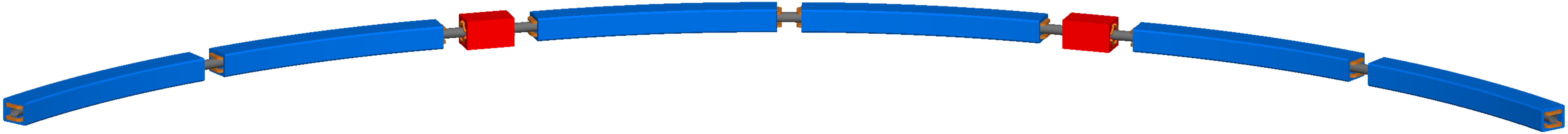
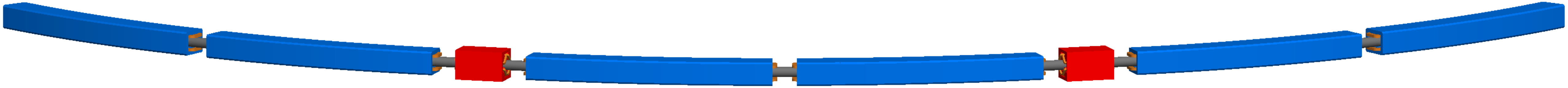


Magnet Design Optimisation with Supervised Deep Neural Networks

F. Stummer[1,2], J. Bernhard[1], S. Gibson[2], M. Prokop[3,4], T. Zickler[1]

[1] CERN, 1211, Meyrin, Switzerland
[2] JAI at Royal Holloway University of London, TW20 0EX, Egham, United Kingdom
[3] TU Munich, Arcisstraße 21, 80333 Munich, Germany
[4] Masaryk University, Žerotínovo nám. 617/9, 601 77 Brno, Czechia



Mantra for Magnet Design

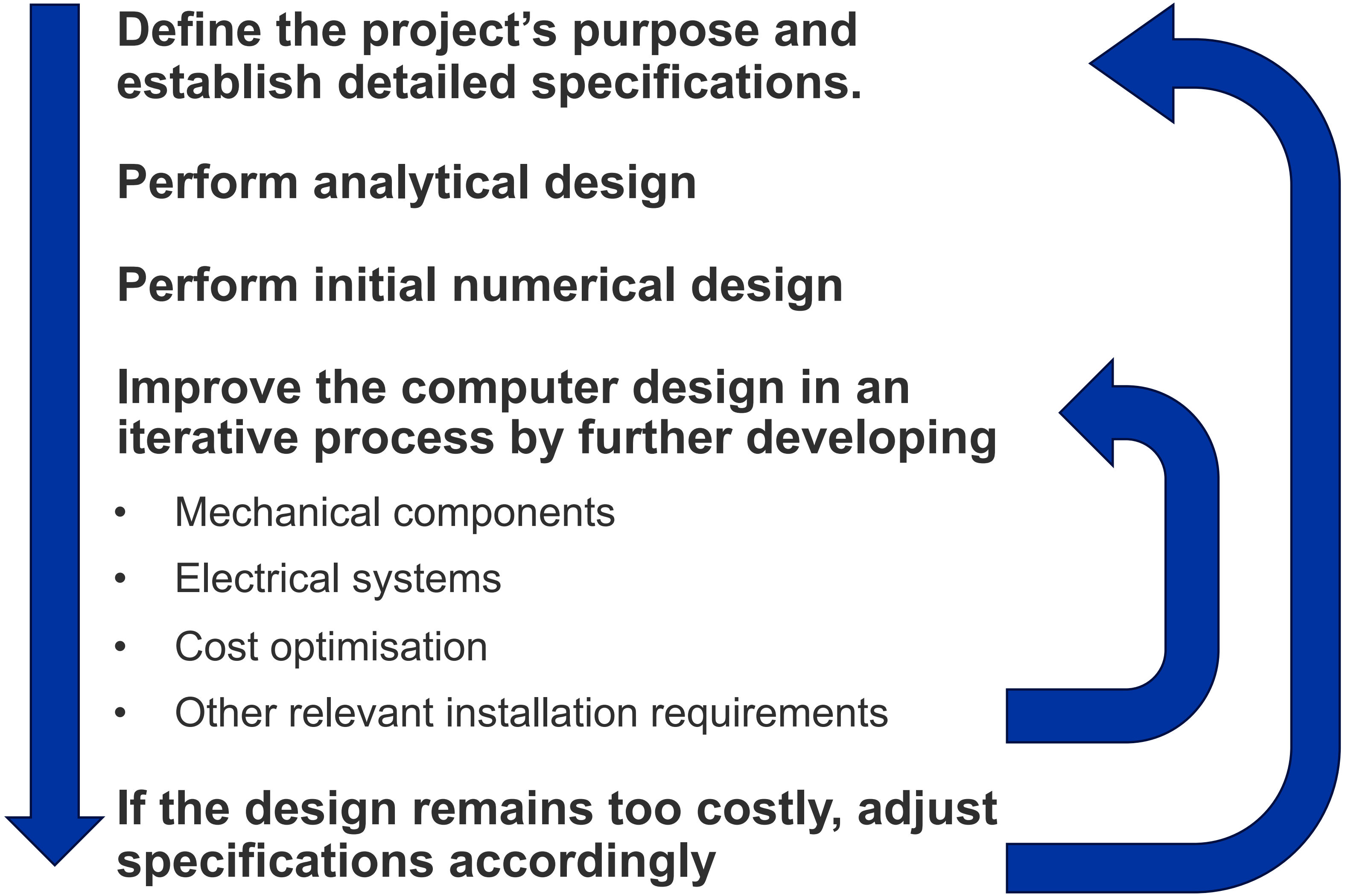
> The goal [in magnet design] is to produce a product just good enough to perform reliably when the machine turns on and with a sufficient safety factor to take care of anticipated (and unanticipated) future requirements at the lowest cost and on the most timely schedule.
>
> --- G. E. Fischer (1985)

Introduction to Magnet design

Challenges Addressed by the Magnet Design

- **Primary Concerns**
  - Meeting performance requirements given by the design optics
- **Secondary Concerns**
  - Minimising costs across the projected lifetime of the magnet
  - Ensuring ease of handling and efficient operation of the magnet
- **Tertiary Concerns**
  - Eliminating beam halo and other disruptive radiation backgrounds that could interfere with detectors and sensitive equipment
  - Reducing radiation levels to ensure safety and minimise exposure

Classical Magnet Design Workflow



Define the project's purpose and establish detailed specifications.

Perform analytical design

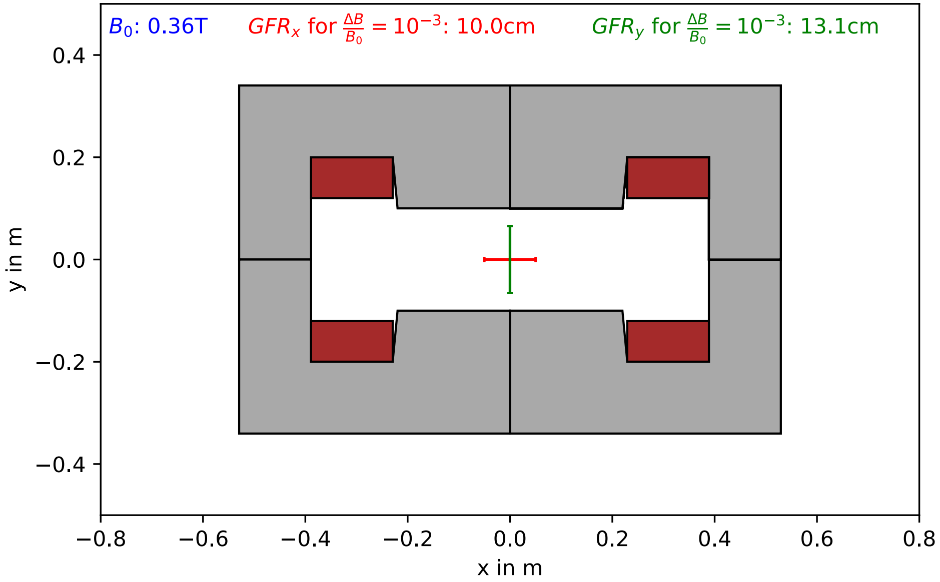
Perform initial numerical design

Improve the computer design in an iterative process by further developing

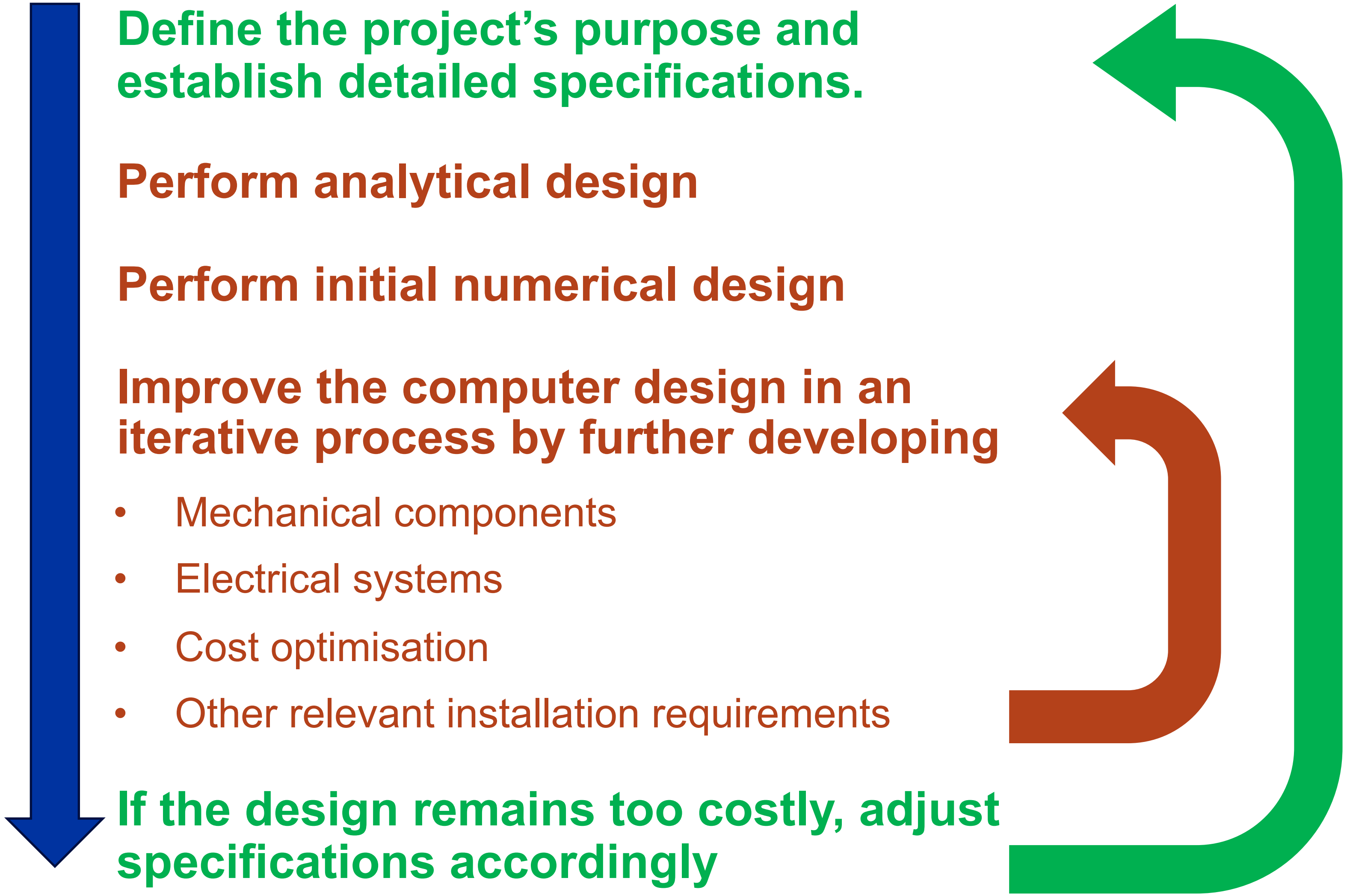
- Mechanical components
- Electrical systems
- Cost optimisation
- Other relevant installation requirements

If the design remains too costly, adjust specifications accordingly

Example: Normal Conducting H-Shaped Dipole



Classical Magnet Design Workflow



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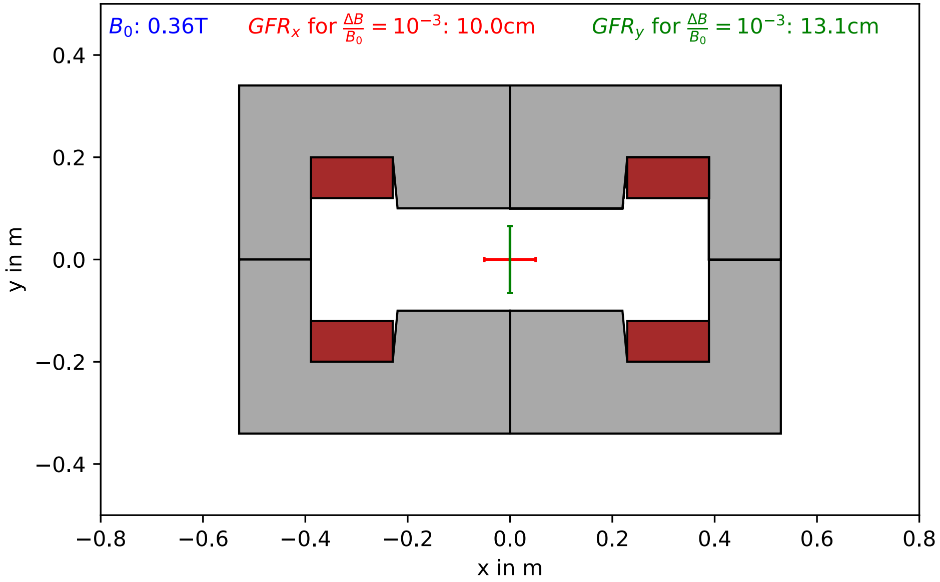


Accelerator Physicist

Magnet Engineer

Enhancing the Design Workflow

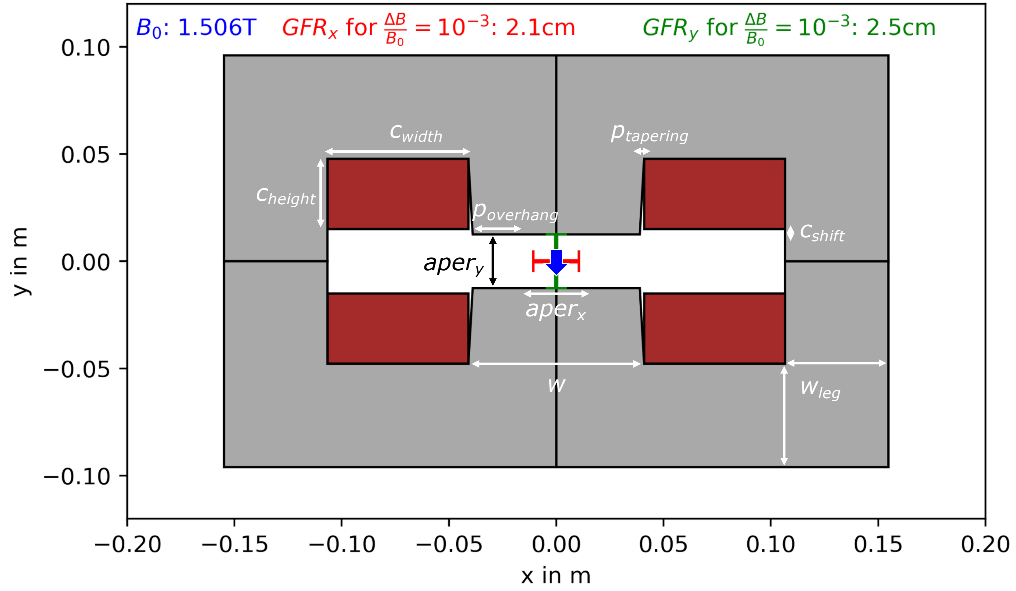
- **Main Problems:**
  - Information gaps on each side – Cost impact for accelerator physicists / Physics impact for magnet engineers
  - Communication barriers – With multiple parties involved, each iteration takes time
- **Solution:**
  - Enhance the flow of information between both ends
- **Our Approach:**
  - Modern workflows (including machine learning) can streamline this process
- **Expected Result:**
  - Enable the identification of the
    “lowest cost magnet fulfilling all requirements on the most timely schedule”

Method 1:

Informing the Design Optimisation with Regression Neural Networks

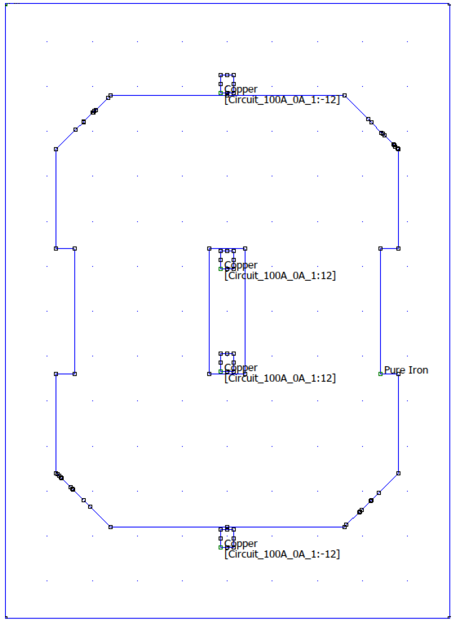
Analytical design

- An analytical design can be developed using a minimal set of input parameters.
- Additional parameters can be derived from these initial parameters (see link)

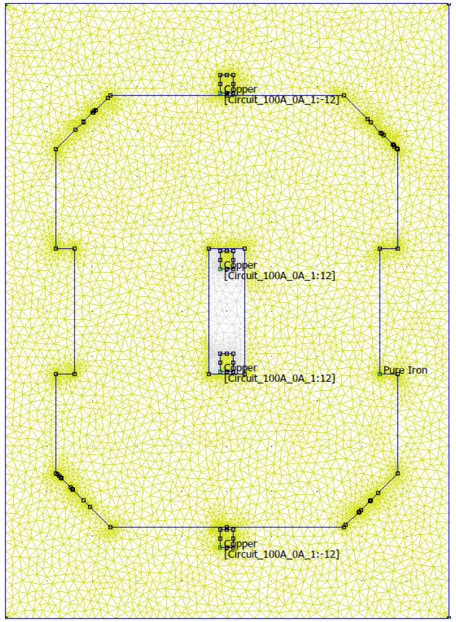


Parameter	Symbol	Explanation
Aperture in x / y	$aper_x$ $aper_y$	The dimensions of the aperture in the x and y directions, typically measured in millimeters or inches.
ρ_0 = Aperture / GFR	ρ_0	The ratio of the aperture size to the good field region.
Max. Current Density	j	The maximum amount of electric current per unit area that can flow through a conductor or material without overheating.
Design Field	B_{design}	The magnetic field strength specified for the design.
Field Tolerance	$\frac{\Delta B}{B_0}$	A parameter indicating the allowable deviation in the magnetic field strength, expressed as a ratio of the change (ΔB) to the nominal field strength (B_0), ensuring the system operates within specified limits.

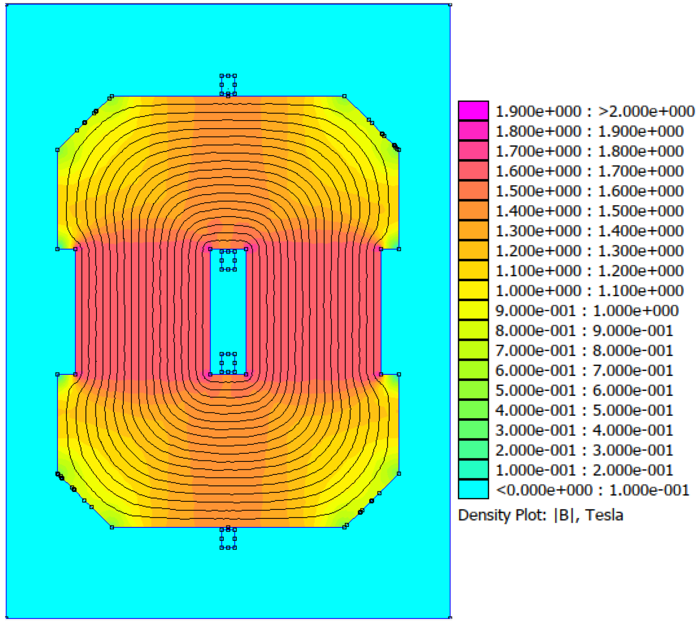
Finite Element Method



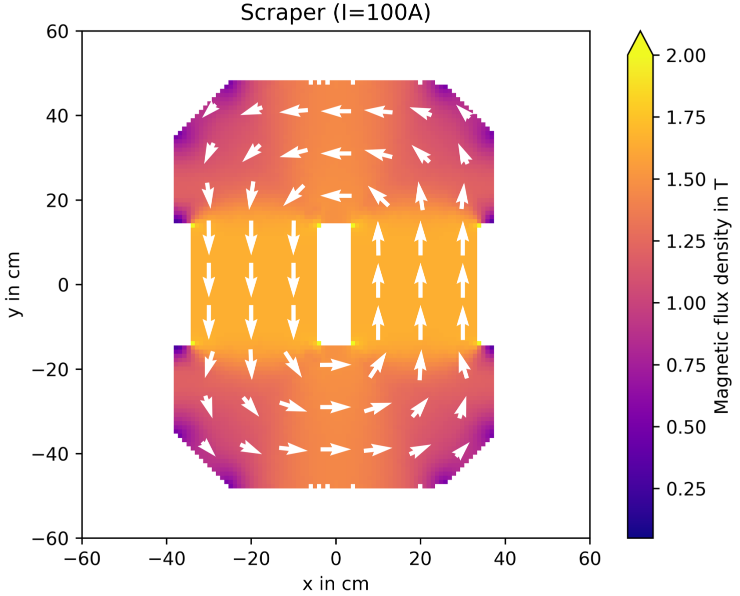
Problem Definition



Mesh



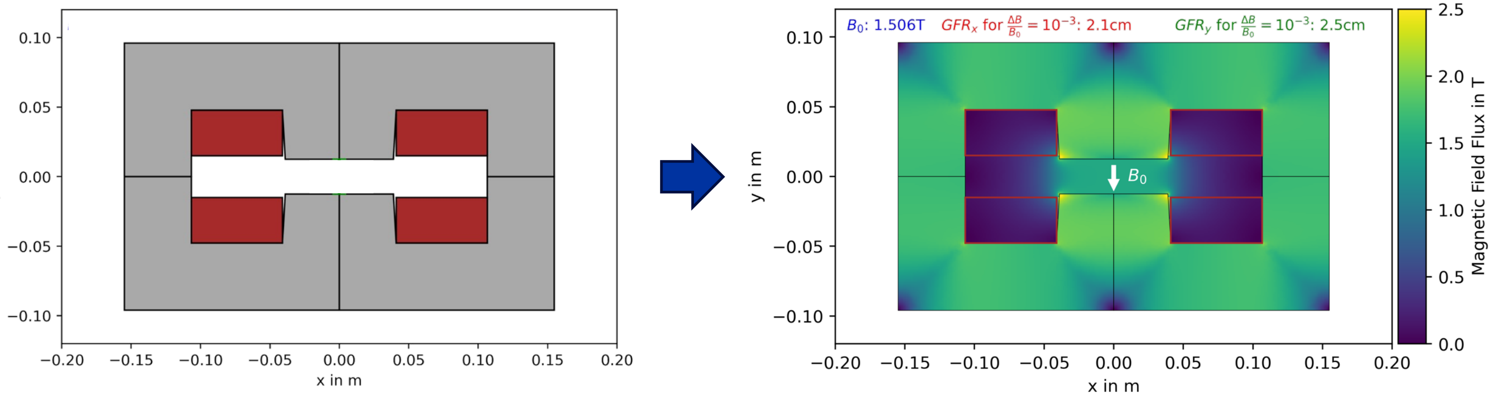
Problem Solution

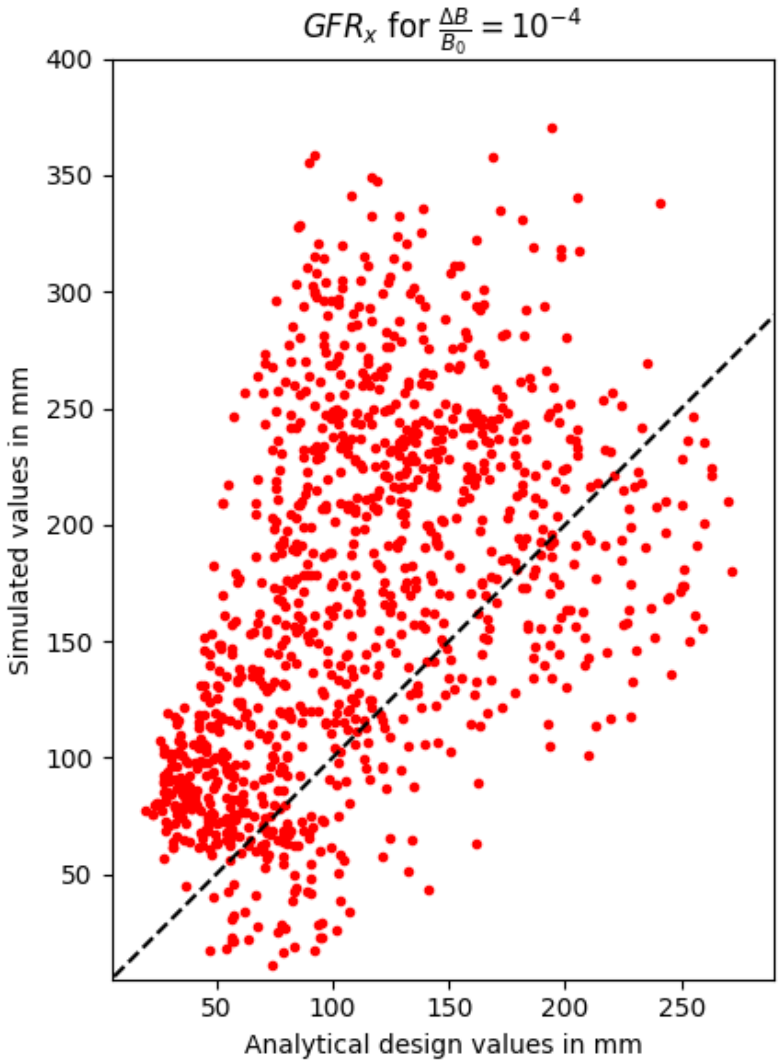


Exported Field Map

The Critical Role of FEM Simulations

- Analytical designs often differ from real-world results
- Finite Element Method (FEM) simulations help resolve these discrepancies
- FEM plays a crucial role in the classical design process

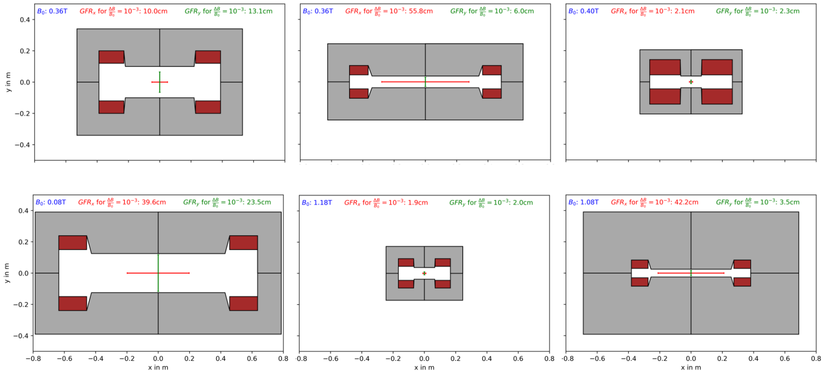




Enhanced magnet design workflow

Magnet Dataset

~75.000 samples created and simulated

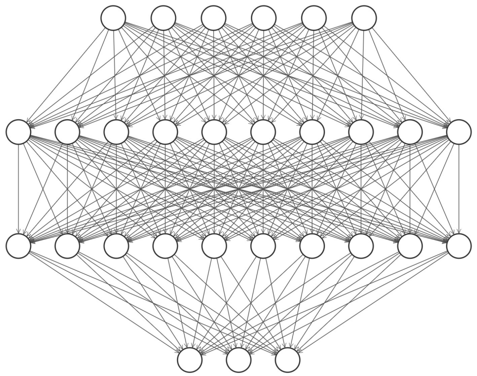


Extract Specifications that they meet from Finite Element Method Simulation

train

Deep Neural Network

Design Parameters

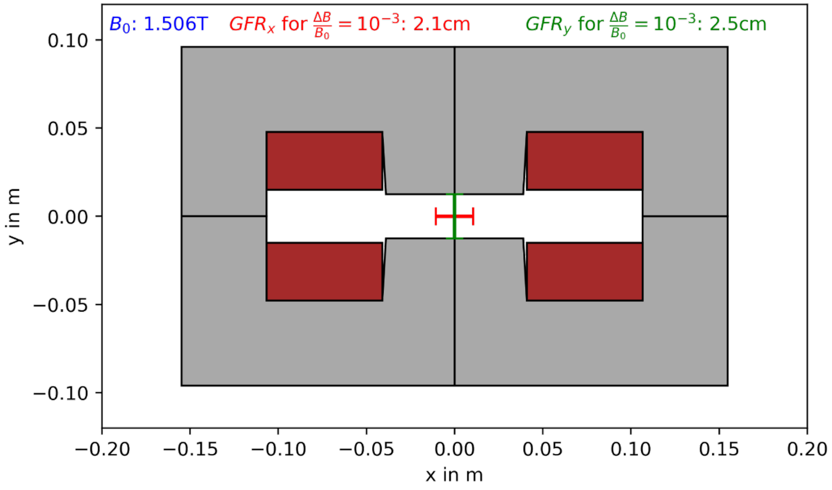


Specifications

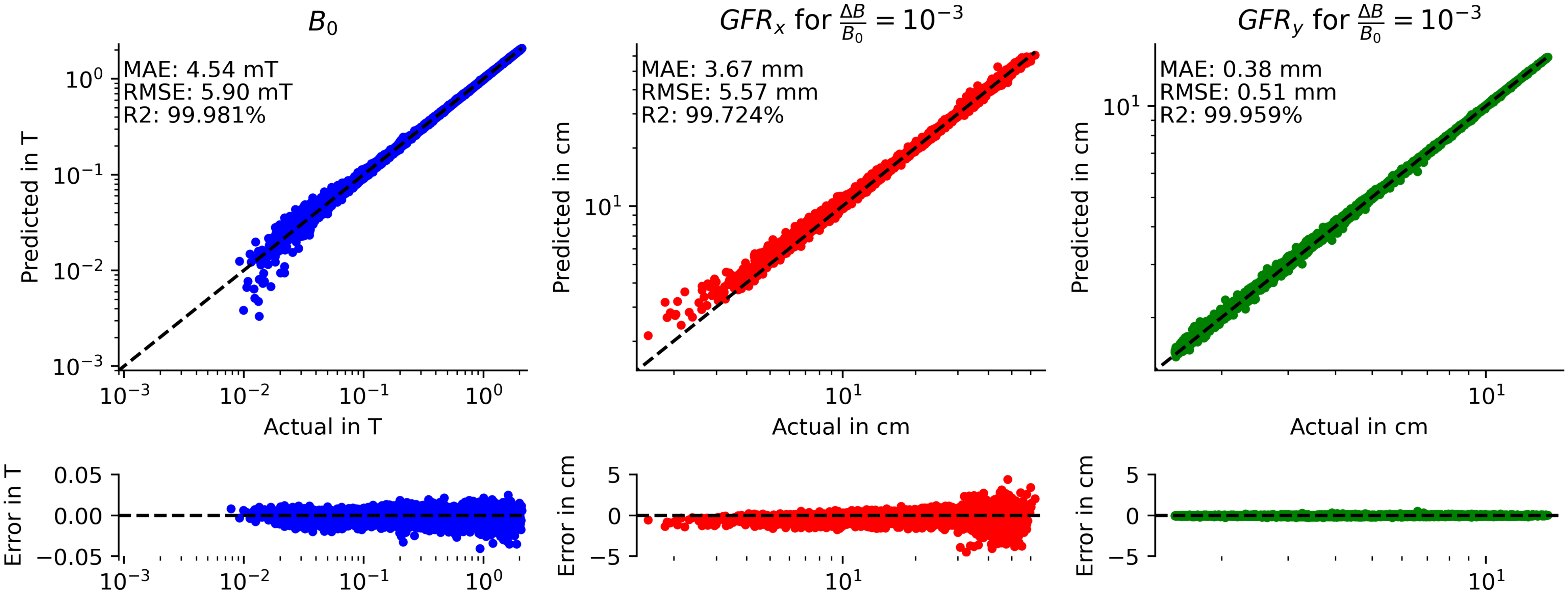
plug into

Optimiser

Design magnet with Specifications:
B_0=1.5 T, $GFR_x > 2$ cm, $GFR_y > 1$ cm for $\frac{\Delta B}{B_0} = 10^{-3}$



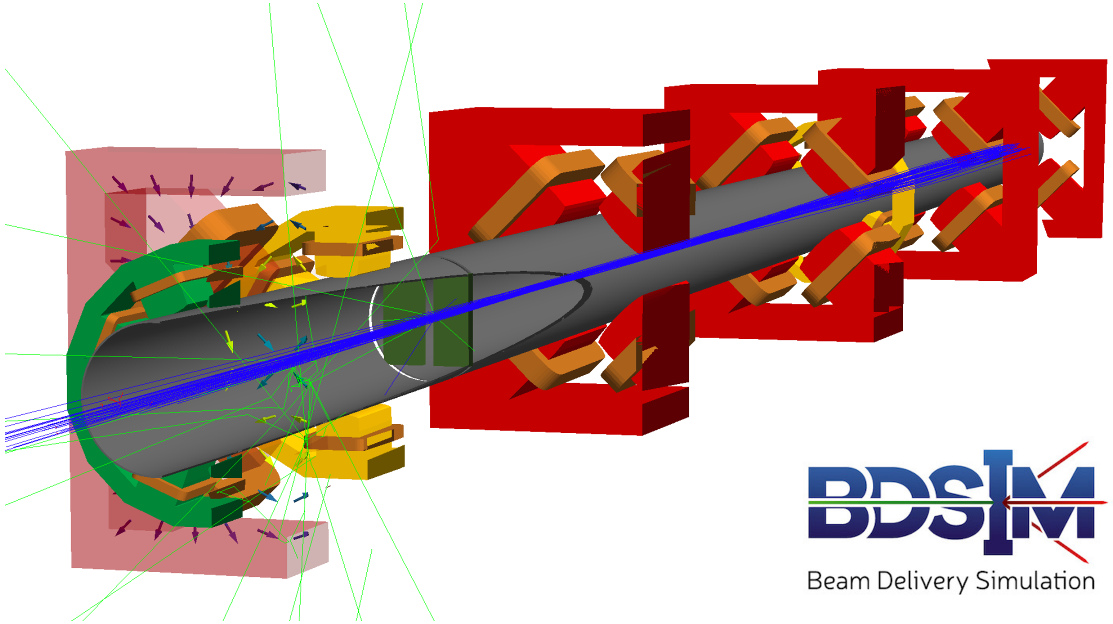
Performance of the Dipole Regression Net



Optimising Magnet Design with Cost Considerations

- **Cost considerations:**
  - **Material/manufacturing costs:** Depend on weight and 2D area of yoke and coils
  - **Operating costs:** Driven by coil current and resistance
  - **Cooling costs:** Vary with current density in coil area (methods include air, water, nitrogen, or helium)
- **Magnet design optimisation:**
  - Beam optics specs (B_0, GFRx, GFRy)
  - Installation constraints (space, weight, cooling)
  - Total cost and other factors
- **Optimiser minimises costs while meeting design specs and constraints**
  - Design specifications are guided by the Regression Net

Taking It a Step Further



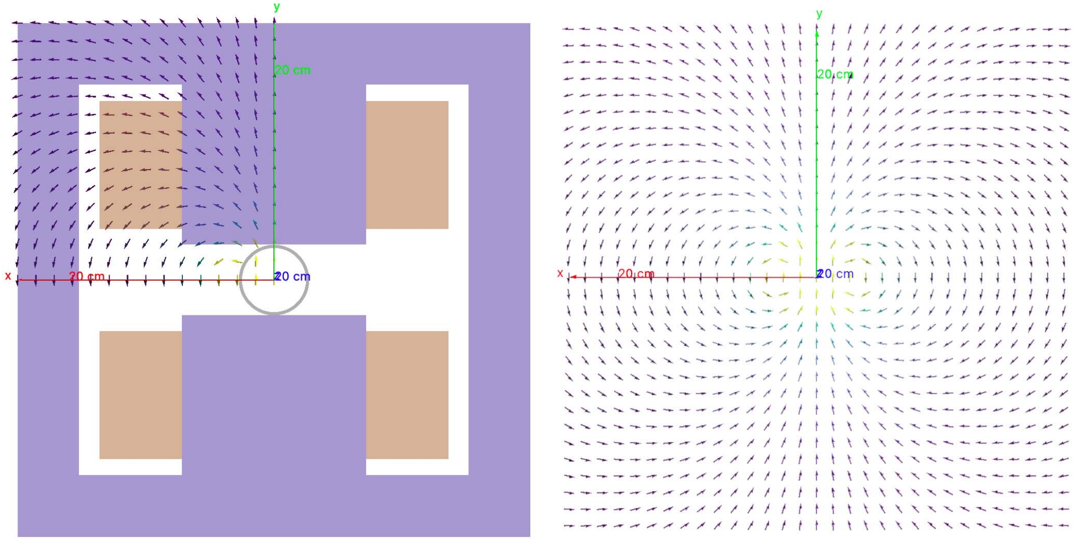
- **Beam optics simulations (MADX)**
  - Transverse beam optics computations are used to optimise the accelerator design
  - Once optimised we know the beam size at all locations and the field strength needed in all magnets
  - **Magnet Specifications**: Required field and GFR sizes
- **Next step: Single-particle tracking simulations (Geant4-based codes like BDSIM)**
  - Studying beam losses to improve the aperture sizes
  - Background estimates to evaluate mitigation strategies in the Machine Detector Interface
  - **Magnet Specifications**: Size adjustments based on beam loss and radiation protection needs

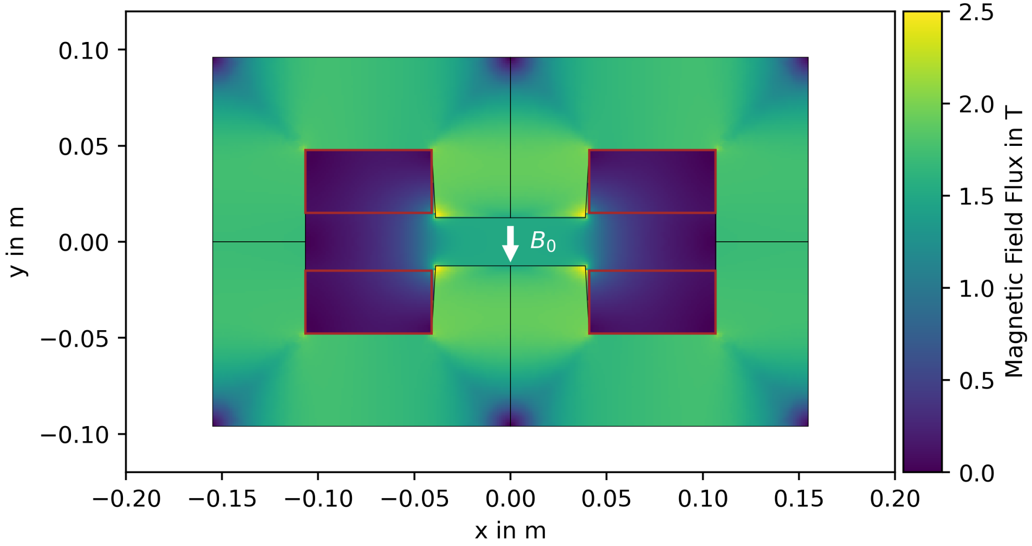
Method 2:

Circumventing FEM simulations with U-Nets

The Role of Field Maps in Accelerator Modelling

- **Why field maps?**
  - More realistic description of the magnetic fields in simulation models (ideal → real)
  - Relevant for background simulations as they include edge effects at the end of the apertures





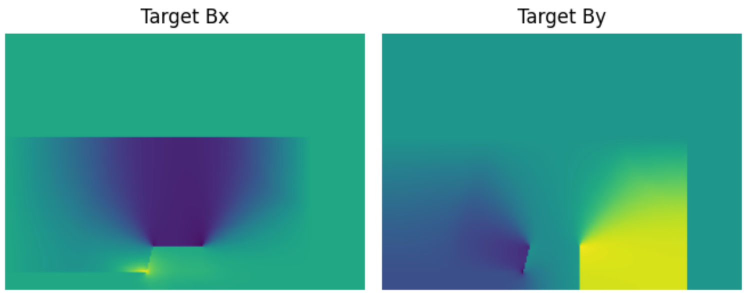
Going from ideal fields (multipole expansion) to realistic fields that give a more complete representation of the magnet.

Circumventing FEM simulations with U-Nets

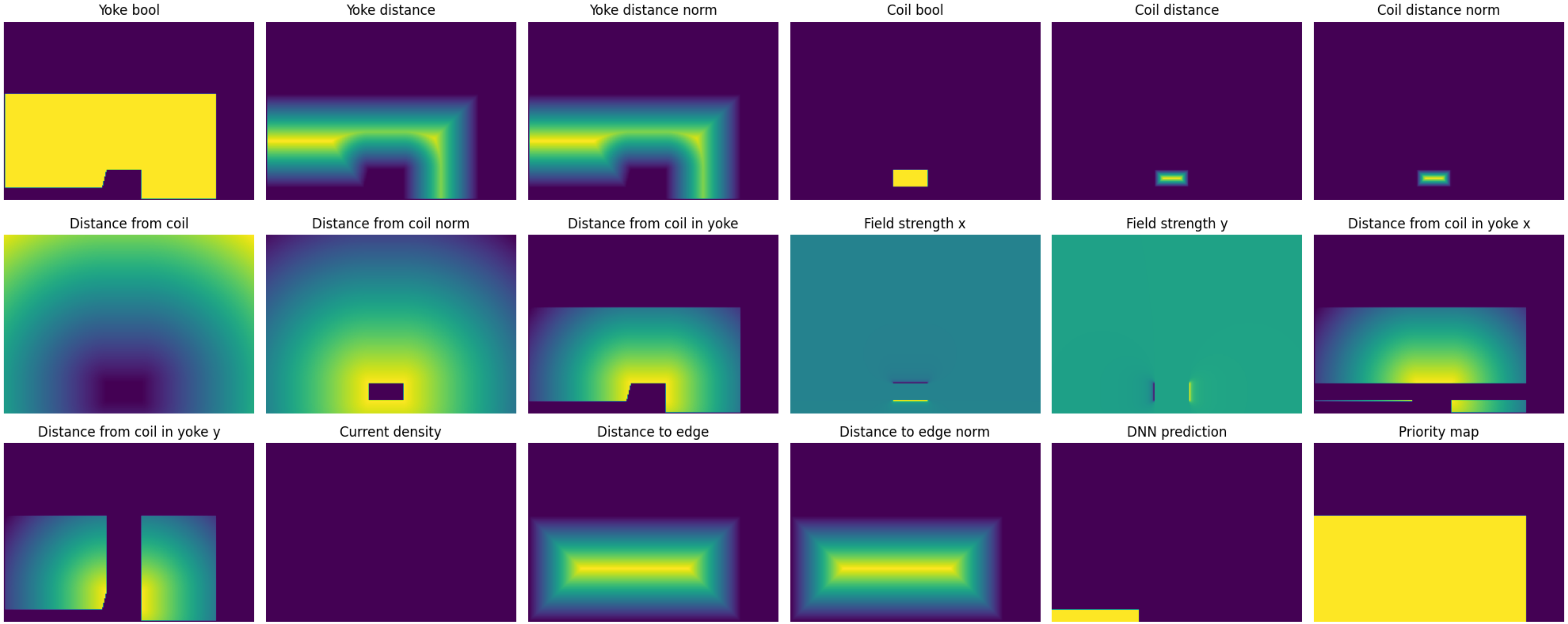
- **Questions**
  - Can machine learning be used not just to predict B_0, but to model the entire magnetic field of a magnet?
  - How can we make this process more efficient?
- **Our Approach**
  - Convolutional neural networks (like U-Nets) can assist in predicting the full magnetic field
  - Reframing the prediction as an image-to-image problem allows us to map images of simple geometric features that are known at the analytical design stage to the full magnetic field
- **For this to work, we need to know…**
  - What input channels should a dataset include to effectively support this approach?
  - How do we ensure a high quality of the prediction? What metric can we use?

U-Net dataset

Target channels:



Input channels:



Quality control for field maps

- **Primary Region of Interest:**
  - **Aperture:** No. The ideal field can be set and simulated accurately without the field map
  - **Coils:** No. The field inside is naturally low, as it’s the source region
  - **Yoke:** Yes. Field maps are crucial here, as they influence the muon flux towards the detector
- **Key Requirement:**
  - We need to determine the maximum acceptable deviation from the target field in the yoke
- **Approach:**
  - **Secondary Effect on Muon Angle:** Multiple-scattering angle.
  - If most field map values are below the secondary effect threshold, the simulated muons remain unaffected

Multiple Scattering as Quality Control for Field Maps

Total angle added by a magnet to a traversing muon is: $\theta_{out} = \sqrt{\theta_{MS}^2 + \theta_F^2}$

Multiple Scattering is dominant if the magnetic field cannot change the overall angle by more than 10%

$$\frac{\theta_{out}}{\theta_{MS}} = \sqrt{1+\left(\frac{\theta_F}{\theta_{MS}}\right)^2} < 1.1$$

or

$$\frac{\theta_{MS}}{\theta_F} < 0.5$$

With magnetic field angle $\theta_F = 299.79\frac{\Delta B\ L}{p}$ **and multiple scattering angle** $\theta_{MS} = \frac{14}{p}\sqrt{\frac{L}{X_0}}$

we can derive a formula for the maximum relevant field deviation:

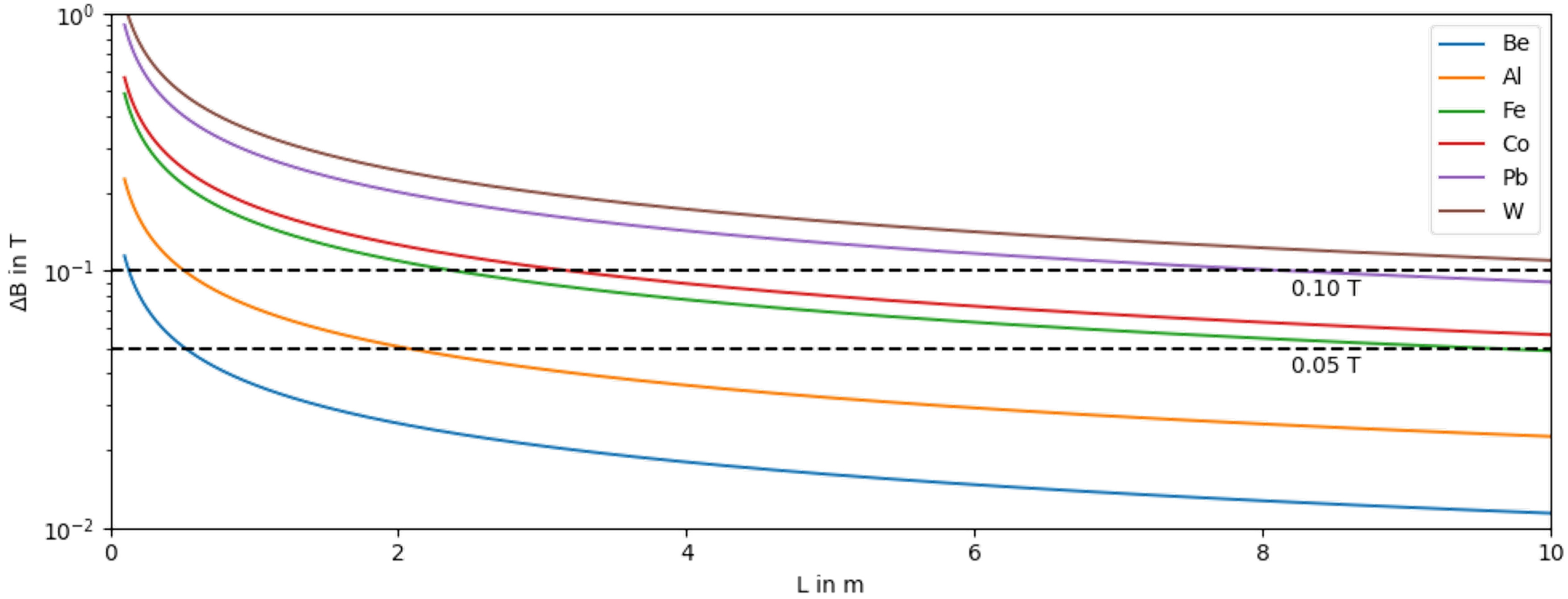
$$\frac{\theta_F}{\theta_{MS}} = \frac{299.79\frac{\Delta B\ L}{p}}{\frac{14}{p}\sqrt{\frac{L}{X_0}}} = 21.4\ \Delta B\ \sqrt{L}\sqrt{X_0} < 0.5$$

which leads to $\Delta B < \frac{0.154}{\sqrt{L}}$ in T

(see Link)

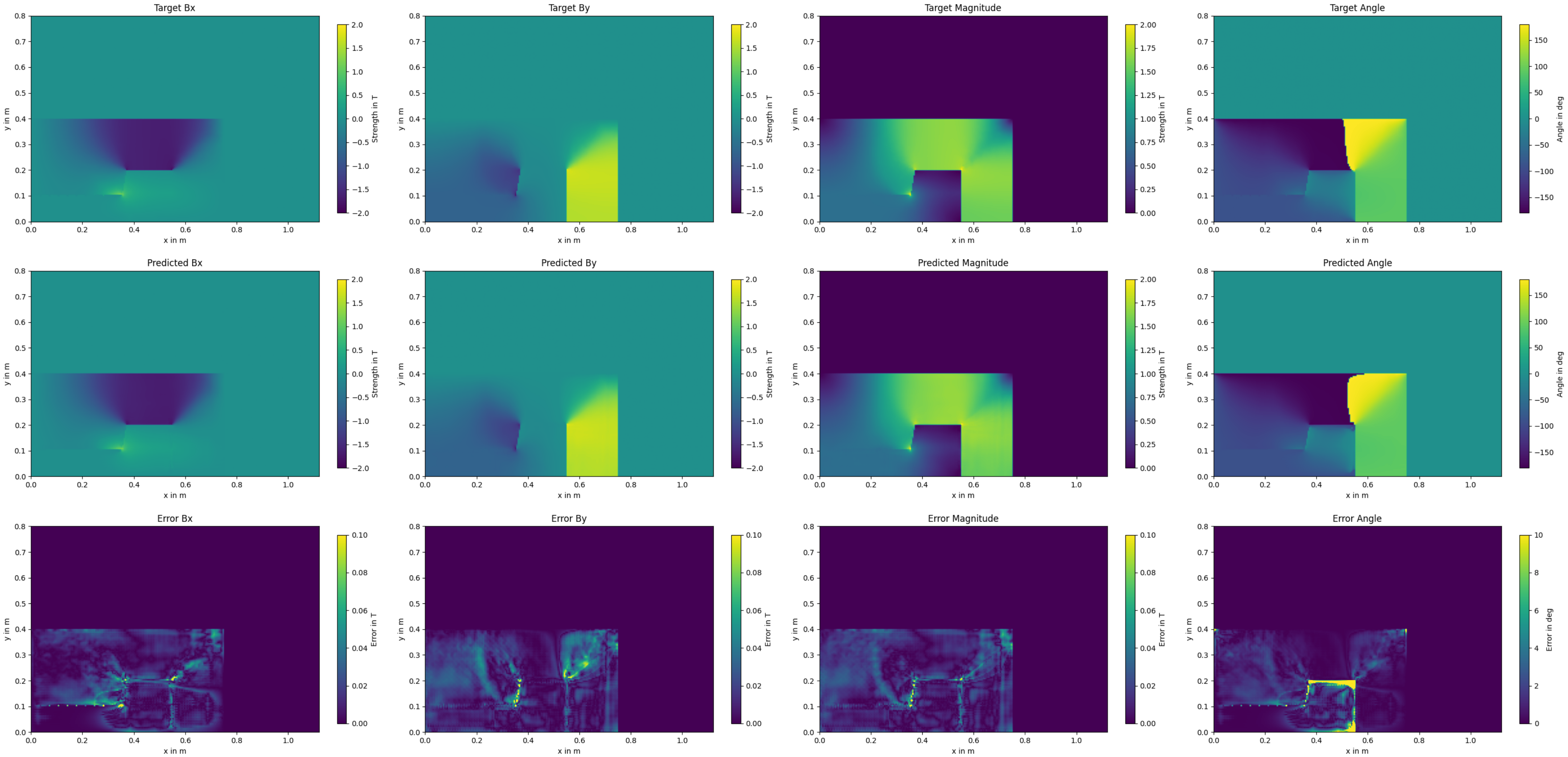
Multiple Scattering as Quality Control for Field Maps

- **Thus, longer magnets have tighter quality constraints**
- **In an iron yoke the maximum tolerable field deviation becomes:**



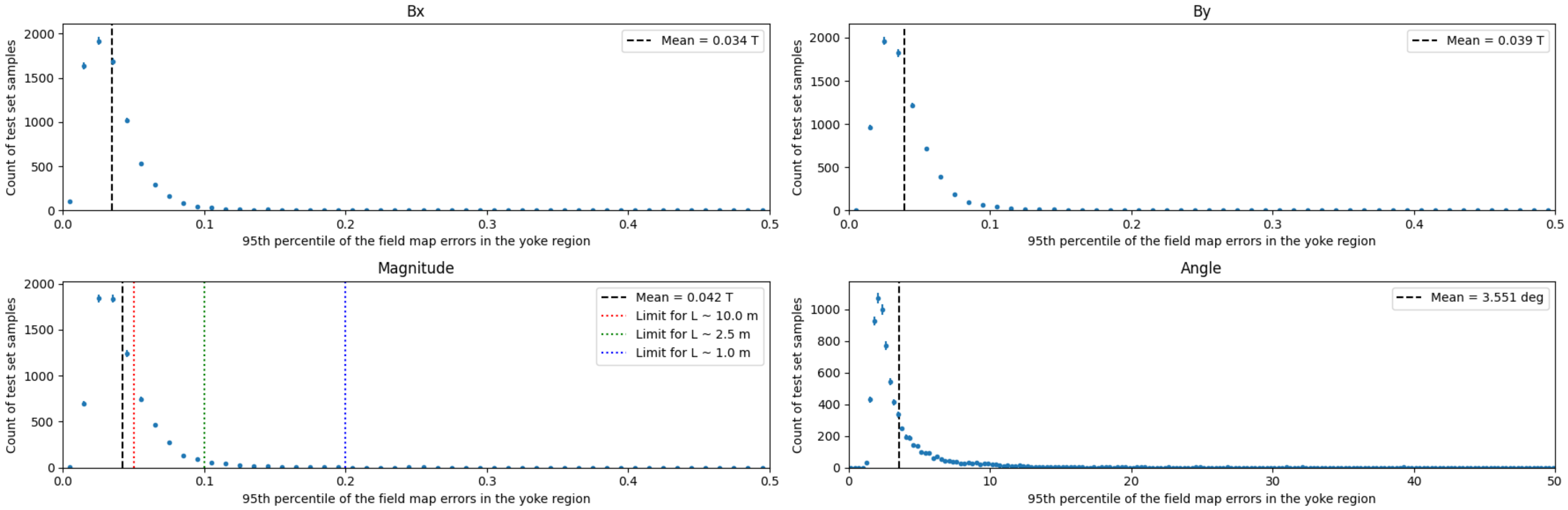
L ~ 1.0 m → ΔB < 0.2 T
L ~ 2.5 m → ΔB < 0.1 T
L ~ 10.0 m → ΔB < 0.05 T

Performance of our latest U-Net



Performance of our latest U-Net

- **95th percentiles of the magnetic field errors**



→ Good quality for L ~ 2.5 m, reasonable quality for L ~ 10 m

Applications of the U-Net Model

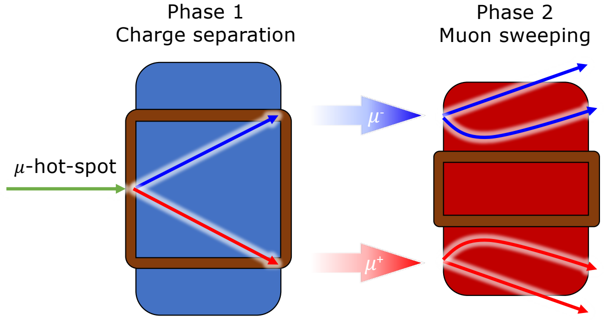
- Offer an alternative method for generating field maps, reducing dependence on time-consuming FEM simulations
- Simplify workflows by eliminating the need for users to learn FEM simulations for standard magnet types
- Guide magnet optimisation by proactively avoiding designs that lead to yoke saturation
- Integrate predicted field maps with single-particle tracking simulations (e.g., BDSIM/Geant4) to enable rapid and efficient muon background optimisation for machine-detector interfaces

Method 3:

Mitigating muon backgrounds with Regression Neural Networks

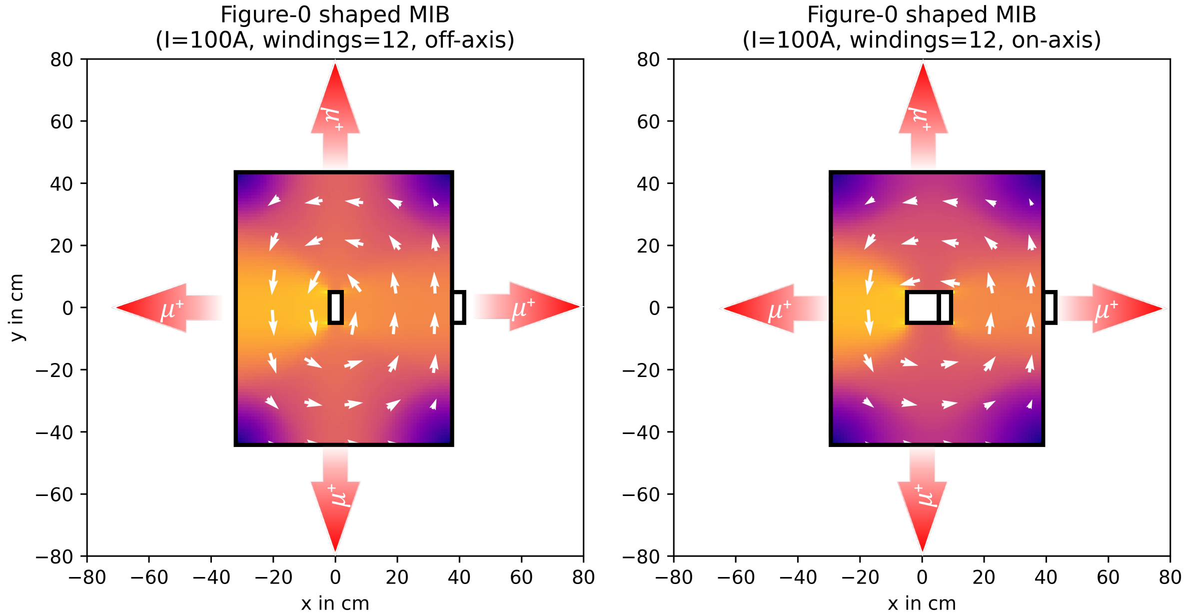
Magnetic shields for muon mitigation

- **Proven mitigation strategies:**
  - Using toroidal magnetic fields
  - → Muon shield made of Magnetised Iron Blocks (MIBs)



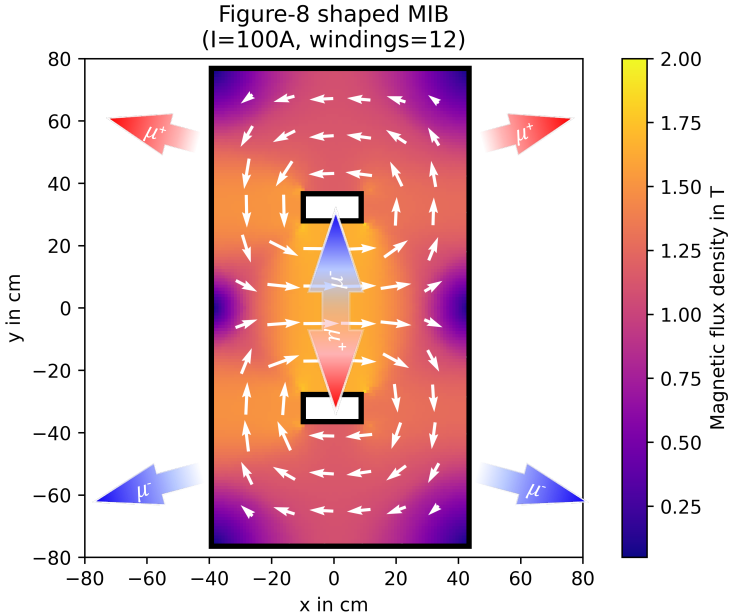
Side view

For single-charge hot spots



Front view

For multi-charge hot spots



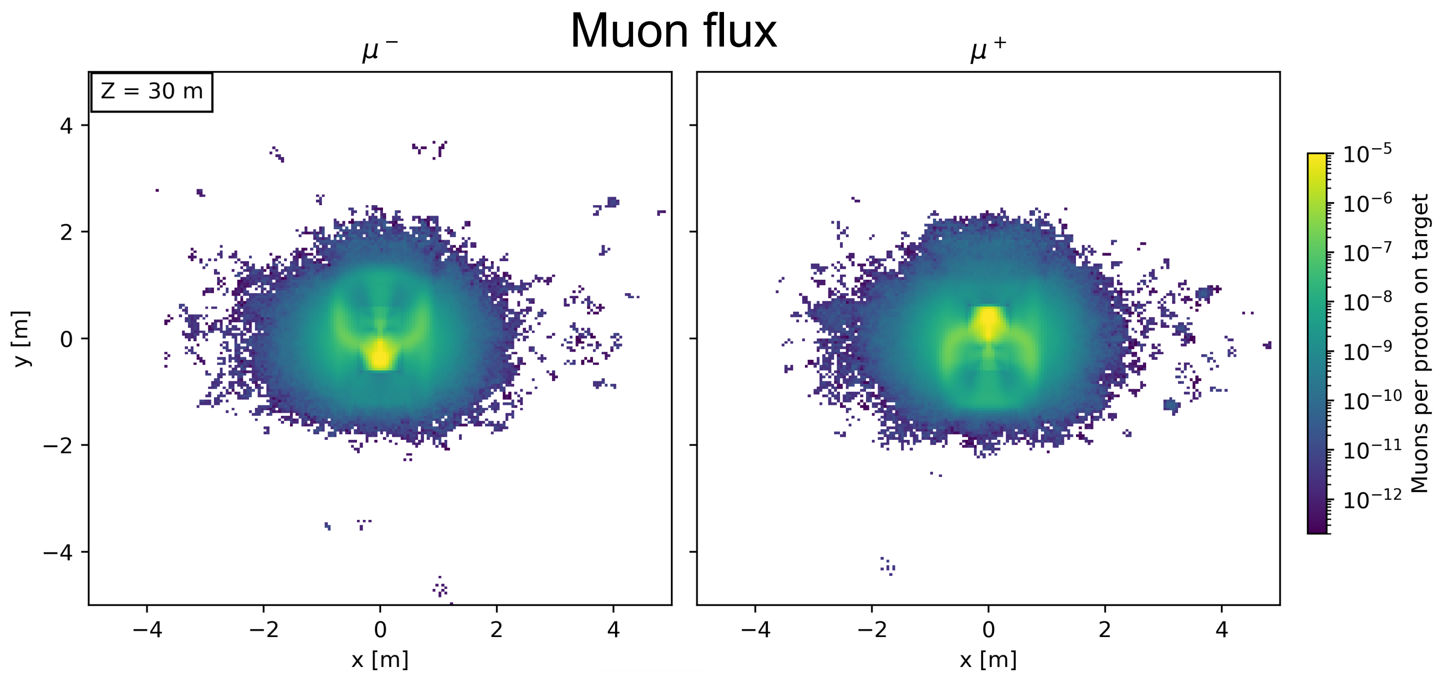
Front view

Magnetic shields for muon mitigation

Toroidal magnets for muon mitigation
already installed in CERN's North Area

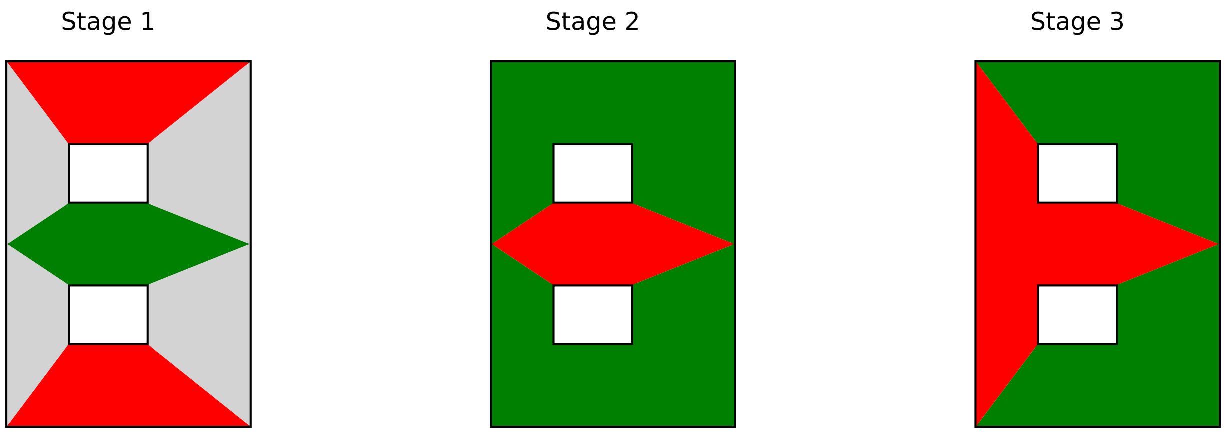
Muon Flux Mitigation Example: SHADOWS

- **SHADOWS was a proposed dark matter experiment at CERN**
- **Minimal particle background tolerance means it required an active muon shield**
- **Supervised learning aided the the shield's design optimisation**

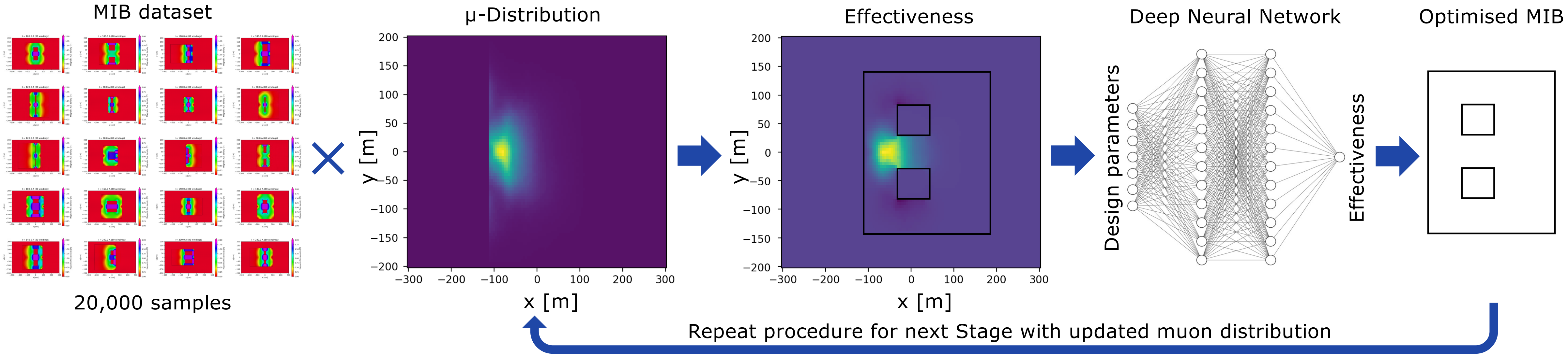


Design optimisation

- **Optimisation needs to combine magnetic field and muon flux**
- **Hence good, bad and neutral field regions need to be defined**

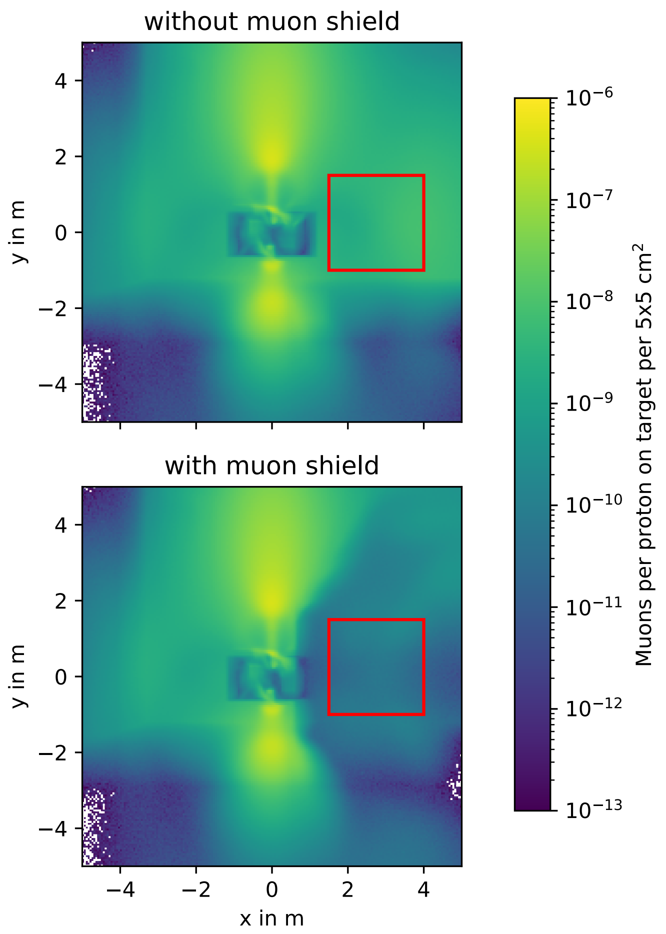


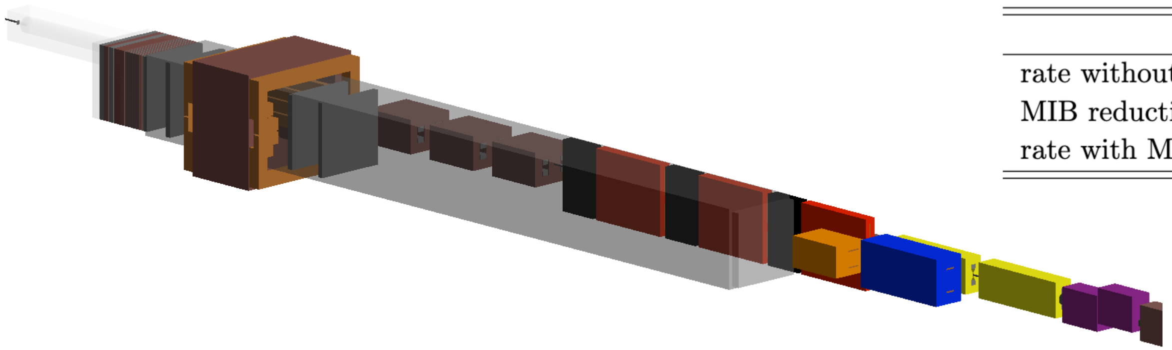
Green: good field region, Red: bad field region, Grey: neutral field region



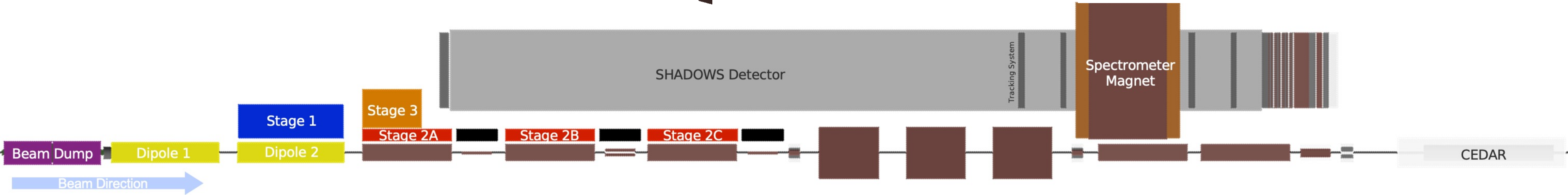
The SHADOWS Muon Shield

- **Muon shield made of three figure-8 shaped MIBs can reduce the muon flux at the experiment by a factor of 70**
- **Design was fine-tuned with Regression Nets**





	$\mu^+ + \mu^-$	μ^+	μ^-
rate without MIB	147 MHz	81 MHz	66 MHz
MIB reduction factor	~ 70	~ 58	~ 94
rate with MIB	2.1 MHz	1.4 MHz	0.7 MHz



Conclusion and next steps

- **Conclusion**
  - Several methods for optimising the design of accelerator magnets were tested
  - Workflows were developed for generating large scale 2D magnet datasets from FEM simulations
- **Next steps**
  - **Method 1 – Magnet Design Optimization with Regression Networks:** Expand this approach to other magnet types, enabling the optimisation of entire accelerators and beamlines
  - **Method 2 – Replacing FEM Simulations with U-Nets:** Explore alternative models to further enhance performance and conduct indirect validation by evaluating their performance in BDSIM simulations
  - **Method 3 – Radiation Mitigation via Regression Networks:** Broaden the application to common accelerator magnets and integrate radiation considerations into Method 1 for comprehensive optimisation
  - **Overall:** Apply these methodologies to other areas such as RF cavity design, collimators, and other key accelerator components

Contact: florian.wolfgang.stummer@cern.ch