AI-assisted Optimization of the ECCE Tracking System at the Electron Ion Collider

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Abstract
The Electron-Ion Collider (EIC) is a cutting-edge accelerator facility that will study the nature of the “glue” that binds the building blocks of the visible matter in the universe. The proposed experiment will be realized at Brookhaven National Laboratory in approximately 10 years from now, with detector design and R&D currently ongoing. Notably, EIC is one of the first large-scale facilities to leverage Artificial Intelligence (AI) already starting from the design and R&D phases. The EIC Comprehensive Chromodynamics Experiment (ECCE) is a consortium that proposed a detector design based on a 1.5T solenoid. The EIC detector proposal review concluded that the ECCE design will serve as the reference design for an EIC detector. Herein we describe a comprehensive optimization of the ECCE tracker using AI. The work required a complex parametrization of the simulated detector system. Our approach dealt with an optimization problem in a multidimensional design space driven by multiple objectives that encode the detector performance, while satisfying several mechanical constraints. We describe our strategy and show results obtained for the ECCE tracking system. The AI-assisted design is agnostic to the simulation framework and can be extended to other sub-detectors or to a system of sub-detectors to further optimize the performance of the EIC detector.

**Keywords:** ECCE, Electron Ion Collider, Tracking, Artificial Intelligence, Evolutionary Algorithms, Bayesian Optimization.
such as Geant4 [5] to simulate the interaction of radiation with matter. Additional computationally expensive steps are present along the data reconstruction and analysis pipeline. The software stack that is utilized in the detector design process involves three main steps: (i) generation of events, (ii) detector simulations and (iii) reconstruction and analysis.

As pointed out in [6], the above bottlenecks render the generation and exploration of multiple design points cumbersome. This in turn represents an obstacle for deep learning (DL)-based approaches that learn the mapping between the design space and the functional space [7] [8] [9], which could facilitate the identification of optimal design points. In principle fast simulations with DL can reduce the most CPU-intensive parts of the simulation and provide accurate results [10], although several design points need to be produced with Geant4 before injection in any DL architecture. Similar considerations exist in deploying DL for reconstruction during the design optimization process.

In this context, a workflow for detector design that has gained popularity in recent years [11] is represented by the schematic in Fig. 1. It consists of a sequential AI-based strategy that collects information associated to previously generated design points, in the form of figures of merit (called objectives in the following) that quantify the goodness of the design, and which suggests promising new design points for the next iteration.

The ECCE AI Working Group achieved a continual multi-objective optimization (MOO) of the tracker design. Our approach deals with a complex optimization in a multidimensional design space (describing, e.g., geometry, mechanics, optics, etc) driven by multiple objectives that encode the detector performance, while satisfying several mechanical constraints. This framework has been developed in a way that can be easily extended to other sub-detectors or to a system of sub-detectors.

The definition of a generic MOO problem can be formulated as follows:

\[
\begin{align*}
\text{min } f_m(x) & \quad m = 1, \ldots, M \\
\text{s.t. } g_j(x) & \leq 0, \quad j = 1, \ldots, J \\
\text{ } & \quad h_k(x) = 0, \quad k = 1, \ldots, K \\
\text{ } & \quad x_i^L \leq x_i \leq x_i^U, \quad i = 1, \ldots, N
\end{align*}
\]

where one has \( M \) objective functions \( f_m \) to optimize (e.g., detector resolution, efficiency, costs), subject to \( J \) inequalities \( g_j(x) \) and \( K \) equality constraints \( h_k(z) \) (e.g., mechanical constraints), in a design space of \( N \) dimensions (e.g., geometry parameters that change the Geant4 design) with lower and upper bounds on each dimension [1]. Notice that overlaps in the design are checked before and during the optimization and are excluded by the constraints and ranges of the parameters. In solving these problems, one can come up with a set of non-dominated or trade-off solutions [12], popularly known as Pareto-optimal solutions (see also Fig. 2).

In this setting, we used a recently developed framework for MOO called pymoo [13] which supports evolutionary MOO algorithms such as Non-Dominated Sorting Genetic Algorithm (or NSGA-II, [14]) [15]. The rationale behind this choice instead of, for example, principled approaches such as Bayesian Optimization [11], emanates from the ECCE needs at the time of the detector proposal, such as the capability to quickly implement and run multiple parallel optimization pipelines implementing different technology choices and the possibility of dealing with non-differentiable objectives at the exploratory stage.

The NSGA workflow is described in Fig. 3. The main features of NSGA-II are (i) the usage of an elitist principle, (ii) an explicit diversity preserving mechanism, and (iii) ability of determining non-dominated solutions. The latter feature is of great importance for problems where objectives are of conflict

Figure 1: Workflow of detector design assisted by AI: physics events are injected in a detector characterized by given design parameters. Reconstructed events are analyzed and figures of merit are quantified and passed to an AI-based strategy, which in turn suggests the next design point in this sequential approach; note that AI can also intervene in the simulation and reconstruction steps.

Figure 2: Example of Pareto frontier in a two-dimensional objective space: The point C is not on the frontier and is dominated by both point A and point B. All the other points which are dominated by the Pareto frontier and that satisfy any constraints in the optimization problem are called feasible solutions; The hypervolume is used as a metric for convergence, and is calculated with respect to a reference point \( r \).
with each other: that is an improved performance in an objective results in worse performance in another objective. For our purposes, we also tested NSGA-III which is suitable for the optimization of large number of objectives [16].

During the design optimization process of the tracking system, we used full GEANT4 simulations of the entire ECCE detector. AI played a crucial role in helping choose a combination of technologies for the inner tracker and was used as input to multiple iterations of the ECCE tracker design, which led to the current tracker layout. This was the result of a continual optimization process that evolved in time: results were validated by looking at figures of merit that do not enter as objective functions in the optimization process (more details can be found in Sec. Appendix B); the decision making is left post hoc and discussed among the Computing, Detector and Physics teams. A flowchart describing this continual optimization process is shown in Fig. 4.

Ultimately this continual AI-assisted optimization led to a projective design after having extended the parametrized design to include the support structure of the inner tracker. The latter represents an ongoing R&D project that is discussed in the next sections.

3. ECCE Tracking System Simulation

The simulation and detector response shown in this document is based on GEANT4 [17] and was carried out using the Fun4All framework [18][19].

The optimization pipelines are based on particle gun samples of pions, where we used $\pi^-$ and tested that the performance with $\pi^+$ were consistent. Performance in the electron-going direction was also checked post-hoc with particle gun samples of electrons. The improved performance is further validated with physics analyses, using the datasets generated during the ECCE simulation campaigns; in Sec. 4 we show in particular results based on semi-inclusive deep inelastic scattering (SIDIS) events.

For $\geq 4$ objectives, NSGA-III is expected to perform better than NSGA-II.

Figure 3: The NSGA Workflow: At time $t$, an offspring $Q(t)$ is created through a genetic algorithm [15] from an $N$-sized population of design points $P(t)$. The two populations are combined into an augmented population which is classified into different non-dominated classes $F_i$, starting from the first front $F_1$. To restore the initial size of the population, the augmented space of solutions is trimmed. A metric called crowding distance is used to reject solutions and eventually provide an updated population of size $N$ at time $t + 1$.

Figure 4: Flowchart of continual optimization during proposal: AI assists the design optimization process by providing insights and capturing hidden correlations among the design parameters. This has been used during the entire detector proposal process to steer the design. At a given instant in time, $N$ alternative candidate configurations are studied. For each we create an optimization pipeline, which results in a Pareto front of solutions. This new information helps steering the design: some configurations are rejected, while other ones (also dubbed ‘new references’) are identified to potentially improve the design. New optimization pipelines are defined inspired by the new results and the process is iterated. During the design process, AI propelled the fundamental interplay between the ECCE Teams working on Physics, Detector and Computing. The ECCE tracking detector [20], represented in Fig. 5 (left), consists of different layers in the barrel and the two end-caps, and is tightly integrated with the PID detectors:

(i) The silicon vertex/tracking detector is an ALICE ITS-3 type high precision cylindrical/disk vertex tracker [21][22] based on the new Monolithic Active Pixel Sensor (MAPS); the barrel detector consists of 5 MAPS layers; the silicon hadron endcap consists of 5 maps disks; and the silicon electron endcap has 4 MAPS disks.

(ii) A gas tracking system is based on $\mu$Rwell technology, that is a single-stage amplification Micro Pattern Gaseous Detector (MPGD) that is a derivative of the Gas Electron Multiplier (GEM) technology. In ECCE $\mu$Rwell layers will form three barrel tracking layers further out from the beam-pipe than the silicon layers; namely, two inner-barrel layers and a single outer-barrel $\mu$Rwell layer. All $\mu$Rwell detectors will have 2D strip based readout. The strip pitch for all three layers will be 400 $\mu$m.

(iii) The tracking system is completed by AC-LGAD-based time of flight (TOF) detectors providing additional hit information for track reconstruction as well. In the central region a TOF (dubbed CTTL) is placed behind the high-performance DIRC (hpDIRC); in the hadron-going side a TOF (dubbed FTTL) is placed before the dual RICH (dRICH) and a $\mu$Rwell placed after the dRICH; in the electron-going direction a $\mu$Rwell layer is placed before the modular RICH (mRICH), which is followed by a TOF later (dubbed ETTL).

An important consideration for all large-scale detectors is the provision of readout (power and signal cables) and other services (e.g., cooling). Clearly the aim is to minimize the impact of readout and services in terms of affecting the detector’s acceptance or tracking resolution, for example. This effort is ongoing R&D for the project.

In the following sections, the reader can find more details on
the implementation of the optimization pipelines and utilized computing resources.

4. Analysis Workflow

The optimization of the ECCE-tracking system [1, 20] has been characterized by two main phases during which the sub-detectors composing the tracker evolved into more advanced renditions.

Phase I optimization. The Geant4 implementation of the detectors were at first simplified, e.g., detector modules were mounted on a simplified conical support structure made of aluminum. The optimization pipelines consisted of symmetric arrangement of detectors in the electron-going and hadron-going directions (5 disks on each side). The DIRC detector for PID in the barrel region was modelled with a simple geometry made by a cylinder and conical mirrors. AC-LGAD-based TOF detectors were modelled as simplified silicon disks at first; the outer trackers had more fine-grained simulations implemented, with realistic support structures and services implemented. The optimization pipelines included various combinations of detector technologies for the inner trackers. At the end of this phase, a decision on the choice of the barrel technology and the disk technologies was made using the AI results.

Phase II optimization. These pipelines had a more realistic implementation of the support structure incorporating cabling, support carbon fiber, cooling system, etc. More detailed simulation of the PID Detectors (e.g., DIRC bars and dRICH sub-systems) were integrated as well as fine-grained simulations of TTL layers (CTTL, ETTL, FTTL) previously simulated as simple silicon layers modules. More stringent engineering constraints were considered such as the sensor size for MAPS detector (ITS3). This phase also considered an asymmetric arrangement of the detectors in the endcap regions, with a maximum of 4 EST disks in the electron-going end-cap and 5 FST disks in the hadron-going end-cap: due to this asymmetric spatial arrangement, the angle subtended by detectors in the two endcap regions could be varied. This eventually developed into the idea of a projective geometry in a pipeline that characterizes an ongoing R&D project for optimizing the design of the support structure.

A detailed description of the most recent parametrization used for the detector proposal can be found in Appendix A, along with the parametrization used in an ongoing R&D project to optimize the support structure of the inner tracker.

Fig. 5 shows a comparison of the ECCE reference non-projective design and the projective design from the ongoing R&D, both of which resulted from the AI-assisted procedure described in this paper.

4.1. Encoding of Design Criteria

Design criteria need to be encoded to steer the design during the optimization process. For each design point we need to compute the corresponding objectives $f_m$, namely the momentum resolution, angular resolution, and Kalman filter efficiency.

We will refer in the following only to the more recent Phase II optimization. Phase II has been characterized by two types of optimization pipelines: the first used a parametrization of the inner tracker during the optimization process and led to the ECCE tracker non-projective design; the second branched off the first as an independent R&D effort that included the

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6Similar considerations apply also for Phase I optimization.
parametrization of the support structure and led to a projective design.

Details on the two types of optimization pipelines can be found in the following tables: Table 1 describes the main hyperparameters and the dimensionality of the optimization problem, in particular of the design space and the objective space; Table 2 reports the range of each design parameter. Table 3 summarizes the constraints for both the non-projective and projective geometries. We also considered in our design a safe minimum distance between the disks of 10 cm and include a constraint on the difference between the outer and inner radii of each disk, namely $R_{\text{out}} - R_{\text{in}}$, to be a multiple of the sensor cell size (17.8 mm $\times$ 30.0 mm), see Table 3. These constraints are common to the non-projective and the projective designs. For more details on the parametrizations and on the corresponding detector performance the reader can refer to Appendix A and Appendix B respectively.

### Table 1: Summary of the hyperparameters of the design optimization

| Description | Symbol | Value |
|-------------|--------|-------|
| Population size | N | 100 |
| Number of objectives | M | 3 |
| Offspring size | O | 30 |
| Design size | D | 11 (9) |
| Number of calls (tot. budget) | $N_{\text{frk}}$ | 200 |
| Number of cores | $N_{\phi}$ | 5 |
| Number of charged tracks | $N_{\bar{p}}$ | 10 |

Table 1: Summary of the hyperparameters of the design optimization: the values reported in the table have been used during the optimization of the non-projective design of the ECCE tracker. For completeness and when they differ from the non-projective case, we also report in parentheses the values corresponding to the ongoing R&D project for the projective design of the support structure.

The objectives depend on the kinematics and are calculated in 5 main bins in pseudorapidity ($\eta$): (i) $-3.5 \leq \eta < -2.0$ (corresponding to the electron-going direction), (ii) $-2.0 \leq \eta < -1.0$ (the transition region in electron-going direction), (iii) $-1.0 \leq \eta < 1$ (the central barrel), (iv) $1.0 \leq \eta < 2.0$ (the transition region in the hadron-going direction) and (v) $2.0 \leq \eta < 3.5$ (the hadron-going direction). The rationale behind this binning is a combination of different aspects: the correspondence with the binning in the EIC Yellow Report, the asymmetric arrangement of detectors in electron-going and hadron-going directions and the division in pseudorapidity between the barrel region and the endcap. Particular attention is given to the transition region between barrel and endcaps as well as at large $|\eta| \sim 3.5$ close to the beamline.

Charged pions are generated uniformly in the phase-space that covers the range in momentum magnitude $p \in [0,20]$ GeV/c and the range in pseudorapidity $\eta \in (-3.5,3.5)$. Each bin in $\eta$ is

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7The design points are normalized in the range $[0,1]$, using a min-max scaler $x_i = \frac{x_{\text{min}} - x_{i,\text{min}}}{x_{\text{max}} - x_{i,\text{min}}}$, where $x_i$ is the normalized design point with a un-normalized design point $x$ generated between the range $[x_{\text{min}}, x_{\text{max}}]$.  

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### Table 2: Ranges of the design parameters

| Design Parameter | Range |
|------------------|-------|
| $\mu$R WELL 1 (Inner) ($r$) Radius | $[17.0, 51.0]$ cm |
| $\mu$R WELL 2 (Inner) ($r$) Radius | $[18.0, 51.0]$ cm |
| EST 4 $z$ position | $[-110.0, -50.0]$ cm |
| EST 3 $z$ position | $[-110.0, -40.0]$ cm |
| EST 2 $z$ position | $[-80.0, -30.0]$ cm |
| EST 1 $z$ position | $[-50.0, -20.0]$ cm |
| FST 1 $z$ position | $[20.0, 50.0]$ cm |
| FST 2 $z$ position | $[30.0, 80.0]$ cm |
| FST 3 $z$ position | $[40.0, 110.0]$ cm |
| FST 4 $z$ position | $[50.0, 125.0]$ cm |
| FST 5 $z$ position | $[60.0, 125.0]$ cm |

| Design Parameter | Range |
|------------------|-------|
| $\mu$R WELL 1 (Support Cone) | $[25.0, 30.0]$ cm |
| $\mu$R WELL 1 (Inner) Radius | $[25.0, 45.0]$ cm |
| ESTTL $z$ position | $[-171.0, -161.0]$ cm |
| EST 2 $z$ position | $[45.0, 100.0]$ cm |
| EST 1 $z$ position | $[35.0, 50.0]$ cm |
| FST 2 $z$ position | $[45.0, 100.0]$ cm |
| FST 5 $z$ position | $[100.0, 150.0]$ cm |
| PTTL $z$ position | $[156.0, 183.0]$ cm |

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### Table 3: Constraints in the design optimization

| Sub-detector | Constraint | Description |
|--------------|------------|-------------|
| EST/FST disks | $\sum_{i=1}^{n_{\text{disks}}} \left| \frac{R_{\text{out}} - R_{\text{in}}}{d} - \frac{R_{\text{out}} - R_{\text{in}}}{d} \right|$ | soft constraint: sum of residuals in sensor coverage for disks. sensor dimensions: $d = 17.8$ (30.0) mm |
| EST/FST disks | $z_{\text{min}} - z_{\text{max}} > 10.0$ cm | strong constraint: minimum distance between 2 consecutive disks |
| Sagitta layers | $\frac{2m_{\text{mass}}}{s_{\text{gap}} m_{\text{track}}}$ | soft constraint: residual in sensor coverage for every layer; sensor step width: $w = 17.8$ mm |
| $\mu$WELL | $t_{\text{min}} - t_{\text{max}} > 5.0$ cm | strong constraint: minimum distance between $\mu$WELL barrel layers |

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Potential overlaps among modules are checked before and during the optimization.
The momentum range was reduced to $[0, 20]$ GeV $\eta$, therefore we needed to extend the $p$ coverage and increase the statistics. Using single-Gaussian (SG) fits (also utilized in Yellow Report), or equivalently the KF inefficiency:

$$R(KF) = \frac{N(\text{tracks not reconstructed})}{N(\text{total number of tracks})}$$

Following the above definitions, the design problem corresponds to minimizing the objective functions defined in Eqs. (4, 5): a weighted average ratio smaller than one and a KF inefficiency as close as possible to zero correspond to an improvement in performance compared to the baseline design.

4.2. Convergence and Performance at Pareto Front

We remind the reader that the Pareto front is the set of trade-off solutions of our problem. Fig. 7 shows the convergence plot obtained utilizing the hypervolume as metric in the objective space. A petal diagram is used to visualize the values of three objectives corresponding to one of the solutions extracted from the Pareto front.

Checkpoints are created to store the NSGA-II-updated population of design points. A survey of the detector performance is created after each call to monitor potential anomaly behavior of the fits. The fitting procedure is quite stable: if an exception occurs the analysis has been automated to adjust the fitting parameters and ranges. In case of persistent anomalous behavior a flag is raised, the critical design point purged from the population and examined.

The improvement obtained with the continual multi-objective optimization process is summarized in Fig. 8 where the momentum resolution obtained during phase-I optimization using a preliminary detector concept is compared to both the non-projective and the projective R&D designs which are instead derived from fully developed simulations in phase-II optimization.

A detailed description of the optimized performance for all the objectives (momentum, angular resolutions and Kalman Filter efficiency) can be found in Appendix B.

8From Phase I to Phase II, the design became asymmetric in the two endcaps, therefore we needed to extend the $\eta$-coverage and increase the statistics. The momentum range was reduced to $[0, 20]$ GeV/c to optimize the computing budget.

9A different definition could be based on the weighted average of the variances $\sigma^2_{DG}$ to obtain the final variance $\sigma^2_{\text{DG}}$. This typically implied a few % relative difference on the final value of $\sigma^2_{\text{DG}}$ which has been considered a negligible effect.

10Early stopping can occur if no change in the hypervolume is observed after a certain number of evaluations.
Figure 7: Metric for convergence and performance at Pareto front: (left) The hypervolume can be used as a metric for convergence. Checkpoints are created during the optimization and snapshots of the evolving designs are saved. (right) A petal diagram with the three objectives corresponding to one solution in the Pareto front. The momentum and angular resolutions are expressed as ratios with respect to a baseline design to improve; the KF inefficiency is taken as an absolute value. An optimal design optimizes all of the above defined objectives.

4.3. Physics Analysis

To show a comparison in physics performance between the non-projective and projective designs, we analysed $D^0$ meson decay into $\pi^+K^-$. Data have been produced utilizing SIDIS events generated with Pythia6 [25], corresponding to ep events with 18 GeV × 275 GeV and high Q^2 [26].

In Fig. 9, the $\pi^+K^-$ invariant mass is fitted with a double-sided Crystal Ball function [27, 28].

The decay events are selected in such a way to have at least one particle (either $\pi$ or $K$, or both) in the pseudorapidity bin $1.0<|\eta|<1.5$, where the projective design is expected to improve the performance by concentrating all the material in a smaller dead area compared to the non-projective design.

The analysis shows that the resolution obtained with the projective design is improved by more than 10% relative to that obtained with the non-projective design. We also calculate the efficiency, defined as the number of reconstructed $D^0$ mesons divided by the number of true $D^0$ mesons. The efficiency obtained with the two designs is consistent within the statistical uncertainties.

5. Computing Resources

Parallelization. A two-level parallelization has been implemented in the MOO framework: the first level creates the parallel simulations of design points, the second level parallelizes each design point (see Fig. 10). The evaluation itself can be distributed to several workers or a whole cluster with libraries like Dask [29].

Computing Budget. Computing time studies have been carried out to evaluate the simulation time of each single design point as a function of the number of tracks generated. We made this study with simulations that included the tracking system and the PID system and estimated an effective simulation time of 0.2 s/track after removing an initial latency time. Similarly we made studies of the computing time taken by the AI-based algorithm in generating a new population of design points. Results of these studies are summarized in Fig. 11.

A larger population allows to approximate the Pareto front with larger accuracy. Extension of the design parameter space and the objective space to larger dimensionality implies a larger amount of CPU time which is mainly dominated by simulations if the population size remains smaller than $10^3$–$10^4$, see Fig. 11.

For our goals the optimization pipelines of the ECCE tracking system were parametrized with 10–20 design parameters and 3–4 objectives; this allowed us to achieve good convergence with evolutionary MOO using a two-level parallelization strategy, and deployment on single nodes of 128 CPU cores available on the sci-comp farm at Jefferson Lab [30].

Planned Activities. As described in this document, detector optimization with AI is an essential part of the R&D and design process and it is anticipated to continue after the detector proposal. The AI-assisted design optimization of the ECCE inner tracker was based on evolutionary algorithms. During the detector proposal multiple optimization pipelines were run each with a population size of 100, representing different detector design configurations. At each iteration, AI updated the population. The total computing budget for an individual pipeline amounted to approximately 10k CPU-core hours. This number depends on the dimensionality of the problem. Larger populations may need to be simulated to cope with the increased complexity in order to improve the accuracy of the approximated Pareto front. Different AI-based strategies will be compared.

Activities are planned to continue the detector optimization: new optimization pipelines can deal with a larger parameter space to include a system of sub-detectors such or to combine tracking and PID in the optimization process. We also plan to optimize other sub-detectors like, e.g., the dRICH, leveraging on the expertise internal to the ECCE collaboration regarding specifically the design of the dRICH with AI-based techniques [11]. As a future activity we aim to encode physics-driven objectives in the MOO problem. A thorough comparison of results obtained with different AI-based strategies (e.g., MOO based on genetic algorithms or bayesian approaches) can be also studied.

We anticipate for 2022 roughly 1M CPU-core hours for these activities.

6. Summary

Large scale experiments in high energy nuclear physics entail unprecedented computational challenges and the optimization of their complex detector systems can benefit from AI-based strategies [6].

In this paper we described the successful implementation of a multi-objective optimization approach to steer the multidimensional design of the ECCE tracking system, taking into account the constraints from the global detector design. This work

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11production: prop.5/prop.51; generator: pythia6; kinematics: ep-18x275-q2-high. More info can be found in [25].

12Work is in progress to efficiently distribute the optimization pipeline to multiple nodes.
The resolution obtained with the non-projective design.
resolution with the projective design is improved by more than 10% relative to
\( \pi \) such that both the tracks

Figure 8: Evolution of momentum resolution driven by the continued MOO: Momentum resolutions in four bins of \( \eta \). From left to right, respectively: \( |\eta| < 1.0 \) corresponding to the barrel, \( 1.0 \leq |\eta| < 1.5 \) corresponding to the transition region, and \( 1.5 \leq |\eta| < 2.5 \) and \( 2.5 \leq |\eta| < 3.5 \) corresponding to the two end-caps. Black points represent the first simulation campaign, and a preliminary detector concept in phase-I optimization which did not have a developed support structure; blue points represent the fully developed simulations for the final ECCE detector proposal concept; red points the ongoing R&D for the optimization of the support structure. Compared to black, there is an improvement in performance in all \( \eta \) bins with the exception of the transition region, an artifact that depends on the fact that black points do not include a realistic simulation of the material budget in the transition region. In the transition region, it can be also appreciate the improvement provided by the projective design.

Figure 9: Analysis of SIDIS events with AI-assisted detector designs: The \( \pi^+K^- \) invariant mass obtained from the SIDIS events reconstructed in ECCE. A comparison of the resolution on the \( D^0 \) meson obtained with the non-projective and the projective design of the ECCE tracker is shown. In order to emphasize the improvement in the region between \( 1.0 < |\eta| < 1.5 \), a selection was made such that both the tracks \( \pi^+ \) or the \( K^- \) are within the region of interest. The resolution with the projective design is improved by more than 10% relative to the resolution obtained with the non-projective design.

Figure 10: Flowchart of the two-level parallelization implemented for detector design: Multiple design points are produced in parallel, and each design point is parallelized. The design is assisted by an AI-strategy, in this case MOO with evolutionary algorithms supported by pymoo [13].

Figure 11: The computing time taken by the genetic algorithm and the sorting in NSGA-II: Performance has been benchmarked with test problems like DTLZ1 [16] (red points) and the scaling ~ \( MN^2 \) (see Table I has been verified with convergence to the Pareto front. The simulation time dominates the AI time during the optimization process (blue point). A two-level parallelization has been introduced in the framework to reduce this bottleneck. The AI contribution typically becomes dominant when very large population size is needed to accurately approximate the Pareto front (cf. [21]).

was accomplished during the EIC detector proposal, and was characterized by a continued optimization process where multiple optimization pipelines integrating different configurations of sub-detectors were compared using full GEANT4 simulations. The insights provided by AI in such a multi-dimensional objective space characterizing the detector performance (e.g., tracking efficiency, momentum and angular resolutions), combined to other aspects like risk mitigation and costs reduction, helped selecting the candidate technology of the ECCE tracker. This approach is being used in an ongoing R&D project where the design parametrization has been extended to include the support structure of the tracking system.

The design optimization can be also extended to tune the parameters of a larger system of sub-detectors. Physics analyses are at the moment done after the optimization for a given detector design solution candidate, but they can be encoded during
the optimization process as physics-driven objectives in addition to objectives representing the detector performance.

Detector optimization with AI is anticipated to continue after the detector proposal, and activities are planned to further optimize the tracking system, including PID sub-detectors, particularly the dual-RICH [11].

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Appendix A. Details on Parametrization

Tracking System Parametrization

Vertex layers. There are three vertex barrel layers in the ECCE tracking system made of MAPS technology. The vertex cylinder consists of strips which are made of pixels, where the individual sensor unit cell size is 17.8 mm × 30.0 mm. The length of the vertex layers is fixed at 27 cm; the radii of the three vertex layers are fixed to 3.4, 5.67, 7.93 cm, respectively. For the...
non-projective design, the angle of the support structure with respect to the interaction point is fixed ($\theta = 36.5^\circ$) and the radius of the support is at 6.3 cm, while the length of it is 17 cm. For the projective design, the radius of the support structure is the same, while the length is calculated based on the angle of projection and the radius as shown in Fig. A.12.

**Sagitta layers.** There are two sagitta barrel layers in the ECCE tracking system. The sagitta barrel layers are made of MAPS technology and have fixed length of 54 cm. For the non-projective design the radii of the sagitta layers are 21.0, 22.68 cm, respectively. For the projective parameterization, the radius of the sagitta barrel is calculated such that there are no gaps in the acceptance of the region enclosed by the barrels, according to the following equation:

$$r_{\text{sagitta}} = \frac{l_{\text{sagitta}}}{2} \tan \theta.$$ 

The radius of the sagitta layers is also constrained since the strips have fixed width $w = 17.8$ mm; therefore we want to minimize the quantity:

$$\min \left\{ \frac{2\pi r_{\text{sagitta}}}{w} - \frac{2\pi r_{\text{sagitta}}}{w} \right\},$$

where $\lceil x \rceil$ represents the ceiling of $x$.

**$\mu$Rwell layers.** In the ECCE tracking system there are three cylindrical $\mu$Rwell layers, each endowed with a support ring. An extended supporting plateau is included at either ends of the $\mu$Rwell to rest the entire cylindrical detector on this platform. This results in a constant shift of the support cone by the plateau length (5 cm) as shown in Fig. A.12. For both the non-projective design and the projective design the $\mu$Rwell-1 radius is a free parameter. The length of the $\mu$Rwell-1 is calculated based on the angle of the conical support structure. In the non-projective design we have the conical support structure angle fixed ($\theta = 36.5^\circ$), therefore the length of $\mu$Rwell-1 depends only on its radius; $\mu$Rwell-2 has its radius as a free parameter; since the angle of the conical support structure is fixed the length of $\mu$Rwell-2 depends on its radius. In the projective design instead the $\mu$Rwell-2 has a fixed radius of 51 cm (i.e., $r_{\text{max}} + 1$ cm). The length of the $\mu$Rwell-2 is calculated based on the angle of the conical support structure. The length of the $\mu$Rwell takes into account the constant shift due to the plateau. The dimensions of $\mu$Rwell-3 are fixed in both non-projective and projective designs; the $\mu$Rwell-3 is outside of the inner tracking system and it has radius of 77 cm and a total length is 290 cm.

**EST/FST disks.** For both the non-projective and projective designs, $R_{\text{min}}$ of the disks must be compatible with the beam pipe envelope which increases in radius as a function of $z$: $R_{\text{out}}$ of the disks is parametrized to be compatible with the support cone structure shown in Fig. A.12 which has an angle $\theta$ that is variable in the projective design and fixed in the non-projective case. For the non-projective design, the $z$ positions of the disks were all free parameters in the first optimization pipelines. However, to maximize the hit efficiency, some disks have been eventually placed within the support cone at the beginning of every plateau (Fig. A.12 with fixed angle $\theta = 36.5^\circ$). Therefore, two disks in the electron-going direction and two disks in the hadron-going direction are not free to vary in $z$. For instance, consider Fig. 5 (right), where EST3, EST4, FST3, FST4 are placed at the begin of the plateau, whereas the disks EST1, EST2, FST1, FST2, FST5 are free to vary in $z$ position. The same parameterization is extended to the projective design and made compatible with a varying conical support structure.

As the disks are tiled up using MAPS pixels, the difference between $R_{\text{min}}$ and $R_{\text{out}}$ is constrained to optimize the sensor coverage for all disks; this is implemented by means of two functions, namely:

$$\min \left\{ \sum_{i} \left| \frac{R_{\text{out}} - R_{\text{in}}}{d} - \frac{R_{\text{out}} - R_{\text{in}}}{d} \right| \right\},$$

where $d = 17.8$, and 30.0 mm. This limits the amount of violation made by a design solution.

**TOF system.** The central barrel TOF (CTTL) is an AC-LGAD based TOF detector with a fixed radius of 64 cm and a fixed length of 280 cm. The TOFs at the electron-going endcap (ETTL) and the hadron-going endcap (FTTL) are AC-LGAD-based TOF disks. For the non-projective design the TOF detectors have fixed dimensions. For the projective design the TOF detectors in the end cap regions have their $z$ positions as free parameters. $R_{\text{in}}$ and $R_{\text{out}}$ of the ETTL/FTTL disks depends on the position of the disk $z$. The $R_{\text{in}}$ of the disk should be compatible with the radius of the beam envelope which increases linearly as a function of $z$; $R_{\text{out}}$ of the disks varies as a function of $z$ such that the acceptance coverage by the ETTL/FTTL is roughly unaltered.

**PID Detectors.** The Detection for Internally Reflected Cherenkov light (DIRC) is a detector for PID in the barrel region. DIRC system has fixed dimensions and occupies a radial space from 71.5 cm to 76.6 cm. The modular RICH (mRICH) is a Ring Imaging Cherenkov detector system in the e-going direction with fixed dimensions. mRICH has a $z$ position starting at -135 cm extending in the $z$ to -161 cm. The dual Radiator Imaging Cherenkov (dRICH) detector is a detector system in the forward direction with fixed dimensions. dRICH has a $z$ position starting at 180 cm and extends up to 280 cm. The thickness of the detectors and support structures are also taken into account to avoid overlaps between the detectors. The most recent optimization pipelines were extended to also include in the parametrization the outer tracking layers in the two endcaps, as explained in Sec. 4.1. An overlap check is performed each time a new design point is evaluated during the optimization process.

**Support Structure Parametrization**

The implementation of the projective geometry of the inner tracker is described in Fig. A.12 which shows the parametrization used for the support cone structure of the inner tracker.
Some parameters have been considered fixed and other free to vary within their ranges. Parameters that are fixed typically do not have much room for optimization considering the constraints of the design and potential overlaps. The non-projective design can be realised by fixing the support structure angle to \( \theta = 36.5^\circ \) shown in [A.12]. Therefore, the non-projective design solutions are a subset of solutions that can be achieved by this parameterization.

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**Figure A.12: Parametrization of the support cone for the inner tracker:**
The inner tracker support is characterised by five variables: \( \theta \) (the angle of projection of the support cone structure), \( r_{vtx} \) (radius of vertex support structure), \( r_{\mu Rwell-1} \) (radius, plateau length), \( r_{max} \) (maximum allowed radius of inner tracker).

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**Appendix B. Baseline and R&D designs**

**Resolutions and Efficiency**

A thorough comparison between the non-projective ECCE simulation and the ongoing R&D was carried out to optimize the support structure through a projective design. Fig. B.13 shows a study of the obtained momentum resolution in bins of pseudorapidity. Similarly, Fig. B.14 shows the angular resolution while Fig. B.15 shows the Kalman filter efficiency as defined in Eq. (5).

**Validation**

Validation is performed by looking at figures of merit that are not used during the optimization process. In Sec. 4.3 we already described a physics analysis with SIDIS events that further consolidates our conclusions. We show here additional examples of validation: Fig. B.16 and Fig. B.17 display the azimuthal angular resolution and the reconstruction efficiency obtained for both the non-projective and the projective tracker designs. The azimuthal resolution looks consistent within the uncertainty while the reconstruction efficiency looks in general better for the projective design, particularly in the \( 1 < |\eta| < 1.5 \) region where the non-projective design has a larger dead area that affects the reconstruction of tracks.

A comparison between the non-projective and projective designs of the inner tracker is also shown in Fig. B.18, where the projective design concentrates the material in a smaller dead area resulting in better resolution on a wider range of the pseudorapidity.
**Figure B.13:** Momentum resolution for the ECCE tracker reference design and the projective design (ongoing R&D): The $\Delta p/p$ are extracted with single-gaussian (SG) fits (circles) to be consistent with the YR PWG and compared to double-gaussian (DG) fits (triangles). DG (see Eq. (3)) is used in the AI-assisted pipelines as it provides more stable fits. DG results are systematically larger than the SG ones as they capture more realistic distributions (see Fig. 3). This effect is larger in $1 < |\eta| < 1.5$ for the non-projective design (blue points) since more material is traversed by the tracks; the same effect is moderately present also in $0.5 < |\eta| < 1$ for the same reason. In the same bins, the ongoing R&D design shows a significant reduction of the impact of the readout and services and SG (red circle) and DG (red triangles) are close to each other. DG points are systematically large in $3 < \eta < 3.5$ and in $-3.5 < \eta < 3$, and this corresponds to edge effects at large $|\eta|$ values close to the inner radii of the disks in the endcaps. In the region $-1 < \eta < 1$, $\Delta p/p$ is consistent with the YR physics requirements with SG. Note that physics in the backward region relies on the EM calorimeter also, and in the proposal it has been demonstrated that larger resolutions are acceptable.

**Figure B.14:** Angular resolution ($d\phi$) for ECCE projective geometry and ECCE simulation: The resolution shows an improvement in the transition region between $1.0 < |\eta| < 1.5$. These plots have been produced using double-Gaussian fits.
Figure B.15: **KF Efficiency for ECCE projective geometry and ECCE simulation:** Reconstruction efficiency shows an improvement in the transition region between $1.0 < |\eta| < 1.5$. There is a significant drop in the transition region caused due to multiple scattering of the support structure.

Figure B.16: **Angular resolution (d\phi) for ECCE projective geometry and ECCE simulation:** The resolution shows an improvement in the transition region between $1.0 < |\eta| < 1.5$. These plots have been produced using double-Gaussian fits.
Figure B.17: Reconstruction efficiency for ECCE projective geometry and ECCE simulation: Reconstruction efficiency shows an improvement in the transition region between $1.0 < |\eta| < 1.5$.

Figure B.18: Comparison between non-projective and projective inner tracker: a comparison in momentum resolution as a function of the pseudorapidity $\eta$ between the non-projective and the projective designs in three bins of momentum. The projective design concentrates the material in a smaller dead area resulting in better resolution on a wider range of the pseudorapidity.