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RF 2.0 RESEARCH FACILITY

Efficient Accelerator Operation with Artificial Intelligence Based Optimization Methods

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CASE STUDY: Misalignment of the injection line beam of KARA Accelerator

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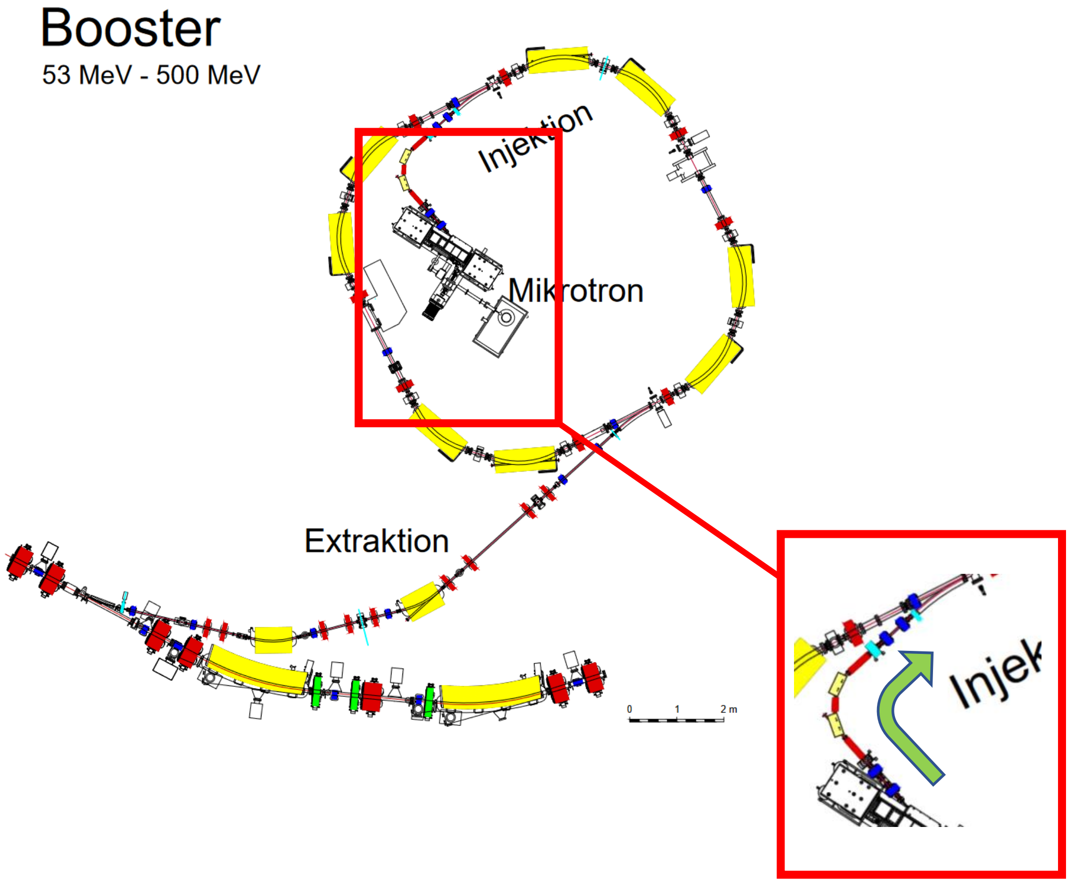

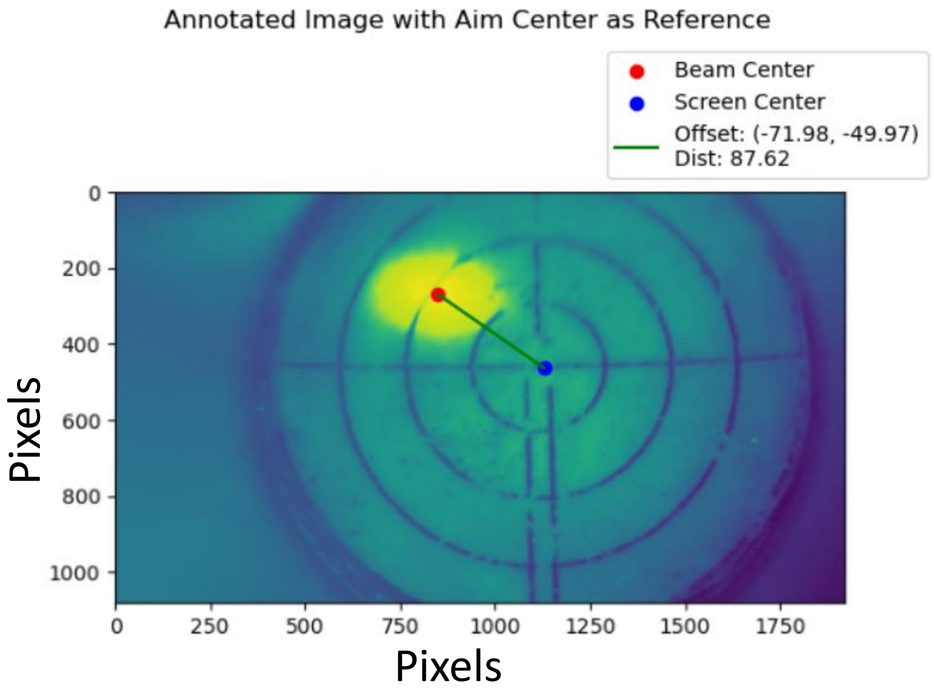

Main causes :
hysteresis, **calibration errors**, or **deviations from the modeled lattice**.

- **Deflection of the particle beam** in the injection line as it passes through the quadrupole magnets.
- **Increased Energy Loss**.
- **Reduced Beam Efficiency and Performance**.
- **Unreliable Experimental and Image Data** leading to errors in diagnostics.

CASE STUDY: Misalignment of the injection line beam of KARA Accelerator

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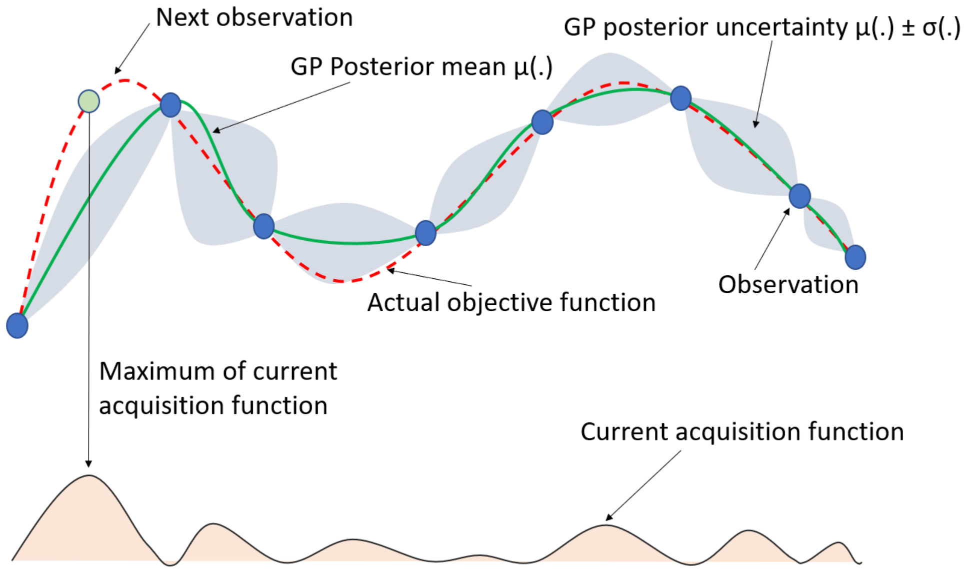
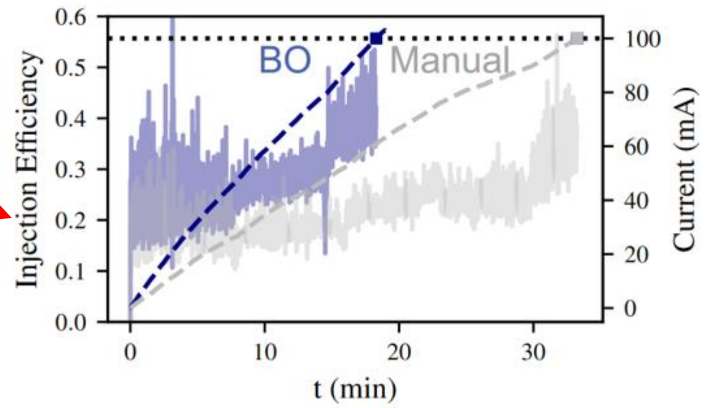
Solution : Application of Bayesian Optimization (BO) to control steering and quadrupole magnets in KARA

- **Faster tuning** with fewer tests
- **Accurate alignment** by handling complex parameter interactions.
- **Automated optimization** reduces manual effort.



Optimizations with comparable machine condition.
Reduced injection time for 100 mA from 30 min to 18 min.



(C.Xu et al. 2023)

Bayesian Optimization in Accelerator Tuning

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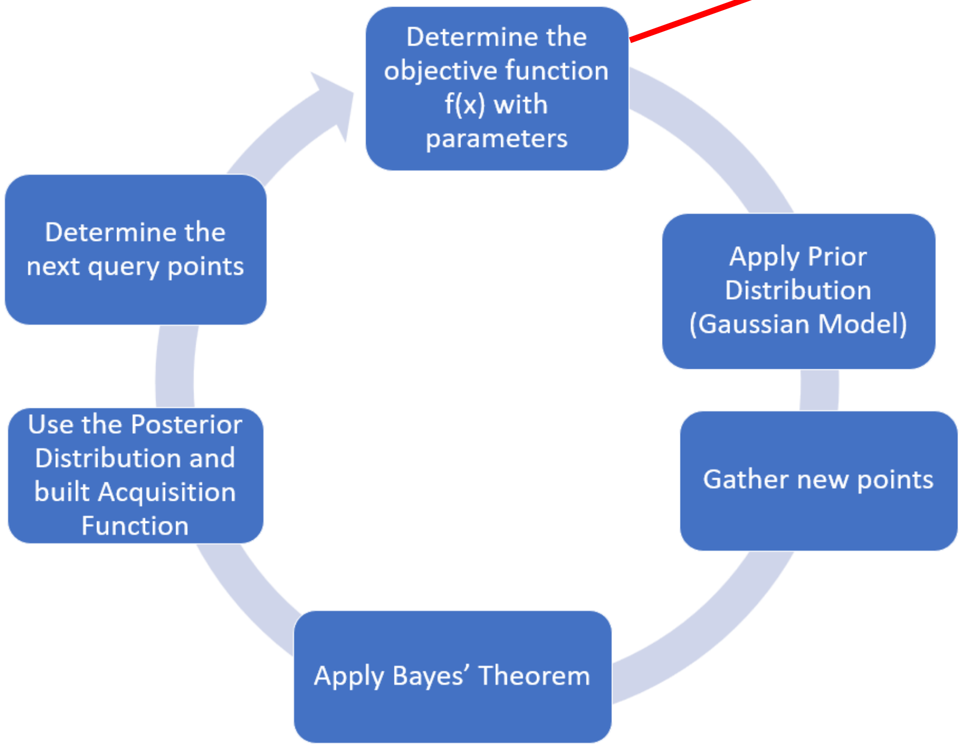
How does it work?

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coordinates = []
angles_recorded = []

# Define the objective function for Bayesian Optimization
def fun(angles):
    global coordinates

    segment = get_segment()
    # Set angles
    segment.M1.angle = torch.tensor(angles["angle_1"])
    segment.M2.angle = torch.tensor(angles["angle_2"])

    # Track beam
    outgoing_beam = segment.track(incoming_beam)

    # Get sensor reading
    array = segment.SCREEN.reading.numpy()

    # Get the coordinates of the max value
    coords = np.unravel_index(np.argmax(array), array.shape)
    coordinates.append(coords)

    # Store angles
    angles_recorded.append((angles["angle_1"], angles["angle_2"]))

    # Compute Manhattan distance from center
    return {"distance": abs(coords[0] - 1024/2) + abs(coords[1] - 1024/2)}

# Define the Bayesian optimization problem
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    variables={
        "angle_1": [-6e-4, 6e-4],  # Search range for angle 1
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Define obj. function with varying angles to control 2 steering magnets

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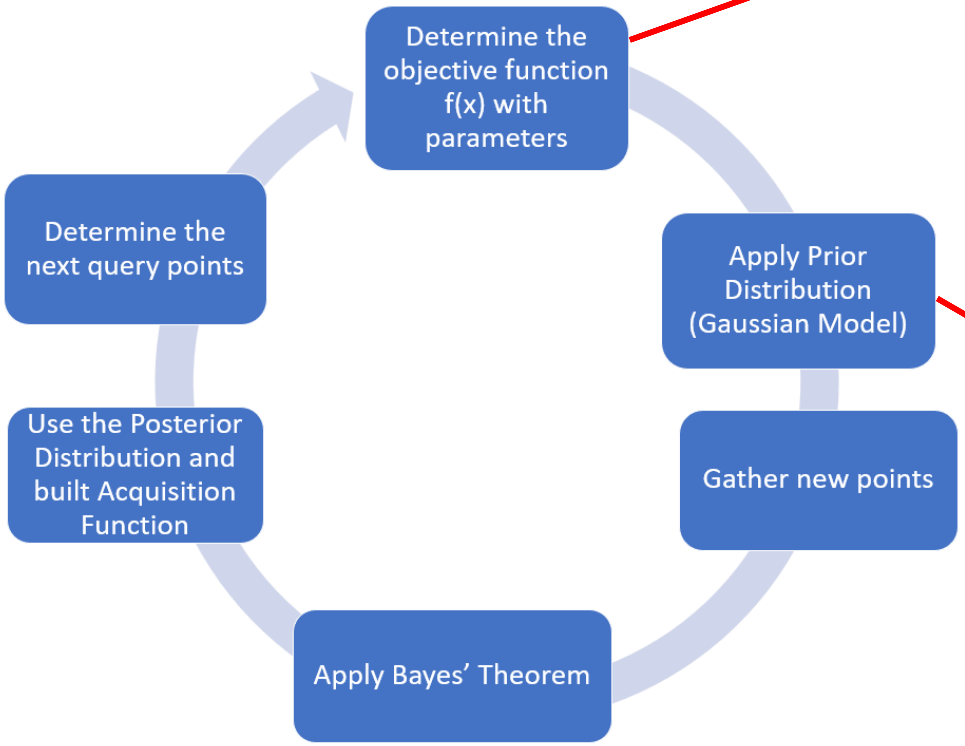


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for i in range(50):
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This sets up the Gaussian model

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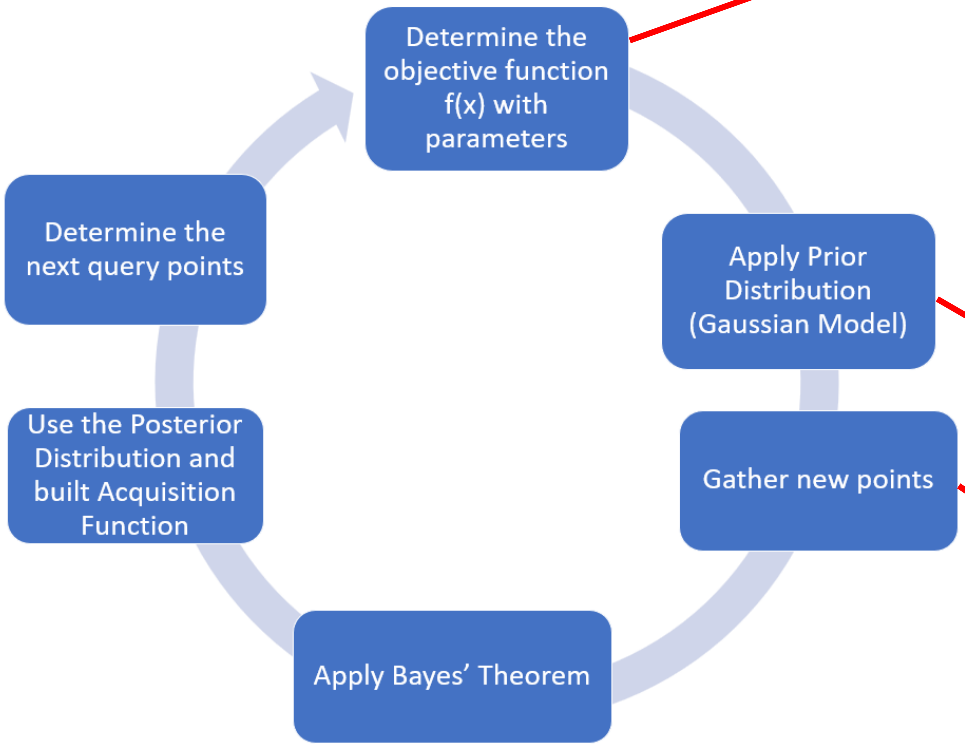


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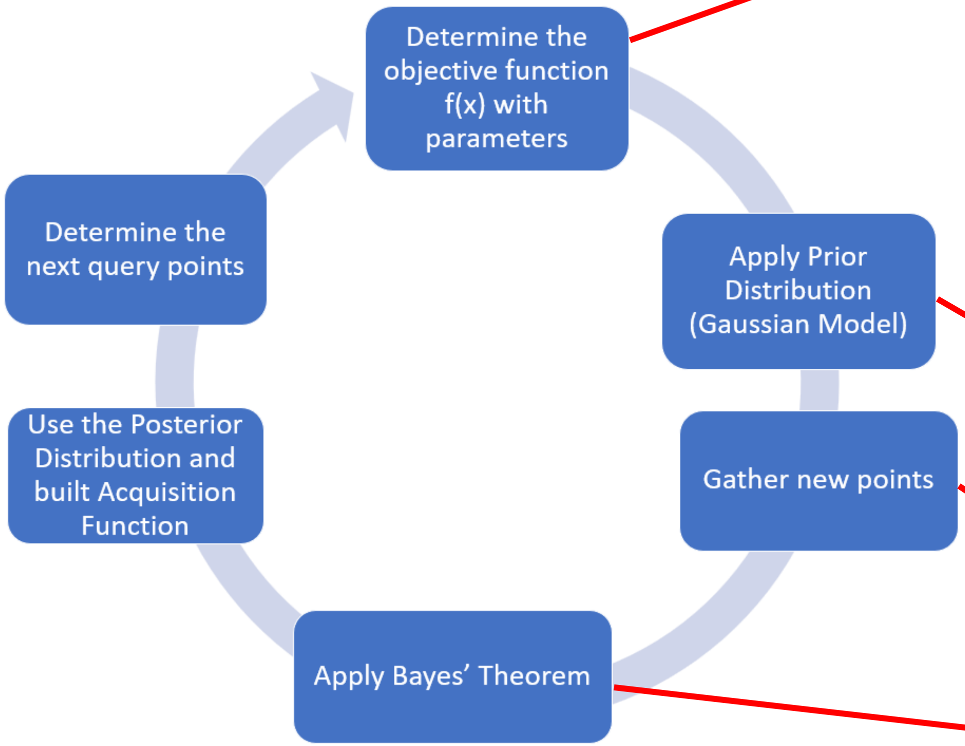


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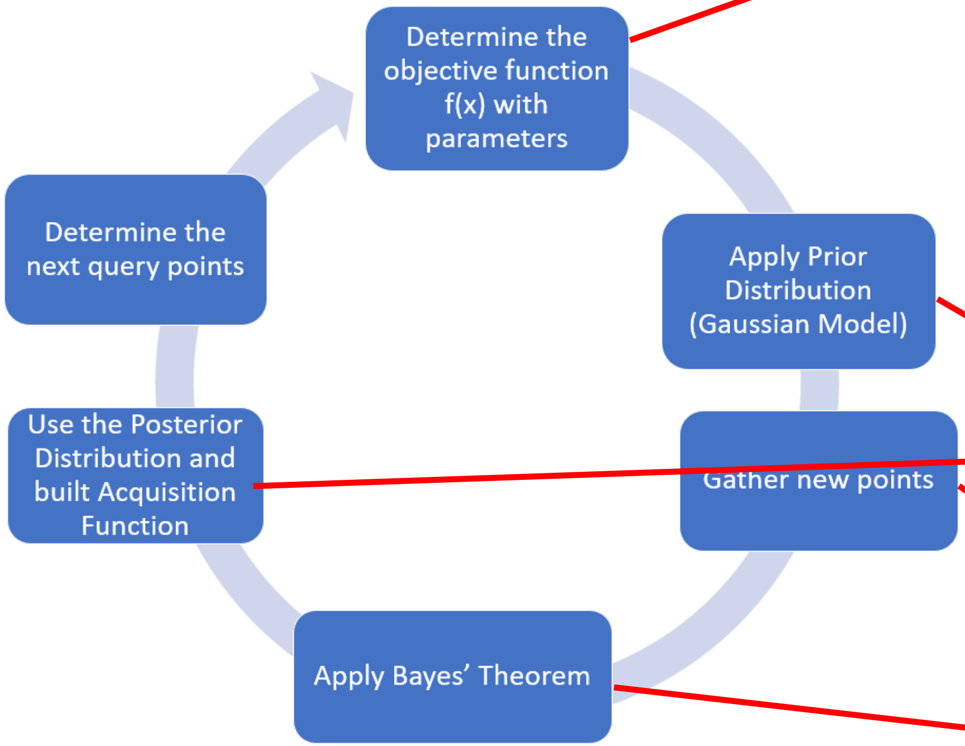


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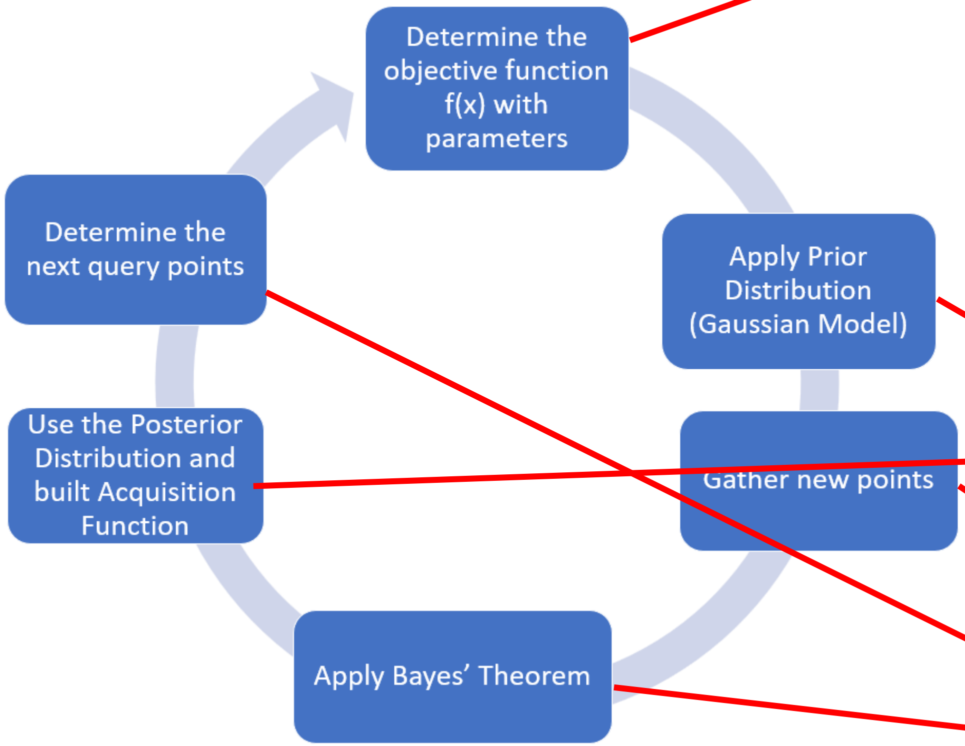


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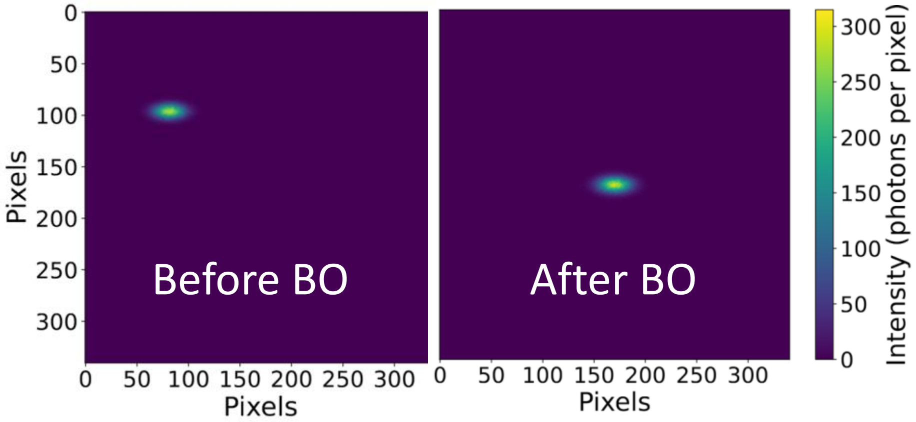
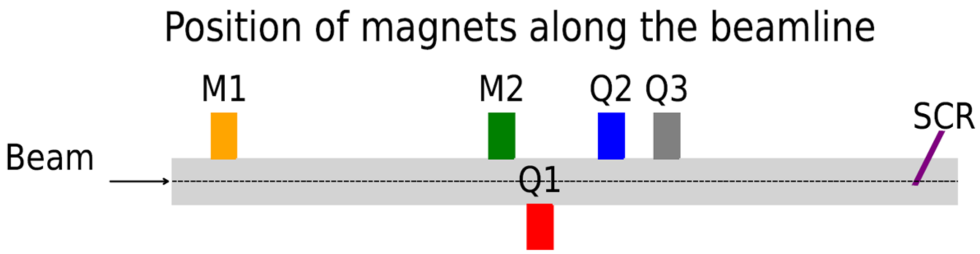
Repeatedly **choosing the next best point to evaluate**, using the acquisition function Exploitation / Exploration

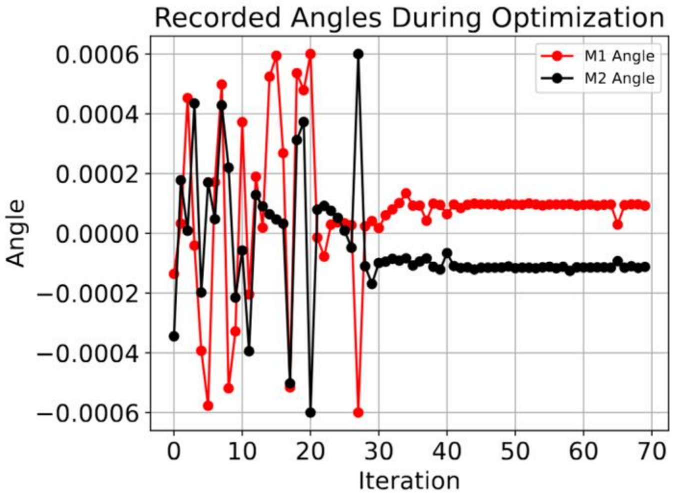
Results

Control of the steering magnets

Cheetah Simulation software: https://github.com/desy-ml/cheetah







- Successful centering of the beam in the centre of the screen after (BO)

Results

Control of the steering magnets

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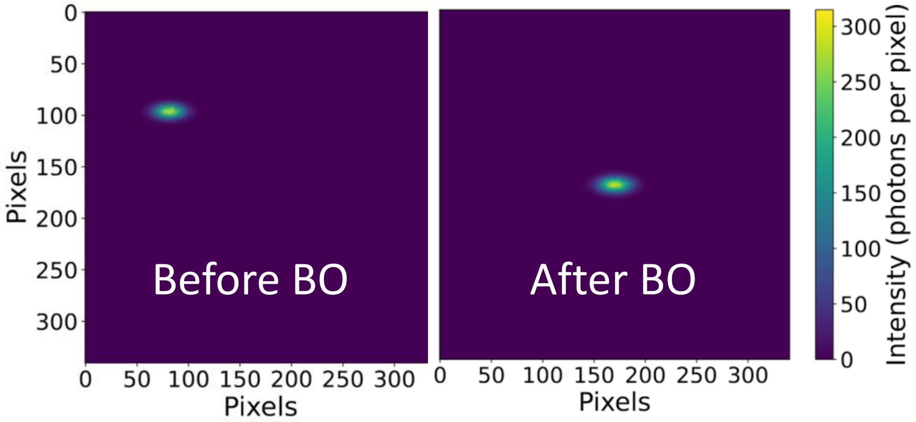
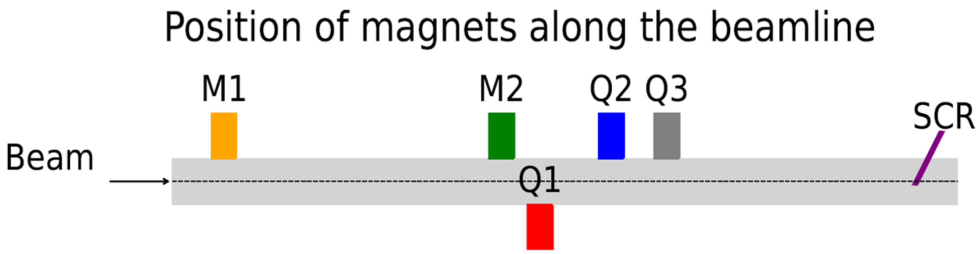
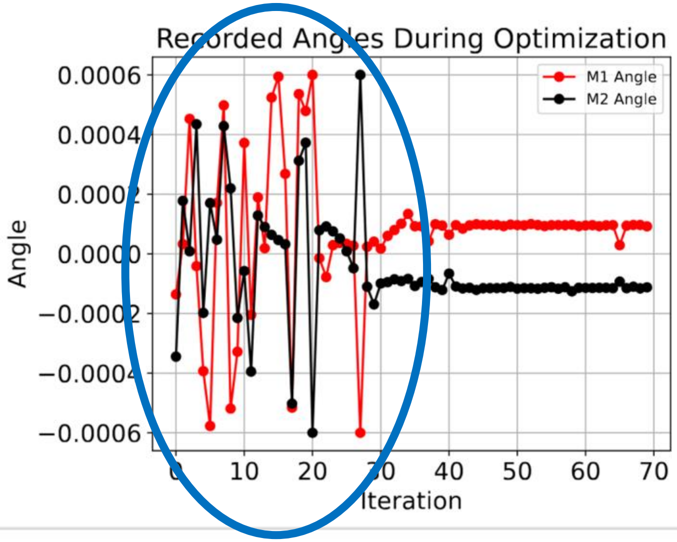


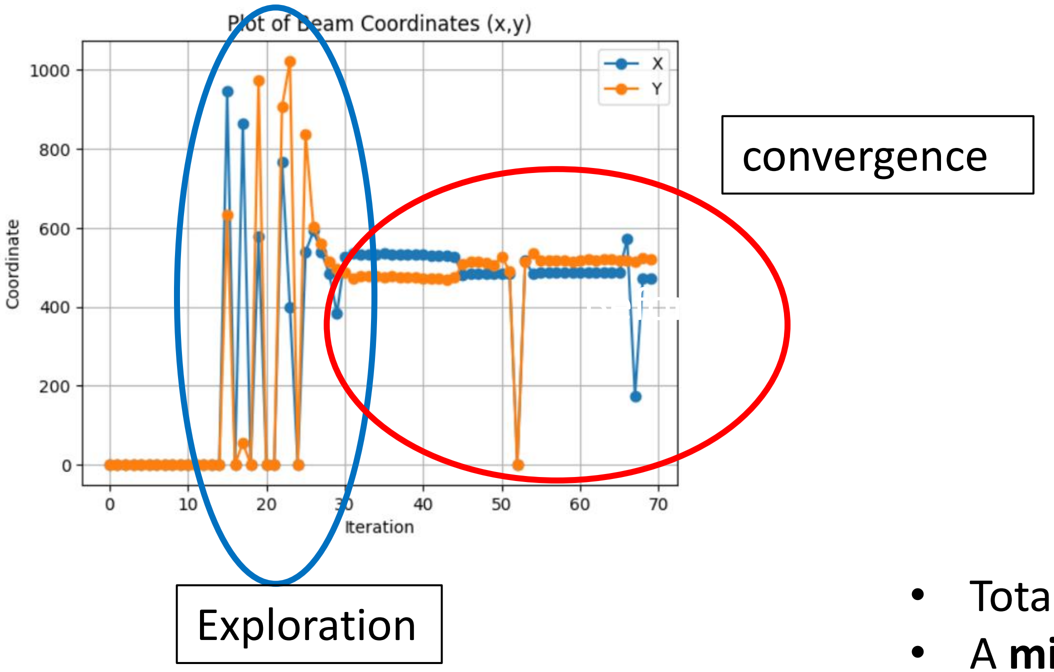


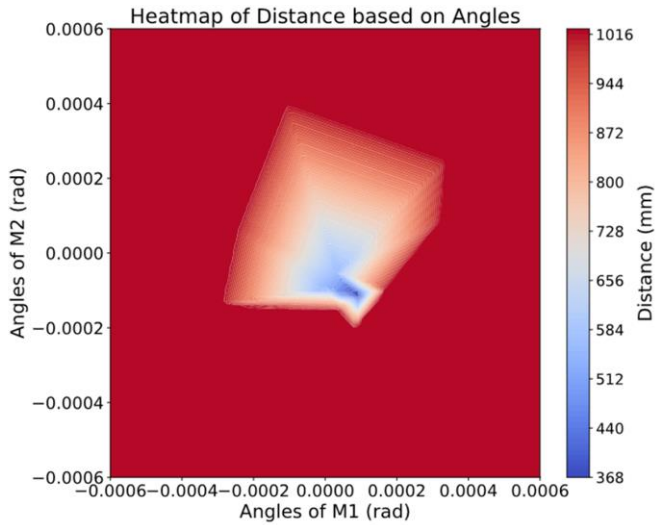


- Successful centering of the beam in the centre of the screen after (BO)
- After iteration 30 both angles **stabilize**

Results

Control of the steering magnets

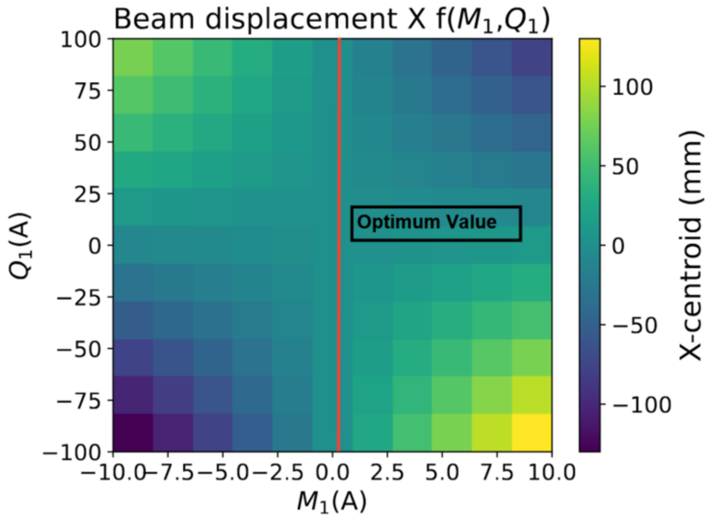


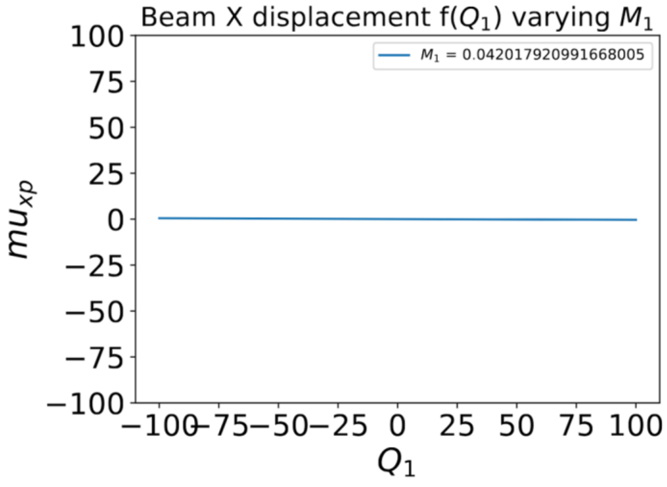


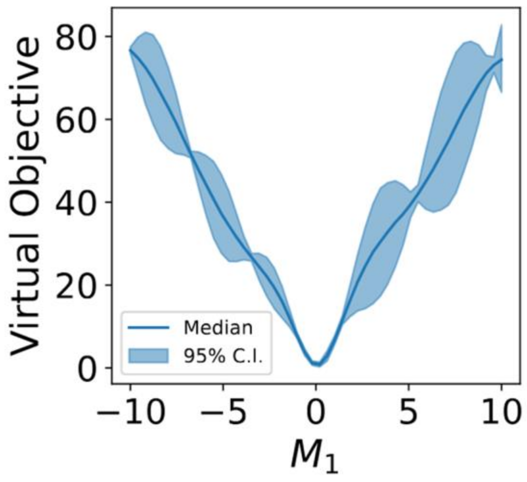
- Total beam displacement as a function of these angular settings
- A **minimum region** appears where the beam approaches the optical axis
- Highlights the **strong sensitivity of the trajectory** to small steering deviations
- Defines a low-displacement region that would serve as an ideal starting point or prior for downstream optimization

Results

BAX to align beam through quadrupole centre (M_1, Q_1)







- Need of multi-objective algorithm
- **Minimize a virtual objective** defined as the difference slope in the position of the beam, calculated by varying the quadrupole strength $Q1$

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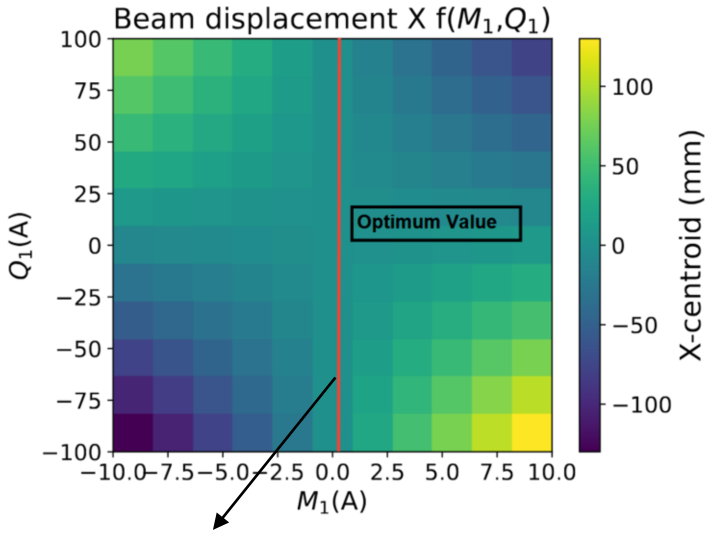

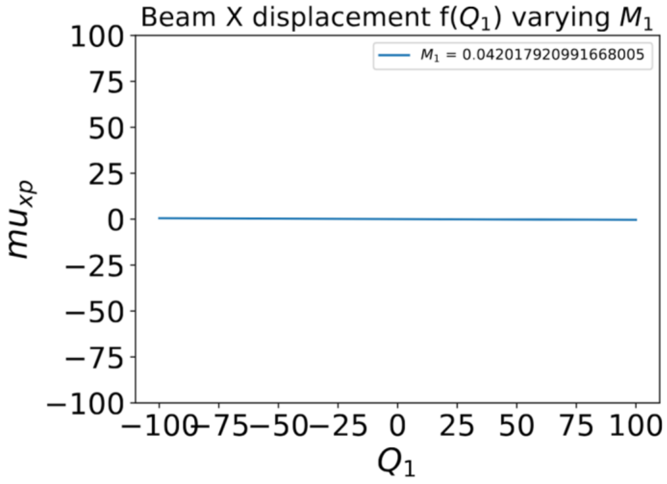

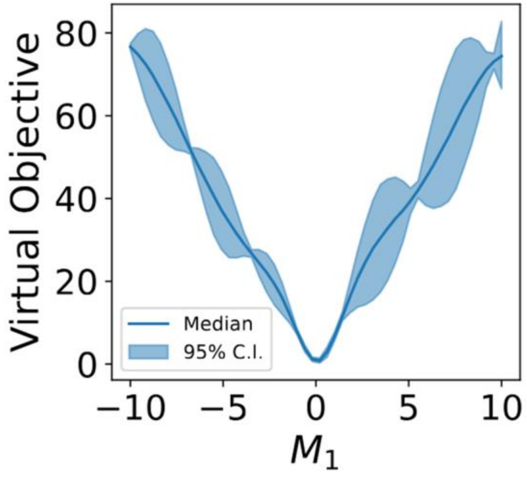

The beam remains minimally displaced across varying quadrupole strengths, indicating ideal alignment.

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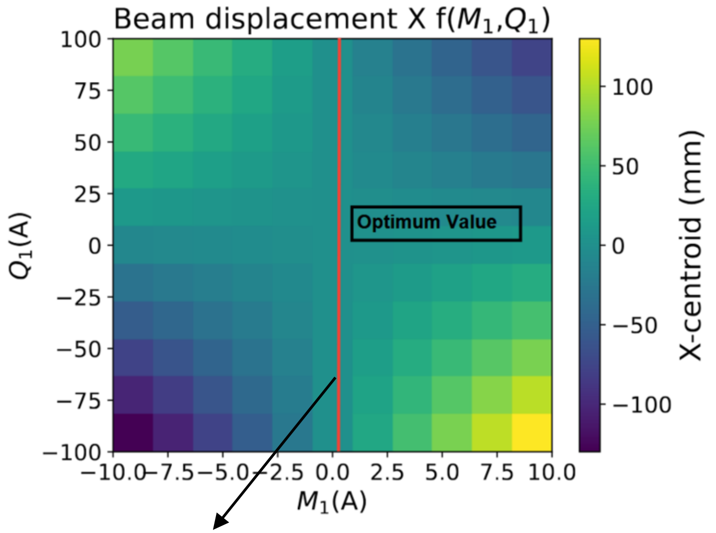

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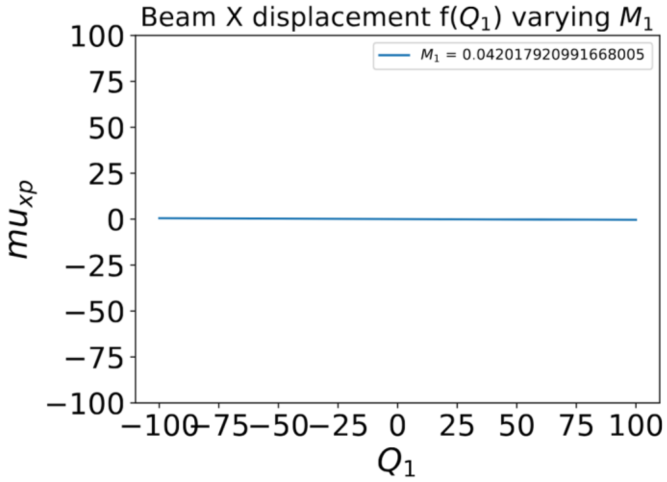
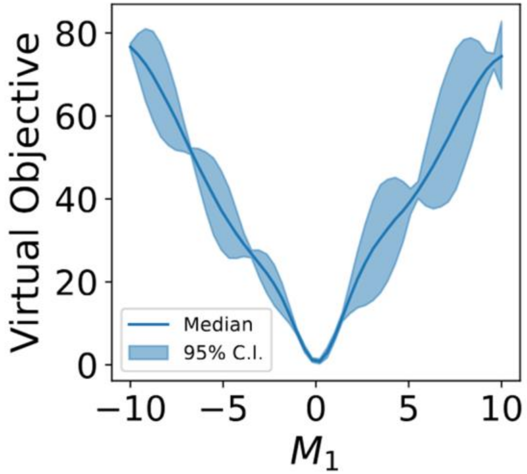


The beam x-displacement as a function of quadrupole strength $Q1$ is near zero, confirming flat response and effective decoupling



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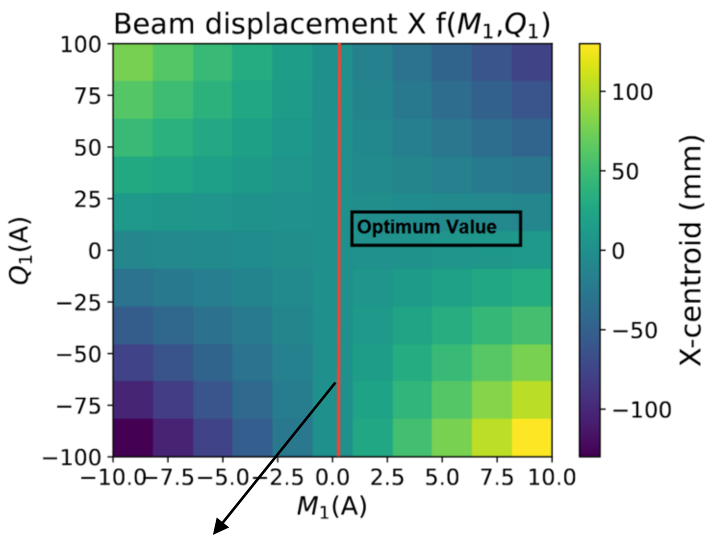

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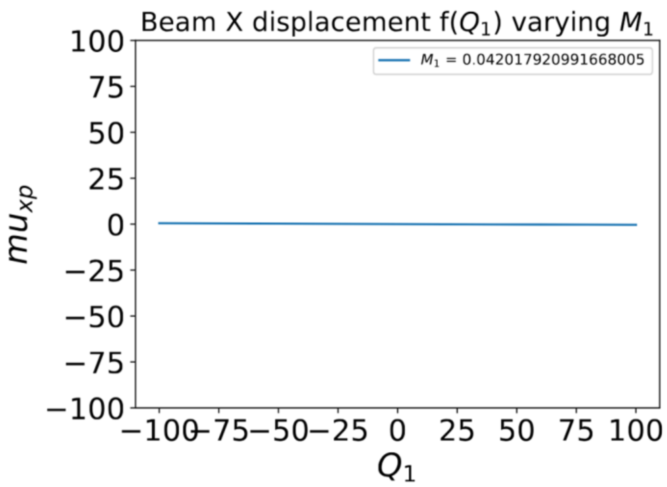

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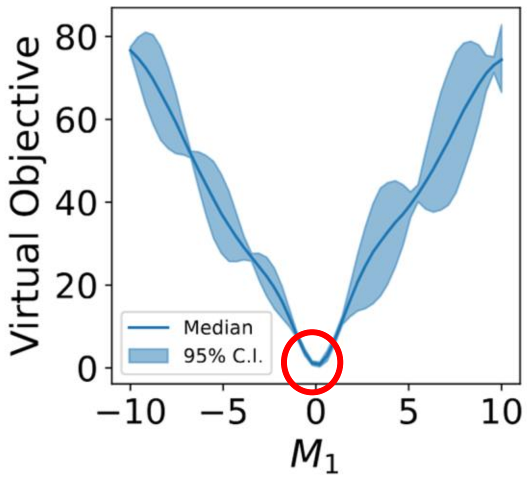

BAX algorithm's ability to infer optimal alignment from indirect measurements with high confidence

- Need of multi-objective algorithm
- **Minimize a virtual objective** defined as the difference slope in the position of the beam, calculated by varying the quadrupole strength $Q1$

Conclusion

Now

- Extract data from KARA, injection line beam measurements
- Perform Simulations with Cheetah using (BO) and BAX. Steering magnets, quadrupoles
- Test (BO) and BAX code in KARA facility.

Maybe RL? Open for discussions


Thank you!