Advancing the Pixelated Resistive Silicon Readout and Charge Collection Techniques

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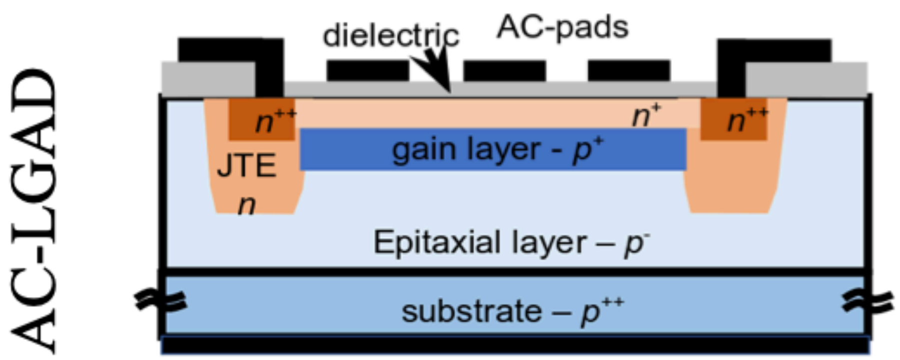
Introduction

- Low Gain Avalanche Diodes (LGADs) and AC-coupled Low Gain Avalanche Diodes (AC-LGADs):



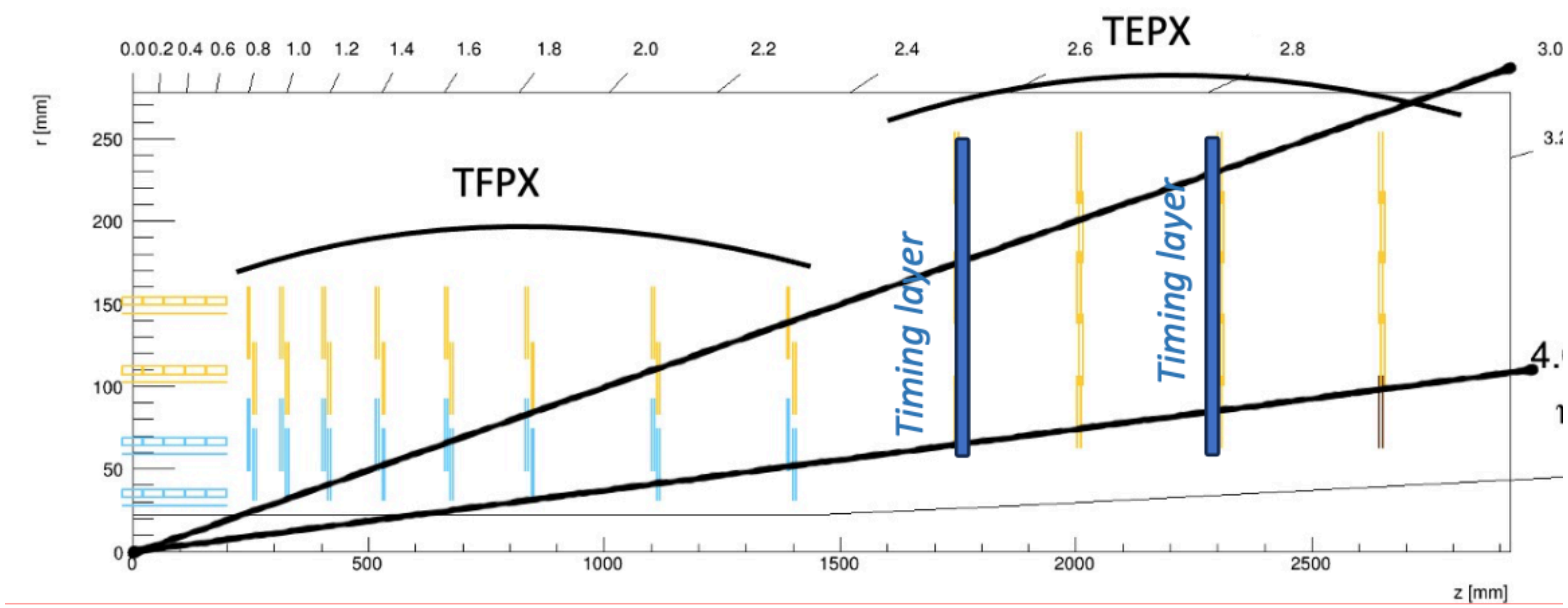
  - AC-pad coupled to the resistive n+ layer via dielectric coupling
  - Not segmented gain layer: 100% fill factor

- Good spatial resolution with a relaxed pitch
  - O(30) ps timing performance and 4D extension with O(10) μm spatial resolution in RSD variant

- Applications:
  - Electron-Ion Collider, LHCb Velo Upgrade, CMS tracker Phase-3 upgrade, FCC-ee.
  - Time of Flight Applications
  - Medical applications.

Introduction

- High Energy Physics Applications in low to moderate radiation regimes: FCC-ee and LHC upgrades:
- High-Luminosity LHC:
  - LHCb Velo Upgrade, CMS tracker Phase-3 upgrade:
    - Extension of CMS timing capabilities in the forward region (currently ETL)
    - Higher rapidity coverage
    - Replace one or two disks, instrumenting them with (AC)LGADs



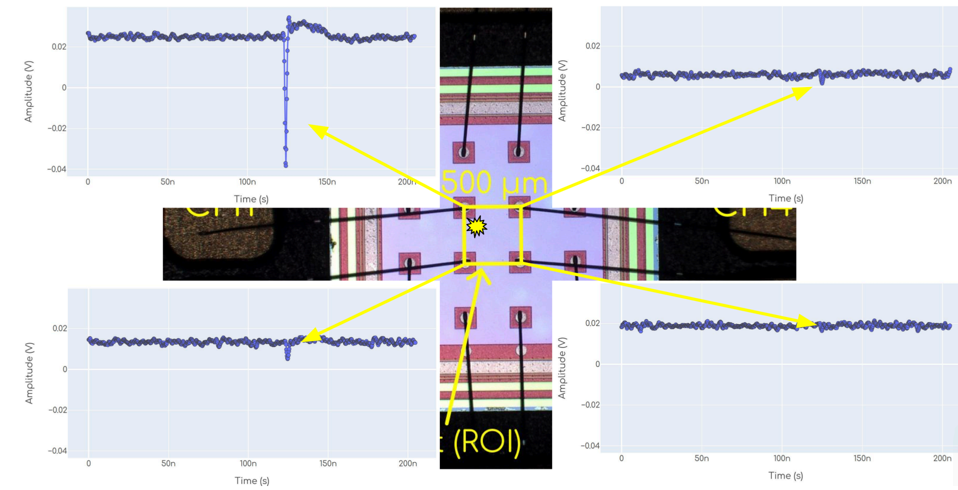
- FCC-ee:
  - Timing capabilities in the outermost silicon
  - Enhance particle identification
  - Reduce the systematic uncertainty on beam energy .

Charge sharing

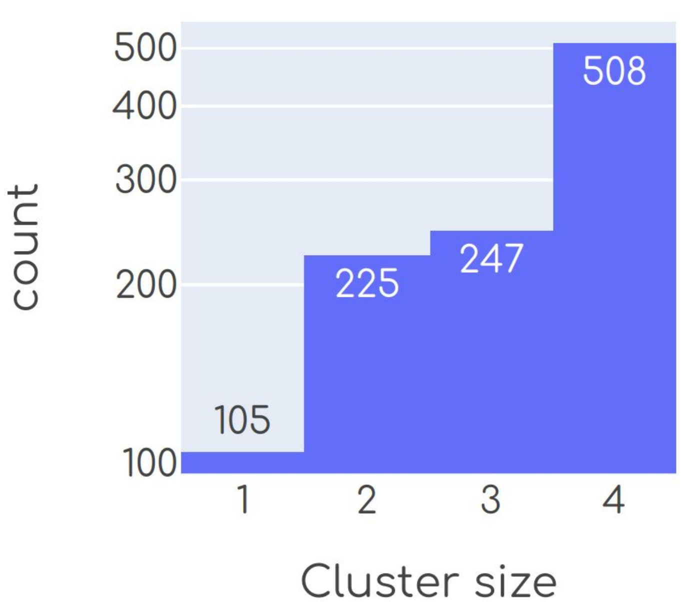
- Increased charge-sharing is an intrinsic property of RSD/AC-LGADs.
  - With α_i the area of each pad i and for r_i the distance between the true hit and the pad i, the signal seen by each pad:

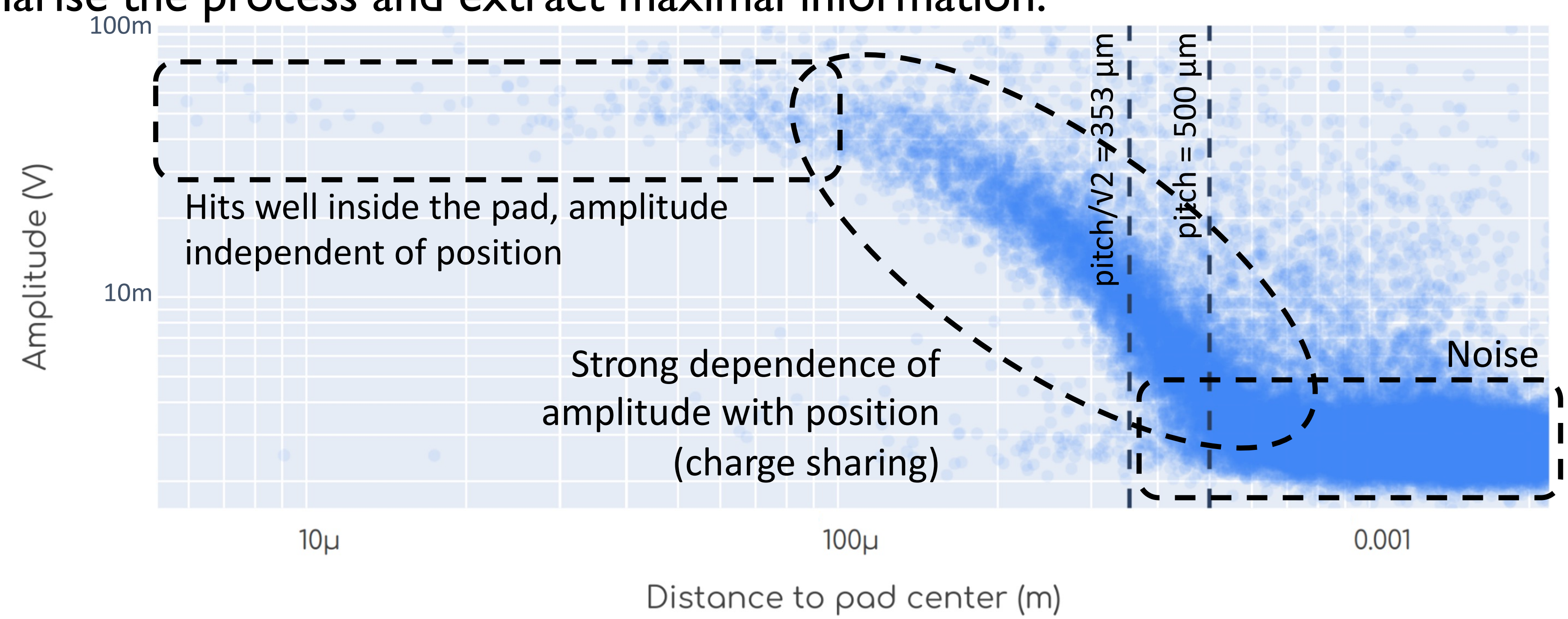
$$S_i = \frac{\alpha_i / \ln r_i}{\Sigma_i^n \alpha_i / \ln r_i}$$

  - Waveforms from all pads coupled → $n \times n$ problem.



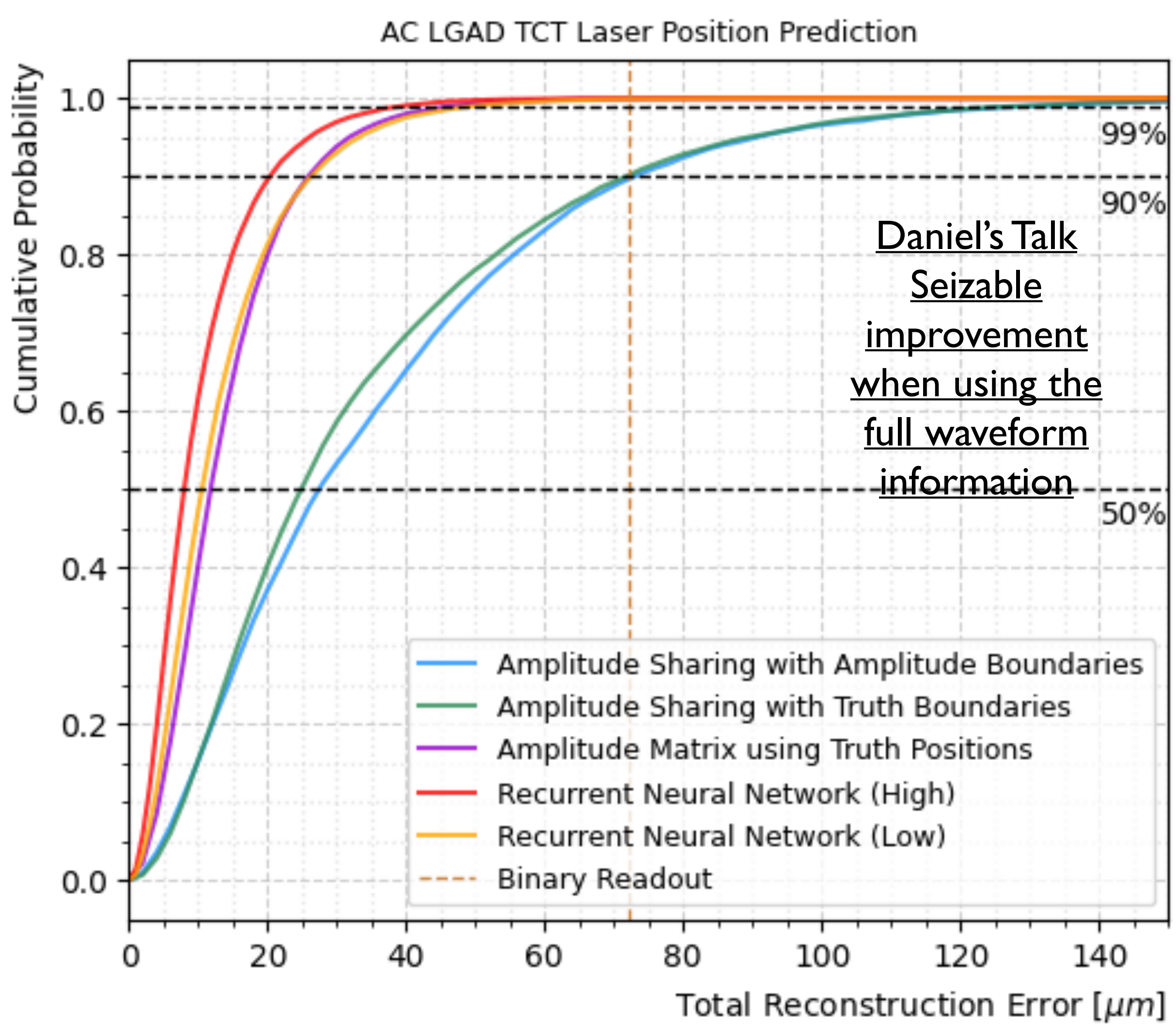
- Noise threshold traditionally puts a limit on the amount of useful *information* in the sharing.
  - How much more information can be recovered?
  - Multiple correlated signals, matrix inversion for position determination:
    - Computationally challenging.
    - Off-diagonal noise leads to large fluctuations and biases.
- Use Machine Learning to regularise the process and extract maximal information.

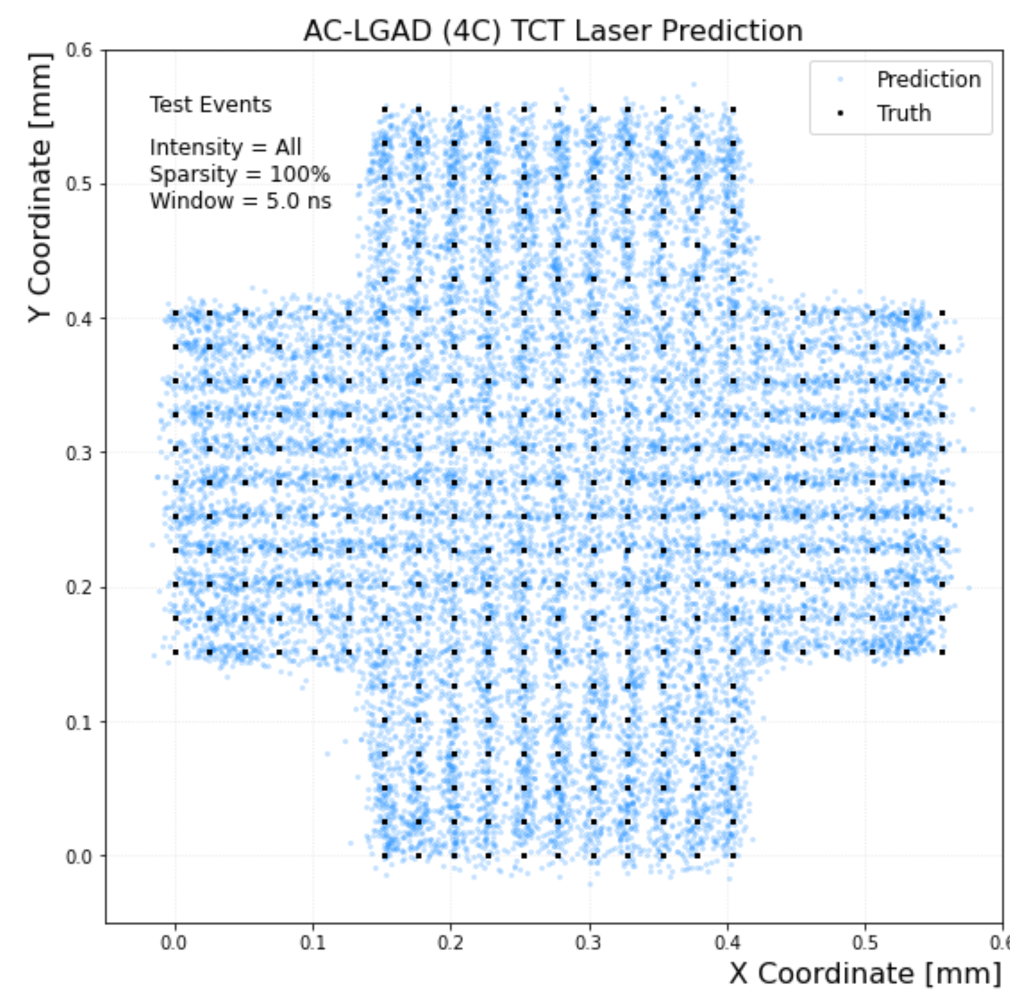




ML

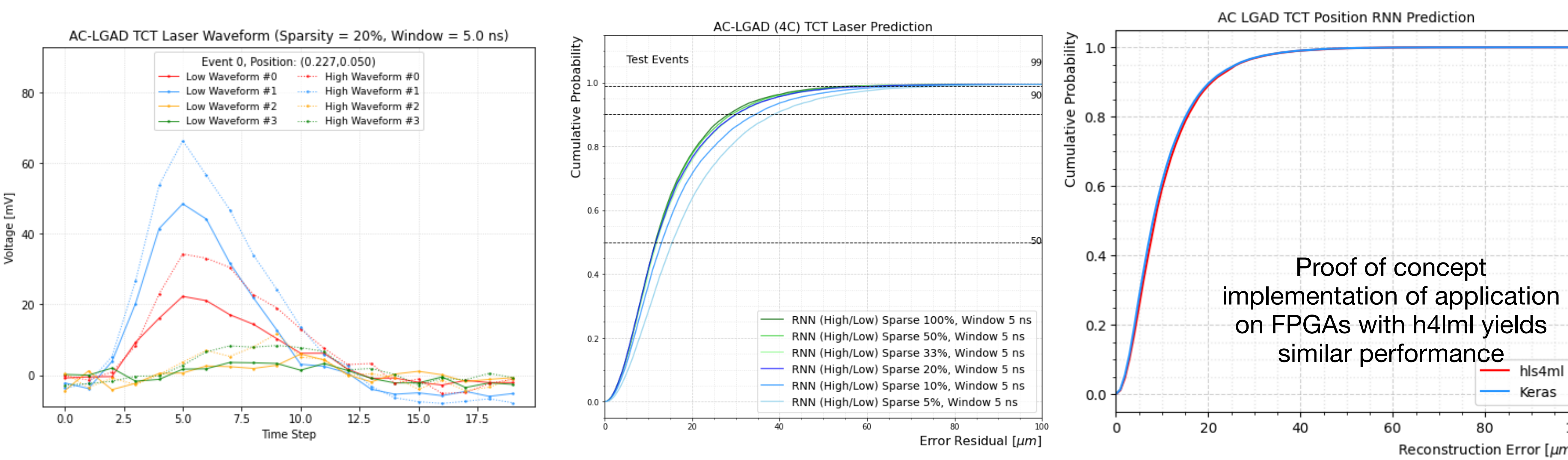
- Use Machine Learning to regularise the process and extract maximal information.
  - Independent of pad arrangement → optimal geometry maximizes position resolution.
  - Full waveform processing → harness shape correlations between leading and all pads.
  - Harness all the information from all the pads, including correlations → improvement of the position resolution.
- Preliminary studies using the full digitized amplitude instead of relative amplitude fractions
  - On lasers indicate a potential resolution of ~ 10 μm from pixels with 500 μm x 500 μm
  - Previous studies using relative amplitude fractions on less advanced networks:
    - ~ 20 μm on same sensor with laser and ~ 44 μm on MIPs





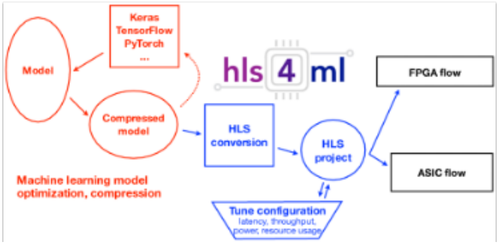
Challenges

- Callenges:
- Landau fluctuations:
    - ➡ Use laser-assisted test beam (MIP) training.
    - ➡ Parametrization as a function of deposited charge.
- Degradation in performance with radiation damage
    - ➡ Parametrization as a function of given fluences.
- ASIC/readout electronics limitation:
    - ➡ Implement processing in off-detector electronics, FPGA
    - ➡ Wave-form rasterization in training/evaluation: preliminary still 10-15 μm resolution on 500 μm x 500 μm pixels.

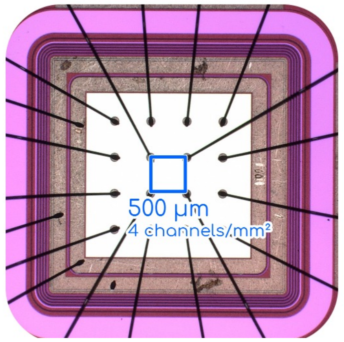


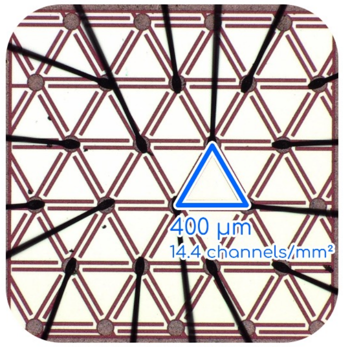
Deliverables

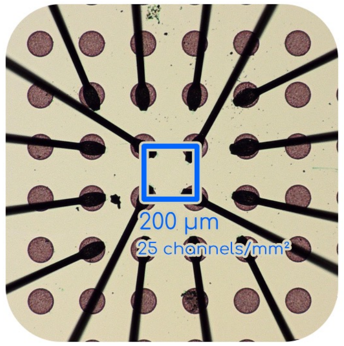
- Our goal:
  - Combining the response from infra-red laser measurements and the responses from test-beam operations as a function of the irradiation dose of the sensors to construct a laser-assisted ML map capable of weighting out the proportion of intrinsic noise.

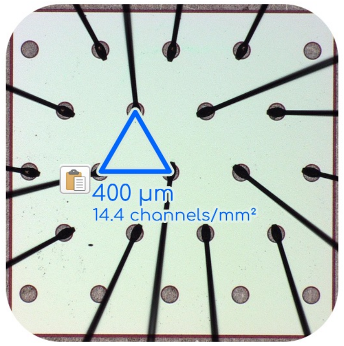


- **O1**: Sensor Fabrication And Analog-Based ML Development
  - Study BNL-fabricated sensors with varying gain layer doses from $2.8\ 10^{12}\ cm^{-2}$ to $2.25\ 10^{12}\ cm^{-2}$
  - Study different how behaviors as a function of different pad patterns









  - Training based on both TCTs and test beams
  - Investigate noise mitigation techniques with attention mechanisms and/or adversarial training.
  - Optimize geometry based on application.
  - Study performance as a function of sensor irradiation

- **O2**: Digital Readout And Firmware Development
  - Transition from proof-of-concept to FPGA implementation
  - Study the amount of compression needed for maintaining targeted spatial precision

Conclusion/Collaborations

- Optimizing the information contained in the charge collection of RSD will:
  - Accelerate the goals of achieving improved spatial resolution with current production technologies.
  - Drive future technologies toward optimized designs,
  - Output of this effort in the context of RG 2.3 area.
- Participants:
  - Brown University: sensor characterization, ML implementation, and readout development.
  - Brookhaven National Laboratory: sensor fabrication and readout development.
  - University of Zurich: FEE design, sensor, and hybrid characterization, test beam setup.
- Resources:
  - Personpower: staggered approach for **O1** and **O2.**
    - 2 to 4 FTE of personpower to reach its targets:
    - ~1 FTE of project guidance: 0.4 from Brown University and 0.2 and 0.2 from UZH and Brookhaven National Laboratory,
    - 1 to 2 transient appointments
  - Characterization facilities in UZH, Brown, and BNL and Sensor fabrication at BNL.
  - Further resources (inc. personpower) are envisioned through future funding requests.
- Collaborations and coactions within the DRD3 Collaboration at CERN:
  - Open to collaboration with facilities (WG5).
  - Benefit from shared resources and joining of new persons in the team.
  - Coactions with TCAD simulations are used to emulate RSDs' response.
  - Collaboration with further readout experts towards full testing in complete hybrids.

Additional material.

Bonding scheme