AI-optimized Detector Design
AI-optimized detector design for the future
Electron-Ion Collider: the dual-radiator RICH case


AI techniques that can optimize the design of complex, large scale experiments can revolutionize the way experimental nuclear and particle physics is done.
Electron Ion Collider

EIC will be the only electron-nucleus collider operating in the world and will be built in partnership with JLab.

It will consist of two intersecting accelerators, one producing an intense beam of electrons, the other a high-energy beam of protons or heavier atomic nuclei.

A machine for delving deeper than ever before into the building blocks of matter.
Different detector concepts…

**h-endcap**: a dual-radiator RICH needed to cover continuously momenta up to 50 GeV/c

**e-endcap**: a small lens focused aerogel RICH for momenta up to 10 GeV/c

**barrel**: DIRC provide a compact and cost effective way to cover momenta up to 6 GeV/c

TOF (and or dE/dx in the TPC) can cover the low momenta region
Bayesian Optimization

- BO is a strategy developed for global optimization.

- After gathering evaluations BO builds a posterior distribution used to construct an acquisition function.

- This cheap function determines what is next query point.

\[ y_{\text{new}} = f(\theta_{\text{new}}) \]

Evaluate performance of \( f \) with parameters \( \theta \)

Choose \( \theta \) that maximizes some utility over the current belief
Workflow @ JLab farms

EARLY STOPPING

control convergence

yes

no

tell \{x\}, y

ask \{x\}

monitoring

BOWIE WRAPPER

OPTIMIZATION BO+ML/DL

updated model

SIMULATION

multithreaded

FOM \(i\)

FOM \(j\)

... 

FOM \(k\)

N detector configurations

N cores

settings \(x\)

settings \(x\)

settings \(x\)

STARTING CONFIGURATION

STARTING \{x\}
Case Study: dRICH

- 6 Identical open sectors (petals)
- Optical sensor elements: 8500 cm\(^2\)/sector, 3 mm pixel
- Large focusing mirror

aerogel (4 cm, n(400 nm) 1.02) + 3 mm acrylic filter + gas (1.6 m, nC\(_2\)F\(_6\) 1.0008)

- Continuous momentum coverage. Simple geometry/optics, cost effective.
- Legacy design from EICUG2017
Figure of Merit

\[ N\sigma = \frac{||\langle \theta_K \rangle - \langle \theta_{\pi} \rangle|| \sqrt{N_\gamma}}{\sigma_{1p.e.}} \]

\[ N_\gamma = \frac{(N_\gamma^\pi + N_\gamma^K)}{2} \]

\[ h = 2 \cdot \left[ \frac{1}{{(N\sigma)_1}} + \frac{1}{{(N\sigma)_2}} \right]^{-1} \]

@ \( p_1 = 14 \text{ GeV/c (aerogel) and } p_2 = 60 \text{ GeV/c (gas)} \)

considering the two parts disentangled
dRICH Performance @ the optimal design point

- Statistically significant Improvement in both parts.
- In particular in the gas region where the 5σ threshold shifted from 43 to 50 GeV/c and the 3σ one extended up to
- Notice that before this study we did not know “how well” the legacy design was performing.

The Model and the Optimized FoM

\[ N\sigma = \frac{\|\langle \theta_K \rangle - \langle \theta_\pi \rangle \|}{\sqrt{N_\gamma}} \]

Comparison with Random Search

![Diagram showing comparison between random search and Bayesian optimization (GP)]

**Graph 1:**
- **Y-axis:** Optimized figure of merit
- **X-axis:** Number of observations
- **Legend:**
  - Random search
  - Bayesian optimization (GP)

**Graph 2:**
- **Y-axis:** Time [s] with 20 cores
- **X-axis:** Number of calls
- **Legend:**
  - Random search
  - Bayesian optimization (GP)
Convergence Criteria

- We defined a set of conditions to ensure convergence.
- These correspond to the logic AND of booleans on each feature and on the variation of the figure of merit.
- They are built on standardized Z and Fisher statistics.
- Pre-processing of data required to remove outliers.
Tolerance Regions

- BO provides a model of how the FoM depends on the parameters, hence it is possible to use the posterior to define a tolerance on the parameters (regions ensuring improved PID, see previous slide).

- Larger than the construction tolerances on each parameter.
  Notice a small lateral shift of the tiles has negligible impact on the PID capability.
“AI techniques that can optimize the design of complex, large scale experiments can revolutionize the way experimental nuclear and particle physics is done”

- AI for detector design
- Intelligent detection systems able to self-calibrate/align
- etc
Summary

● Presented AI-driven detector design for the case of the dual-RICH in EIC.
● Key-features: automated, highly-parallelized, self-consistent.
● These same tools can be extended and applied to other detectors and possibly to the entire experiment, making the EIC R&D one of the first programs to systematically exploit AI in the detector-design phase.
● AI can help coordinate the efforts of different groups developing different sub-detectors towards the final global detector design.
BACKUP
Bayesian Optimization

It basically consists of three steps:

1. Evaluate performance of $f$ with parameters $\theta$.

2. Update current belief of loss surface of $f$.

3. Choose $\theta$ that maximizes some utility over the current belief.

Mathematically:

$y_{new} = f(\theta_{new})$

$f|y_{new}$
**Update**

- GPs are the generalization of a Gaussian distribution to a distribution over functions, instead of random variables.

- GP is completely specified by its mean function and covariance function.

- How should I read this?
  - **Solid line**: function we are trying to min/max
  - **Shaded region**: probability model (we know the actual points already evaluated but we are more uncertain in regions where we haven’t).
  - In every point a normal distribution of the potential performance function
- Where am I going to sample next?
- We use utility functions called acquisition functions (formalize what is the best guess)
- Expected improvements is one example: find next point that improves the performance the most.

$$EI(\theta) = \begin{cases} 
\left(\mu(\theta) - f(\hat{\theta})\right) \Phi(Z) + \sigma(\theta) \phi(Z), & \text{if } \sigma(\theta) > 0 \\
0, & \text{otherwise}
\end{cases}$$

$$Z = \frac{\mu(\theta) - f(\hat{\theta})}{\sigma(\theta)}$$
The Model and the Optimized FoM

<table>
<thead>
<tr>
<th></th>
<th>FoM (h)</th>
<th>$(N\sigma)$ @ 14 GeV/c</th>
<th>$(N\sigma)$ @ 60 GeV/c</th>
</tr>
</thead>
<tbody>
<tr>
<td>BO</td>
<td>3.23</td>
<td>3.16</td>
<td>3.30</td>
</tr>
<tr>
<td>legacy</td>
<td>2.9</td>
<td>3.0</td>
<td>2.8</td>
</tr>
</tbody>
</table>


C. Fanelli The AI for Nuclear Physics workshop Mar 4, 2020
Noise Studies

- Dedicated studies to characterize the noise as this is an optimization of a noisy function
- We choose N tracks = 400 based on the studies on noise to minimize as much as possible computing time during simulation.

<table>
<thead>
<tr>
<th>symbol</th>
<th>description</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>maximum number of calls</td>
<td>100</td>
</tr>
<tr>
<td>M</td>
<td>points generated in parallel (GP)</td>
<td>20</td>
</tr>
<tr>
<td>N</td>
<td>pions (and kaons) per sample</td>
<td>200</td>
</tr>
<tr>
<td>kappa</td>
<td>controls variance in predicted values</td>
<td>1.96</td>
</tr>
<tr>
<td>xi</td>
<td>controls improvement over previous best values</td>
<td>0.01</td>
</tr>
<tr>
<td>noise</td>
<td>expected noise (relative)</td>
<td>2.5%</td>
</tr>
</tbody>
</table>

(list of hyperparameters)
Construction Constraints

The idea is that we have a bunch of parameters to optimize that characterize the detector design. We know from previous studies their ranges and the construction tolerances.

<table>
<thead>
<tr>
<th>parameter</th>
<th>description</th>
<th>range [units]</th>
<th>tolerance [units]</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>mirror radius</td>
<td>[290,300] [cm]</td>
<td>100 [µm]</td>
</tr>
<tr>
<td>pos r</td>
<td>radial position of mirror center</td>
<td>[125,140] [cm]</td>
<td>100 [µm]</td>
</tr>
<tr>
<td>pos l</td>
<td>longitudinal position of mirror center</td>
<td>[-305,-295] [cm]</td>
<td>100 [µm]</td>
</tr>
<tr>
<td>tiles x</td>
<td>shift along x of tiles center</td>
<td>[-5.5] [cm]</td>
<td>100 [µm]</td>
</tr>
<tr>
<td>tiles y</td>
<td>shift along y of tiles center</td>
<td>[-5.5] [cm]</td>
<td>100 [µm]</td>
</tr>
<tr>
<td>tiles z</td>
<td>shift along z of tiles center</td>
<td>[-105,-95] [cm]</td>
<td>100 [µm]</td>
</tr>
<tr>
<td>n_{aerogel}</td>
<td>aerogel refractive index</td>
<td>[1.015,1.030]</td>
<td>0.2%</td>
</tr>
<tr>
<td>t_{aerogel}</td>
<td>aerogel thickness</td>
<td>[3.0,6.0] [cm]</td>
<td>1 [mm]</td>
</tr>
</tbody>
</table>

Ranges depend mainly on mechanical constraints and optics requirements. These requirements can change in the next future based on inputs from prototyping.