Machine Learning/AI for Accelerators : Activities at Fermilab and in the "Vicinity"

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BSW22/iFAST (Valencia, Spain)

March 29 – April 1, 2022

Issues to address

- Part I: Examples and Aspirations
  - At FNAL
  - two workshops
  - Snowmass

- Part II: Limits of AI/ML – “real complexities”
  - What is complexity
  - Hamlet → EO and Faust
  - Katsnelson and Kolmogorovs
  - Complexity of accelerators

Part I:
AI/ML at Fermilab and "Around"

Two Workshops

AI/ML for Particle Accelerator, X-Ray Beamlines and Electron Microscopy

Nov 1, 2021, 10:00 AM → Nov 3, 2021, 4:00 PM US/Central

https://indico.fnal.gov/event/50731/

Virtual

Description **AI for Particle Accelerators, X-ray Beamlines, and Electron Microscopy Workshop @ ANL**

Advances in instrumentation have dramatically increased the complexities associated with experimental facilities. This includes enhanced facility capabilities as well as a substantial increase in the data generated. Consequently, the control and diagnostics of these experimental facilities are becoming increasingly complex, and the large output data streams necessitate smarter and more automated management and analyses of the data. Artificial Intelligence (AI) methods hold the promise of substantially improved management, control, and data analyses with the potential to dramatically increase experimental efficiencies as well as expanding and accelerating scientific discoveries.

Argonne is the home to world-leading facilities such as the Advanced Photon Source (APS), the Argonne Tandem Linear Accelerator (ATLAS), the Argonne Wakefield Accelerator (AWA), and the Electron Microscopy Center at the Center for Nanoscale Materials (CNM). In order to highlight AI opportunities in these facilities, Argonne is hosting a workshop on AI for with participants drawn from 3 communities: particle accelerators, X-ray beamlines and electron microscopy. The goals of the workshop are:

AI for Accelerators - A Snapshot at Fermilab

https://indico.fnal.gov/event/52417/

Friday Jan 14, 2022, 1:00 PM → 2:40 PM US/Central

Anthony Tiradani (Fermilab), Erik Gottschalk (Fermilab), Lila Anderson (Fermilab), Tia Miceli (Fermilab)

Description Showcase of current work on AI/ML for accelerators. (no registration needed)

What's the buzz about Artificial Intelligence for our accelerator systems?

Efforts have been ramping-up in the past couple of years to use Artificial Intelligence and Machine Learning (AI/ML) to enhance the performance of our accelerators and beamlines. We anticipate even more action in the coming year. Come hear from machine experts and engineers as they present advances in our latest AI/ML projects and what the future holds.

Audience take-aways:

1. What are the current AI/ML accelerator controls projects
2. What are the plans for modernizing the accelerator control system to support AI/ML
3. How do Accelerator Division's AI/ML endeavors support Fermilab

Examples of AI/ML Activities/Projects

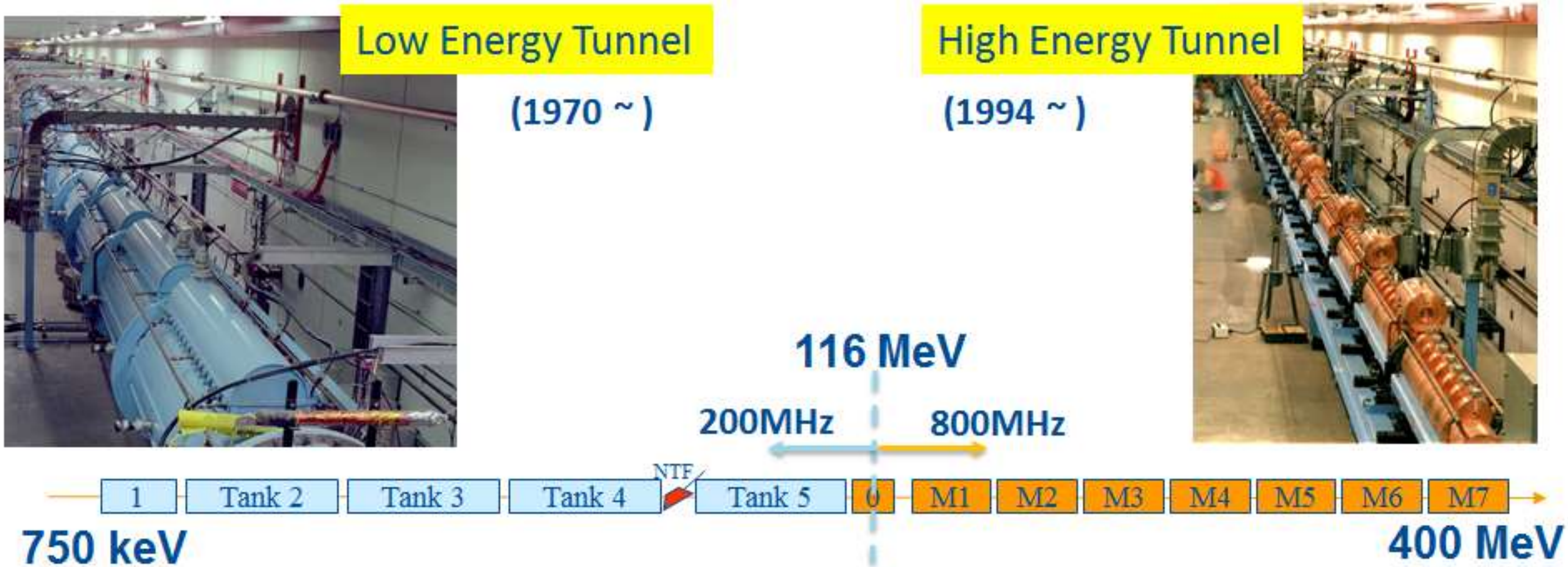
1. Machine learning for Linac RF Optimization Longitudinal optimization
2. Booster Gradient Magnet Power Supply Control
3. "Big Data" Booster Control
4. Orbit Alignment at PIP2IT Using Bayesian Optimization
5. AI/ ML for NuMI Target System Monitoring
6. Real-time quench detection
7. FAST/IOTA RF gun stabilization and optimization
8. MI loss minimization vs MI or RR situation
9. Stabilization of 8 GeV slow extraction from Muon-C ring
10. 6D Cooling optics design with ML elements

1.Machine learning for Linac RF Optimization

R. Sharankova, K. Seiya, M. Wesley, M. Mwaniki

- Goal: deliver stable, high intensity beam to users
  - Daily tuning of RF parameters to reduce beam loss and increase beam output
- Challenges
  - Tuning relies on robust and stable diagnostics data
  - Correlation of diagnostics data & RF parameters not always trivial
  - Cannot manually tune many RF parameters simultaneously
- Approach
  - Revisit/improve/add instrumentation
  - Explore ML techniques for RF regulation
    - Offline optimization of multiple RF parameters
    - Real-time momentum control
- Success:
  - Some visible… on the way to make operational

1.Fermilab Linac



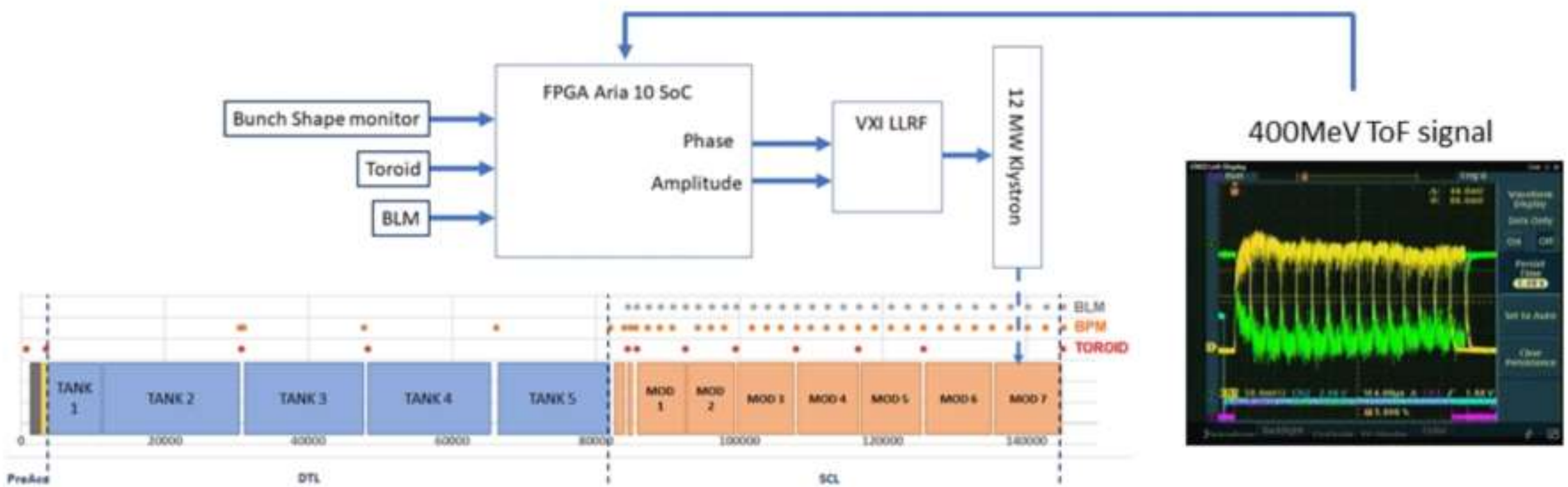
- Drift tube Linac: 5 tanks
  - Resonant RF frequency 201 MHz
- Side-coupled Linac: 7 modules
  - Resonant RF frequency 805 MHz
- Transition section: Buncher & Vernier
  - Match beam structure b/n DTL & SCL

Status

Linac output:	25mA
Pulse length:	35 μsec
Efficiency:	94%

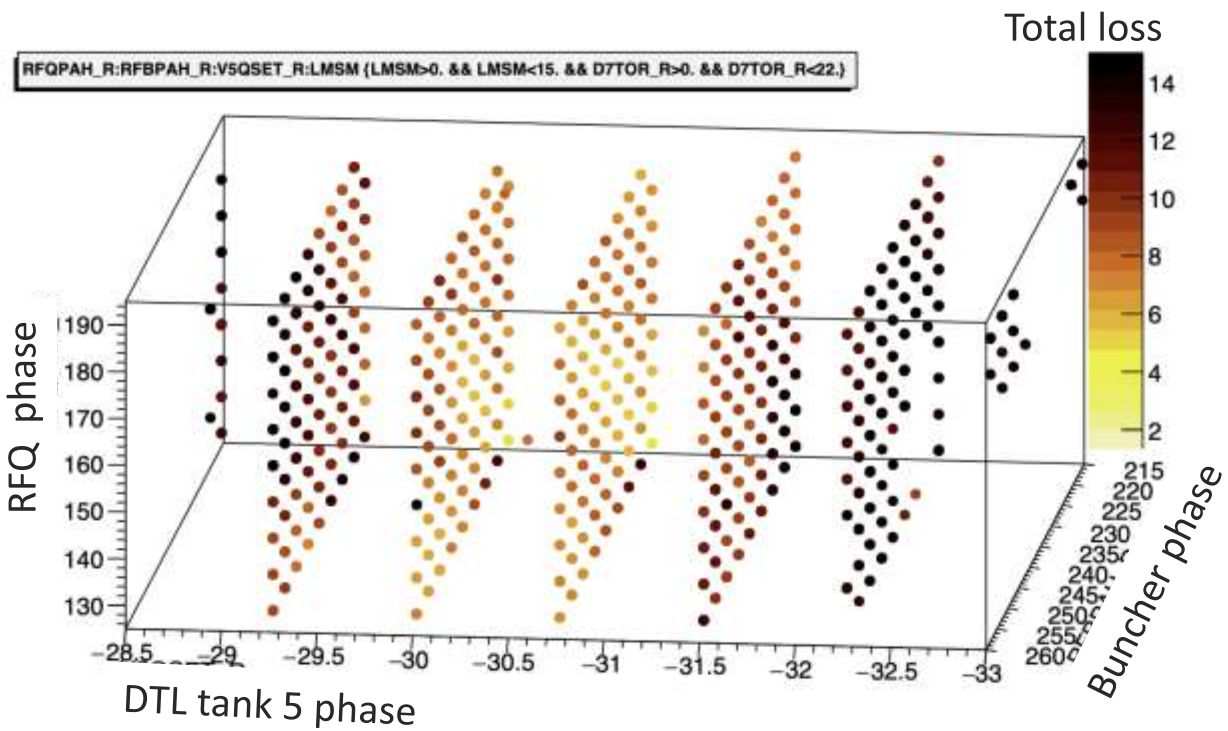
1.Real-time momentum control of a single cavity

- Beam loading causes energy spread along the Linac pulse
- Beam momentum going into Booster regulated by adjusting phase of SCL module 7
- Goal: reduce long-term momentum drift as well as momentum deviation in pulse
  - Real-time regulation based on ToF and other diagnostics



2. Offline optimization of multi-RF phases with ML

- Loss monitor, toroid and BPM patterns are correlated with RF parameters
- We aim to train a model to recognize those correlations, and find optimal RF setting for daily operations



3D pattern of total loss vs RFQ, Buncher and DTL tank 5 phase set points

2. Machine Learning for the Booster Gradient Magnet Power Supply

Jason St. John for the GMPS-AI team

PHYSICAL REVIEW ACCELERATORS AND BEAMS **24**, 104601 (2021)

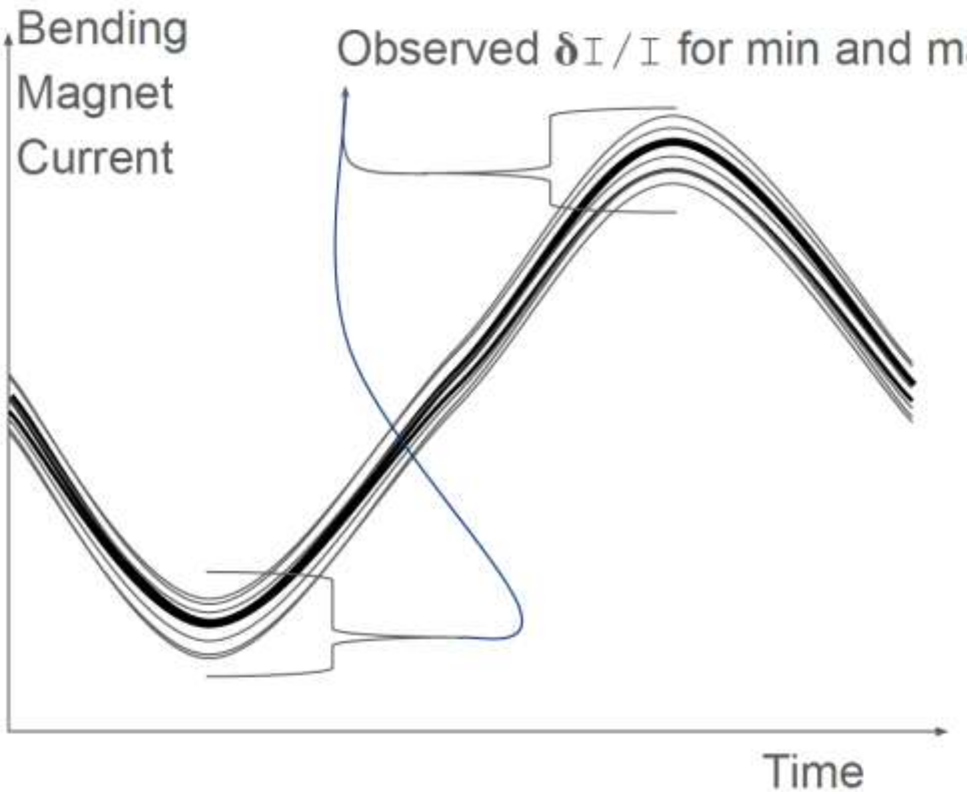
Real-time artificial intelligence for accelerator control: A study at the Fermilab Booster

- Booster injection efficiency is strongly dependent on the Booster RCS magnet current stabilization
- Proof-of-principle success:
  - machine learning models and demonstrated the feasibility of embedding such a model on a field-programmable gate array (FPGA) for a high-uptime, low-latency implementation
  - first developed a surrogate LSTM model, based on a recurrent neural network, to reproduce the behaviors of the real GMPS system in the context of the accelerator complex, establishing a safe environment for training reinforcement learning algorithms → then trained a deep Q-network, based on a multilayer perceptron, to choose an optimal action (adjustment of one control knob) to maximize the long-term reward, taken from the negative absolute value of the regulation error (difference between the set and observed values of the minimum GMPS current)
  - found this surrogate-trained network achieved a factor of 2 improvement over the existing controller in terms of the achieved rewards (goal was x10).
- Operational implementation ongoing

2. Booster GMPS – 15 Hz cycle

GMPS AI: The Need for Improving Regulation

Observed $\delta I/I$ for min and max currents: ~10^{-3} each



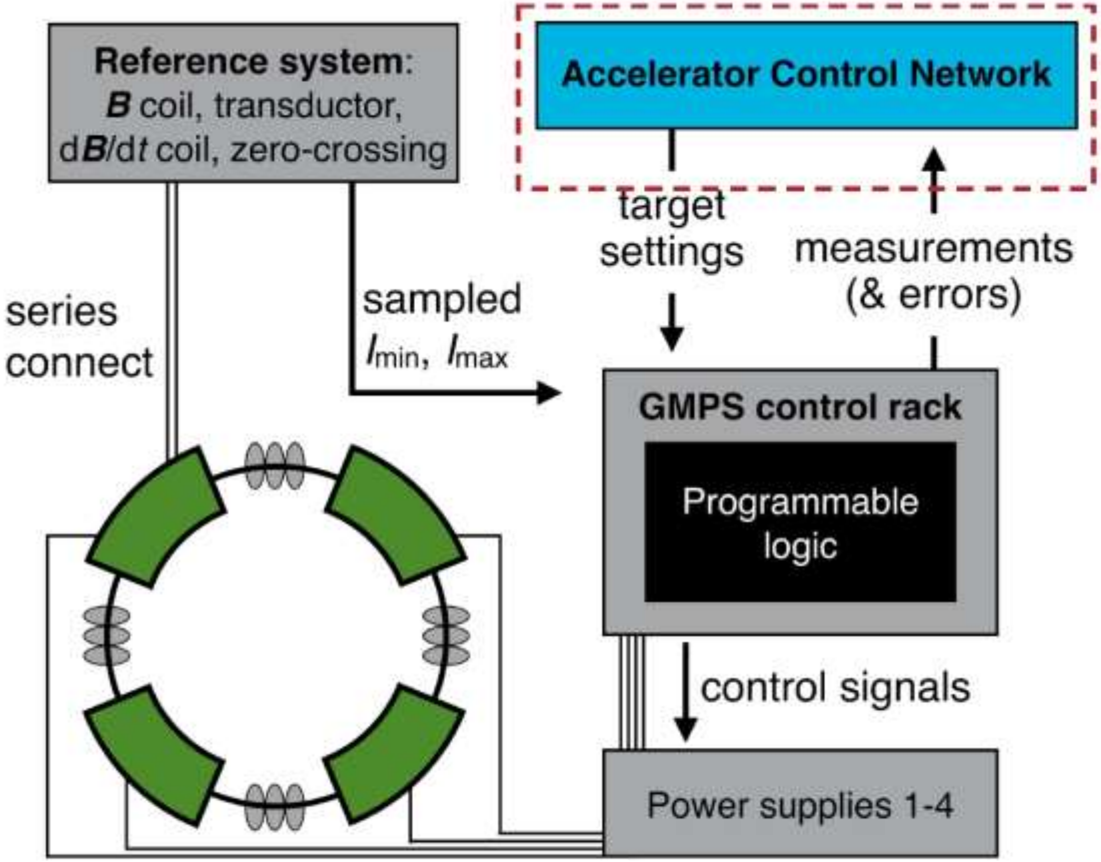
Perturbing influences:

- Recent corrections made
- Other nearby synchrotrons
- Fluctuation of 60 Hz power
- Temperatures, etc

Available data mostly with the current PID regulator

Spread in B-field degrades beam quality, degrades repeatability, & contributes to losses

2. Booster GMPS – Existing PID Circuit Regulation



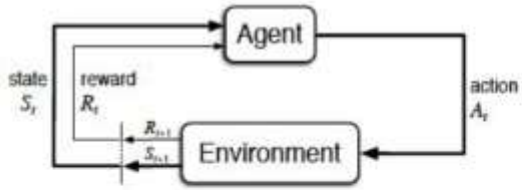
Human experts adjust target settings from time to time via control system

Also records settings & readings with some unknown latency

Known factors excluded from PID control logic:
Line Voltage variation,
Gallery temperatures, etc.

2. Booster GMPS – AI Improves Stabilization ~x2

GMPS AI: Digital Twin as RL Environment



With LSTM providing environment, trained an MLP agent to tweak **B:VIMIN** prescription each timestep

- Reward function: neg. abs. error = -|**B:IMINER**|
- Q-learning @ 50 timestep episodes
  - Double DQN (target & policy model distinct)
  - 32-experience (random) to update policy model
  - ϵ-greedy decay factor 0.9995 (min: 0:0025)
  - Discretized options to change **B:VIMIN**: 0 (no change), ±0.0001, ±0.005, and ±0.001.
  - 3 layers of 56 ReLU nodes

3. “Big Data” Booster Control System

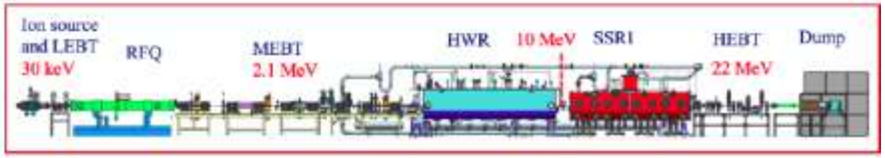
Bill Pellico

- Problem:
  - “Data loggers” stores ~2500 channels of Booster control
  - Operators use only some… trained on repeating problems
  - Understanding reasons for any changes is challenging and time consuming
- Goal:
  - Find a way for faster optimization/return to stable opertation
- Approach
  - Train AI/ML circuits to analyse “data logger” data
- Status:
  - Just started.. Asked DOE for $$

4. Orbit Alignment at PIP2IT Using Bayesian Optimization

Pavlo Lyalyutskyy, Eduard Pozdeyev

- Beam orbit alignment in PIP2IT using **Bayesian Optimization with Gaussian Processes**
- PIP-II Injector Test (PIP2IT) facility is near-complete Front End of PIP-II accelerator with two first cryomodules
- Beam trajectory is perturbed by misaligned cavities and magnets
  - Measured by **Beam Position Monitors (BPMs)**
  - Orbit is steered by orbit **corrector** magnets
- Task: reduce orbit deviation in BPMs



4. PIP2IT Bayesian Optimization with Gaussian Processes

1. Choose a surrogate model and define a **prior**.

$$f(x_{1:k}) \sim \text{Normal}\left(\mu_0(x_{1:k}), \Sigma_0(x_{1:k}, x_{1:k})\right)$$

2. Use Bayes Rule to update our prior to get the **posterior**.

$$\begin{aligned} f(x)|f(x_{1:n}) &\sim \text{Normal}(\mu_n(x), \sigma_n^2(x)) \\ \mu_n(x) &= \Sigma_0(x, x_{1:n})\Sigma_0(x_{1:n}, x_{1:n})^{-1}\left(f(x_{1:n}) - \mu_0(x_{1:n})\right) + \mu_0(x) \\ \sigma_n^2(x) &= \Sigma_0(x, x) - \Sigma_0(x, x_{1:n})\Sigma_0(x_{1:n}, x_{1:n})^{-1}\Sigma_0(x_{1:n}, x). \end{aligned}$$

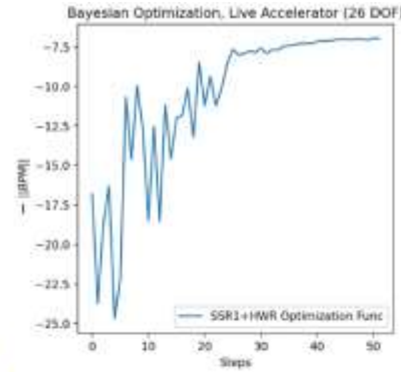
3. Use an acquisition function *α(x)* to decide next point to sample.

$$x_t = \text{argmax}_{x \in A}\, \alpha(x)$$

4. Add newly sampled point to the observations and go to step #2, until convergence.

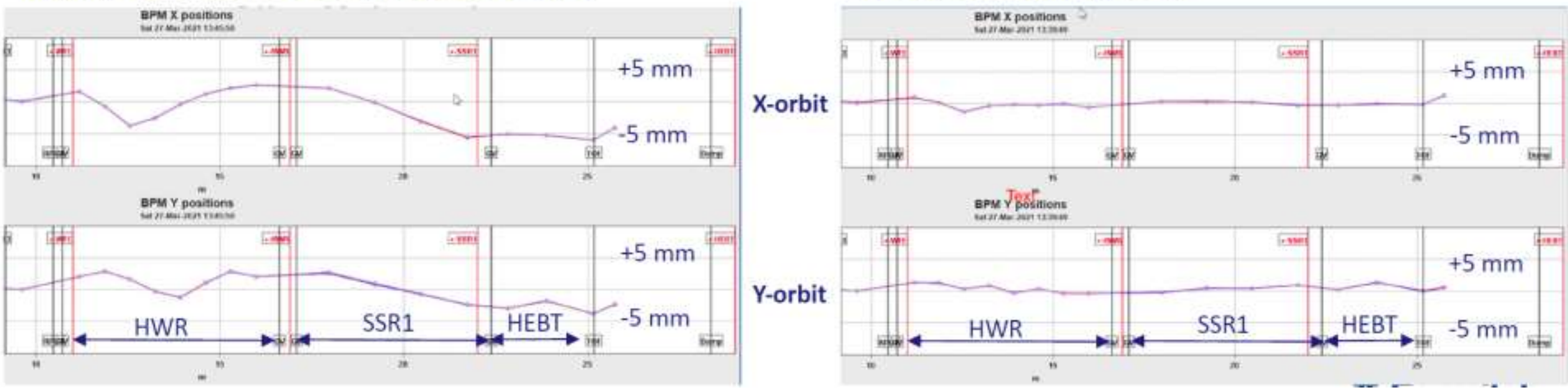
4. PIP2IT Success – x2-3 faster convergence than Simplex

Convergence with 26 free parameters (degrees of freedom).
Convergence in ~30 steps.
Convergence several times faster than Simplex



Orbit before correction (not acceptable)

After correction (good)



5. AI/ ML for NuMI Target System Monitoring

Athula Wickremashinghe, Katsuya Yonehara

Challenge:

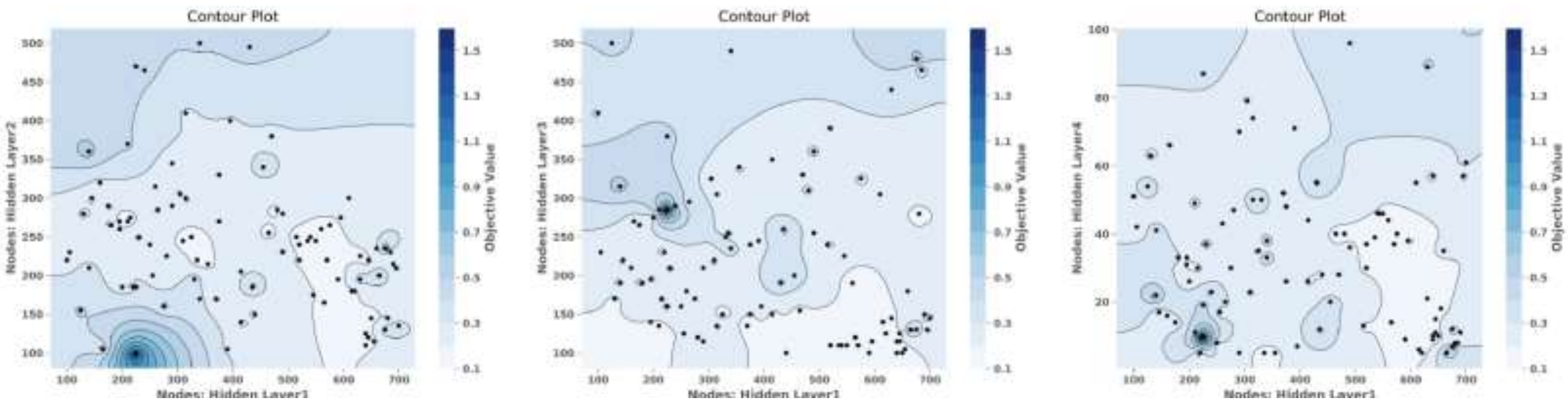
NuMI target system is world's brightest neutrino beam source for neutrino oscillation experiments. The goal of target system AI is predicting a beam related systematic uncertainty for a neutrino flux per beam spill.

Context:

- ***The Validation of target system AI (present work)***
  - There are three layers of muon monitors and each monitor provides 9 x 9 pixel image. Our first AI analyzes the image to predict beam position at the target, horn current, and beam intensity per beam spill.
- ***Anomaly detection (future work)***
  - Collect muon monitor and other instrumentation signals to catch any accidental changes of beam element (target density deterioration, misalignments of elements, water condensation in the beam line, etc)
- ***Prediction of neutrino flux (future work)***
  - Train AI with Monte Carlo simulations to predict a neutrino flux at neutrino detectors by using the observed muon monitor signals

5. AI/ML for NuMI Target Results

- The contour plot is mapping out the regions based on the high to low values of the standard errors on predictions



- The tuned model has a good capability of predicting the beam position horizontal and vertical, beam intensity and horn current with the standard error of +/- 0.018 mm, +/-0.013mm, +/- 0.05 E12 and +/- 0.10 kA respectively. **Those are well below the required accuracy of beam related systematic uncertainty.**
- Planning to implement the ML model predictions for daily NuMI beamline data monitoring
- NuMI beam simulation studies are ongoing to predict neutrino flux

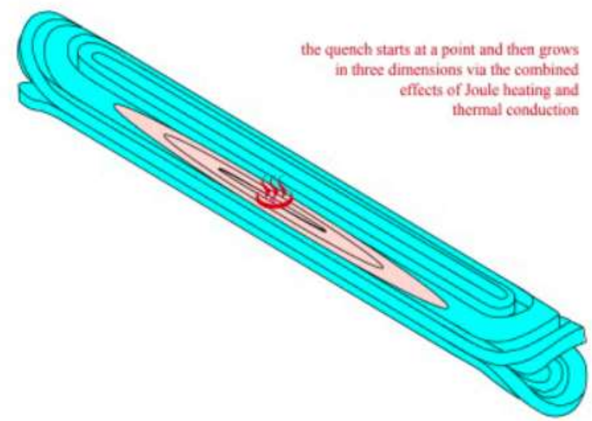
6. Real-time quench detection

Duc Hoang, Christian Boffo, et al

Superconducting Magnet Quenches

- In order to maintain superconductivity, superconducting magnets typically operate **at or below liquid helium temperature.**
- Due to several reasons (mechanical imperfections, conductor motions, …), **a specific spot** in the magnet may **heat up**.
- This can eventually cause the whole magnet to **become resistive**. And with huge amount of current pumping through, it can be **catastrophic**.

Growth of the resistive zone



Wilson et al. Superconducting magnets for accelerators.

Magnet "training" requires 10s of quench events

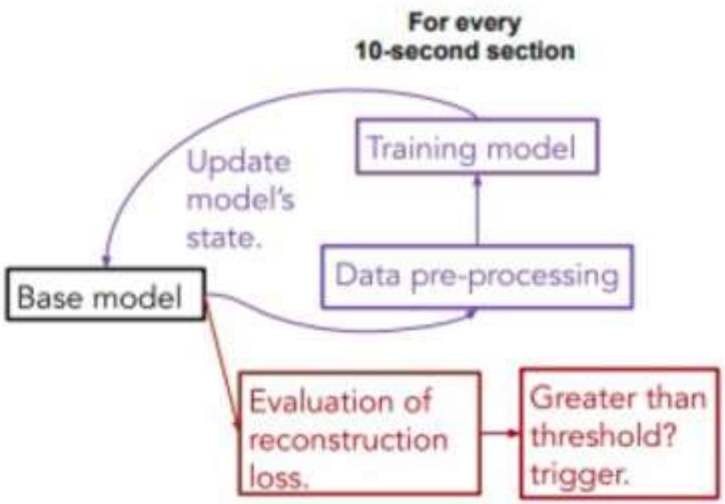
6. Real-time quench detection

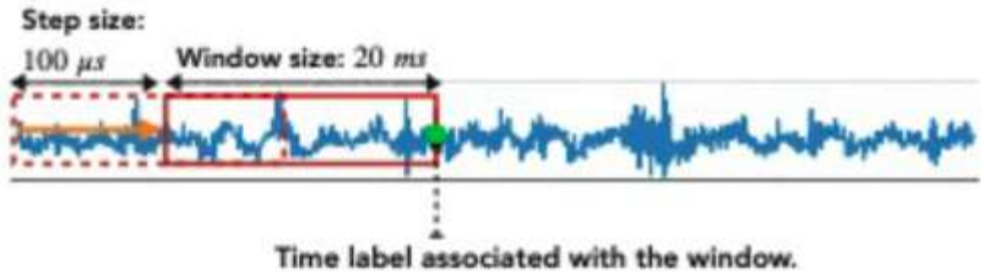
Challenges:

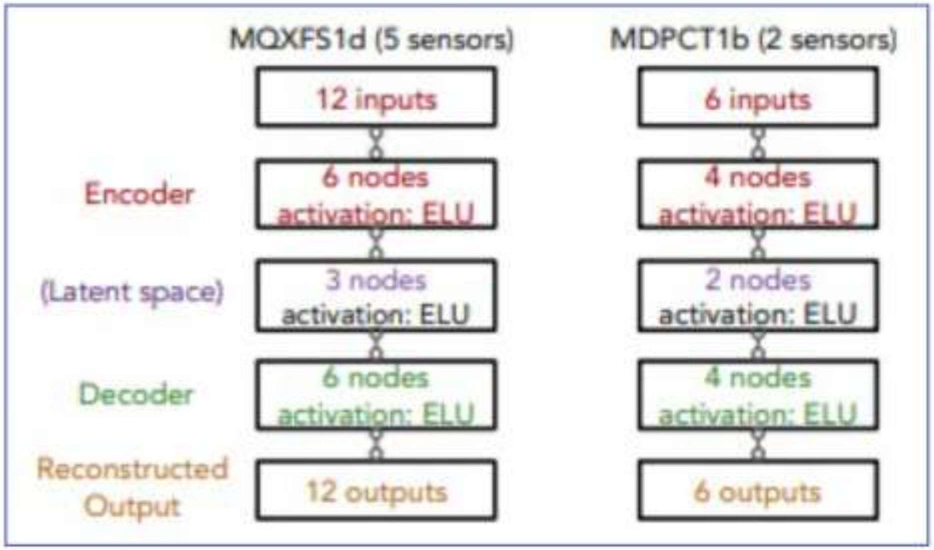
Physics of quenches are not well-understood

- Typically are detected (milli-)seconds after the event happens
- Magnet training is expensive (~$300k, 2 weeks per magnet)
  - future colliders and high TC superconductors even more important
- Can we understand and potentially mitigate quench events?
- Use (acoustic and other) sensors to detect precursors to the quench

6. Anomaly detection with continuous learning

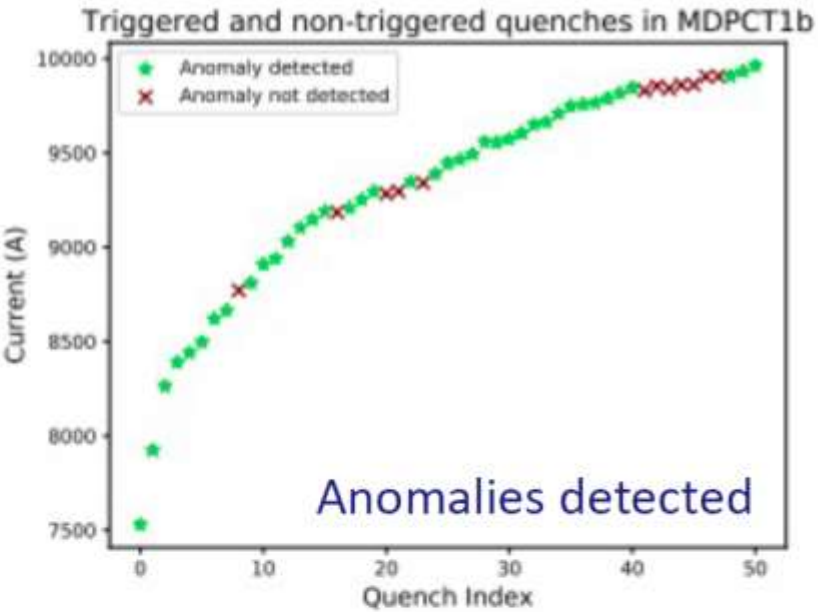


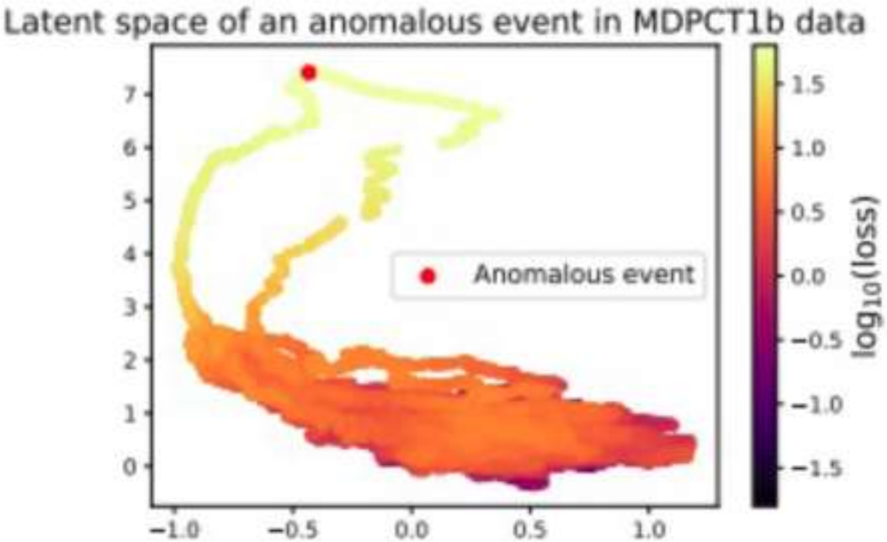




"Simple" ML algos using statistical features of time series data

6. Success: Detected 77% of anomalous events ahead of the quench (<15s)





Characterizing anomalous events

A lot more interesting data analysis that can be done and would like to build a real-time platform!

7. FAST/IOTA RF gun stabilization and optimization

A.Edelen, J.Edelen, J.Ruan, etc

Auralee started at FAST…

878 IEEE TRANSACTIONS ON NUCLEAR SCIENCE, VOL. 63, NO. 2, APRIL 2016

Neural Networks for Modeling and Control of Particle Accelerators

A. L. Edelen, *Student Member, IEEE*, S. G. Biedron, *Senior Member, IEEE*, B. E. Chase, *Member, IEEE*, D. Edstrom Jr., S. V. Milton, *Senior Member, IEEE*, and P. Stabile, *Member, IEEE*

.. then Argonne and SLAC

Neural Networks for Modeling and Control of Particle Accelerators

Auralee Edelen

9th International Particle Accelerator Conference
Vancouver, BC
29 April – 4 May, 2018

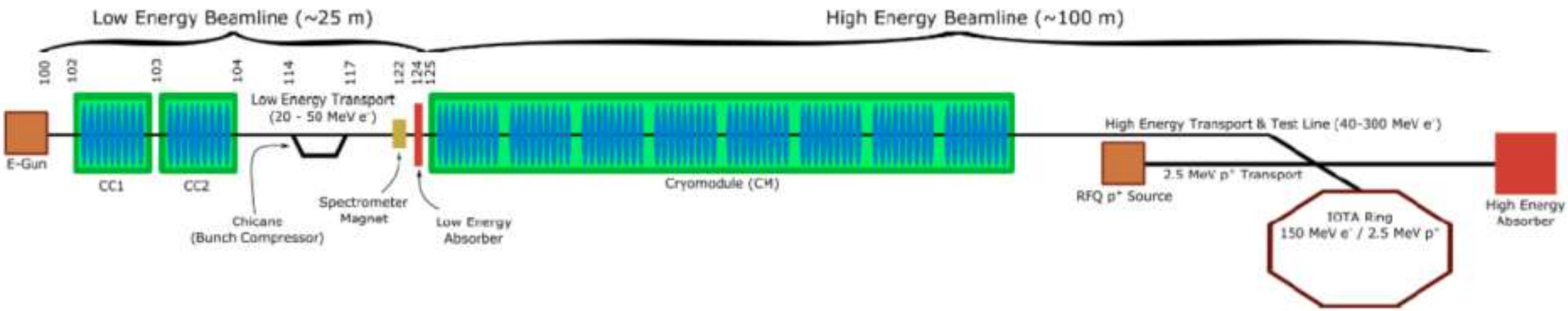
PHYSICAL REVIEW ACCELERATORS AND B

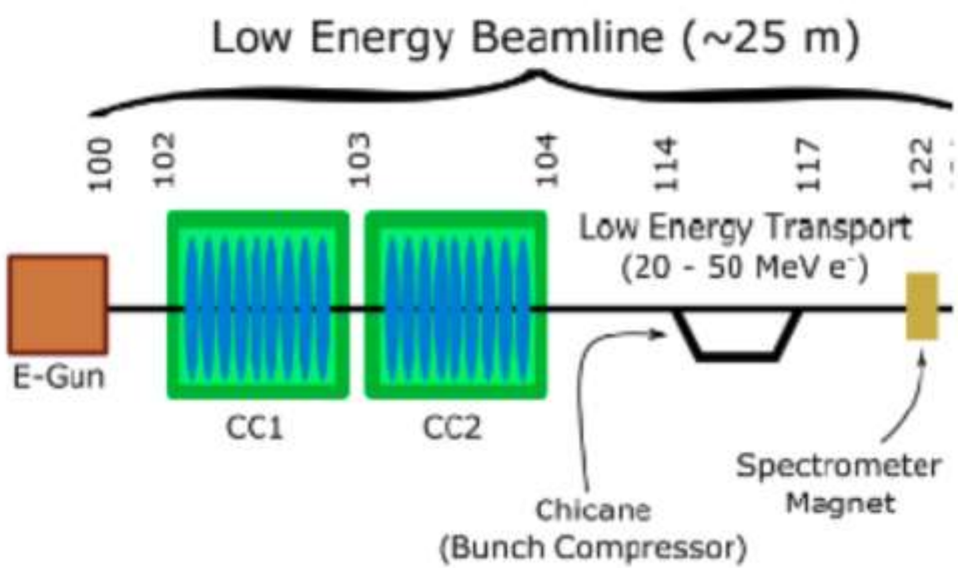
Machine learning for orders of magnitude speedup in multiobjective optimization of particle accelerator systems

Auralee Edelen,[1,*] Nicole Neveu,[1] Matthias Frey,[2] Yannick Huber,[2]
Christopher Mayes,[1] and Andreas Adelmann[2,†]
[1]*SLAC National Laboratory, Menlo Park, 94025 California, USA*
[2]*Paul Scherrer Institut, 5232 Villigen, Switzerland*

.. Now Jinhao Ruan trying to make the ML system operati-onal at FAST Run 4

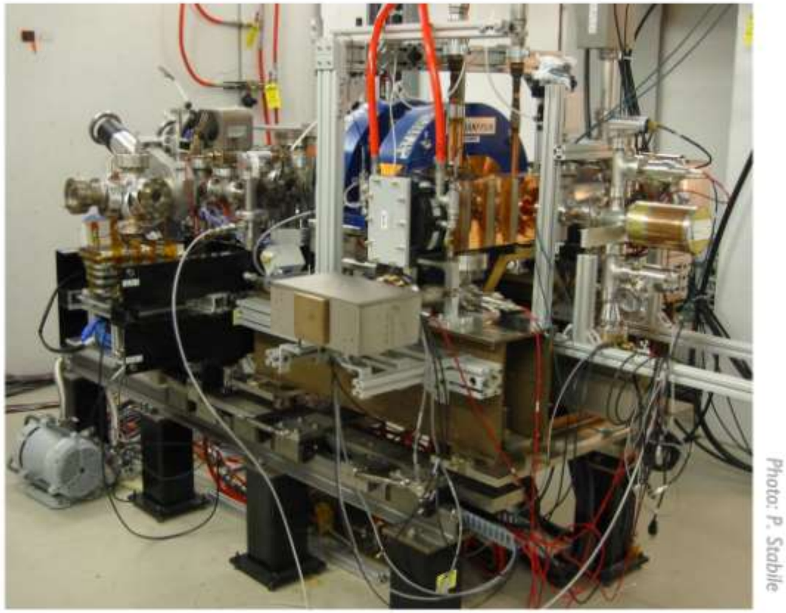
Overview of IOTA & FAST linac

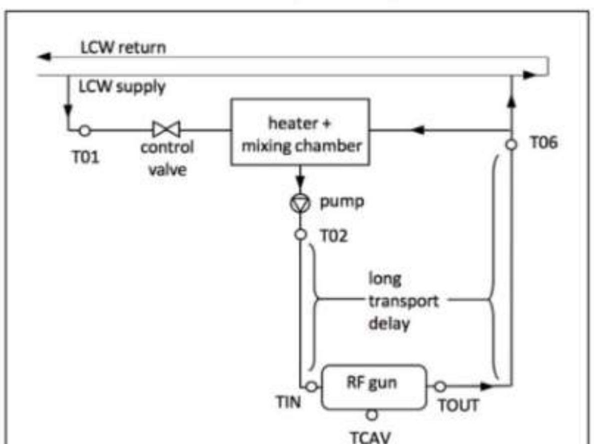




- 1.3 GHz photocathode RF gun
  - *PITZ style gun with solenoid and bucking coil*
  - *Beam accelerated to ~4 MeV*
- 1.3 GHz 9-cell Tesla type cavities
  - *Beam accelerated to ~35 MeV*

RF electron gun at the Fermilab Accelerator Science and Technology (FAST) facility

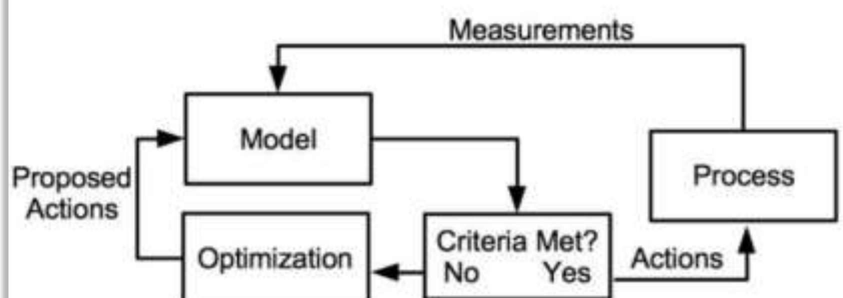




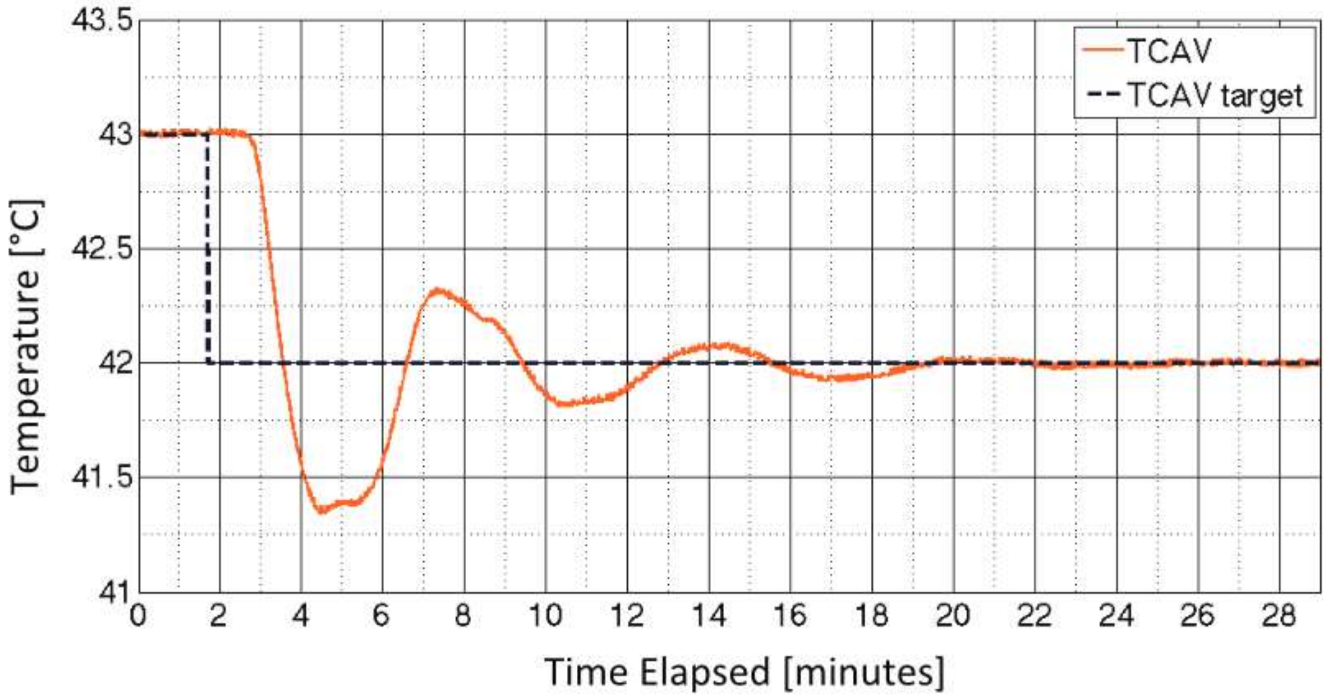
ML to stabilize FAST 1.3 GHz (Copper) RF gun

Basic concept:

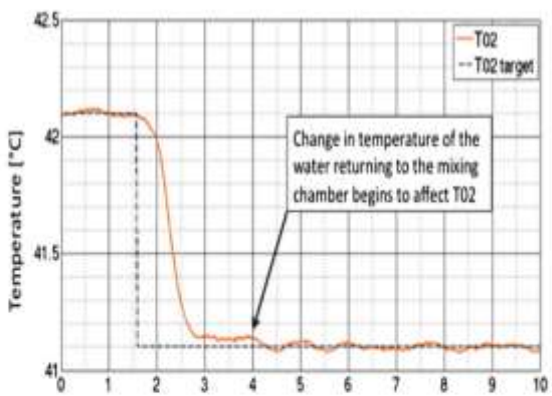
1. Use a predictive model to assess the outcome of possible future actions
2. Choose the best series of actions
3. Execute the first action
4. Gather next time step of data
5. Repeat



Improvement: x5 faster stabilization or RF gun



A 1-◦C step change under the existing feed-forward/PI controller. Note that the oscillations are due to the time delays, thermal responses, and recurrent effect of the water system, not a poorly tuned set of PI gains.

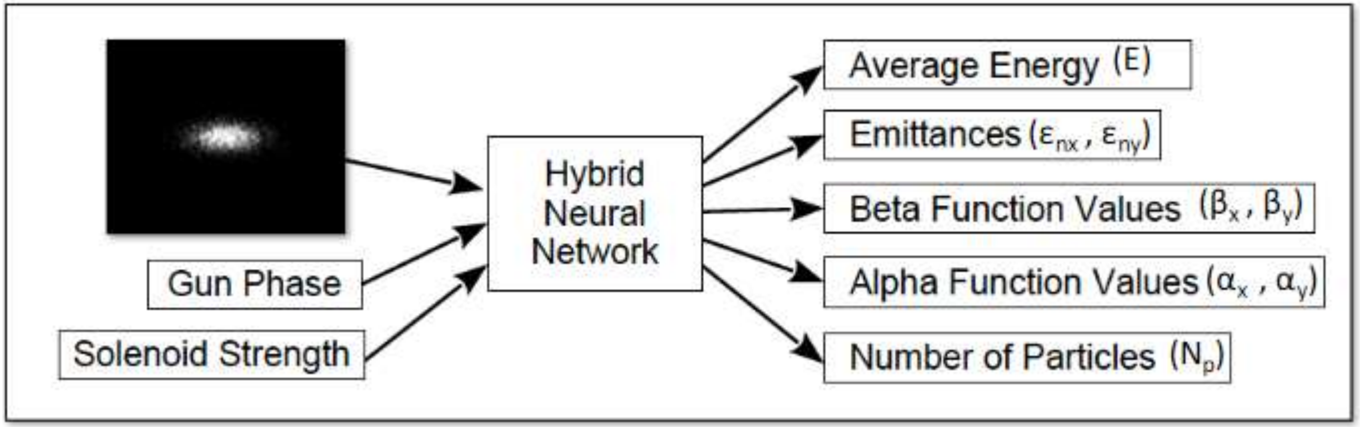


(same scale plot) A 1-◦C step change in TCAV under the benchmark MPC. Note that the scales are smaller than those of Fig. 2. These data were recorded as part of a series of steps in the TCAV set point. Note that this is not a perfect 1-◦C step, as there is an offset between the original TCAV set point and the final value it obtained in the prior to step.

Current developments (J.&A.Edelen, D.Edstrom)

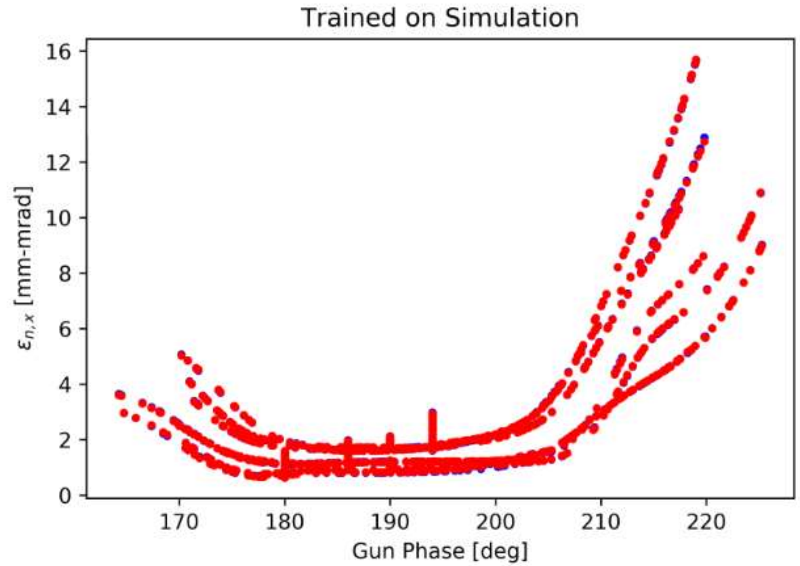
- Expand the AI/ML exrience onto FAST emittance optimization

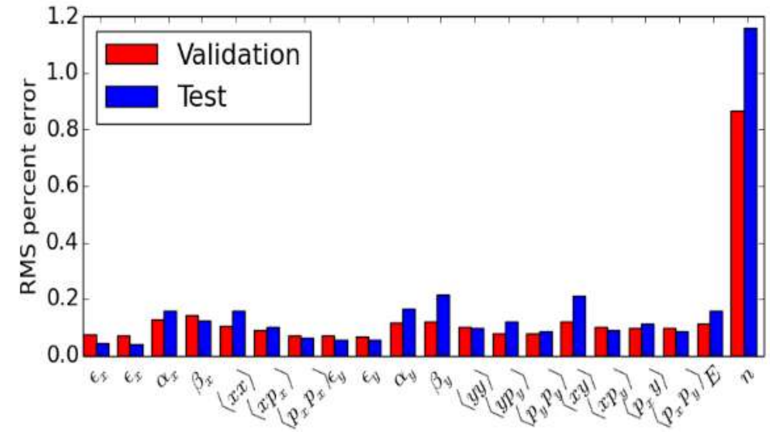
Goal: Full phase-space control at the entrance of the cryomodule using virtual cathode images, magnet settings, cavity phases, and cavity amplitudes



NN Architecture: 1st trained on Simulations

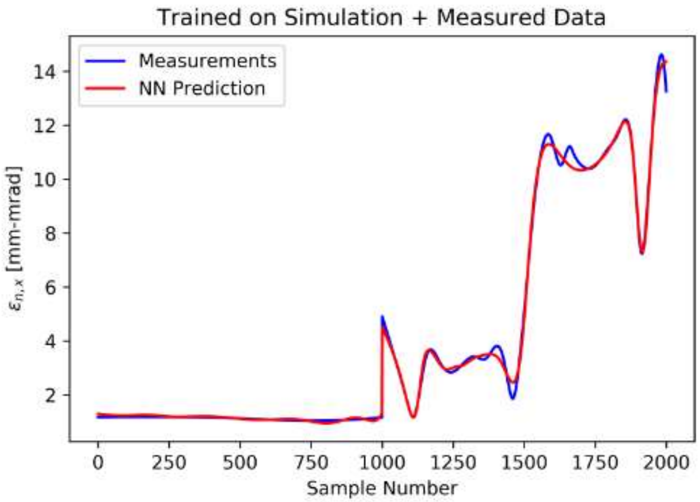
- Data separated into Training, Validation, and Test sets
  - *Training set: used directly in training*
  - *Validation set: interleaved with training data but not used explicitly in training*
  - *Test set: outside range of training data*
- Noise added to the data before training
- Performance across validation and test set
  - *Top: prediction and simulation as a function of gun phase*
  - *Bottom: rms percent error between neural network and simulations*
- All output parameters perform well except transmission
  - *All transmission is 100% in our range of simulations so this is dominated by noise added during training*

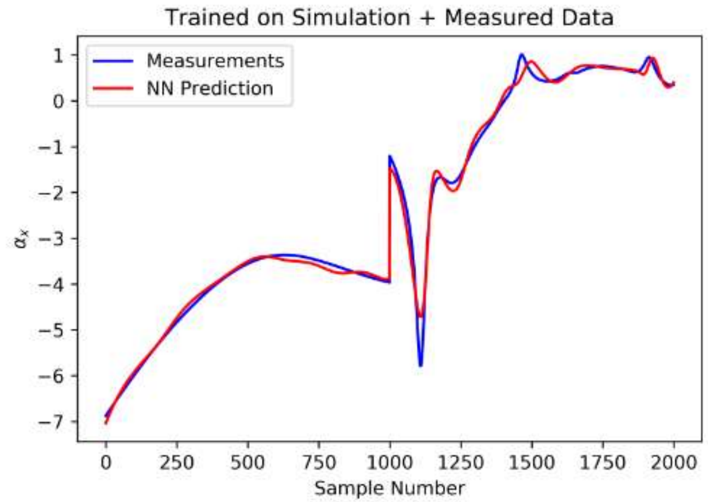




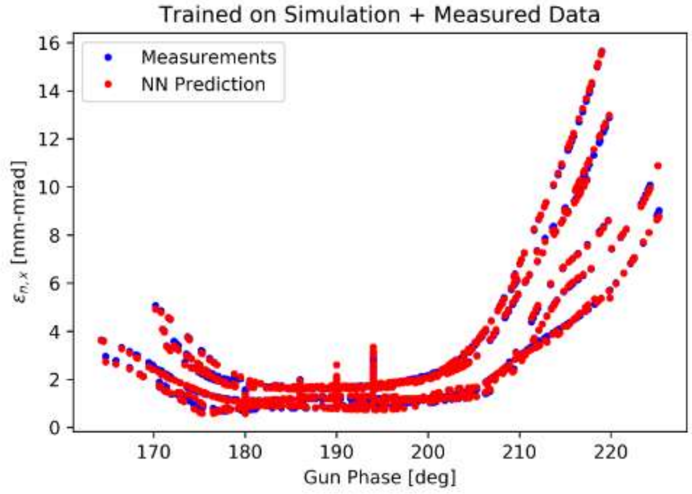
Fermilab

NN: Then trained on measurements





- Updating with measurements
  - *Top Left: Normalized emittance as a function of sample number for updated dataset*
  - *Top Right: Alpha as a function of sample number for updated dataset*
- Network retains the information from the simulations
  - *Right: comparison of network prediction for phase scan data from before and after updating with measurements*



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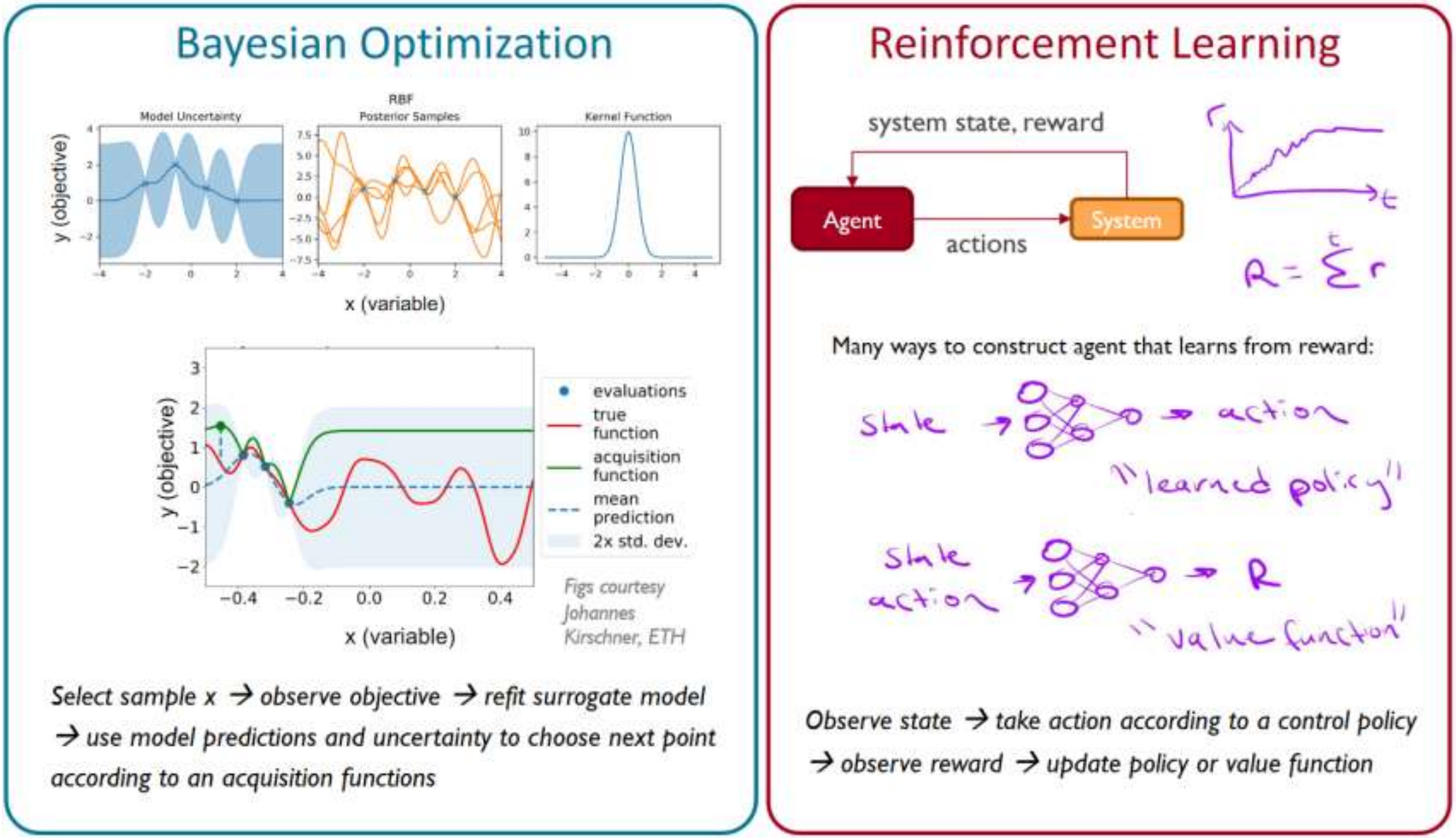
Auralee’s Comments (2022 Workshop)



Analogous concepts, different terminology and usually different setting:

objective → reward

surrogate model → value function

acquisition function → policy

acquire new sample → take an action

8-10. (very briefly)

8. **MI loss minimization vs MI or RR situation**
   - Losses at extraction from MI (120 GeV) depend on Main Injector RCS and on injector (8 GeV RecyclerRing)
   - ML algorithm allow to decouple causes MI vs RR
9. **Stabilization of 8 GeV slow extraction from Muon-C ring**
   - Efficiency and stability slow extr (2nd order) proton current from Muon-Campus ring depends on may parameters
   - AI/ML to help to stabilize
10. **6D Cooling optics design with ML elements**
    - Muon Collider needs ~50 6-D ionization cooling cells, final emittance strongly dependent on ~200 parameters
    - AI/ML help to get optimum and predict the best way to tune the system in the future

Part II:
On Truly Complex Systems

(which AI & ML are not yet capable of, but might be some day…)

What is complexity?

- Something that we immediately recognize when we see it, but very hard to define quantitatively
- S. Lloyd, “Measures of complexity: a non-exhaustive list” – 40 different definitions
- Can be roughly divided into two categories:

  - computational/descriptive complexities
  - effective/physical or structural complexities

Computational and descriptive complexities

- Prototype – the *Kolmogorov complexity:*
the length of the shortest description (in a given language) of the object of interest

- Examples:

  - Number of gates (in a predetermined basis) needed to create a given state from a reference one
  - Length of an instruction required by file compressing program to restore image

That was a preface to get onto the *Complexity of Accelerators*

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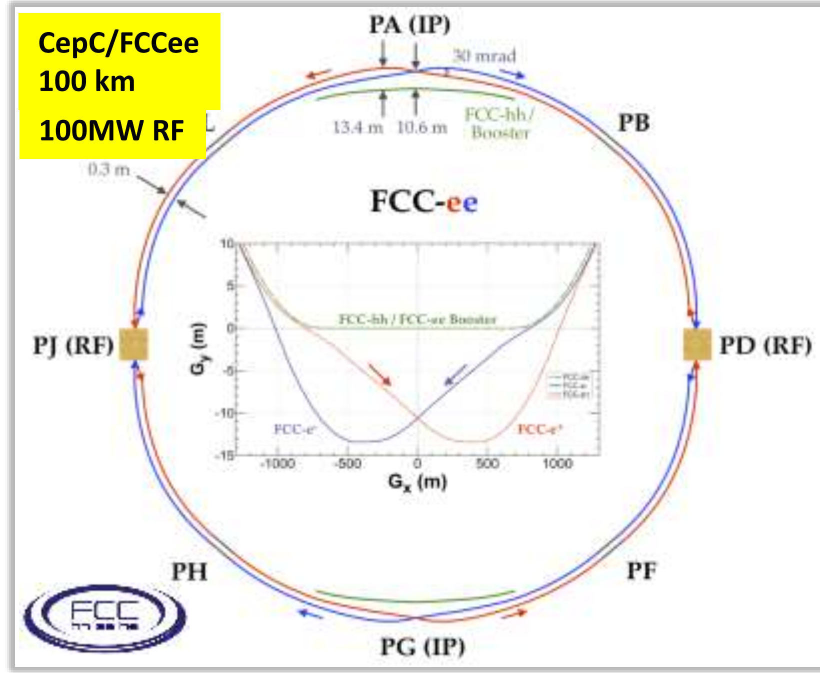
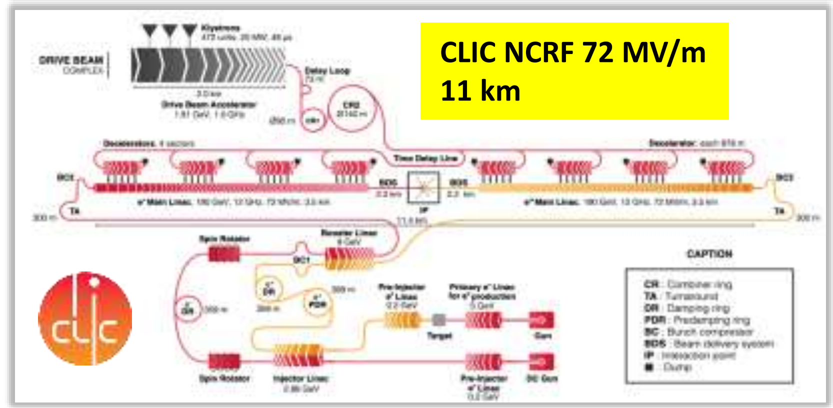
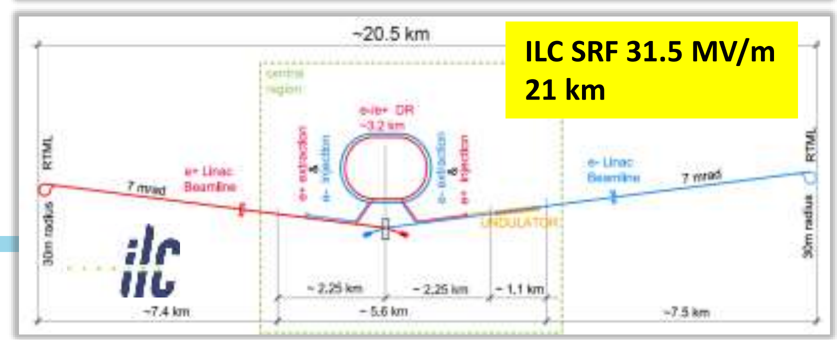
Future Collider Proposals: 8 Higgs/EW factories

Name	Details
CepC	e+e-, $\sqrt{s} = 0.24$ TeV, L= 3.0 $\times 10^{34}$
CLIC (Higgs factory)	e+e-, $\sqrt{s} = 0.38$ TeV, L= 1.5 $\times 10^{34}$
ERL ee collider	e+e-, $\sqrt{s} = 0.24$ TeV, L= 73 $\times 10^{34}$
FCC-ee	e+e-, $\sqrt{s} = 0.24$ TeV, L= 17 $\times 10^{34}$
gamma gamma	X-ray FEL-based $\gamma\gamma$ collider
ILC (Higgs factory)	e+e-, $\sqrt{s} = 0.25$ TeV, L= 1.4 $\times 10^{34}$
LHeC	ep, $\sqrt{s} = 1.3$ TeV, L= 0.1 $\times 10^{34}$
MC (Higgs factory)	$\mu\mu$, $\sqrt{s} = 0.13$ TeV, L= 0.01 $\times 10^{34}$

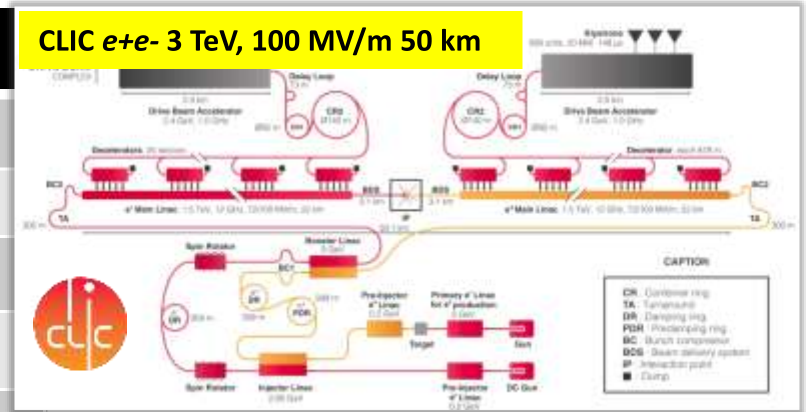


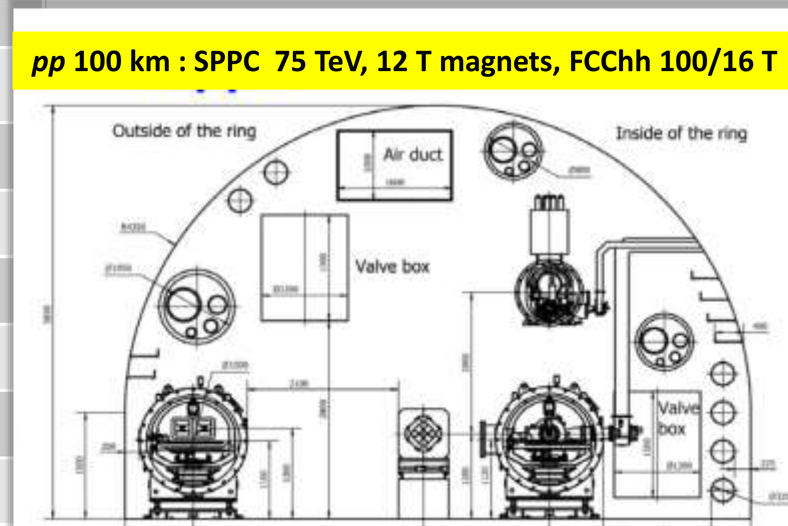


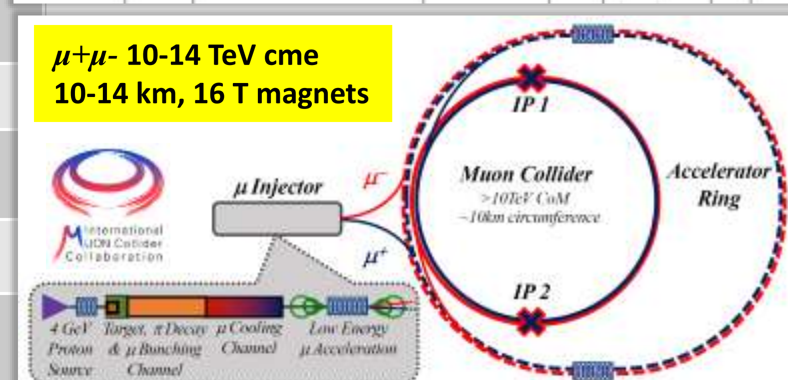


17 (!) High Energy Collider Concepts/Proposals

Name	Details
Cryo-Cooled Copper linac	e+e-, $\sqrt{s} = 2$ TeV, L= 4.5 $\times 10^{34}$
High Energy CLIC	e+e-, $\sqrt{s} = 1.5-3$ TeV, L= 5.9 $\times 10^{34}$
High Energy ILC	e+e-, $\sqrt{s} = 1-3$ TeV
FCC-hh	pp, $\sqrt{s} = 100$ TeV, L= 30 $\times 10^{34}$
SPPC	pp, $\sqrt{s} = 75/150$ TeV, L= 10 $\times 10^{34}$
Collider-in-Sea	pp, $\sqrt{s} = 500$ TeV, L= 50 $\times 10^{34}$
LHeC	ep, $\sqrt{s} = 1.3$ TeV, L= 1 $\times 10^{34}$
FCC-eh	ep, $\sqrt{s} = 3.5$ TeV, L= 1 $\times 10^{34}$
CEPC-SPPpC-eh	ep, $\sqrt{s} = 6$ TeV, L= 4.5 $\times 10^{33}$
VHE-ep	ep, $\sqrt{s} = 9$ TeV
MC – Proton Driver 1	$\mu\mu$, $\sqrt{s} = 1.5$ TeV, L= 1 $\times 10^{34}$
MC – Proton Driver 2	$\mu\mu$, $\sqrt{s} = 3$ TeV, L= 2 $\times 10^{34}$
MC – Proton Driver 3	$\mu\mu$, $\sqrt{s} = 10-14$ TeV, L= 20 $\times 10^{34}$
MC – Positron Driver	$\mu\mu$, $\sqrt{s} = 10-14$ TeV, L= 20 $\times 10^{34}$
LWFA-LC (e+e- and $\gamma\gamma$)	Laser driven; e+e-, $\sqrt{s} = 1-30$ TeV
PWFA-LC (e+e- and $\gamma\gamma$)	Beam driven; e+e-, $\sqrt{s} = 1-30$ TeV
SWFA-LC	Structure wakefields; e+e-, $\sqrt{s} = 1-30$ TeV

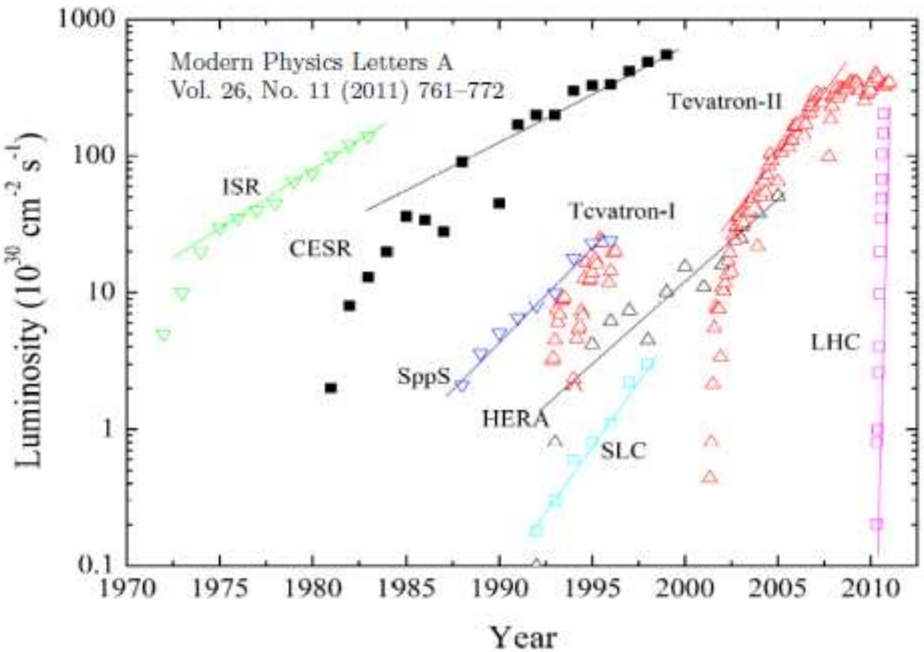






Accelerator Complexity

- Complexity to design (many dissimilar systems)
- Complexity to build (# elements, # of systems, level of each system – “standard/off-shelf, special, unique”)
- Complexity to reach energy =“make it work” (reliability)
- Complexity to reach performance “lumi” – **CPT theorem**:



$$\boxed{C \cdot P = T} \quad L(t_0 + T) = L(t_0) \times e^{T/C}$$

ON PERFORMANCE OF HIGH ENERGY PARTICLE COLLIDERS AND OTHER COMPLEX SCIENTIFIC SYSTEMS

VLADIMIR SHILTSEV
Fermi National Accelerator Laboratory, P. O. Box 500, Batavia, IL 60510, USA

Table 1. “Complexities” of colliding beam facilities.

	C, years	Interval
SLC e^+e^-	1.6 ± 0.1	1989–1997
Tevatron Run II p–$\bar{p}$	2.0 ± 0.2	2002–2007
RHIC p–p	2.2 ± 0.3	2000–2004
HERA p–e	2.8 ± 0.4	1992–2005
SppS p–$\bar{p}$	3.3 ± 0.2	1982–1990
LEP e^+e^-	3.3 ± 0.3	1989–1995
ISR p–p	3.7 ± 0.3	1972–1982
CESR e^+e^-	4.4 ± 0.4	1984–1997

LHC Lx100 in 2010-2018 (8 yrs) → Complexity=8/4.6=1.74

On Complexity as Measure of Difficulty to Reach Performance (#4)

Holmes, Moore, Shiltsev 2011 JINST 6 T08001

Table 3. Tevatron Collider Run II major luminosity improvements history.

Improvement		Luminosity gain
Optics correction in Accumulator (AA) to Main Injector (MI) beam line	12/2001	2...
Tevatron quenches on abort stopped by electron lens	02/2002	...bility
Antiproton loss at the step #13 of Tevatron low-beta squeeze fixed	04/2002	
New Tevatron injection helix implemented	05/20...	
New AA lattice reduces IBS, emittances	07/...	
Beam Line Tuner to reduce emittance dilution at Tevatron injection		
Antiproton multi-bunch coalescing efficiency improved in MI		...%
Small aperture Lambertson magnets removed from Tevatron C0 sec...		15 %
Tevatron sextupoles tuned / SEMs taken out of antiproton beam ...		10 %
New Tevatron helix implemented on ramp to reduce beam lo...	...03	2 %
Tevatron magnet reshimming (to center coils inside iron y...	.../2003	10 %
MI dampers operations / HEP store length increased	02/2004	30 %
Improved efficiency of 2.5 MHz antiproton transfer...	04/2004	8 %
Reduction of Tevatron β^* to 35 cm	05/2004	20 %
Antiproton injections from both Recycler and...	07/2004	8 %
Electron cooling system in Recycler opera...	01–07/2005	∼ 25 %
Longitudinal slip-stacking system in M... ...ional	03/2005	∼ 20 %
Tevatron octupoles optimized at inj... ...0 GeV	04/2005	∼ 5 %
Further reduction of the Tevatron... ...s β^* to 28 cm	09/2005	∼ 10 %
Antiproton production optimi...	02/2006	∼ 10 %
Tevatron helical separation... ...V improved, more protons	06/2006	∼ 10 %
Tevatron collision helic... ...ne improved, better lifetime	07/2006	∼ 15 %
New Recycler work... ...smaller antiproton emittances	07/2006	∼ 25 %
Faster antiproton... ...m AA to RR (1 hour → 1 min)	12/2006	∼ 15 %
New antiprot... ...r gradient Li lens operational	01/2007	∼ 10 %
Tevatron s... ...rcuits set up for new working point	2007	∼ 10 %
Compe... ...r chromaticity in Tevatron beam optics	2008	∼ 5 %
Sho... ...d by multi-bunch proton injection	2008–09	∼ 5 %
Bette... ...quality by scraping in Main Injector	2008	∼ 5 %
Antipr... ...size dilution at collisions / B0 aperture opened up	2008	∼ 5 %
Booster p... ...n emittances reduced / tune up of P1 and A1 transfer lines	04/2010	∼ 10 %
Tevatron collimators employed during low-beta squeeze, more protons	04/2011	∼ 8 %

x43 in luminosity in 32 steps

CPT Theorem for Accelerators

$$C \times P = T$$

C = Complexity of the machine

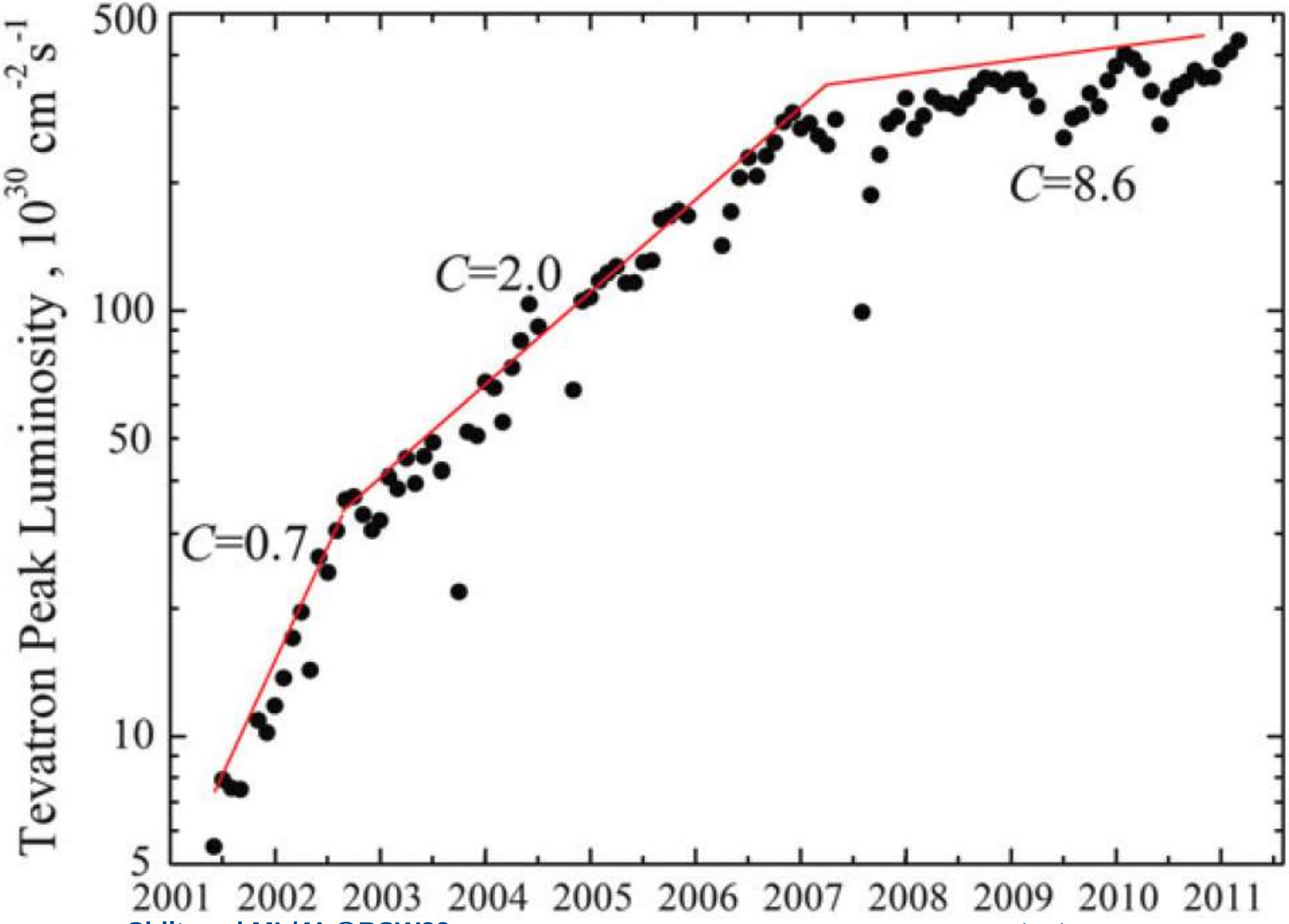
P = Performance (or Challenge)

= Ln(*Lumi Increase Ratio*)

T = Time to reach P

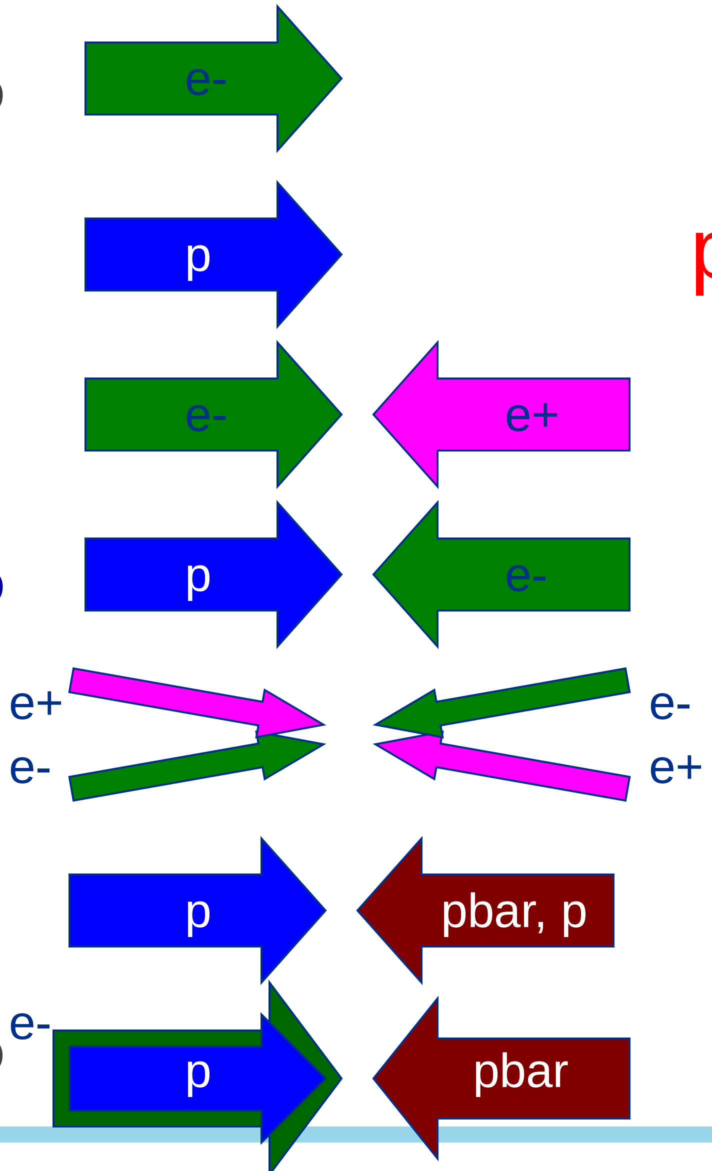
$$\boxed{\text{i.e., } L(T)=L(0) \times \exp\,(T/C)}$$

Tevatron Luminosity Progress



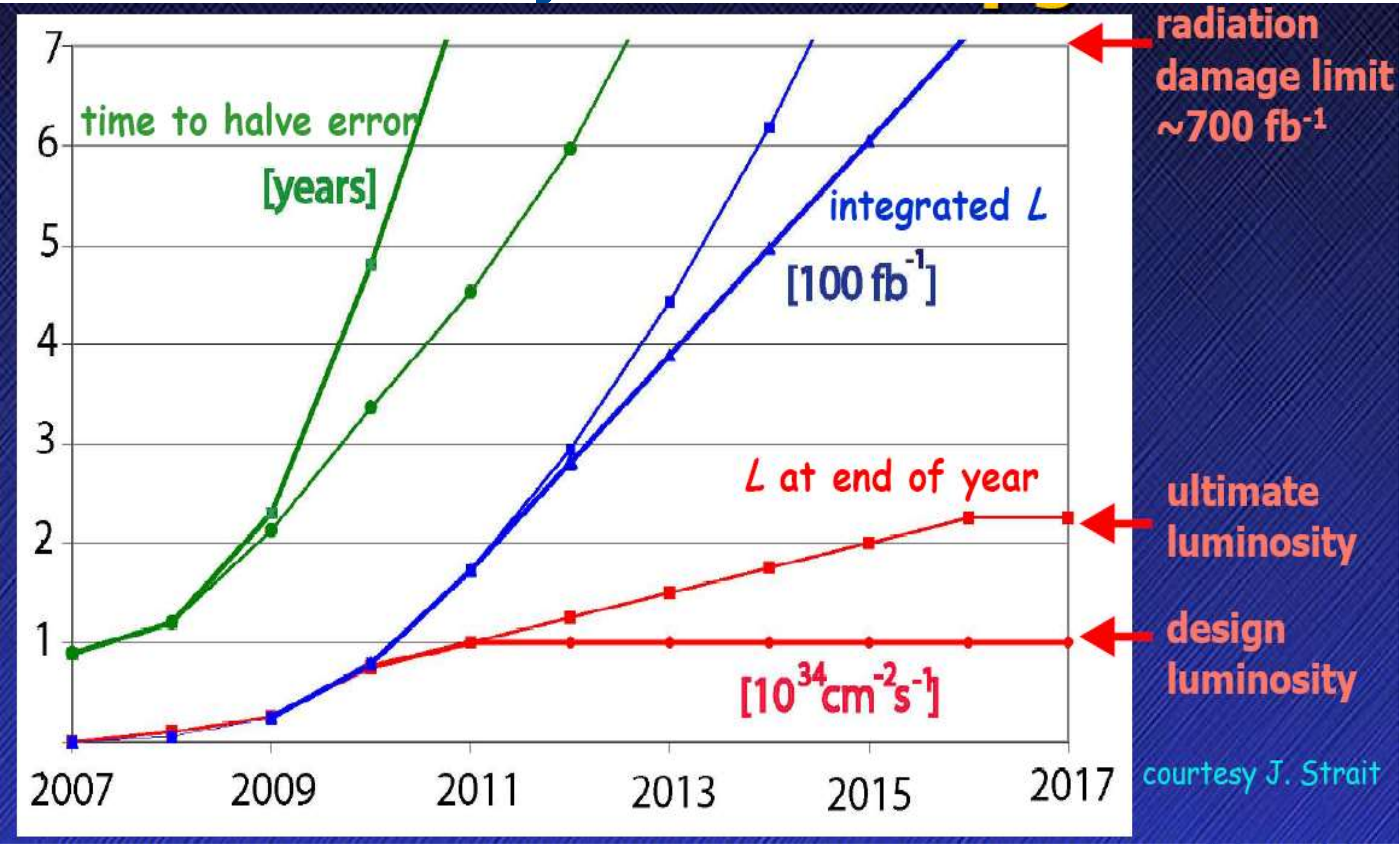
Complexity of Beams in *log*-Scale (TV tube=0)

Complexity 0.5	light sources
Complexity 1	p-synchrotron
Complexity 1	B-factories
Complexity 1.5	eCool,HERA,EIC
Complexity 2	DCI-Orsay,'80
Complexity 2	Tevatron,LHC
Complexity 2.5	Tev+elens BBC

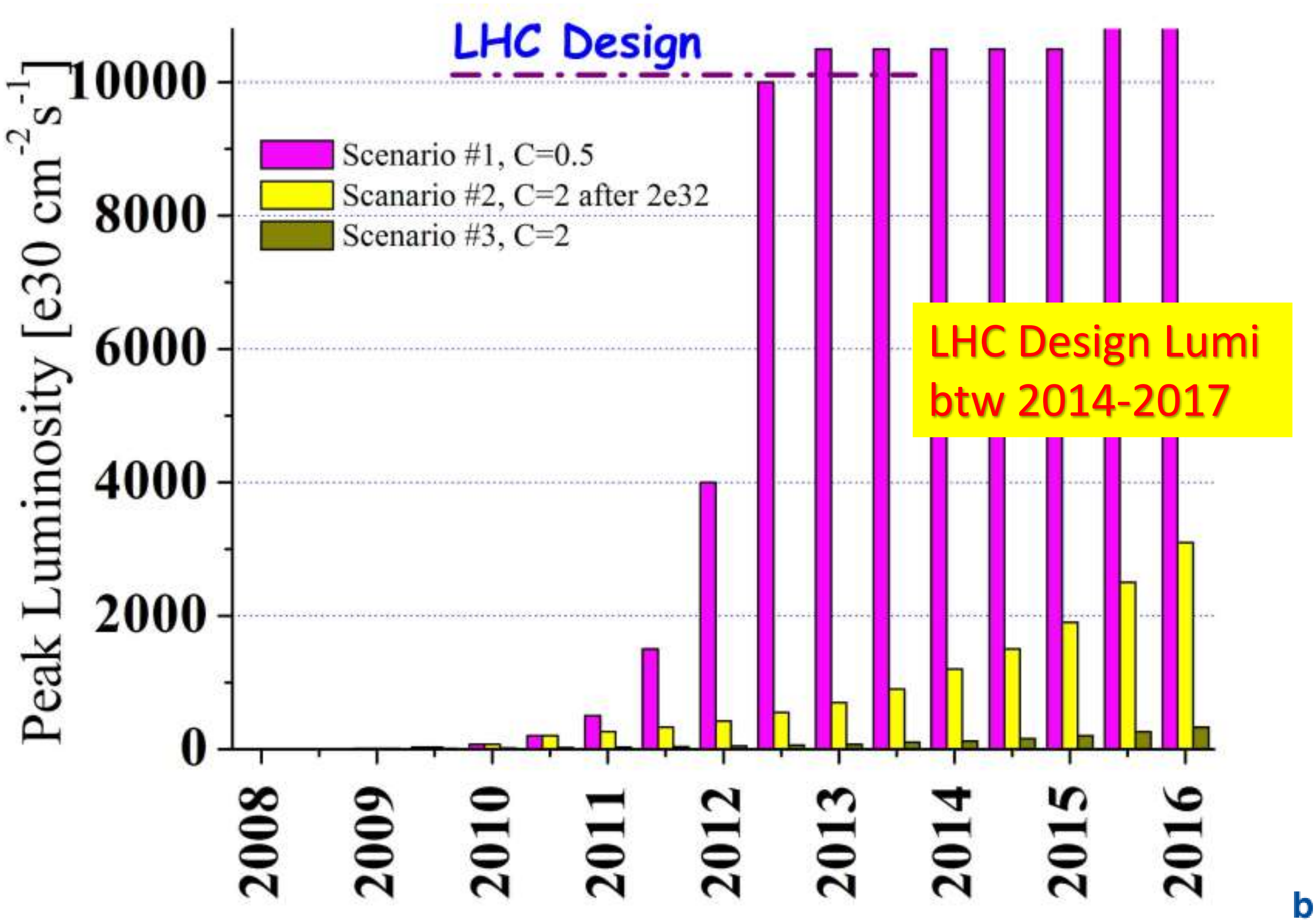


Fermilab

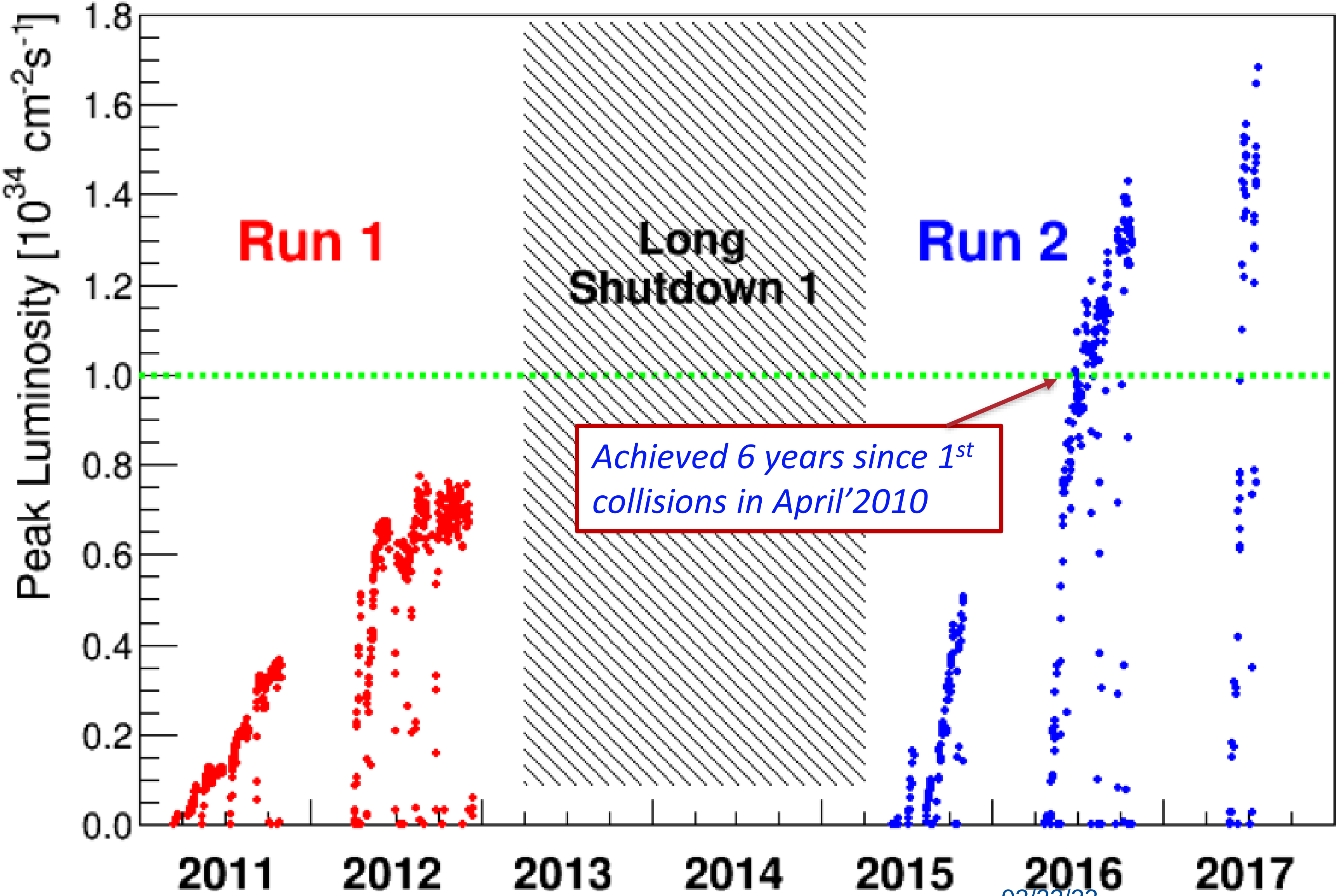
LHC Luminosity Outlook: 2003 Vision



LHC Luminosity CPT-Prediction (2006)



LHC: Design Lumi in July 2016



Structural Complexity: Hierarchy and Patterns

Multi-scale structural complexity of natural patterns arXiv:2003.04632

Andrey A. Bagrov,[1,2,*] Ilia A. Iakovlev,[2,†] Mikhail I. Katsnelson,[3,2,‡] and Vladimir V. Mazurenko[2]

The idea (from holographic complexity and common sense):
Complexity is dissimilarity at various scales

Let $f(x)$ be a multidimensional pattern

$f_\Lambda(x)$ its coarse-grained version (Kadanoff decimation, convolution with Gaussian window functions,…)

Complexity is related to distances between $f_\Lambda(x)$ and $f_{\Lambda+d\Lambda}(x)$

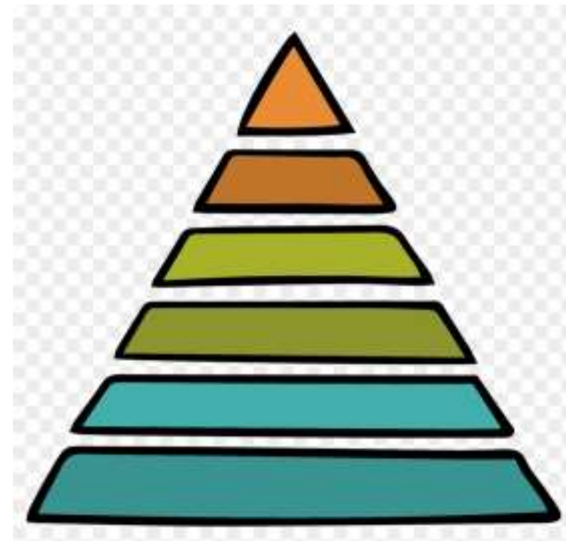
$$\langle f(x)|g(x)\rangle = \int_D dx f(x)g(x)$$

$$\Delta_\Lambda = |\langle f_\Lambda(x)|f_{\Lambda+d\Lambda}(x)\rangle - \frac{1}{2}\left(\langle f_\Lambda(x)|f_\Lambda(x)\rangle + \langle f_{\Lambda+d\Lambda}(x)|f_{\Lambda+d\Lambda}(x)\rangle\right)| = \frac{1}{2}|\langle f_{\Lambda+d\Lambda}(x) - f_\Lambda(x)|f_{\Lambda+d\Lambda}(x) - f_\Lambda(x)\rangle|,$$

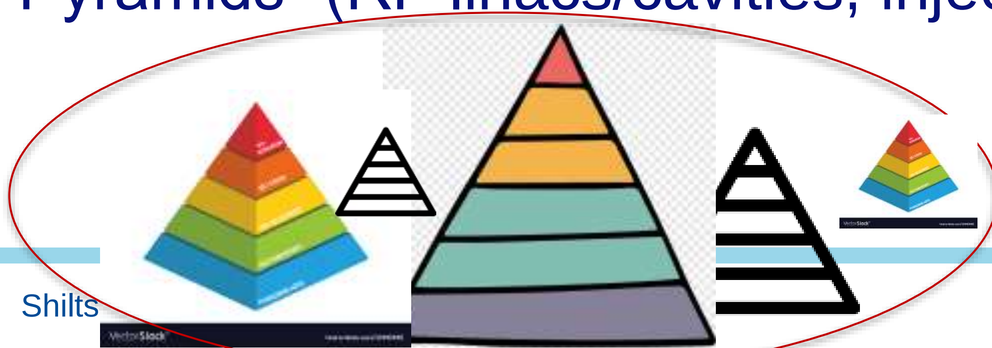
$$\mathcal{C} = \sum_\Lambda \frac{1}{d\Lambda}\Delta_\Lambda \to \int |\langle \frac{\partial f}{d\Lambda}|\frac{\partial f}{d\Lambda}\rangle| d\Lambda, \text{ as } d\Lambda \to 0$$

Main Message

- Complexity is about
  - Dissimilarity
    - Magnets, RF, plasma, cooling, drivers, FF, etc
  - And Hierarchy:
    - Eg LHC 1 ring
      O(10) sectors
      O(100) cells
      O(1000) main magnets
      O(10^4) aux magnets,
      O(10^5) control channels



- Other "Pyramids" (RF linacs/cavities, injectors, etc)



More on Hierarchy and Complexity

- Complexity is ~ Log(# elements):
  - Eg if

complexity of 1	element is	1
complexity of 10	elements is	2
complexity of 100	elements is	3
complexity of 1000	elements is	4
complexity of 10^4	elements is	5
complexity of 10^5	elements is	6

- Unfamiliarity is another factor
  - Advanced vs Traditional - add a unit (ie 10 SC 8 T ~ 100 NC) or more
  - Beyond state-of-art vs advanced – add a unit (16T ~10x 8 T) or more
- Complexity of accelerators change in time
  - As technology progresses and experience accumulated
  - i.e. building the LHC looked much harder 20 years ago than now…

Thanks for your attention!

Some references

- Many images/slides “borrowed” from presentations of the two above cited AI/ML workshops (ANL’21 and FNAL’22)
- Some slides on structural complexity borrowed from M.Katsnelson presentation at the RASA’21 Conference; extra details can be found in A.Bagrov et al arXiv:2003.04632
- CPT Theorem for Accelerators - V.Shiltsev, Modern Physics Letters A Vol. 26, No. 11, pp. 761-772 (2011)