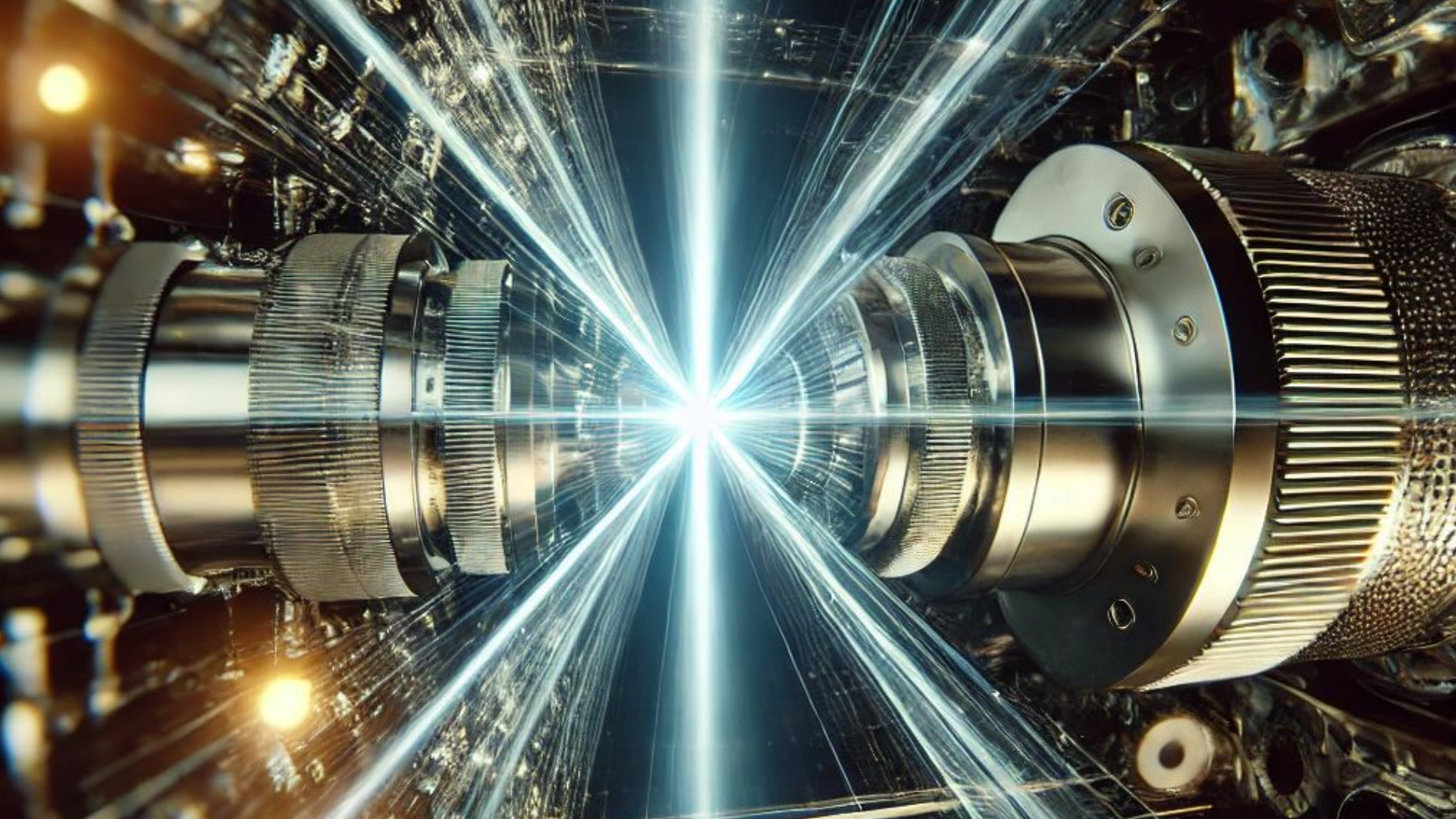


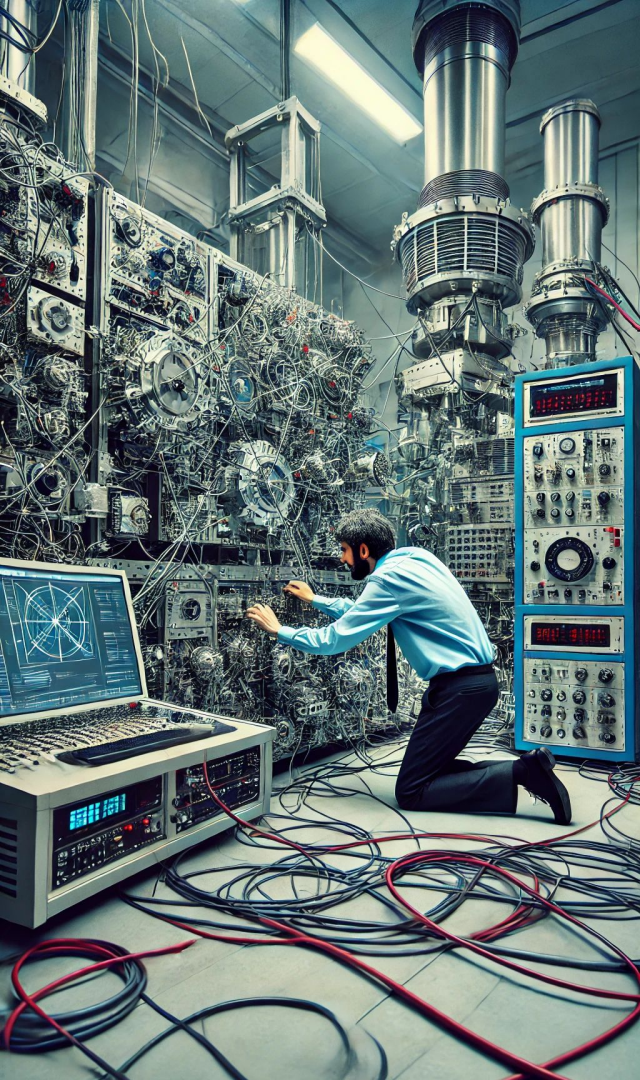
PROPOSTA DI GRANT GIOVANI IN CSN5 ANNO 2024

OPTIMAL

Simone Manti

Frascati, 09/07/2024





Challenges in X-ray Beamline Optimization

Manual Optimization of Parameters

Dependence on human input

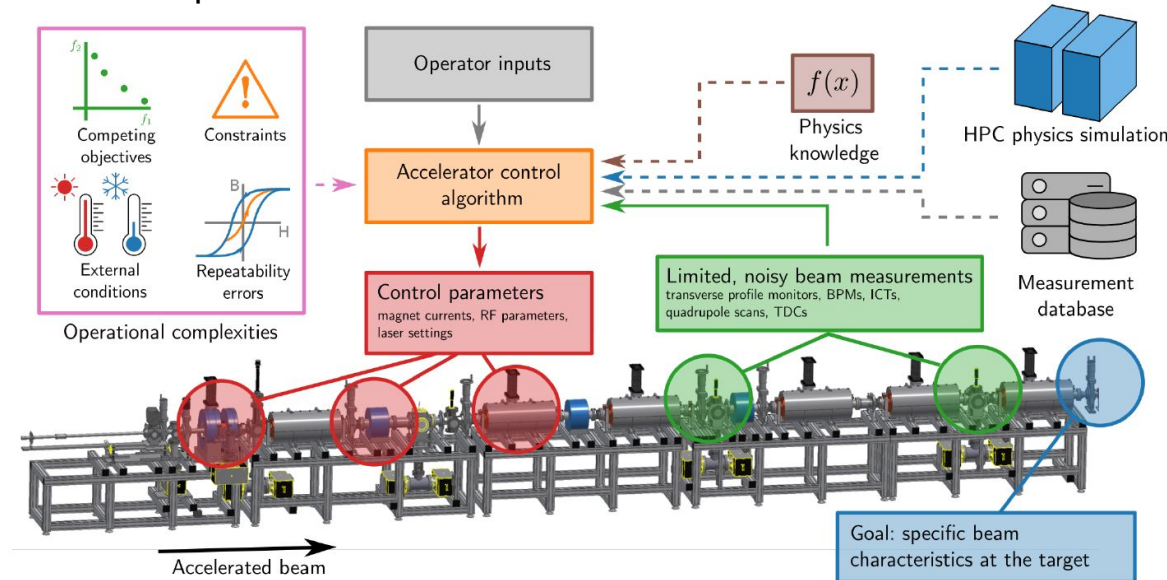
Challenges in reproducibility

Time constraints

State of the Art

Advancements:

- **Machine Learning** algorithms can learn from data to identify optimal settings.
- **Bayesian Optimization (BO)** utilizes surrogate models (Gaussian Processes) to guide optimization, effective for problems with noisy and time-consuming acquisition functions.
- **Reinforcement Learning (RL)** builds a model through iterative feedback suitable for scenarios requiring large numbers of control parameters.



State of the Art

Advancements:

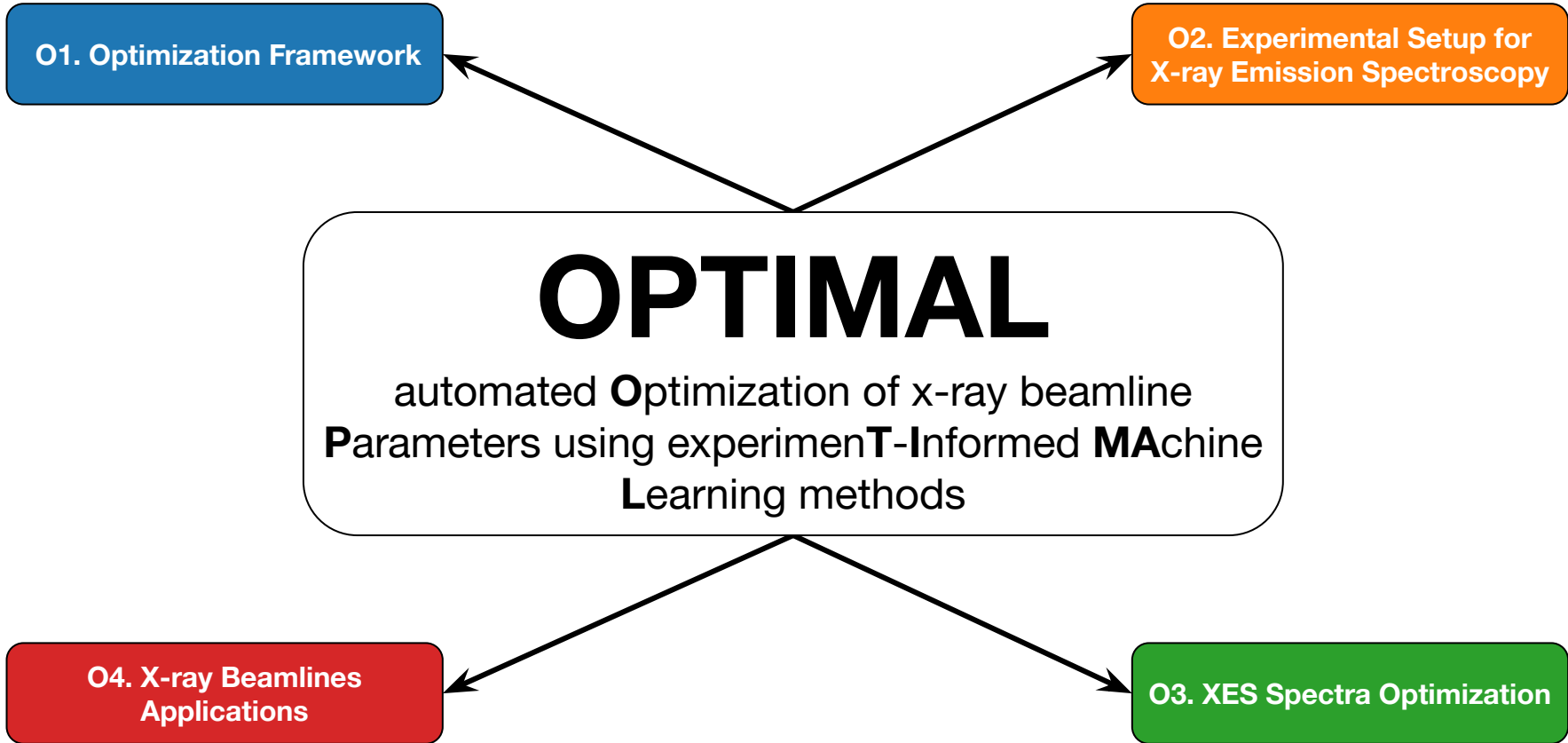
- **Machine Learning** algorithms can learn from data to identify optimal settings.
- **Bayesian Optimization (BO)** utilizes surrogate models (Gaussian Processes) to guide optimization, effective for problems with noisy and time-consuming acquisition functions.
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Applications:

- BO and RL have been successfully applied in various domains, including particle accelerators, detector designs, and laser pulse optimization in Free-Electron Lasers.
- **X-ray Beamlines:**
 - Optimize parameters for X-ray Absorption Spectroscopy
 - Autoalignment of a X-ray focusing system

Current Gaps:

- Fewer applications of BO in X-ray beamlines compared to other areas.
- Opportunity to develop ML-aided techniques to enhance efficiency and in X-ray experiments.



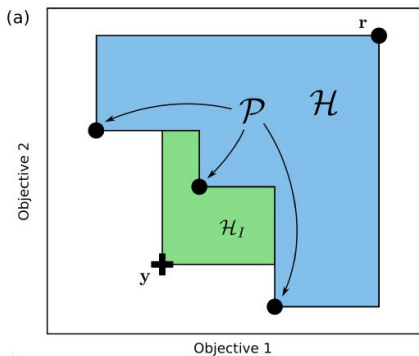
O1. Optimization Framework

Framework for optimizing experiments based on X-ray detection

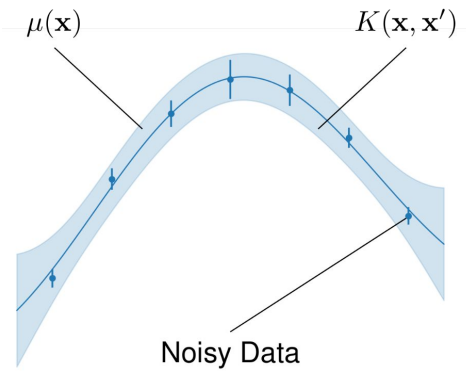
Modules for Data Acquisition, Setup Control, Simulations, and **Multi-Objective Optimization**

Two techniques: **Bayesian Optimization** and **Reinforcement Learning**

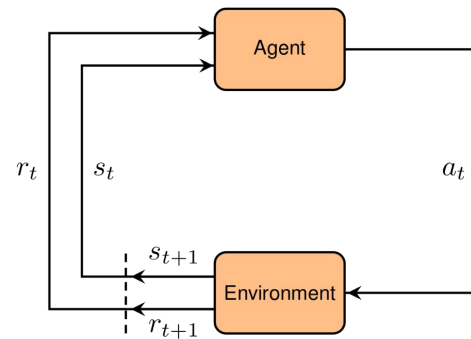
Employ **Machine Learning** models trained on **Ray-Tracing simulations** of the experiment



Pareto Front



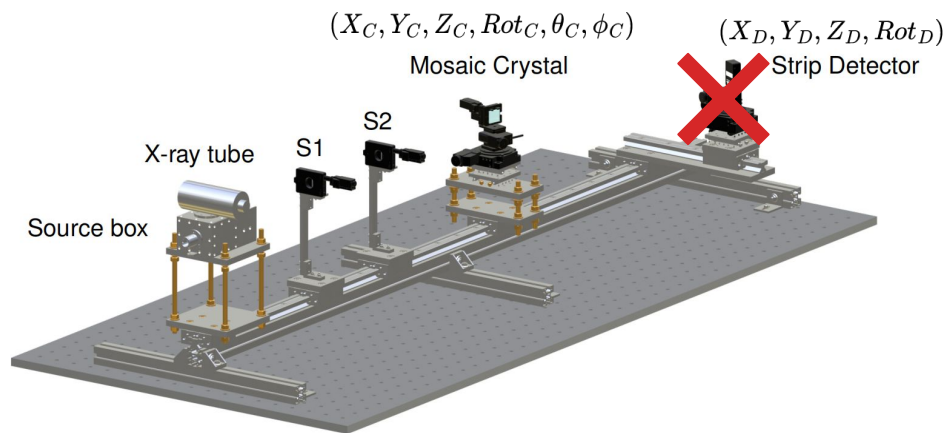
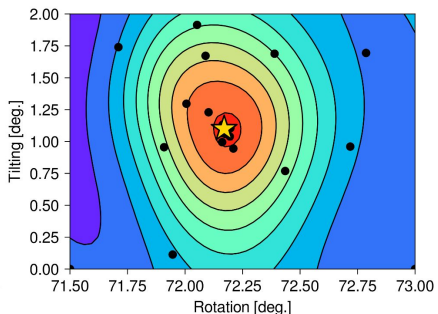
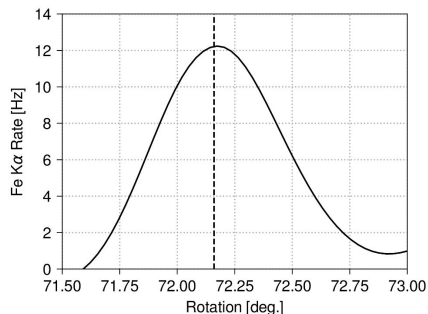
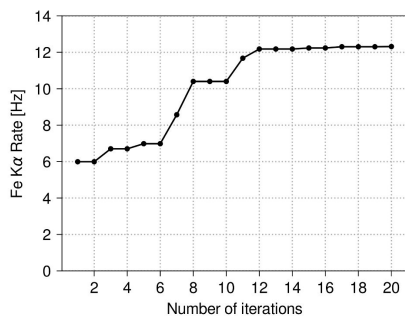
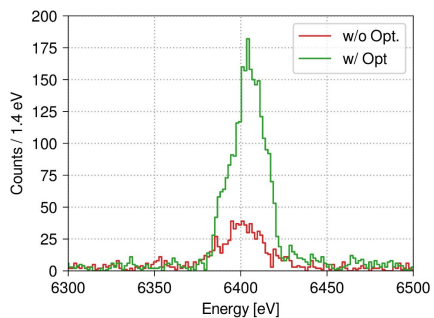
Bayesian Optimization



Reinforcement Learning

O2. Experimental Setup for X-ray Emission Spectroscopy (XES)

I performed **feasibility test** at the LNF studying FeK α emission line, have shown that optimizing parameters for XES, can lead to a significant improvement of the emission line's rate under study, with a gain of a **factor 10** in the **overall acquisition time**



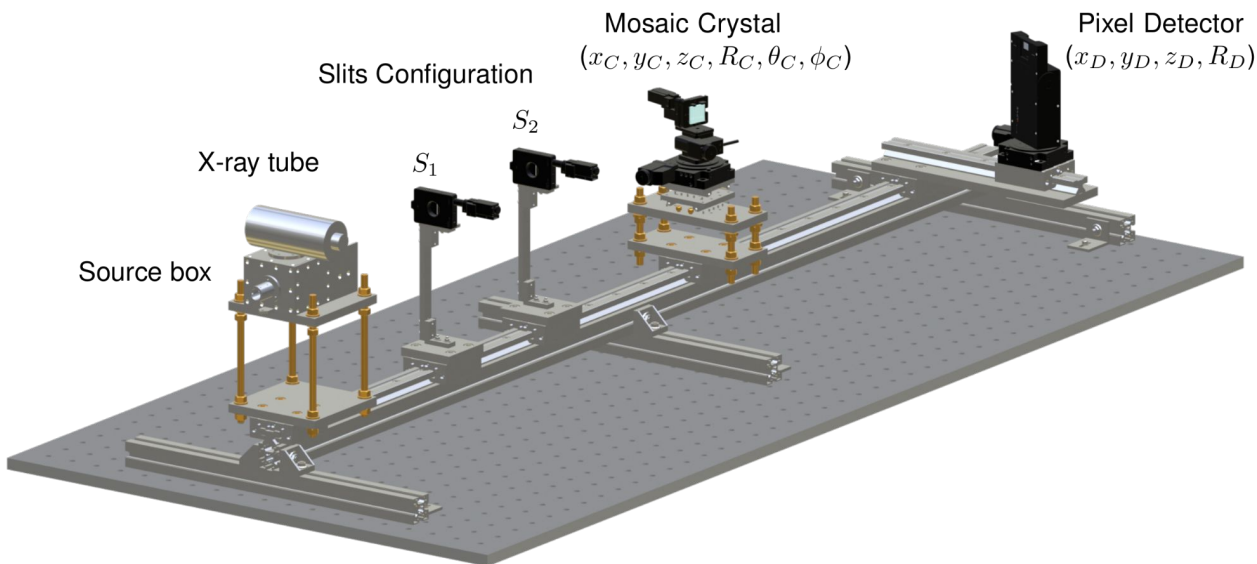
The current VOXES setup is inadequate for this purpose, as a **Strip Detector** with 1D spectra data limits the effectiveness of ML features extraction for the optimization loop!

O2. Experimental Setup for XES

A pixel detector with a **2D spectrum** offers significantly more information, enhancing the training phase, and thus the spectral feature extraction part

The best balance solution between cost and project requirements is the **AdvaPIX Timepix3** from **ADVACAM** (Prague, Czech Republic).

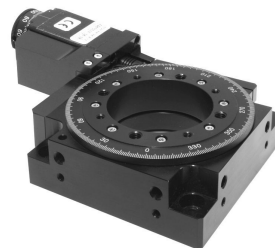
Plus a **4-axis motorized stage** system from **STANDA** company, like the old ones, for their easy communication interface with the framework using the **libximc** package.



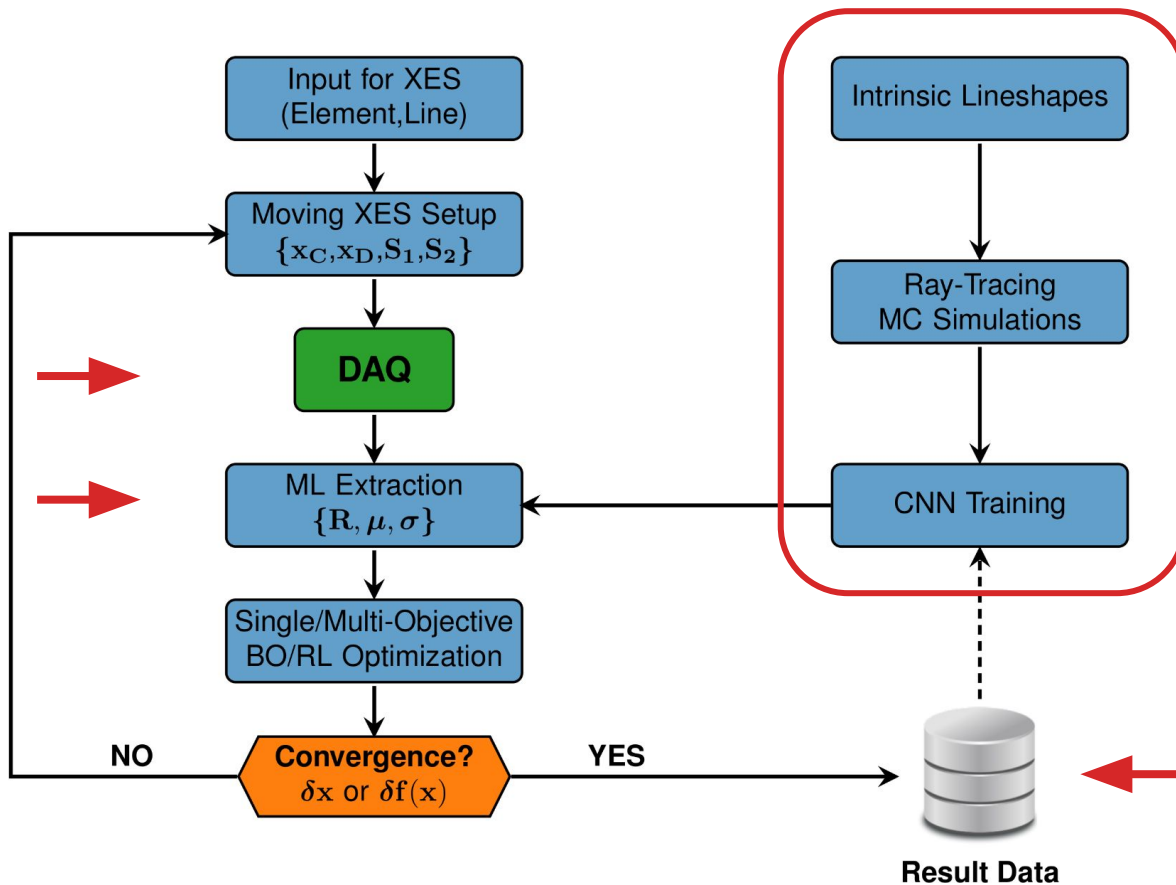
AdvaPIX Timepix3

- Energy range of 5.4 to 20 keV
- Si sensor thickness of 300 μm
- Pixel size of 55 μm
- Resolution 512x256 pixels
- Sensitive Area 14x14 mm

STANDA motorized stage



O3. Spectra Optimization Workflow



Kristian Piscicchia, Sandro Donadi, **Simone Manti**, Angelo Bassi, Maanel Derakhshani, Lajos Diósi, Catalina Curceanu, "X-Ray Emission from Atomic Systems Can Distinguish between Prevailing Dynamical Wave-Function Collapse Models." *Physical Review Letters* 132.25 (2024): 250203.

Simone Manti, Fabrizio Napolitano, Alberto Clozza, Catalina Curceanu, Gabriel Moskal, Kristian Piscicchia, Diana Sirghi and Alessandro Scordo. "Enhancing Performances of the VOXES Bragg Spectrometer for XES Investigations." *Condensed Matter* 9.1 (2024): 19.

Simone Manti, Mark Kamper Svendsen, Nikolaj R. Knøsgaard, Peder M. Lyngby & Kristian S. Thygesen, "Exploring and Machine Learning structural instabilities in 2D materials." *npj Computational Materials* 9.1 (2023): 33.

Simone Manti, Fabian Bertoldo, Sajid Ali & Kristian S. Thygesen, "Quantum point defects in 2D materials-the QPOD Database." *npj Computational Materials* 8.1 (2022): 56.

O4. X-ray Beamlines Applications

Goal:

- Test the possibility of applying the developed optimization framework to the **DAFNE-Light** beam facility at LNF.

Expected Outcomes:

- **Demonstrate Framework's Potential:** Showcase the adaptability of the framework to any X-ray beamline.
- **Identify Applications:** Document potential applications or experiments that can benefit from these enhancements, both within LNF and externally.

Organization

WP1 - Developing the Optimization Framework (Months 1-12)

- D1.1 Technical note on the optimization framework (Month 6)
- D1.2 Documentation on raytracing simulations (Month 6)
- D1.3 Summary of training and validation of ML models (Month 6):
- M1 Framework implemented (Month 12).

WP2 - Assembling the experimental setup (Months 1-15)

- D2.1 Report on the integration of detector (Month 6)
- D2.2 Summary on measurements with the new detector (Month 12)
- M2 Detector integrated (Month 6)

WP3 - Optimization of XES measurement (Months 13-24)

- D3.1 Results of optimization with the new setup (Month 21)

WP4 - Dissemination and Validation of results (Months 19-24)

- M3 Measurement at DAFNE-Light (Month 21)



Simone Manti (INFN,LNF)
FTE:1.0 All WPs



Alberto Clozza (INFN,LNF)
FTE:0.3 WP2



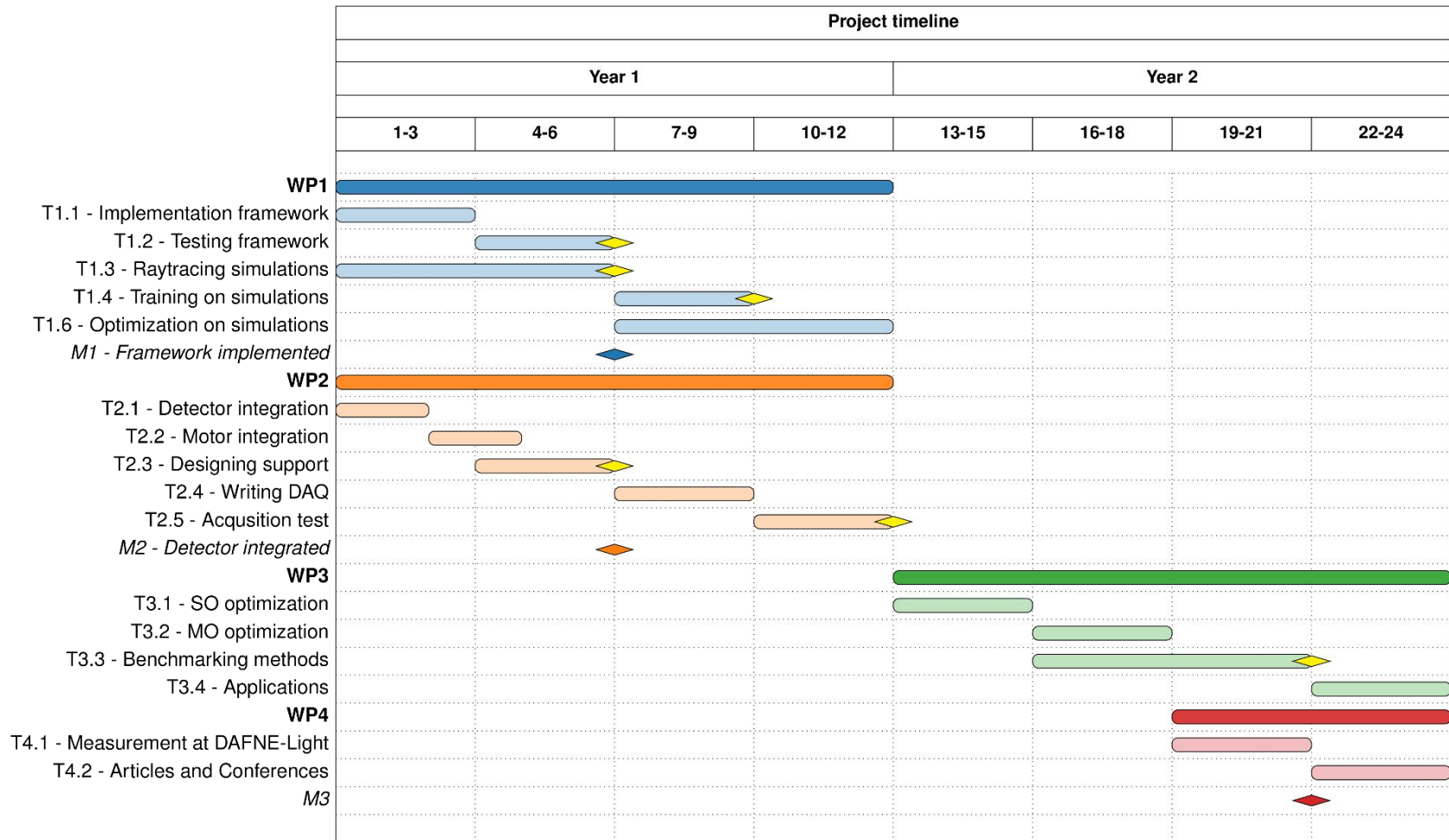
Alessandro Scordo (INFN,LNF)
FTE:0.3 WP1,WP3



Massimiliano Bazzi (INFN,LNF)
FTE:0.1 WP2



Catalina Curceanu (INFN,LNF)
FTE:0.1 WP4



Synergies

INFN Scientific Commissions and Collaborations:

- VOXES (LNF)
- DAFNE-Light (LNF)
- EuAPS (LNF)
- EuPRAXIA (LNF)

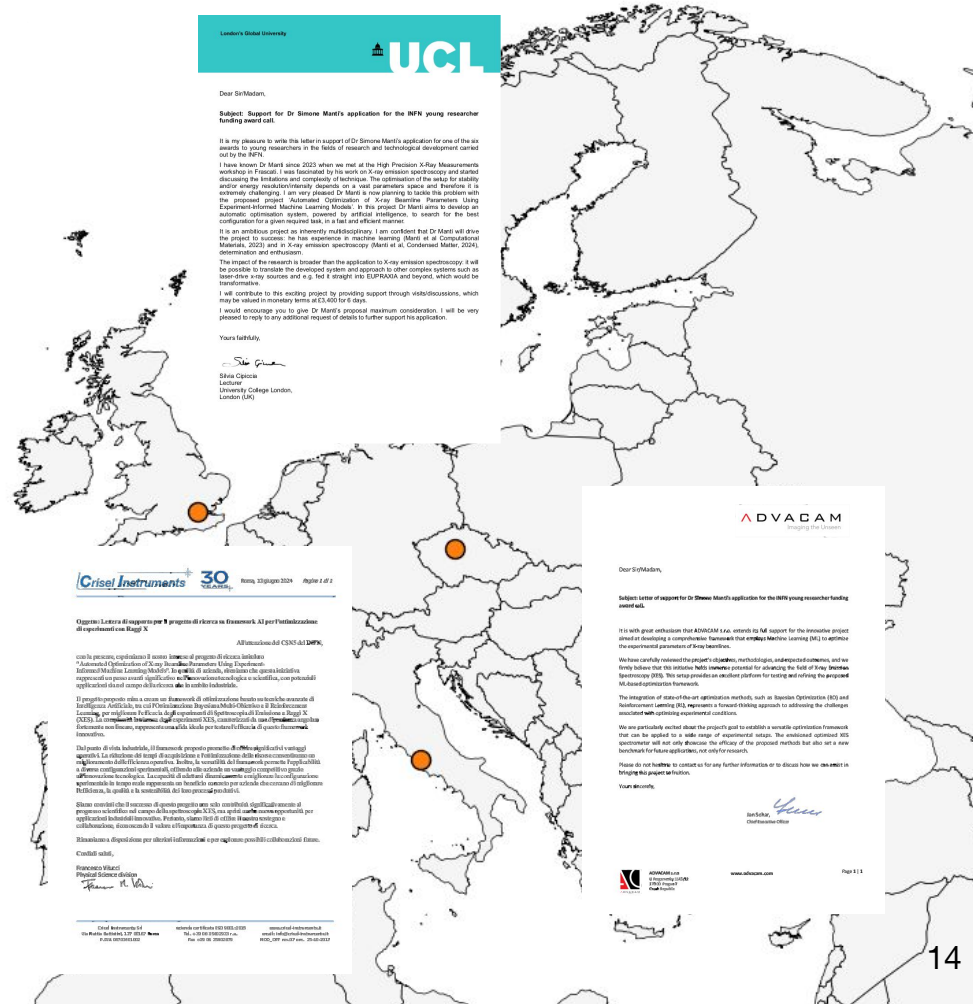
- SPHINX (CSN5)

National and International Research Institutions:

- Advanced X-Ray Imaging Group (London)

Industry and Private Sector

- ADVACAM (Prague)
- CRISEL (Rome)



Cost

The overall cost of **OPTIMAL** is **230 k€**, of which **124 k€** are in-kind contributions, and **106 k€** are requested for the project: **70 k€** for the first year and **36 k€** for the second year of the project.

Year	Activity	Cost (€)	In-Kind Cost (€)
Year 1	XES setup	0	120000
Year 1	Pixel Detector	50000	0
Year 1	Motors	10000	0
Year 1	Support	3000	0
Year 1	Workstation + GPU	7000	0
Year 2	Jetson Xavier GPU	3000	0
Year 2	Travel to AXIm	0	4000
Year 2	Target elements	2000	0
Year 2	Publications	3000	0
Year 2	Conferences	3000	0
Year 2	Travel	15000	0
Year 2	Workshop	10000	0
Total Cost	-	106000	124000

In-kind contributions:

- XES Setup
- Travel to AXIm

Financial requests:

- Setup
- Publications
- Dissemination

Support to LNF Services

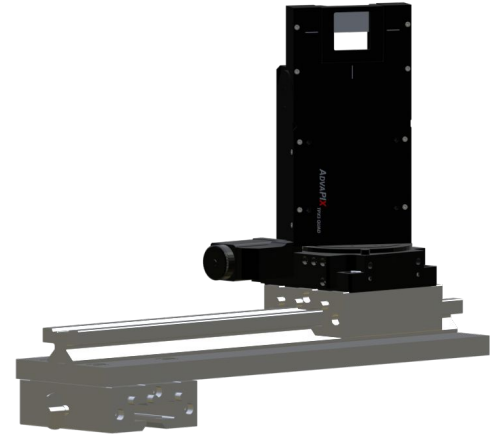
Design Services (0.5 Man-Month):

- **CAD Modeling:** Detailed 3D models for integration support of the **pixel detector** and **motorized stages** with the VOXES setup.

Mechanical Workshop Services (0.5 Man-Month):

- **Custom Fabrication:** Precision fabrication and mounting of integration supports to perfectly fit with the existing setup.

Pixel Detector
(x_D, y_D, z_D, R_D)



Impact:

- **Advancements in X-ray Beamline Optimization:**
 - Generalized framework for enhanced collaboration and data reproducibility.
 - Open-source software potential.
 - Automation reduces human errors and improves efficiency.
 - Tenfold reduction in acquisition time, leading to cost savings.
- **Social and Technological Benefits:**
 - Improved safety in high-radiation environments.
 - Enhanced efficiency for material science and high-throughput elemental analysis.

Risks Assessment:

- Inaccuracy of Ray-Tracing Simulations (T1.3)
- Data Integration and Feature Extraction Issues (T1.5)
- Delays in Ordering or Integrating New Equipment (T2.1, T2.2, T2.3)
- Single/Multi-Objective Optimization Complexity (T3.1, T3.2)

Conclusion

Challenges in X-ray Beamline Optimization:

- Complex parameter adjustments requiring **innovative solutions**.

OPTIMAL Project:

- Advanced framework using **Bayesian Optimization** and **Reinforcement Learning** with **Machine Learning** for efficient **Multi-Objective optimization**.

Project Organization and Costs:

- Structured approach with **detailed planning** and **budget management**.

Thank you for the attention!

SPARE

Risks Assessment

1. Inaccuracy of Ray-Tracing Simulations (T1.3)

- Risk: The ray-tracing simulations may not accurately describe the XES experiment, as they are typically devoted to X-ray beamlines optics and sources, but they are not optimized for simulating mosaic crystals. Such materials have been indeed included in the XOP package only by M. Sanchez del Rio [17].
- Mitigation: Maintain close contact with the developer of the SHADOW-XOP program, Manuel Sanchez del Rio, to seek assistance to improve the accuracy of the simulations.

2. Data Integration and Feature Extraction Issues (T1.5)

- Risk: Integrating data from different sources and accurately extracting features from XES spectra using deep learning may present technical challenges.
- Mitigation: Use historical data to bridge gaps between simulated and real-world data.

3. Delays in Ordering or Integrating New Equipment (T2.1, T2.2, T2.3)

- Risk: Potential delays in the procurement or integration of the pixel detector and other new equipment could affect project timelines.
- Mitigation: Use a CCD from the VOXES project as a temporary measure to initiate measurements until the pixel detector integration is complete. This CCD, although less efficient and with too small sensitive area, will allow for continued progress on the project.

4. Single/Multi-Objective Optimization Complexity (T3.1,T3.2)

- Risk: Balancing multiple objectives (e.g., acquisition time, energy precision, and resolution) in the optimization process may be complex and computationally intensive.
- Mitigation: Regularly evaluate and adjust the optimization strategies based on intermediate results. Engage with experts in optimization and machine learning to refine and enhance the optimization algorithms. Specifically, contact Lucio Anderlini (Florence Section of INFN), whose expertise in artificial intelligence and deep learning can provide valuable insights and support for the project.