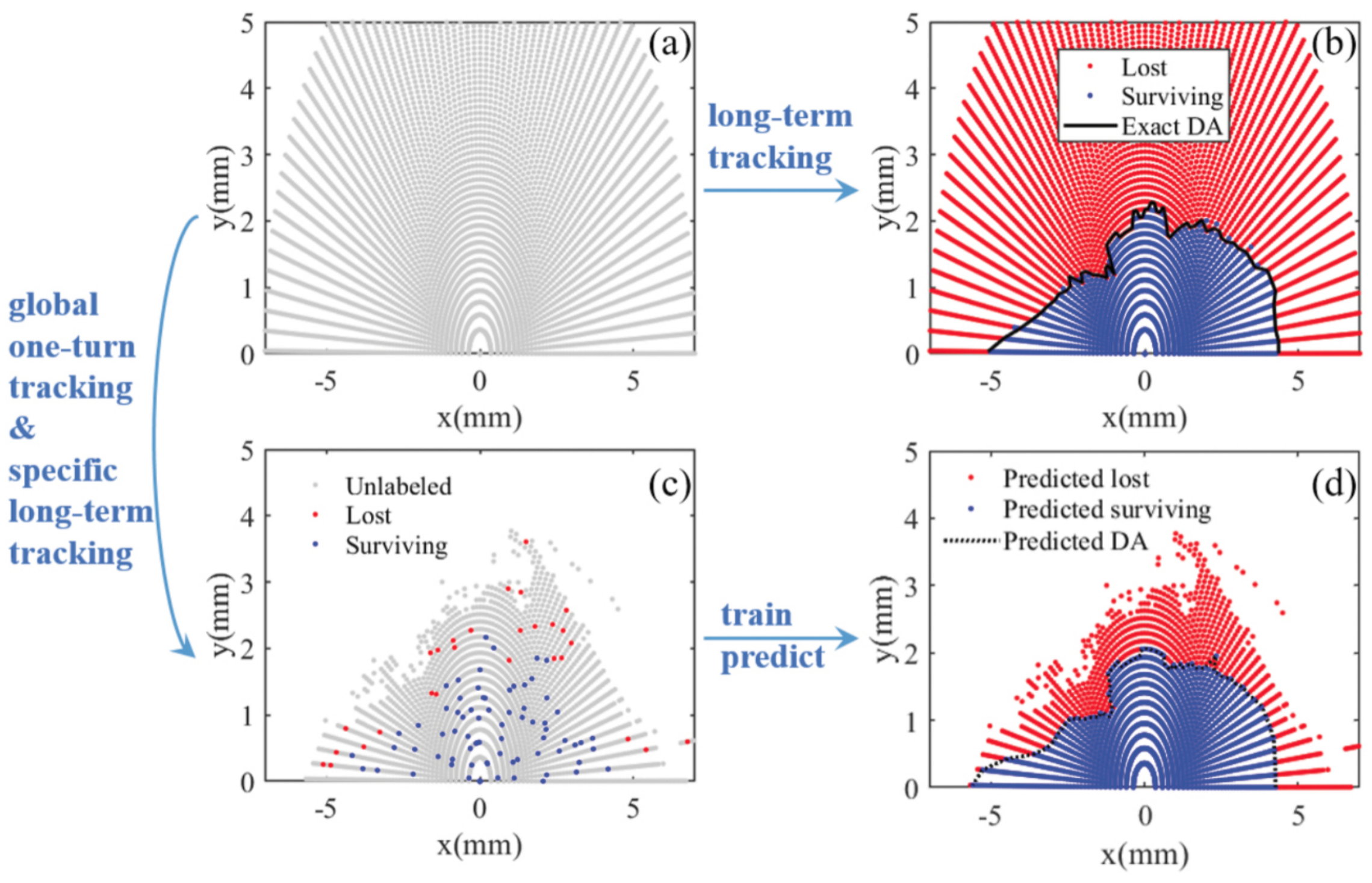


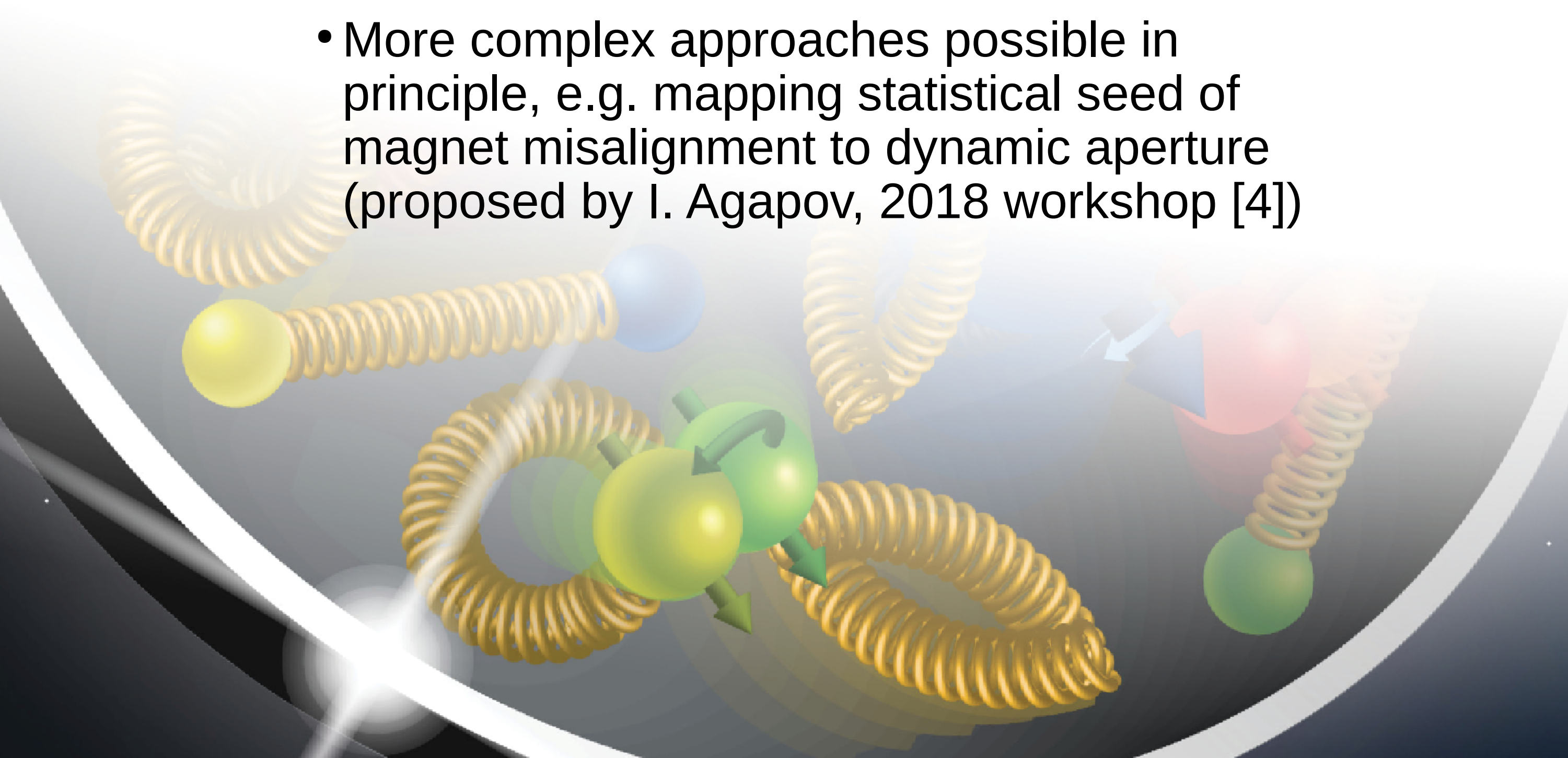
Image from [3]: Comparison of the DA calculation with pure long-term particle tracking and the ML-based method

Can ML play a role in developing an online tuning model for optimization of lifetime in the presence of errors and other physical effects?

- The physics is highly complex due to the interplay of many different effects, including nonlinear beam dynamics, beam-beam, polarization, and many possible error sources
- Full simulations including all these effects are very time-consuming, and simplifying assumptions have to be made
- A fast digital model would certainly help in commissioning and operation
- Digital twins have been developed for several other accelerators, but each accelerator is unique, and the combination of challenging physical effects at the EIC might add complexity to the mapping
- The EIC will have many different working points, including a wide range of energies, which will mean that there are fewer data available in each regime, especially initially—have to be careful with extrapolating models

References

[1] J. Beebe-Wang *et al.*, "Electron-Ion Collider: Conceptual Design Report". Brookhaven National Laboratory, Jefferson Lab, 2021.
[2] Y. Cai *et al.*, "Optimization of chromatic optics in the electron storage ring of the Electron-Ion Collider". *Phys. Rev. Accel. Beams* **25**, 071001, 2022. DOI: 10.1103/PhysRevAccelBeams.25.071001
[3] J. Wan and Y. Jiao. "Machine learning enabled fast evaluation of dynamic aperture for storage ring accelerators". *New J. Phys.* **24** 063030, 2022. DOI: 10.1088/1367-2630/ac77ac
[4] Ilya Agapov, "Light Source and FEL Simulations". Presented at: Machine Learning Applications for Particle Accelerators Workshop, SLAC, 2018.



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