Implementation of Model Predictive Control for Slow Orbit Feedback Control in MAX IV Accelerators Using PyTango Framework

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Emory Jensen Gassheld, My Karlsson, Carla Takahashi, Magnus Sjöström, Jonas Breunlin, Pontus Giselsson, Aureo Freitas

Outline

Introduction

- Orbit Control
- Model Predictive Control

Implementation

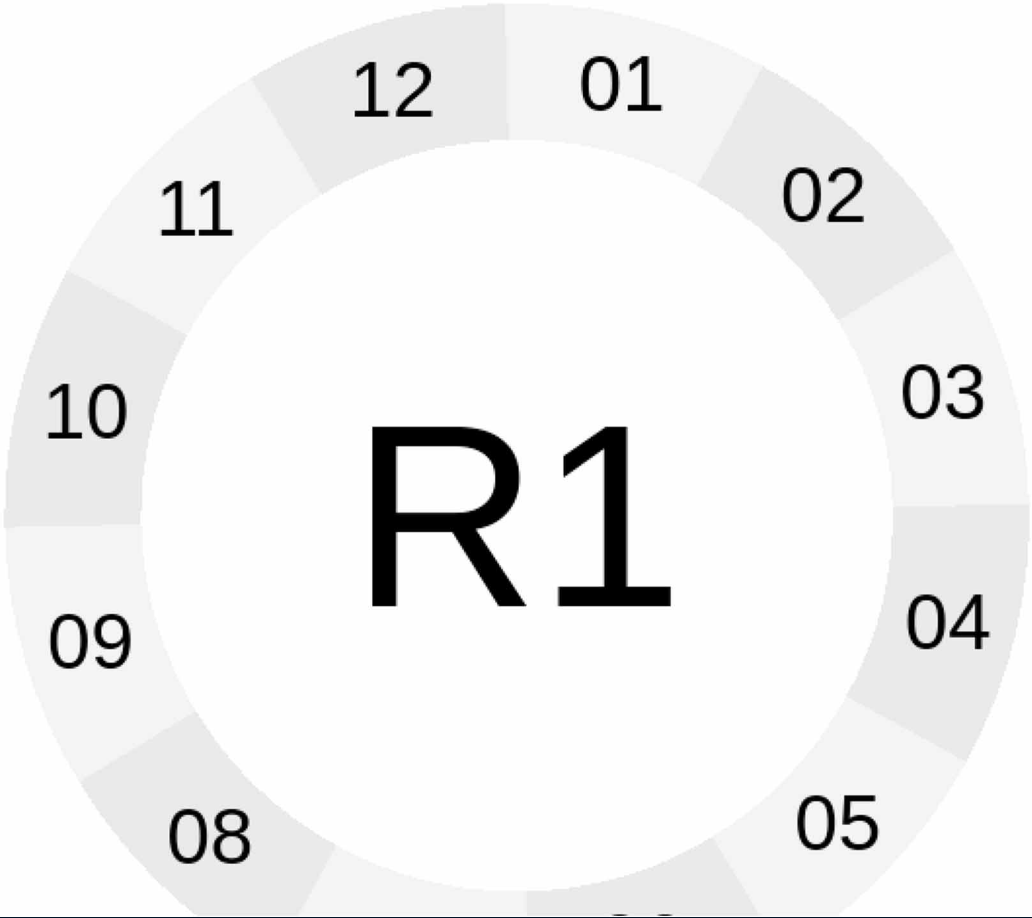
- MPC Design
- Tango Device

Results

- Tests on Storage Rings
- Outcomes

Orbit Control

Storage Rings Orbit at MAX IV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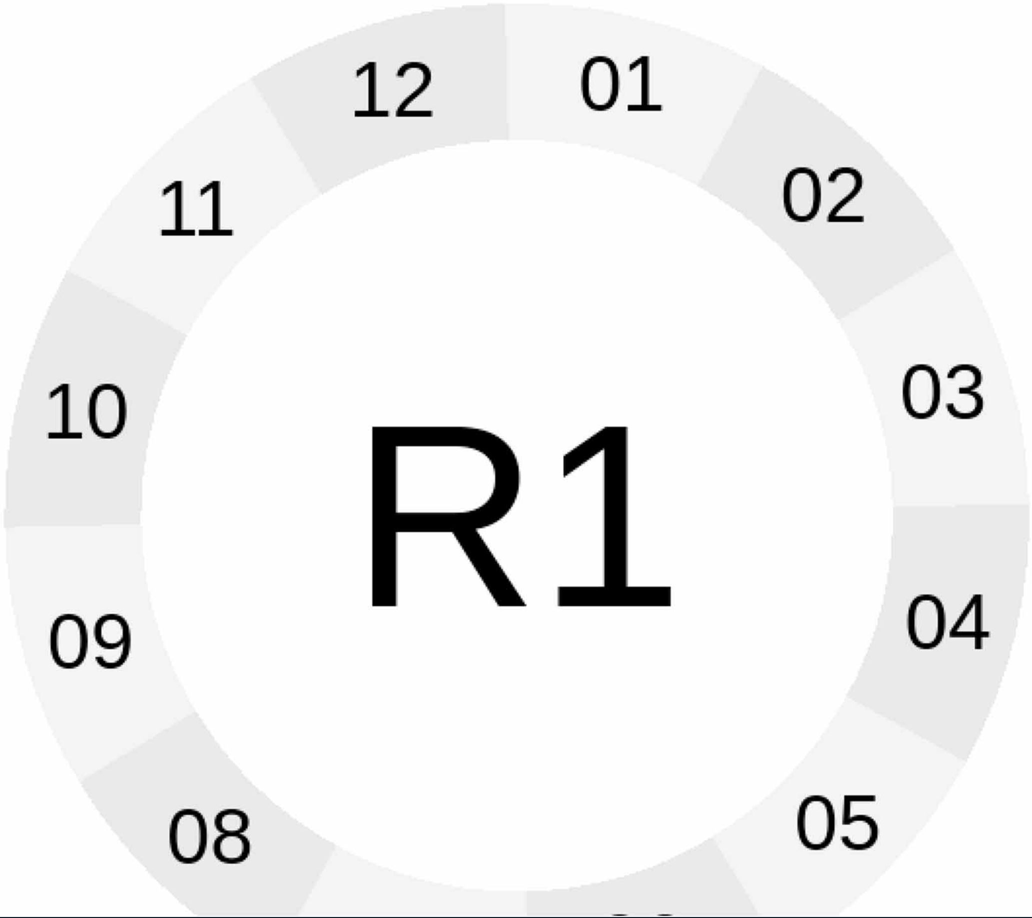
Storage Rings at MAX IV

- The accelerator complex at the MAX IV laboratory consists of a 3 GeV, 250 m long full energy linac, two storage rings of 1.5 GeV and 3 GeV and a Short Pulse Facility.
- Transverse stability of the beam is commonly achieved via feedback solutions with various different implementations.
- At the MAX IV light source, there are two separate feedbacks working together in two different, but overlapping frequency regions and sets of sensors.
- The Fast Orbit Feedback has 10 kHz repetition rate and attenuates noise up to 50 – 150 Hz in the most critical regions.
- The Slow Orbit Feedback is implemented in software over a distributed control system and should work with a rate up to 10Hz.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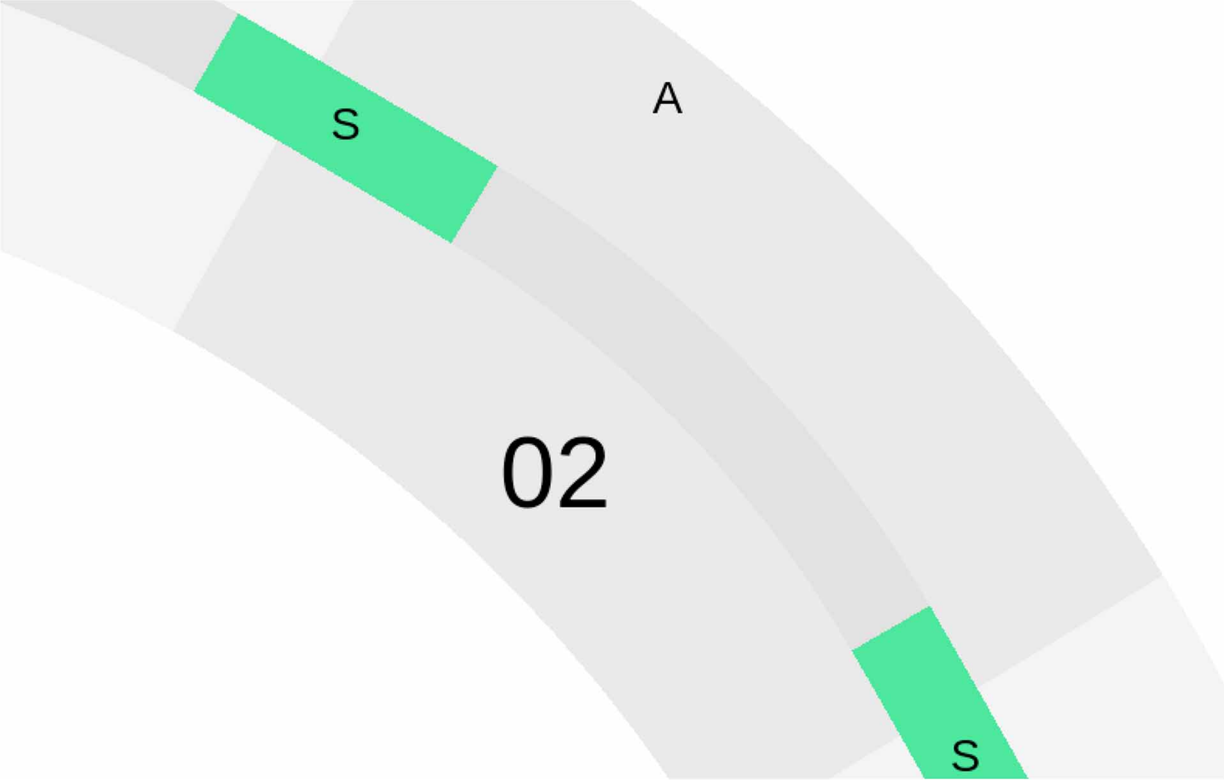
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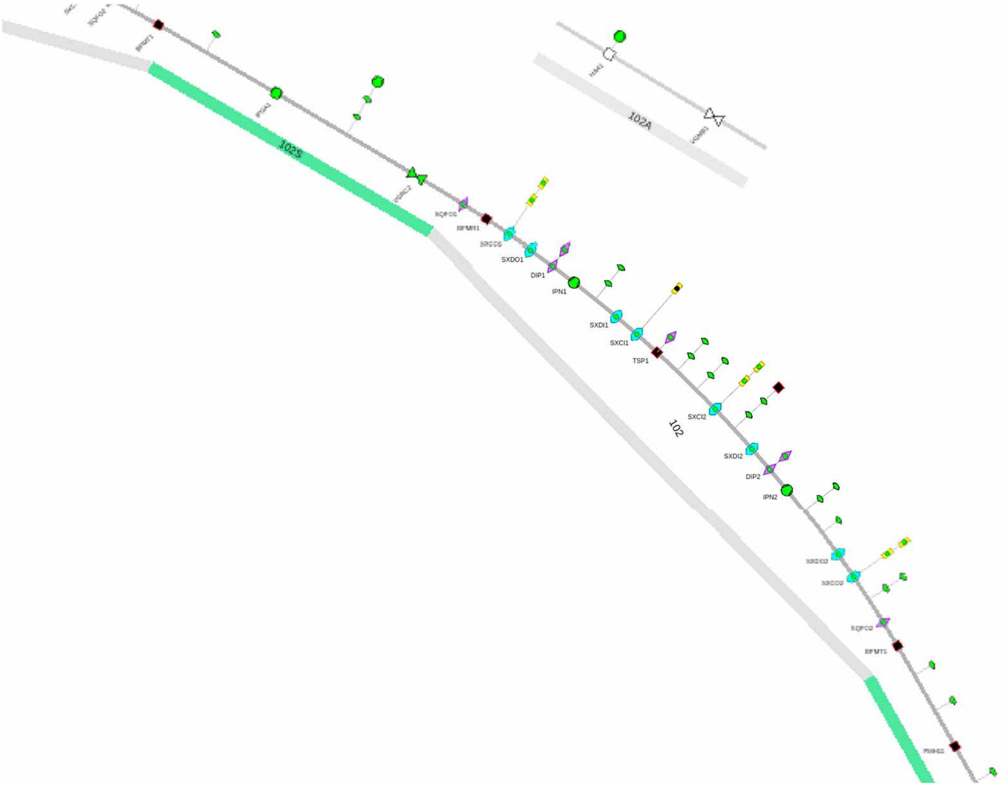

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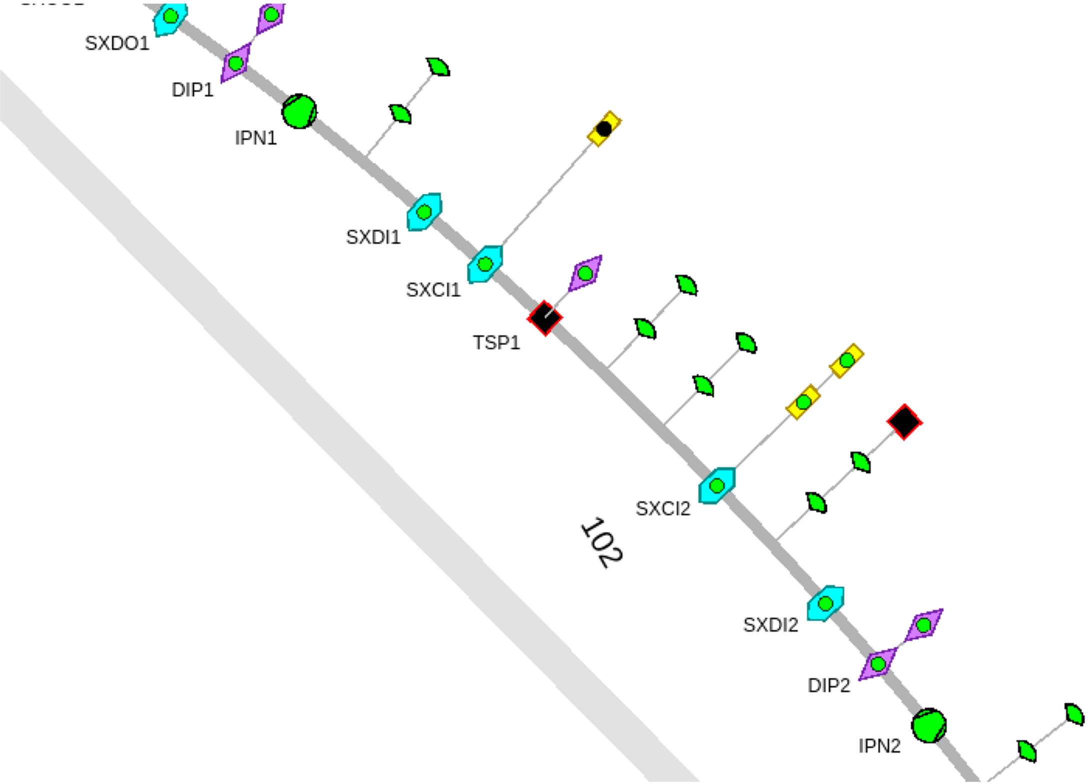
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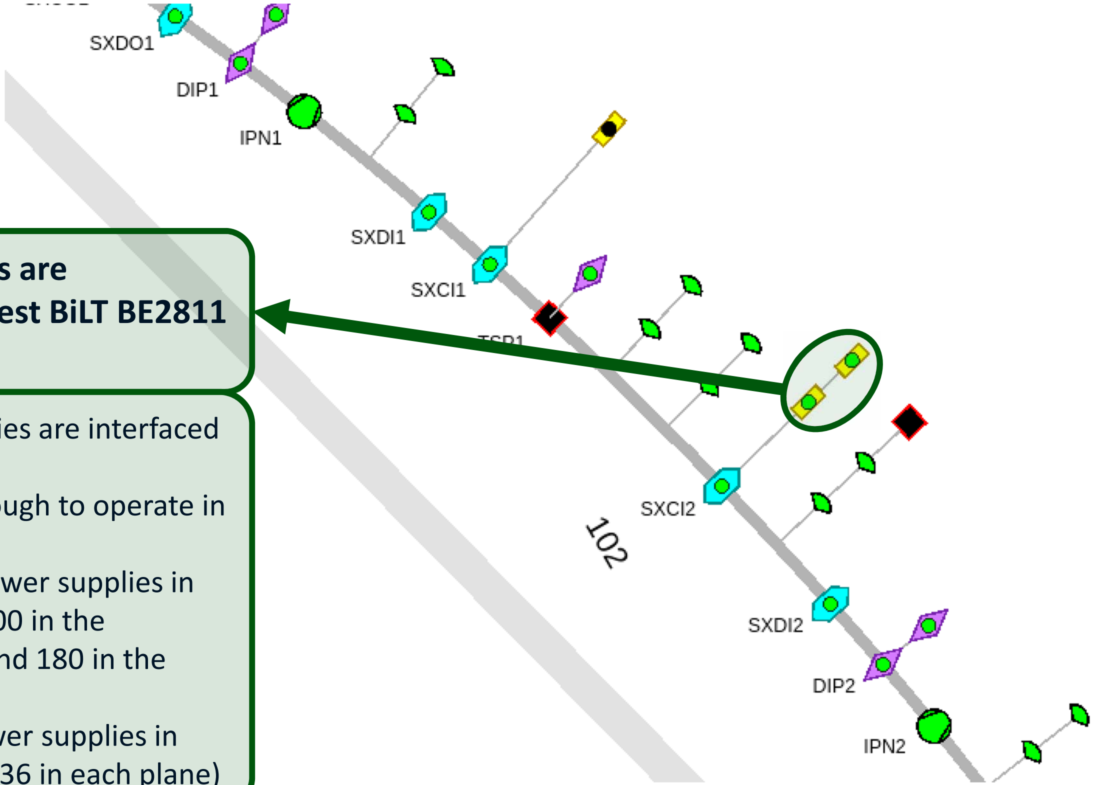
DIP2
IPN2

Corrector Magnets are Controlled with ITest BiLT BE2811 Power Supplies

- The power supplies are interfaced in TANGO.
- They are fast enough to operate in 10Hz.
- There are 380 power supplies in the 3GeV ring (200 in the horizontal plan and 180 in the vertical plane)
- There are 72 power supplies in the 1.5GeV ring (36 in each plane)



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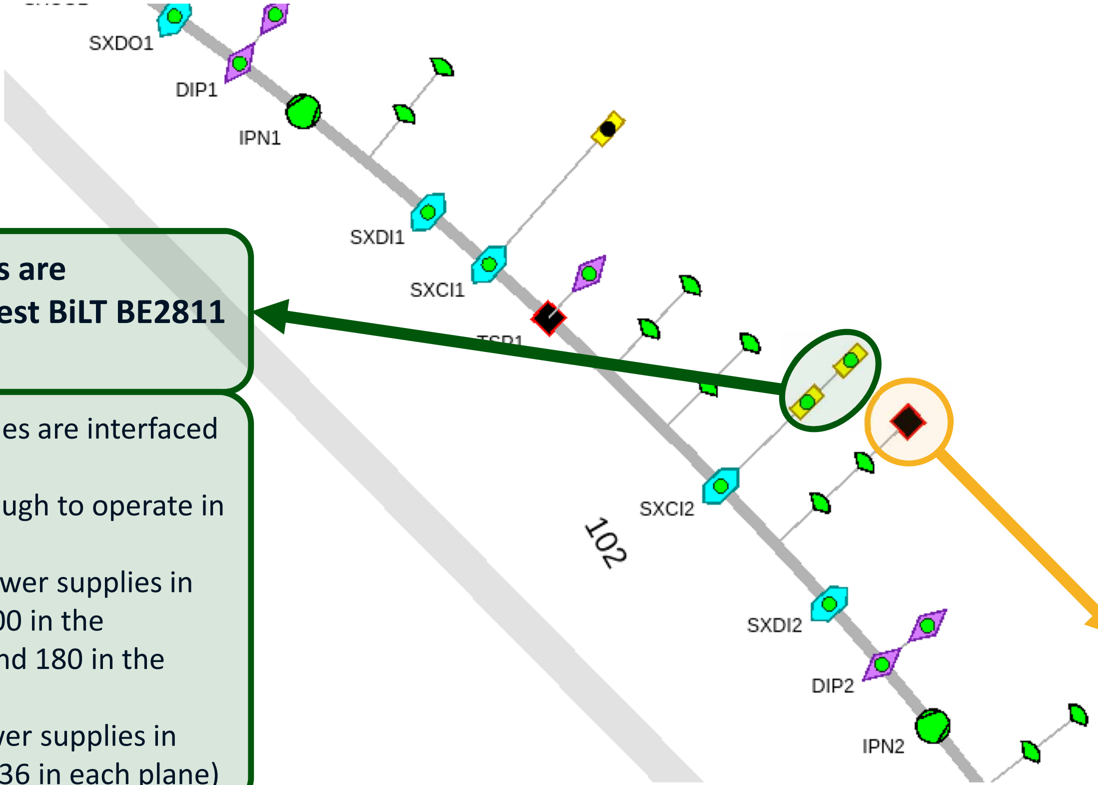


- The BPMs are interfaced in TANGO so the beam positions in both planes are available as attributes.
- The attributes push events at the 10 Hz rate of the “slow” Libera data acquisition stream.
- There are 2 × 200 BPMs in the 3GeV ring.
- There are 2 × 36 BPMs in the 1.5GeV ring.

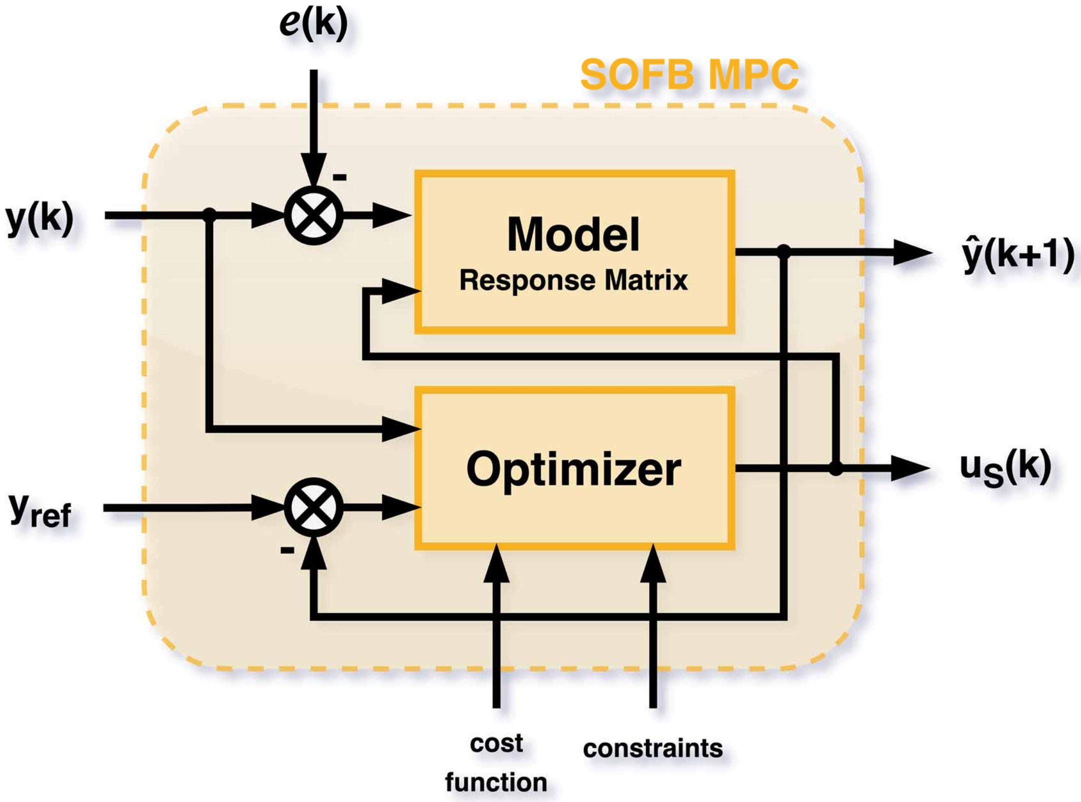
Beam Position Measurements from Libera Brillance+

Issues and Requirements

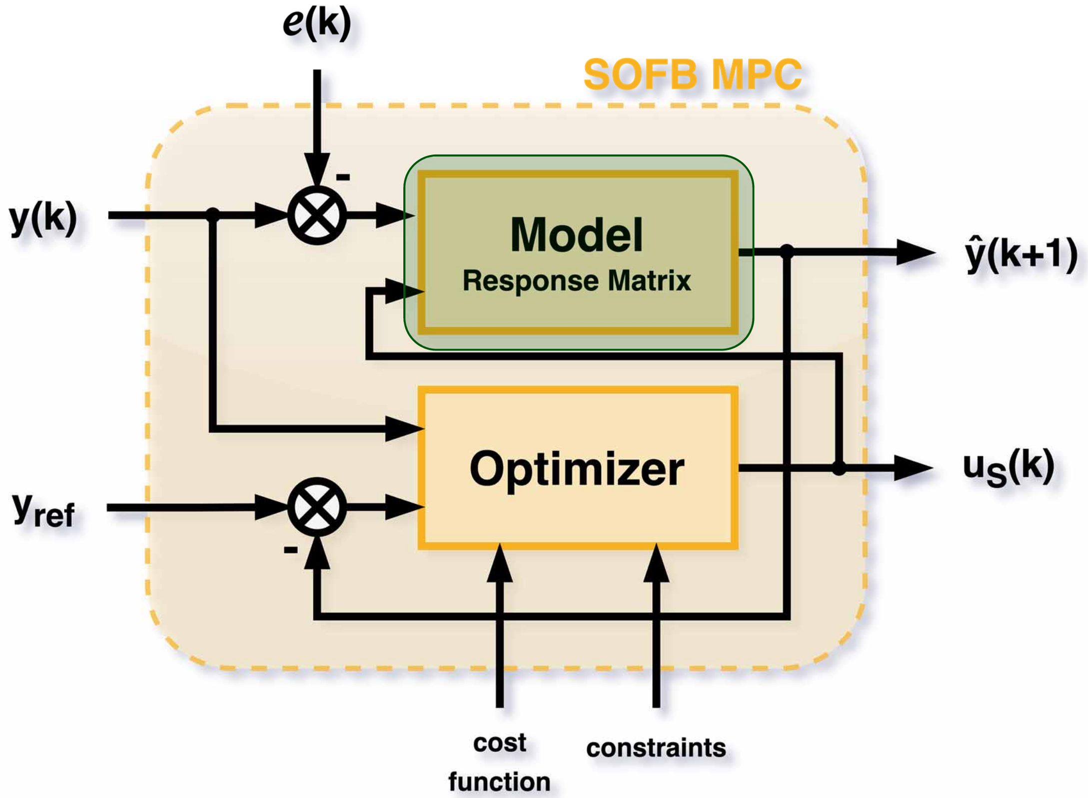
- Corrector magnets are easily saturated, for both the Slow and Fast Orbit FeedBack control systems.
- When some of the the corrector magnets of the SOFB system are satured it can be hard to bring the feedback control system into operation again.
- The BPM sensor readout have particular transient dynamics, in which it takes around 4 or 5 steps, around 0.5s for the sensor to reach the expected value.
- The Fast corrector magnets, have a shorter operational range, thus the SOFB should help the with the offloading of the FOFB system.
- Compensation of energy shifts can be achieved by adjusting the RF, which should also be managed by the SOFB system for an optimal solution.

Model Predictive Control

Optimal Control for Constrained Dynamic Systems

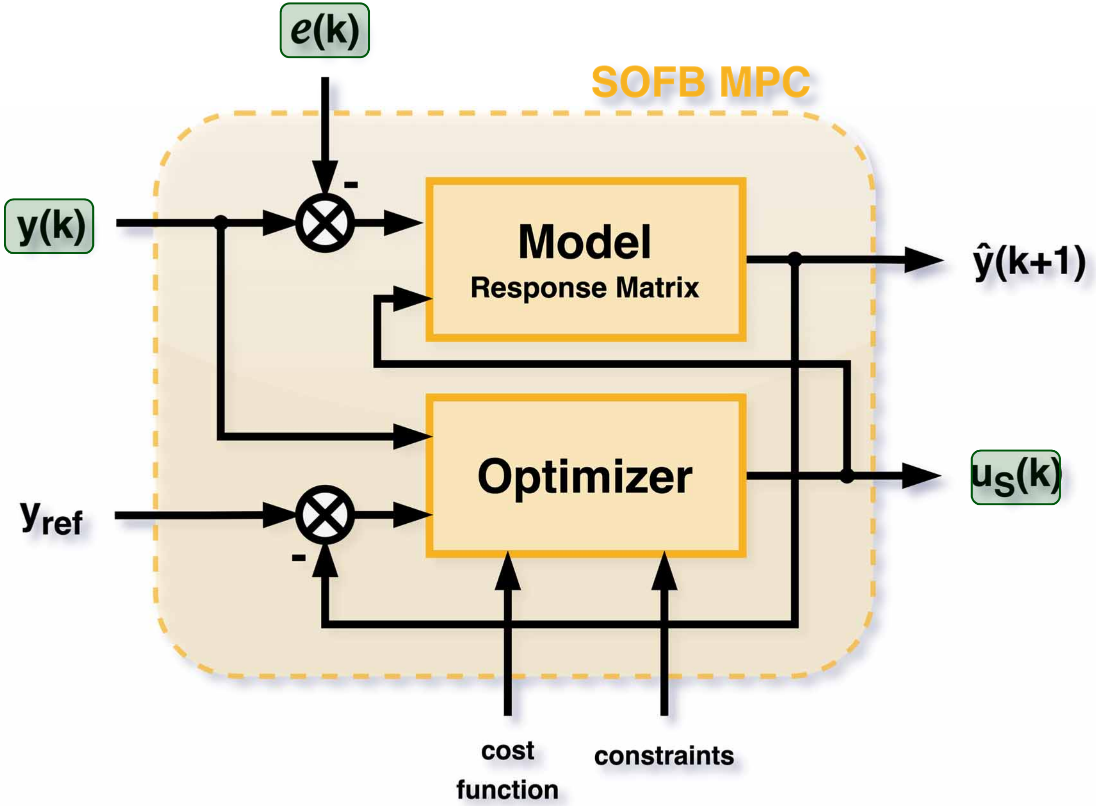


Theoretical Background



Theoretical Background

- Model Predictive Control (MPC) is a control system that uses a model of the system's dynamics to predict its future behaviour over a finite receding horizon.



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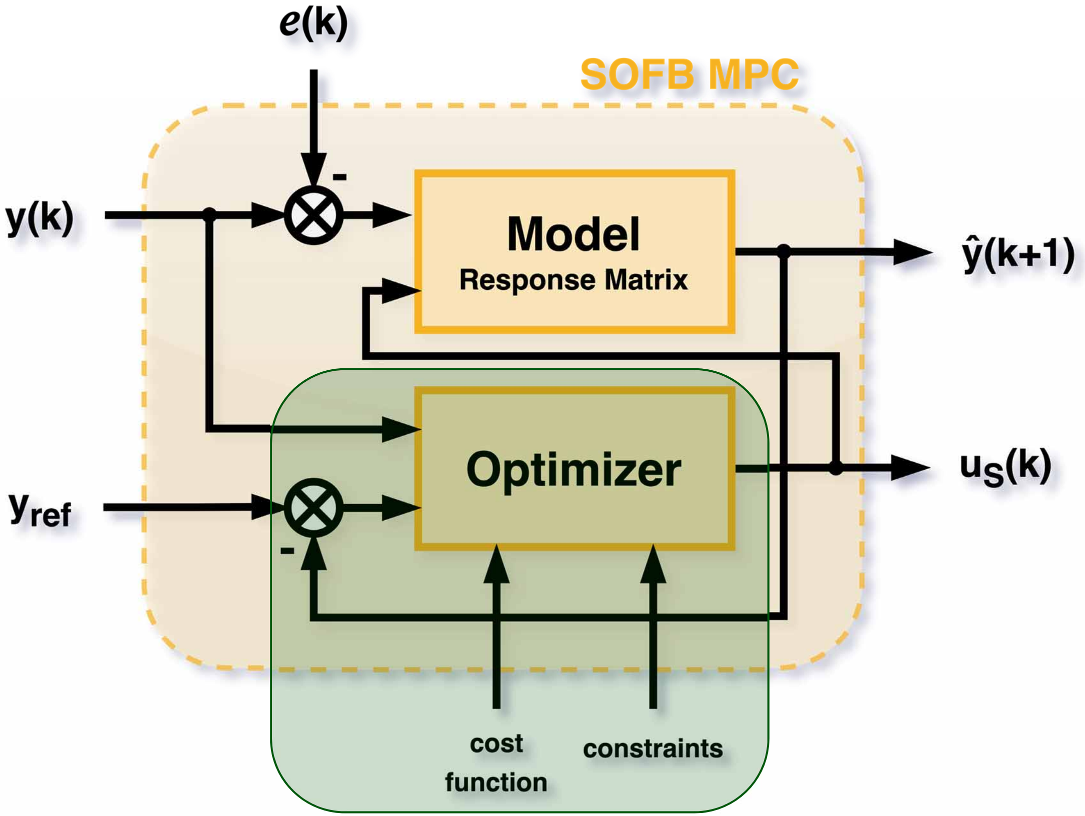

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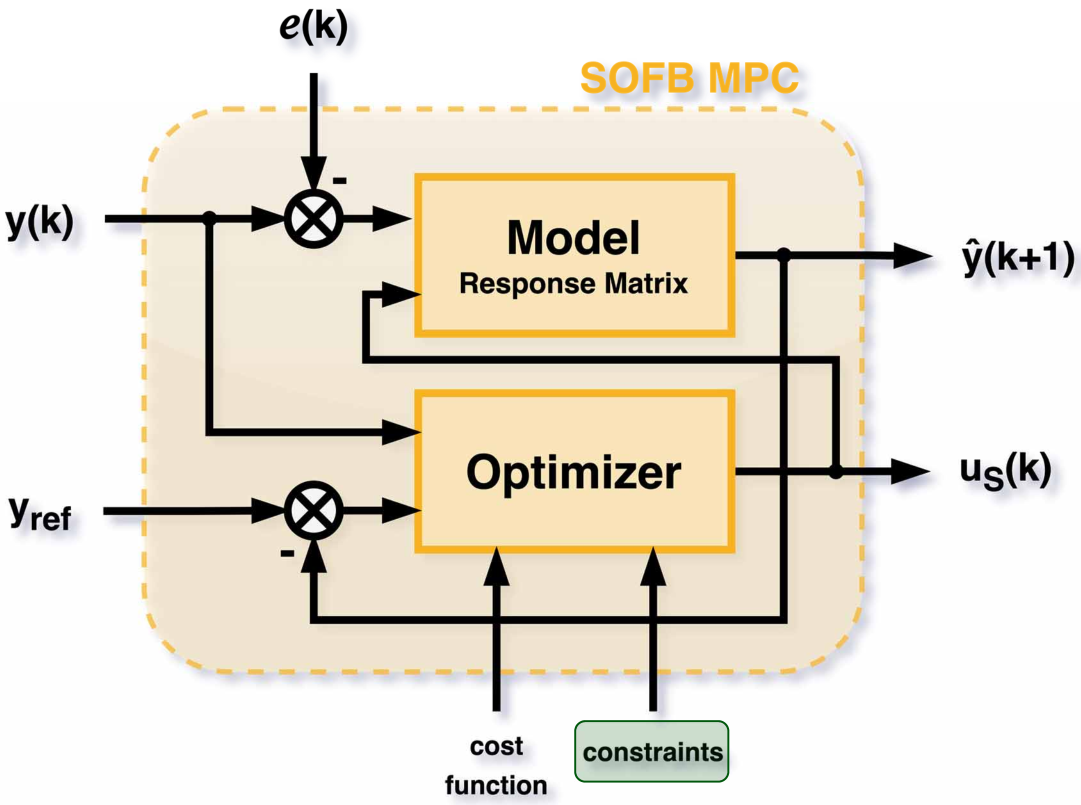

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- The prediction is based on the current states, disturbances, and current and future control signals.
- In each step, the optimization problem to minimize the cost function for the control signal is solved so that constraints on states and control actions are satisfied.
- One of the big advantages of MPC is that the controller handles constraints which can be physical limits or safety limits on states and control signals.

Mathematical Definition

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T \, Q_1 \, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta\boldsymbol{u}_i^T Q_2 \Delta\boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T \, Q_f \, \boldsymbol{e}_{k+H_p}$$

$$\text{s.t.} \quad \boldsymbol{x}_{k+1} = \Phi\boldsymbol{x}_k + \Gamma\boldsymbol{u}_k$$

$$\boldsymbol{y}_k = C\boldsymbol{x}_k$$

$$\overline{\boldsymbol{x}} = \boldsymbol{x}_0$$

$$|\boldsymbol{x}| \leq \boldsymbol{x}_{max}$$

$$|\boldsymbol{u}| \leq \boldsymbol{u}_{max}$$

Mathematical Definition

- **This problem minimizes the cost function *J*.**

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T \, Q_1 \, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta\boldsymbol{u}_i^T Q_2 \Delta\boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T \, Q_f \, \boldsymbol{e}_{k+H_p}$$

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- This problem minimizes the cost function *J*.
- ***e*** is the states error.

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- This problem minimizes the cost function *J*.
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- The initial state is an estimation of the current state.
- The states and control signal constraint can be defined.

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T\, Q_1\, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta\boldsymbol{u}_i^T Q_2 \Delta\boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T\, Q_f\, \boldsymbol{e}_{k+H_p}$$

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MPC Design

Model and Controller Outline

Model

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k+1} = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0 \alpha}\eta_{sensor} \\ -\frac{1}{L_0 \alpha}\eta_{actuator}^T & -\frac{1}{\alpha f} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T \, Q_1 \, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta \boldsymbol{u}_i^T Q_2 \Delta \boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T \, Q_f \, \boldsymbol{e}_{k+H_p}$$

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Model

- **The MPC model uses the Response Matrix as part of the system model.**

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k+1} = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0 \alpha} \eta_{sensor} \\ -\frac{1}{L_0 \alpha} \eta_{actuator}^{T} & -\frac{1}{\alpha f} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T \, Q_1 \, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta \boldsymbol{u}_i^T Q_2 \Delta \boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T \, Q_f \, \boldsymbol{e}_{k+H_p}$$

$$\text{s.t.} \quad \boldsymbol{x}_{k+1} = \Phi \boldsymbol{x}_k + \Gamma \boldsymbol{u}_k$$

$$\boldsymbol{y}_k = C \boldsymbol{x}_k$$

$$\overline{\boldsymbol{x}} = \boldsymbol{x}_0$$

$$|\boldsymbol{x}| \leq \boldsymbol{x}_{max}$$

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Model

- **The MPC model uses the Response Matrix as part of the system model.**
- **The sensors are the BPM.**

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta E}{E} \end{bmatrix}_{k+1} = \mathbf{I}\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta E}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0\alpha}\eta_{sensor} \\ -\frac{1}{L_0\alpha}\eta_{actuator}^T & -\frac{1}{\alpha f} \end{bmatrix}\begin{bmatrix} \Delta\boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I}\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta E}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T Q_1 \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta\boldsymbol{u}_i^T Q_2 \Delta\boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T Q_f \boldsymbol{e}_{k+H_p}$$

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Model

- The MPC model uses the Response Matrix as part of the system model.
- The sensors are the BPM.
- The actuators which receive the are the power supplies of the magnets.

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k+1} = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0 \alpha}\eta_{sensor} \\ -\frac{1}{L_0 \alpha}\eta_{actuator}^{T} & -\frac{1}{\alpha f} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T \, Q_1 \, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta \boldsymbol{u}_i^T Q_2 \Delta \boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T \, Q_f \, \boldsymbol{e}_{k+H_p}$$

$$\begin{aligned} \text{s.t.} \quad & \boldsymbol{x}_{k+1} = \Phi \boldsymbol{x}_k + \Gamma \boldsymbol{u}_k \\ & \boldsymbol{y}_k = C \boldsymbol{x}_k \\ & \overline{\boldsymbol{x}} = \boldsymbol{x}_0 \\ & |\boldsymbol{x}| \leq \boldsymbol{x}_{max} \\ & |\boldsymbol{u}| \leq \boldsymbol{u}_{max} \end{aligned}$$

Model

- The MPC model uses the Response Matrix as part of the system model.
- The sensors are the BPM.
- The actuators which receive the are the power supplies of the magnets.
- The frequency delta can also be incoporeted into the MPC model.

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta E}{E} \end{bmatrix}_{k+1} = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta E}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0 \alpha} \eta_{sensor} \\ -\frac{1}{L_0 \alpha} \eta_{actuator}^T & -\frac{1}{\alpha f} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta E}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T Q_1 \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta \boldsymbol{u}_i^T Q_2 \Delta \boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T Q_f \boldsymbol{e}_{k+H_p}$$

$$\text{s.t.} \quad \begin{aligned} \boldsymbol{x}_{k+1} &= \Phi \boldsymbol{x}_k + \Gamma \boldsymbol{u}_k \\ \boldsymbol{y}_k &= C \boldsymbol{x}_k \\ \bar{\boldsymbol{x}} &= \boldsymbol{x}_0 \\ |\boldsymbol{x}| &\le \boldsymbol{x}_{max} \\ |\boldsymbol{u}| &\le \boldsymbol{u}_{max} \end{aligned}$$

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- The sensors are the BPM.
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- The model is part of the optimization restriction

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k+1} = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0 \alpha}\eta_{sensor} \\ -\frac{1}{L_0 \alpha}\eta_{actuator}^{T} & -\frac{1}{\alpha f} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T \, Q_1 \, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta \boldsymbol{u}_i^T Q_2 \Delta \boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T \, Q_f \, \boldsymbol{e}_{k+H_p}$$

s. t.

$$\boldsymbol{x}_{k+1} = \Phi \boldsymbol{x}_k + \Gamma \boldsymbol{u}_k$$
$$\boldsymbol{y}_k = C \boldsymbol{x}_k$$
$$\overline{\boldsymbol{x}} = \boldsymbol{x}_0$$
$$|\boldsymbol{x}| \leq \boldsymbol{x}_{max}$$
$$|\boldsymbol{u}| \leq \boldsymbol{u}_{max}$$

Model

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- The sensors are the BPM.
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Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k+1} = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0 \alpha}\eta_{sensor} \\ -\frac{1}{L_0 \alpha}\eta_{actuator}^{T} & -\frac{1}{\alpha f} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T \, Q_1 \, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta \boldsymbol{u}_i^T Q_2 \Delta \boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T \, Q_f \, \boldsymbol{e}_{k+H_p}$$

$$\begin{aligned} \text{s.t.} \quad & \boldsymbol{x}_{k+1} = \Phi \boldsymbol{x}_k + \Gamma \boldsymbol{u}_k \\ & \boldsymbol{y}_k = C \boldsymbol{x}_k \\ & \overline{\boldsymbol{x}} = \boldsymbol{x}_0 \\ & |\boldsymbol{x}| \leq \boldsymbol{x}_{max} \\ & |\boldsymbol{u}| \leq \boldsymbol{u}_{max} \end{aligned}$$

Optimization

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k+1} = \mathbf{I}\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0\alpha}\eta_{sensor} \\ -\frac{1}{L_0\alpha}\eta_{actuator}^{T} & -\frac{1}{\alpha f} \end{bmatrix}\begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I}\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T\, Q_1\, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta\boldsymbol{u}_i^T Q_2 \Delta\boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T\, Q_f\, \boldsymbol{e}_{k+H_p}$$

$$\begin{aligned} \text{s.t.} \quad & \boldsymbol{x}_{k+1} = \Phi\boldsymbol{x}_k + \Gamma\boldsymbol{u}_k \\ & \boldsymbol{y}_k = C\boldsymbol{x}_k \\ & \overline{\boldsymbol{x}} = \boldsymbol{x}_0 \\ & |\boldsymbol{x}| \leq \boldsymbol{x}_{max} \\ & |\boldsymbol{u}| \leq \boldsymbol{u}_{max} \end{aligned}$$

Optimization

- **The BPM sensor importances can be addressed by using the control signal cost matrices Q_1 and Q_f.**

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k+1} = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0 \alpha} \eta_{sensor} \\ -\frac{1}{L_0 \alpha} \eta_{actuator}^T & -\frac{1}{\alpha f} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T Q_1 \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta \boldsymbol{u}_i^T Q_2 \Delta \boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T Q_f \boldsymbol{e}_{k+H_p}$$

$$\text{s.t.} \quad \boldsymbol{x}_{k+1} = \Phi \boldsymbol{x}_k + \Gamma \boldsymbol{u}_k$$

$$\boldsymbol{y}_k = C \boldsymbol{x}_k$$

$$\overline{\boldsymbol{x}} = \boldsymbol{x}_0$$

$$|\boldsymbol{x}| \le \boldsymbol{x}_{max}$$

$$|\boldsymbol{u}| \le \boldsymbol{u}_{max}$$

Optimization

- **The BPM sensor importances can be addressed by using the control signal cost matrices Q_1 and Q_f.**
- **The corrector magnets importance can be addressed by using the control signal cost matrix Q_2.**

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k+1} = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0 \alpha}\eta_{sensor} \\ -\frac{1}{L_0 \alpha}\eta_{actuator}^{T} & -\frac{1}{\alpha f} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T \, Q_1 \, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta \boldsymbol{u}_i^T \, Q_2 \Delta \boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T \, Q_f \, \boldsymbol{e}_{k+H_p}$$

$$\begin{aligned} \text{s.t.} \quad & \boldsymbol{x}_{k+1} = \Phi \boldsymbol{x}_k + \Gamma \boldsymbol{u}_k \\ & \boldsymbol{y}_k = C \boldsymbol{x}_k \\ & \overline{\boldsymbol{x}} = \boldsymbol{x}_0 \\ & |\boldsymbol{x}| \leq \boldsymbol{x}_{max} \\ & |\boldsymbol{u}| \leq \boldsymbol{u}_{max} \end{aligned}$$

Optimization

- The BPM sensor importances can be addressed by using the control signal cost matrices Q_1 and Q_f.
- The corrector magnets importance can be addressed by using the control signal cost matrix Q_2.
- The actuators saturation and sensor end scales are used to define the optimization function constraints.

Model

$$\begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k+1} = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k} + \begin{bmatrix} \mathbf{R} & -\frac{1}{L_0 \alpha}\eta_{sensor} \\ -\frac{1}{L_0 \alpha}\eta_{actuator}^{T} & -\frac{1}{\alpha f} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{u} \\ \Delta f \end{bmatrix}$$

$$\boldsymbol{y}_k = \mathbf{I} \begin{bmatrix} \boldsymbol{x} \\ \frac{\Delta \mathrm{E}}{E} \end{bmatrix}_{k}$$

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{u}} J = \sum_{i=k+1}^{k+H_p-1} \boldsymbol{e}_i^T \, Q_1 \, \boldsymbol{e}_i + \sum_{i=k}^{k+H_u-1} \Delta \boldsymbol{u}_i^T Q_2 \Delta \boldsymbol{u}_i + \boldsymbol{e}_{k+H_p}^T \, Q_f \, \boldsymbol{e}_{k+H_p}$$

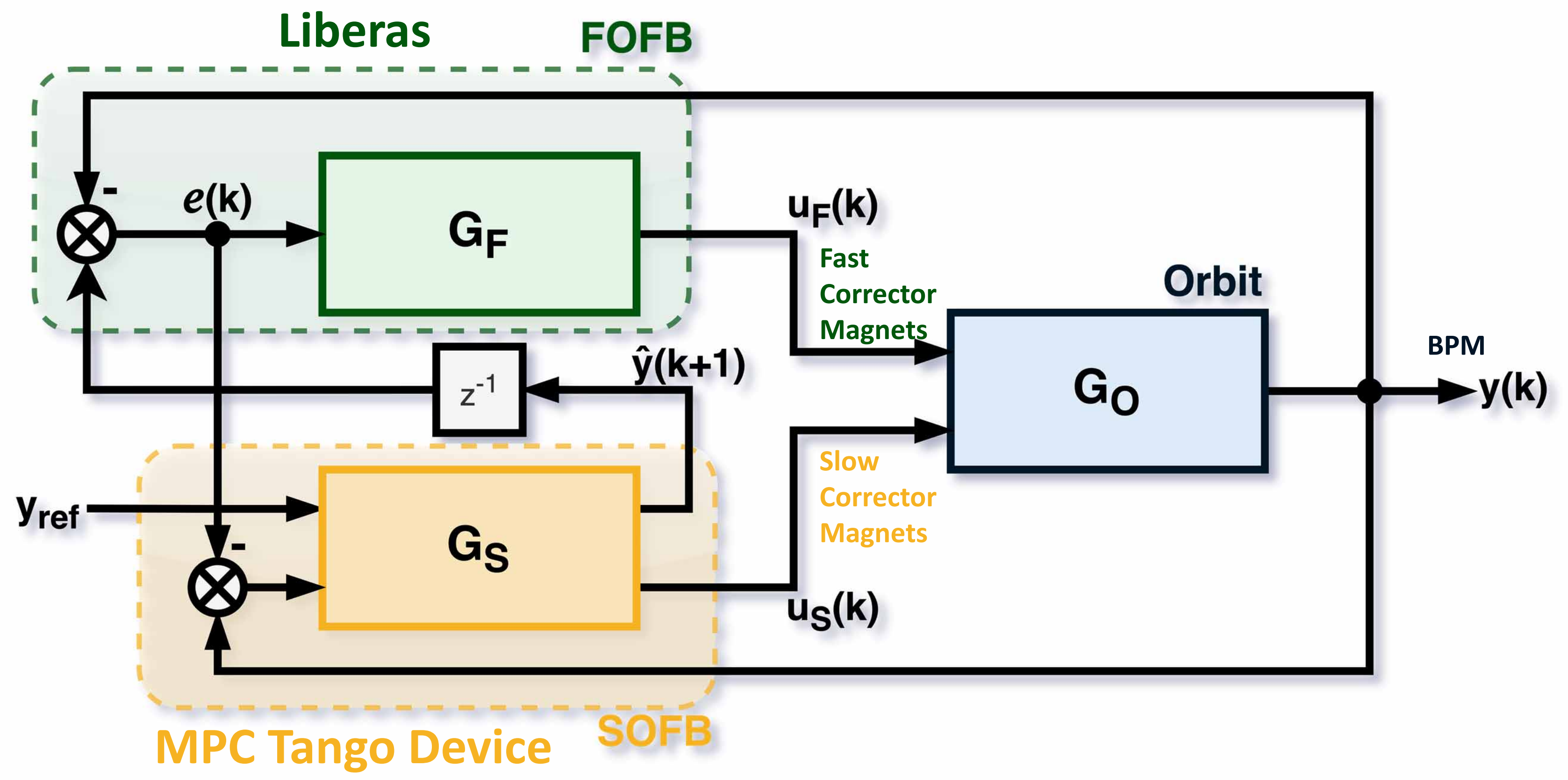
$$\text{s.t.} \quad \boldsymbol{x}_{k+1} = \Phi \boldsymbol{x}_k + \Gamma \boldsymbol{u}_k$$

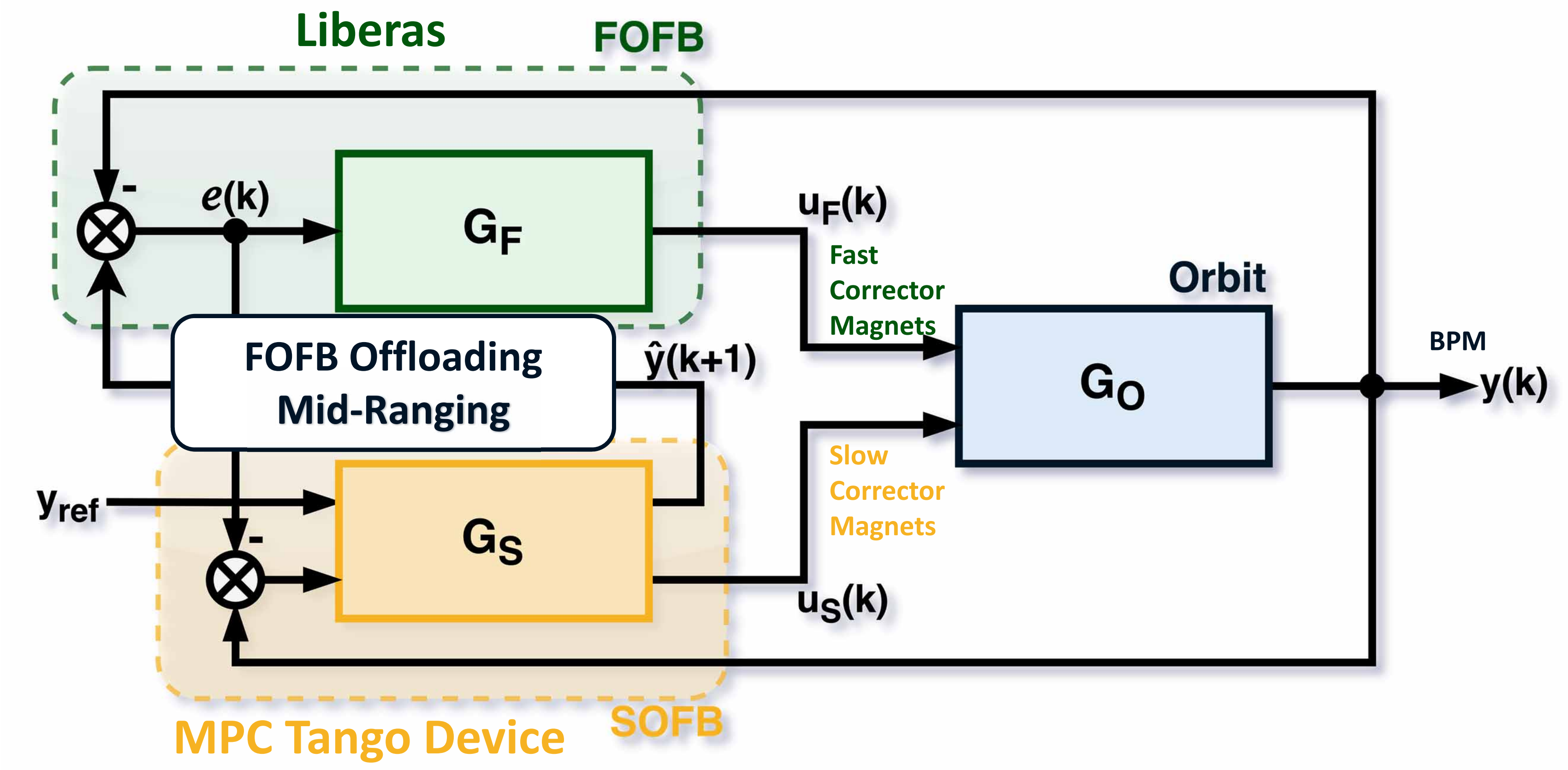
$$\boldsymbol{y}_k = C \boldsymbol{x}_k$$

$$\overline{\boldsymbol{x}} = \boldsymbol{x}_0$$

$$|\boldsymbol{x}| \leq \boldsymbol{x}_{max}$$

$$|\boldsymbol{u}| \leq \boldsymbol{u}_{max}$$


Liberas
FOFB
e(k)
GF
uF(k)
Fast
Corrector
Magnets
Orbit
GO
BPM
y(k)
z-1
ŷ(k+1)
yref
GS
Slow
Corrector
Magnets
uS(k)
SOFB
MPC Tango Device

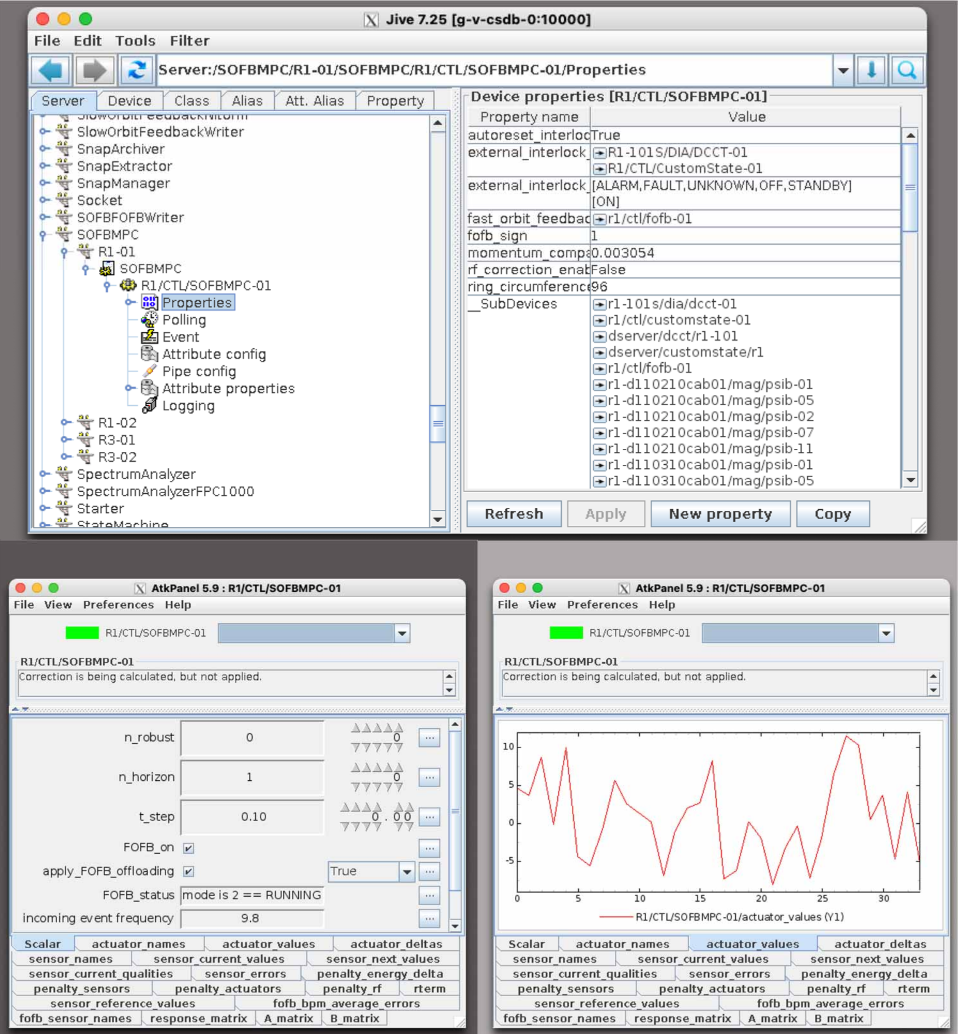

Liberas
FOFB
e(k)
G_F
$u_F(k)$
Fast
Corrector
Magnets
Orbit
FOFB Offloading
Mid-Ranging
ŷ(k+1)
G_O
BPM
y(k)
y_{ref}
G_S
Slow
Corrector
Magnets
$u_S(k)$
MPC Tango Device
SOFB

Mid-ranging Interaction with FOFB

- Saturation is an issue for both the Fast Orbit FeedBack fast correctors and the Slow Orbit FeedBack slow correctors.
- The Fast Correctors should optimally be working in the middle of its operational range.
- A mid-ranging design was in implemented to offload the strain on the FOFB system.
- The reference value of the MPC is adjusted to match the middle of the rage which the FOFB is working.
- This offloading occurs every 5s.

Tango Device

SOFB MPC implementation using PyTango Framework

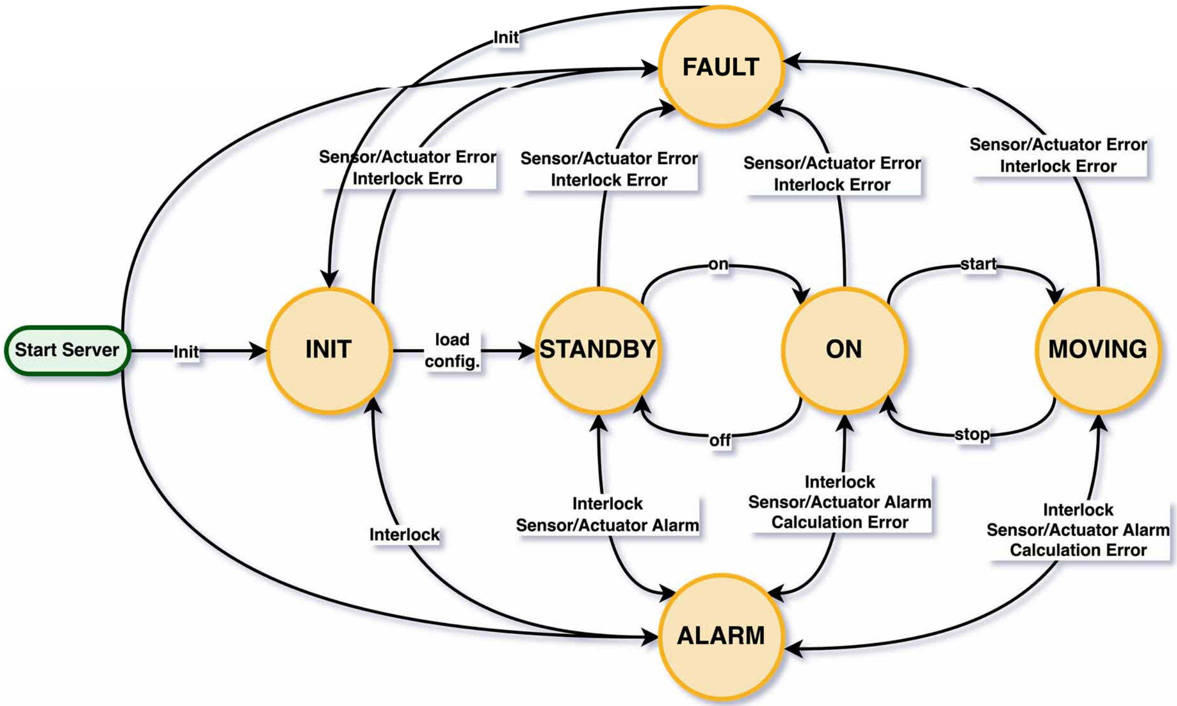


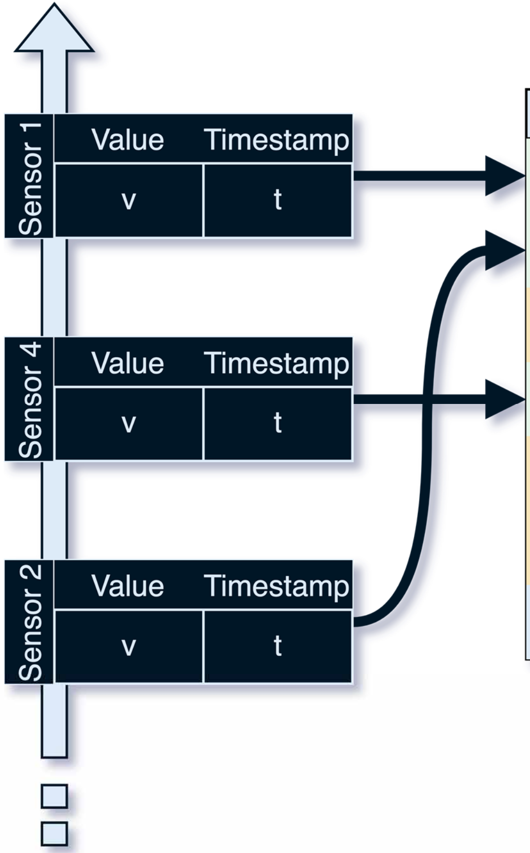
Device Server

- **The device server was implemented using in Python using PyTango framework for distributed control systems.**
- **The Do-MPC library was used for the MPC implementation.**
- **The interaction with the device can be done through Tango's standard GUIs, Jive and Atk Panel.**
- **Aditionaly it is possible to interact with the device using PyTango Client API in Python or its Matlab binding.**

State Handling

- The device transitions to STANDBY when all required cofigurations are finished. The status states which configurations are missing.
- When on ON state, the controller calculates the constrol signal but does not update the MPC state neither apply the control signal to the actuators.
- On MOVING, MPC states are updated and the control signal is applied.
- Issues with read out rates, invalid sensor readings will cause controller to go to a reversible ALARM state.
- Issues with external interlock and sensors or actuators faults will cause device to go to FAULT state, which require human intervention.





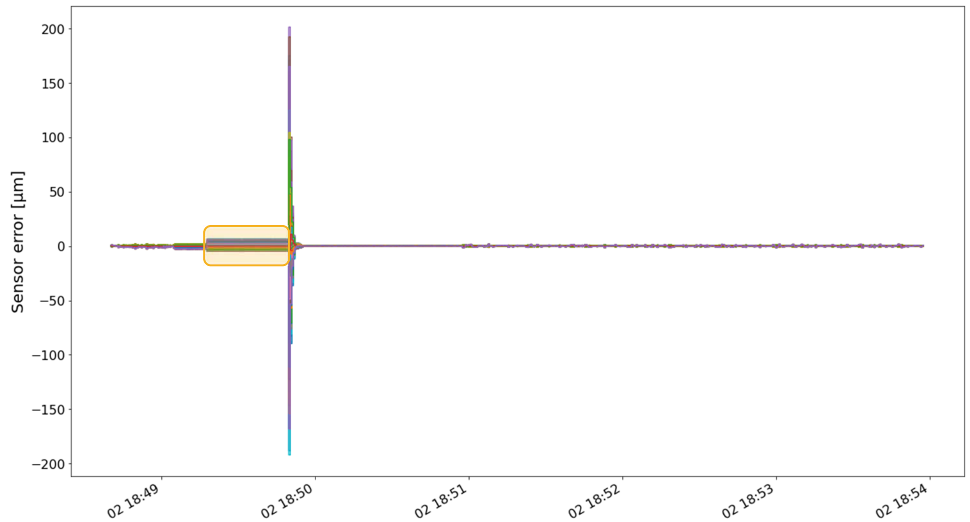
Sensor Index	Timestamp	Sensor Value
1	t	v(1,t)
2	t	v(2,t)
3	t-dt	v(3,t-dt)
4	t	v(4,t)
5	t-dt	v(5,t-dt)
6	t-dt	v(6,t-dt)
⋮	⋮	⋮

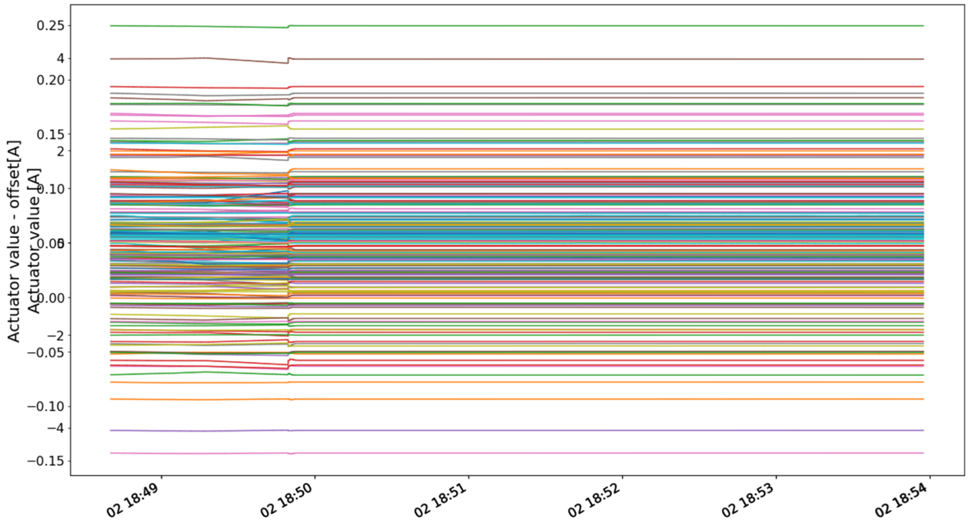
Sensor Events

- The sensors event handling was inherited from the previously implemented orbit controller and it runs on a separated thread from the main control loop.
- For each event that arrives from a sensor, the timestamp and value for that sensor is updated and the spread in the timestamps is calculated.
- Once all events are within a tolerance time range, the sensor signal input can be considered for the next MPC step.

Tests on Storage Ring

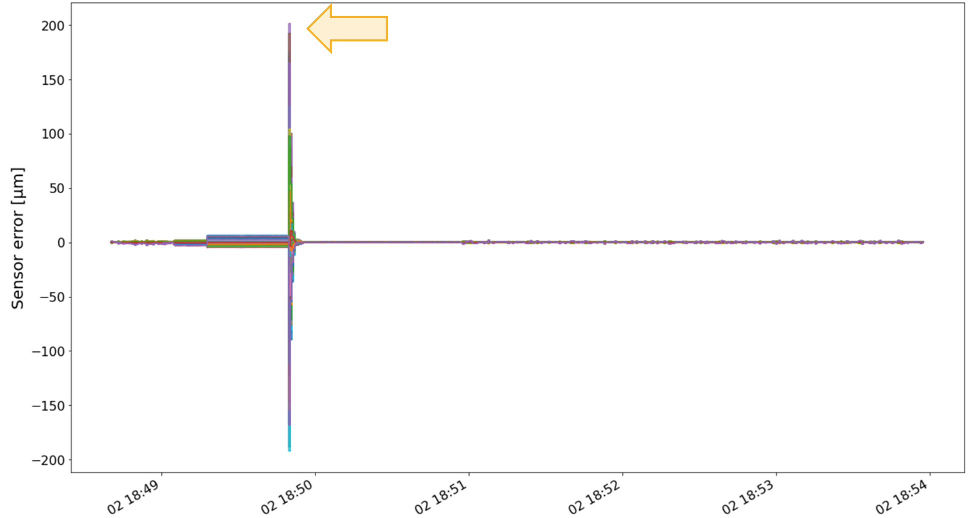
Tests on 3GeV Ring

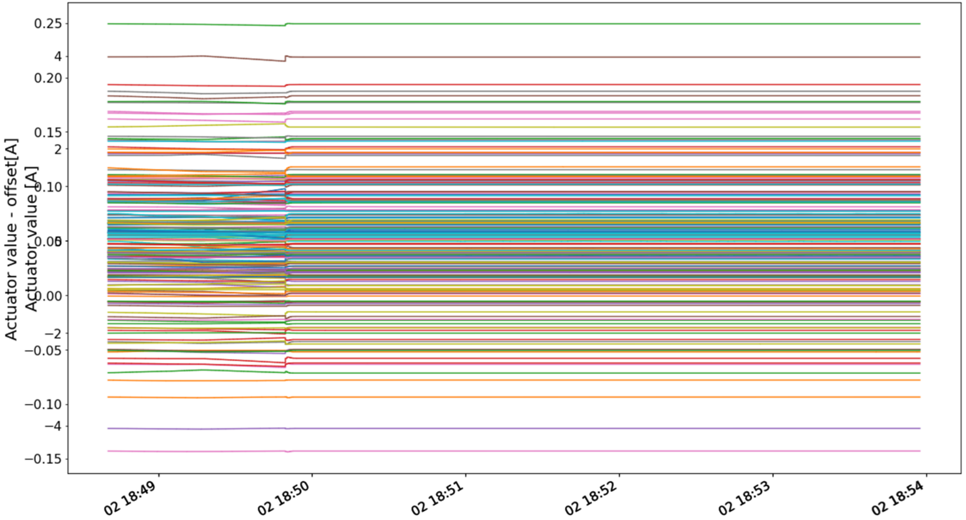




R3 Tests

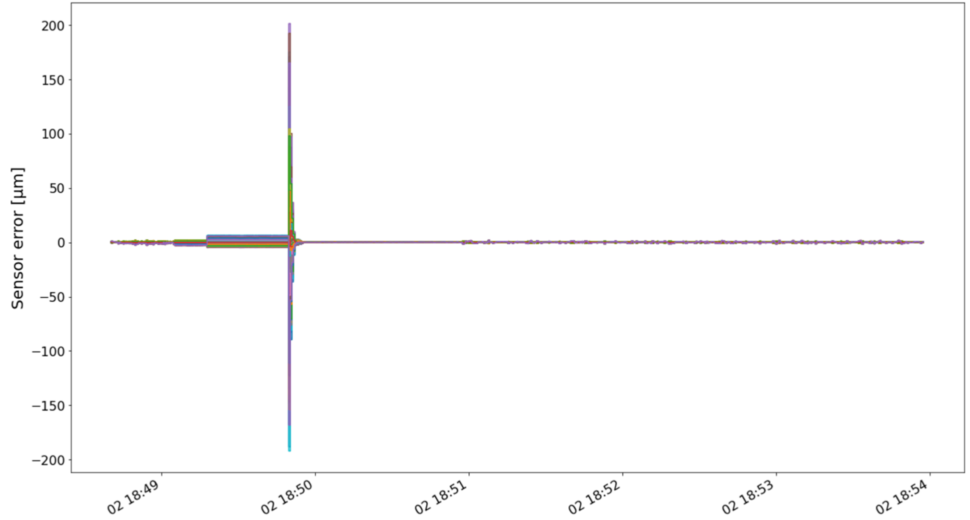
- The starting sensor error as around 20µm.

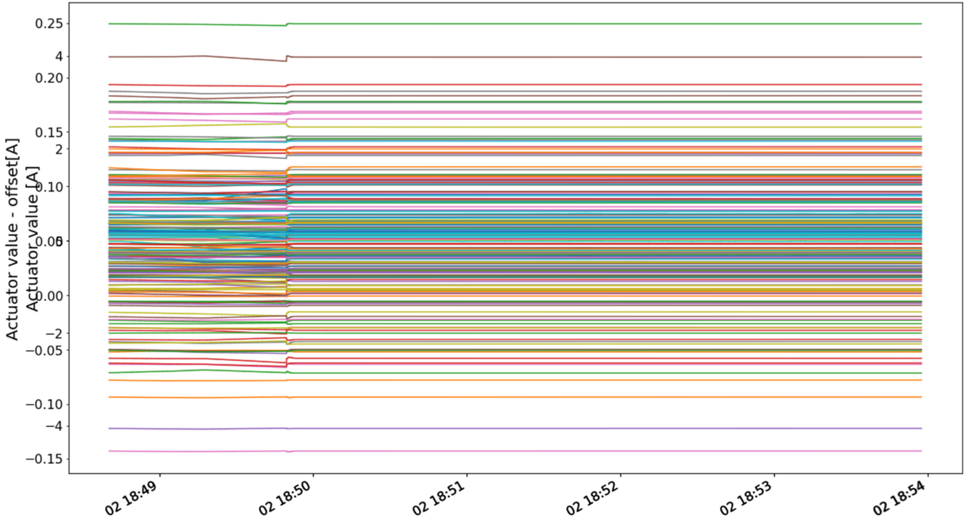




R3 Tests

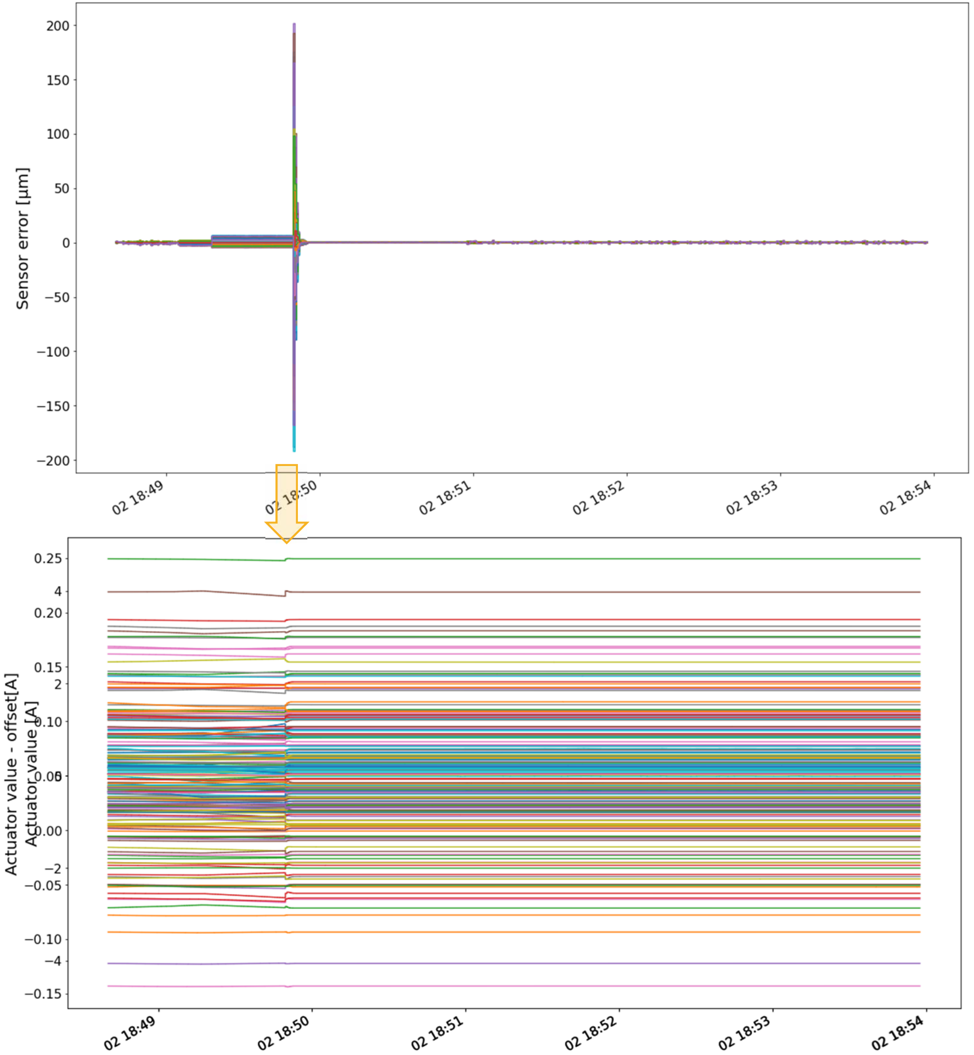
- The starting sensor error as around 20µm.
- When the MPC, started the initial overshoot was around 200 µm.





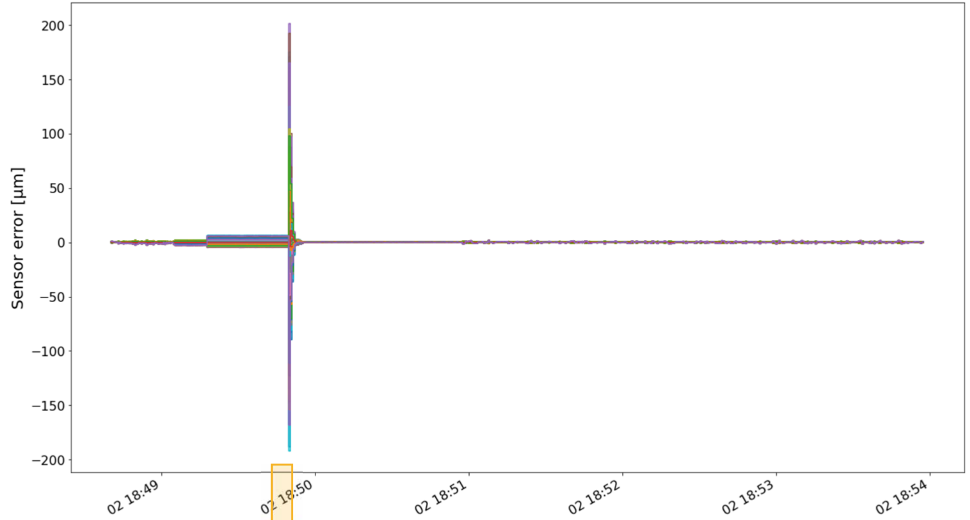
R3 Tests

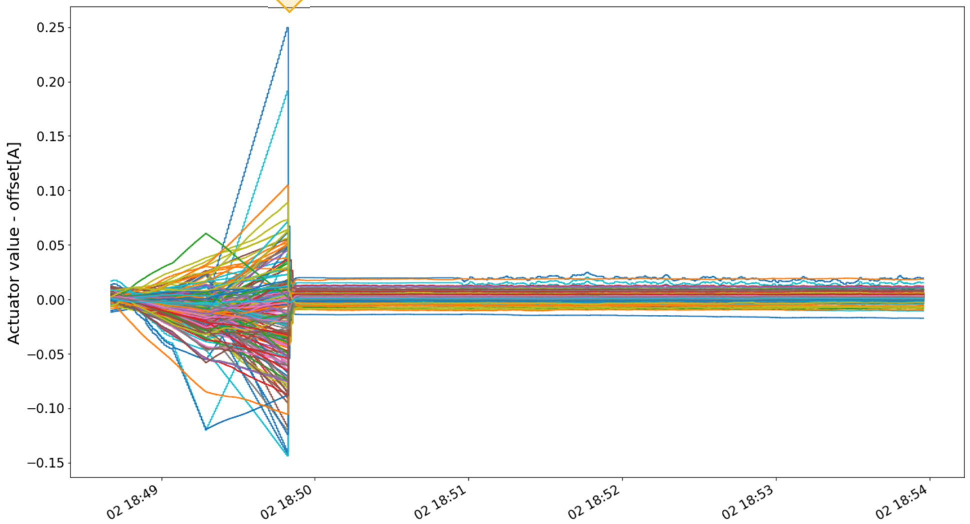
- The starting sensor error as around 20µm.
- When the MPC, started the initial overshoot was around 200 µm.
- Sensor constraints were not defined during this test.



R3 Tests

- The starting sensor error as around 20µm.
- When the MPC, started the initial overshoot was around 200 µm.
- Sensor constraints were not defined during this test.
- On start, actuators had a kick but stabilized, this is more evident if we remove the signal mean.





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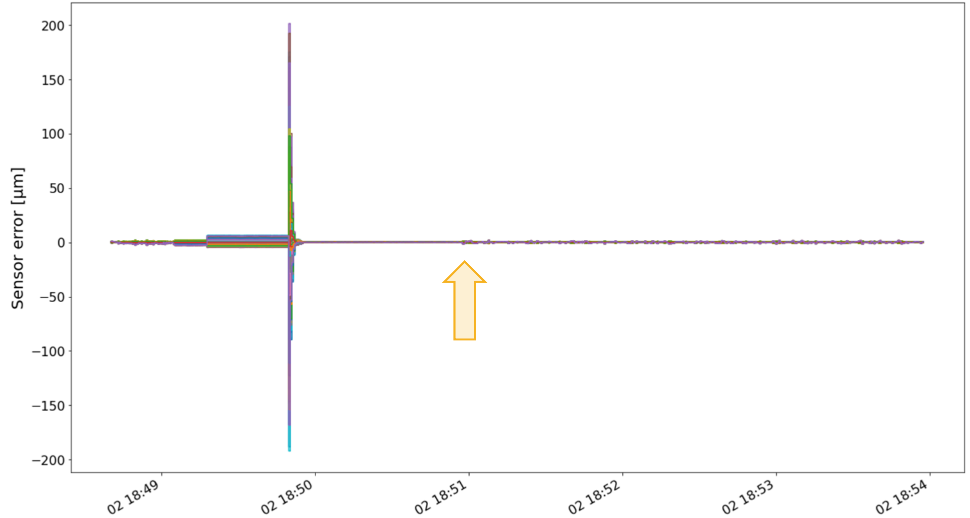
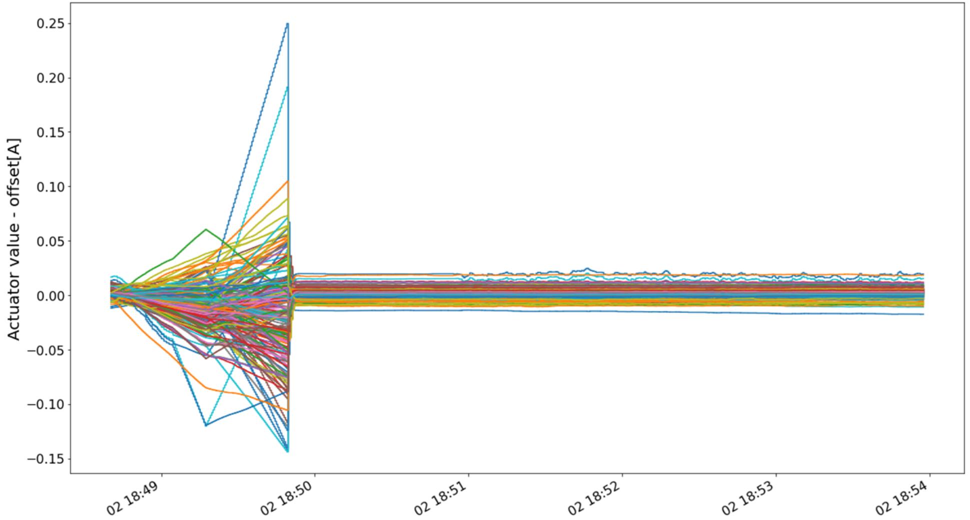
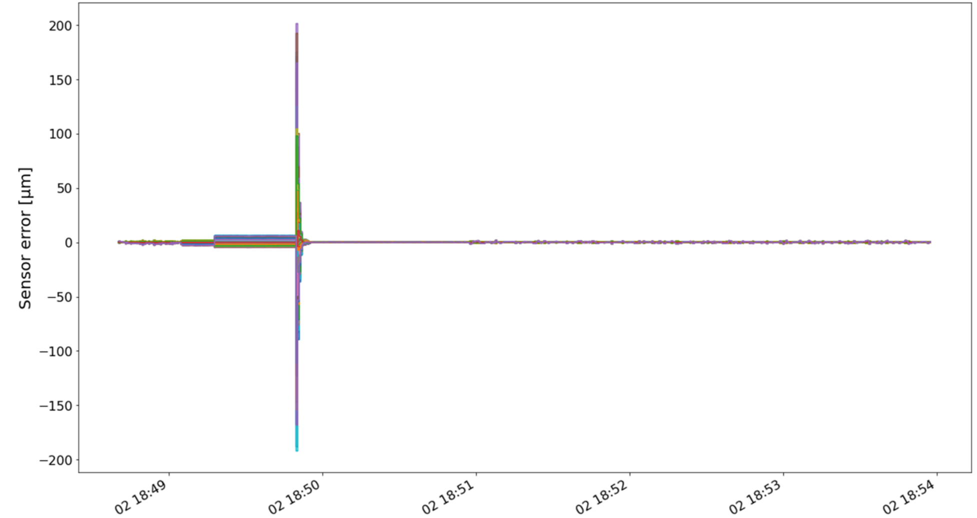
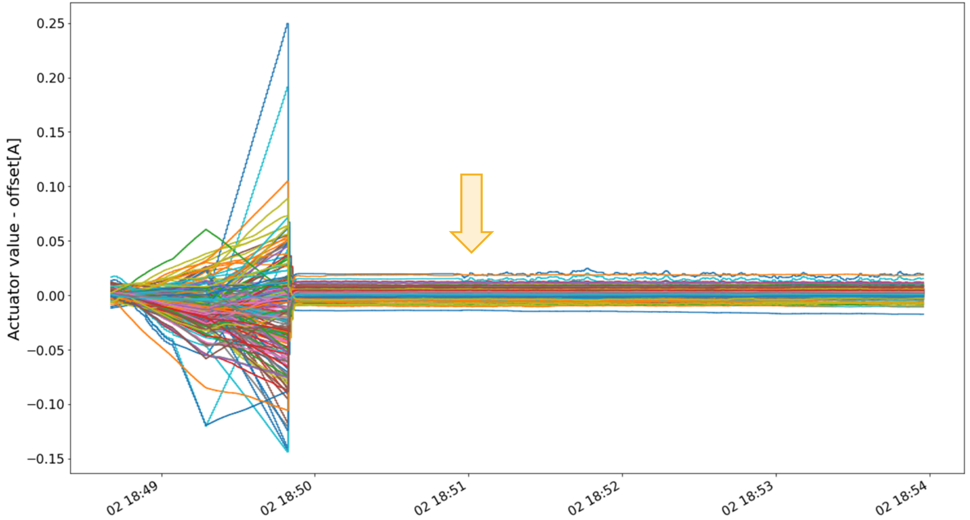




R3 Tests

- The starting sensor error as around 20µm.
- When the MPC, started the initial overshoot was around 200 µm.
- Sensor constraints were not defined during this test.
- On start, actuators had a kick but stabilized, this is more evident if we remove the signal mean.
- The FOFB was started, which introduced some noise.





R3 Tests

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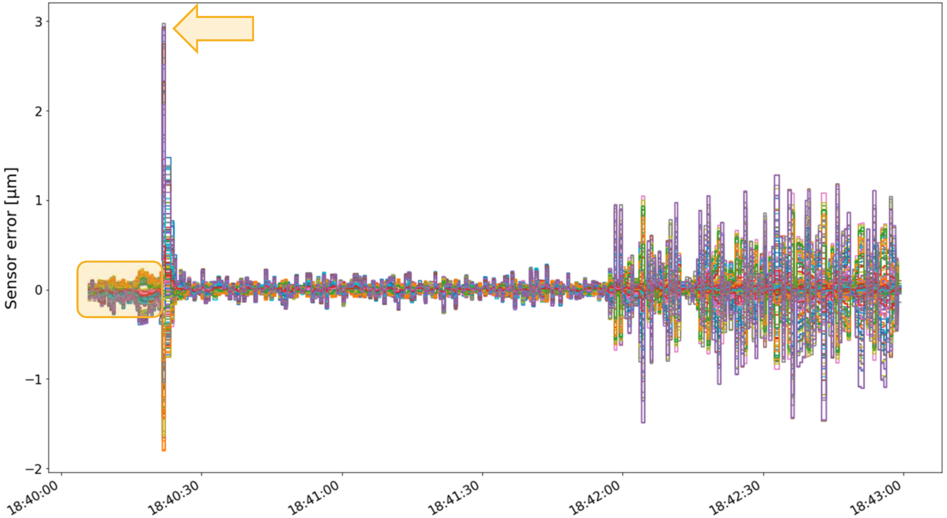
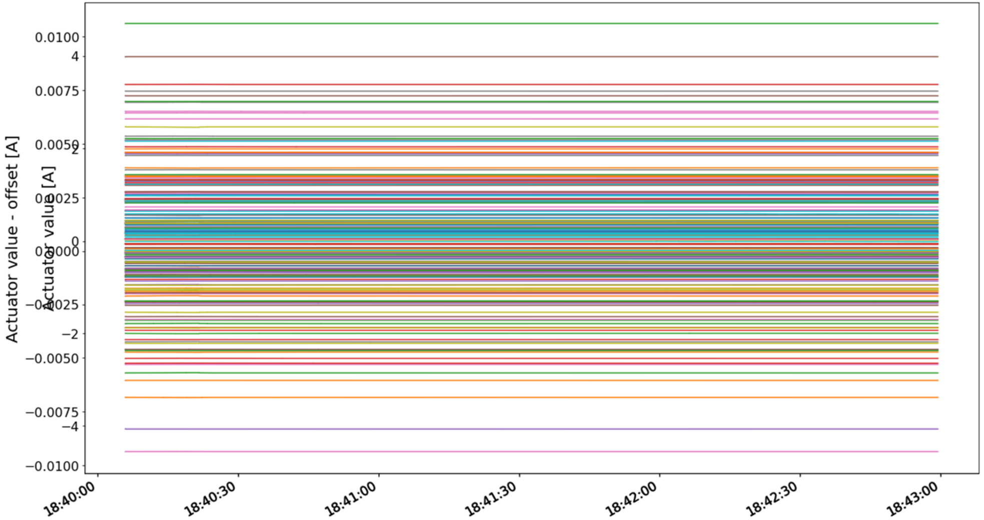
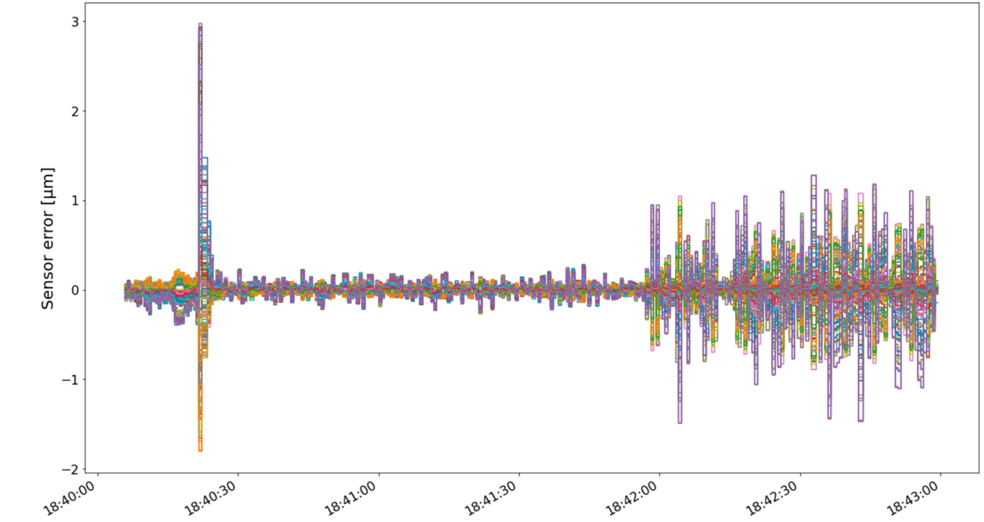
- When the MPC, started the initial overshoot was around 200 µm.
- Sensor constraints were not defined during this test.
- On start, actuators had a kick but stabilized, this is more evident if we remove the signal mean.
- The FOFB was started, which introduced some noise.
- The actuation level remained stable

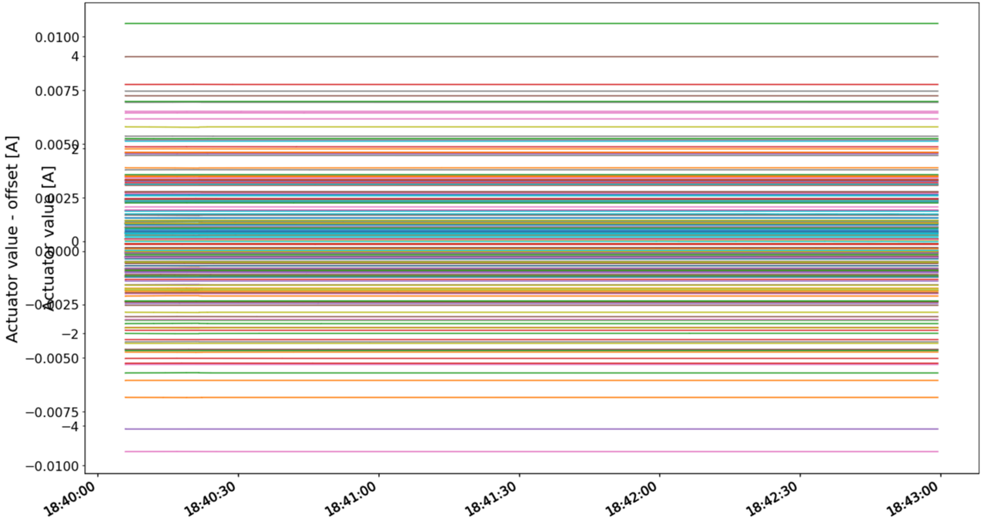




R3 Tests

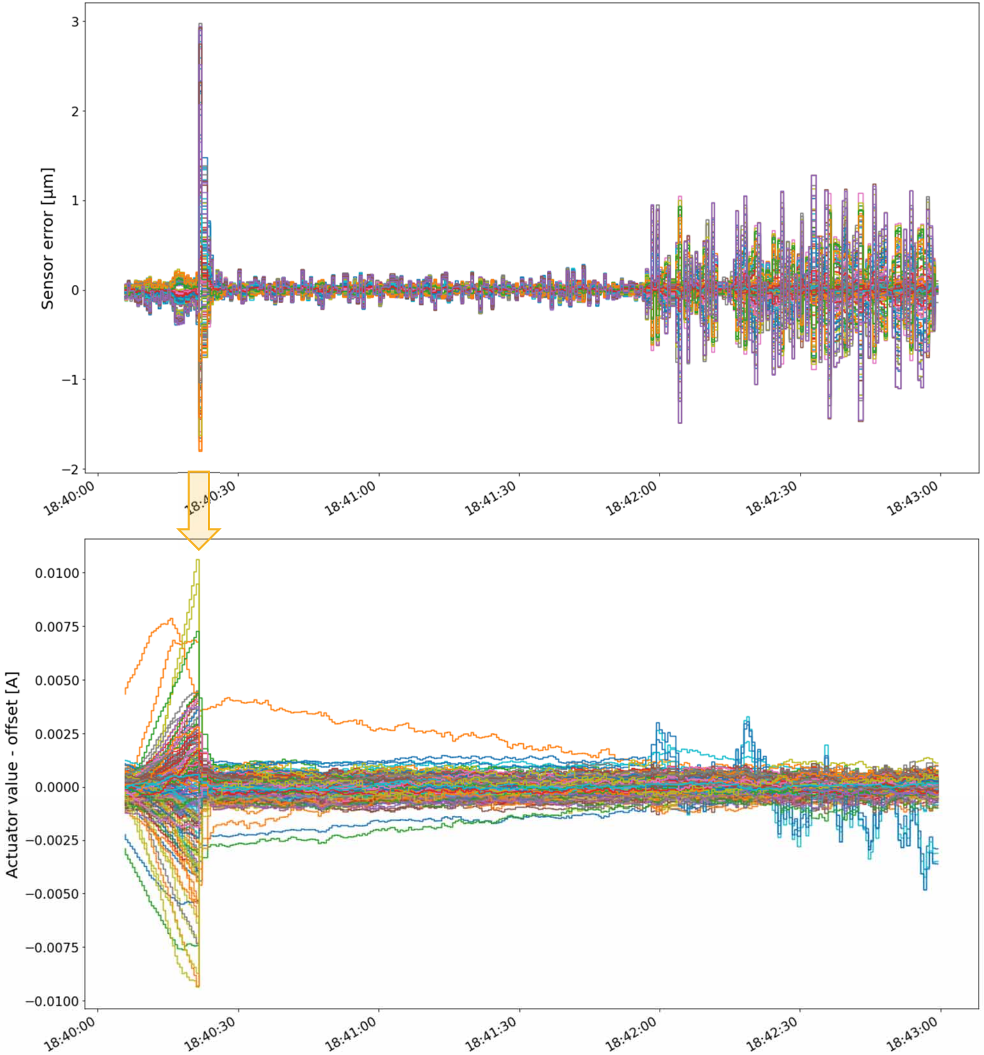
- When the MPC was started with the sensors near the setpoint, the overshoot was significantly smaller.





R3 Tests

- When the MPC was started with the sensors near the setpoint, the overshoot was significantly smaller.
- The actuators kick is barely noticiable in this case, but it is possibel to see the chages around the operational mean values.



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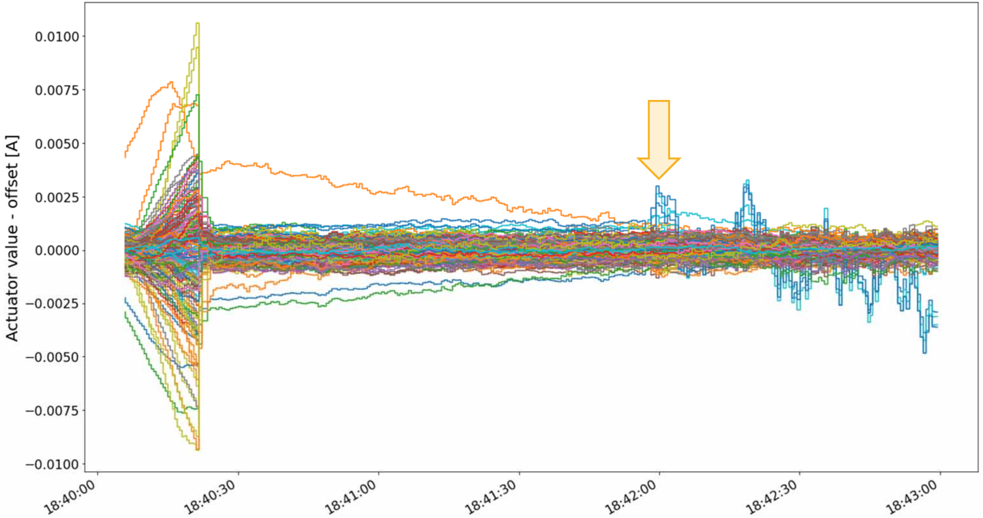

R3 Tests

- When the MPC was started with the sensors near the setpoint, the overshoot was significantly smaller.
- The actuators kick is barely noticiable in this case, but it is possibel to see the chages around the operational mean values.
- When the FOFB was started the noise was introduced.

Outcomes

Findings and Room for Improvement

Conclusions

- The slow correctors are working closer to saturation, but do not saturate.
- The controller can recover the orbit from a unwanted position without saturating the correctors.
- Mid-ranging implementation of the FOFB for the MPC controller was a challenge. Since the error of the FOFB system was considered at defined intervals, the states predicted by the MPC would have a higher error during offloading.

Future Work

- The model can incorporate sensor readout delays, to allow shorter control cycles and increase prediction horizon.
- Improve initial guess by incorparating current actuator readouts.
- Improve sensor and control signal variation constraints.
- Known disturbances can be incorporated to the MPC controller to improve states predictions and increase prediction horizon.

Thank you!

Contact info:
carla.takahashi@maxiv.lu.se
magnus.sjostrom@maxiv.lu.se