Precise Quantum Angle Generator Designed for Noisy Quantum Devices.

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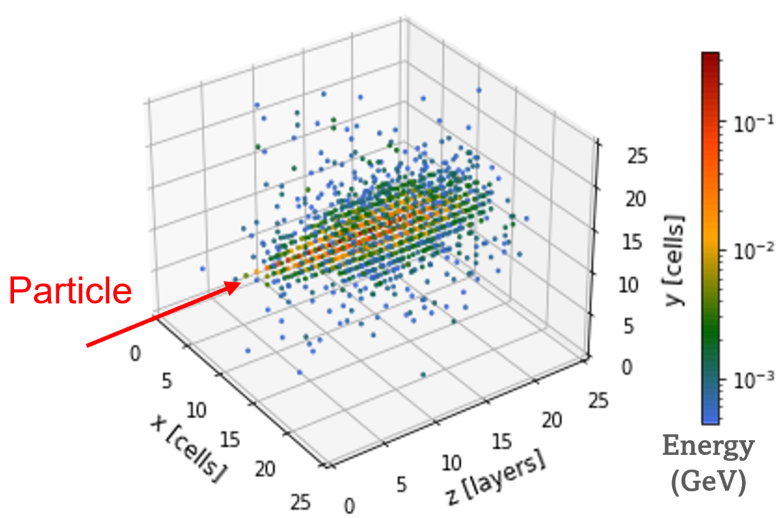
[arxiv:2307.05253]

QAG
Use Case

- Assess the capabilities of quantum computers in **simulating calorimeter showers**
- The **dataset**[1] consists of energy deposits from single-particle showers in the **ECAL** calorimeter of the CLIC detector generated with Geant4
- Training and test datasets consist of **10,000** samples
- The initial particle is an **electron** within an energy range of **[225, 275] GeV**
- **Downsampled** to **8 pixels**



25x25x25 → downsampling → 1x8

[1] zenodo:3603122

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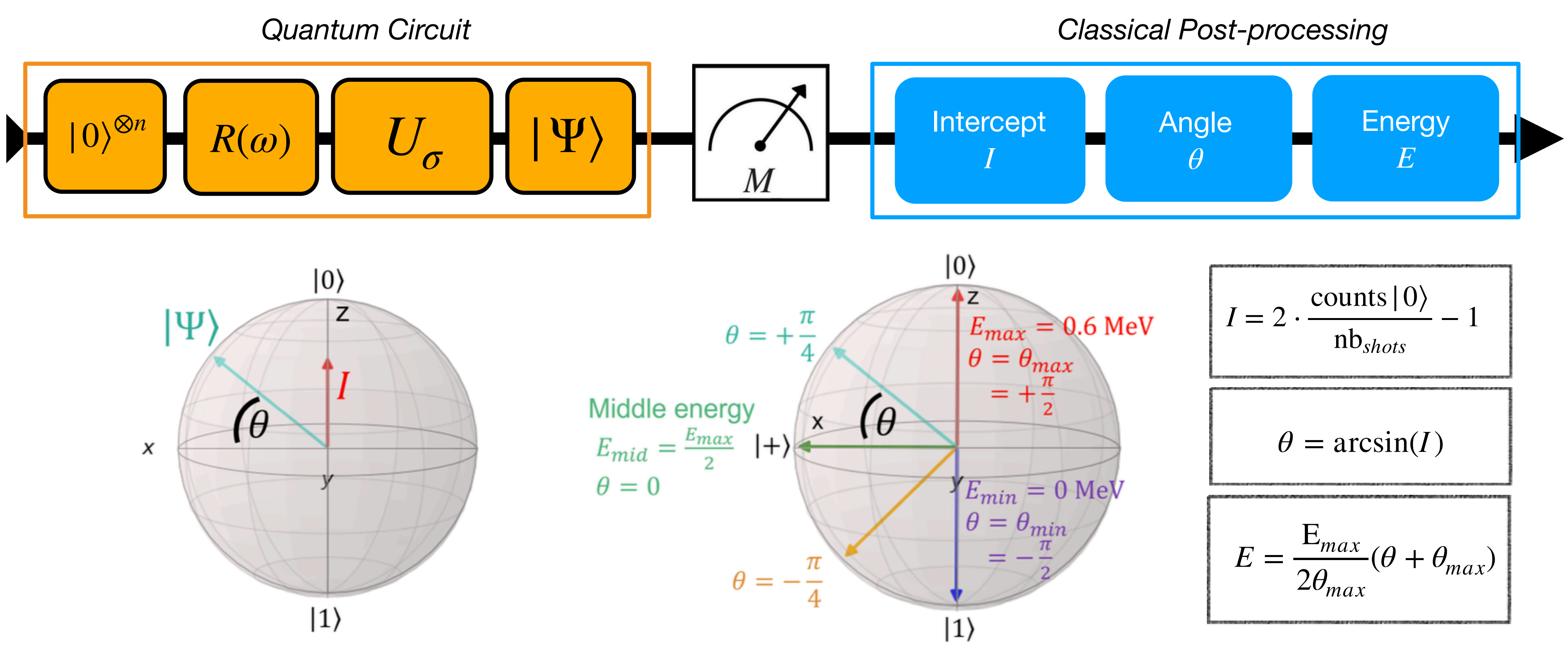
Quantum Angle Generator

- The Quantum Angle Generator is a quantum generative model based on **variational quantum circuits** (VQC)
- The input state is provided by **random angles** ω from a uniform random distribution
- It learns the trainable parameters σ of the VQC U_σ that map $R(\omega)\,|0\rangle^{\otimes n} \rightarrow |\psi\rangle$
- Multiple **measurements of the qubits for each shower**
- A **classical post-processing** algorithm translates the **measurements into pixel energy**



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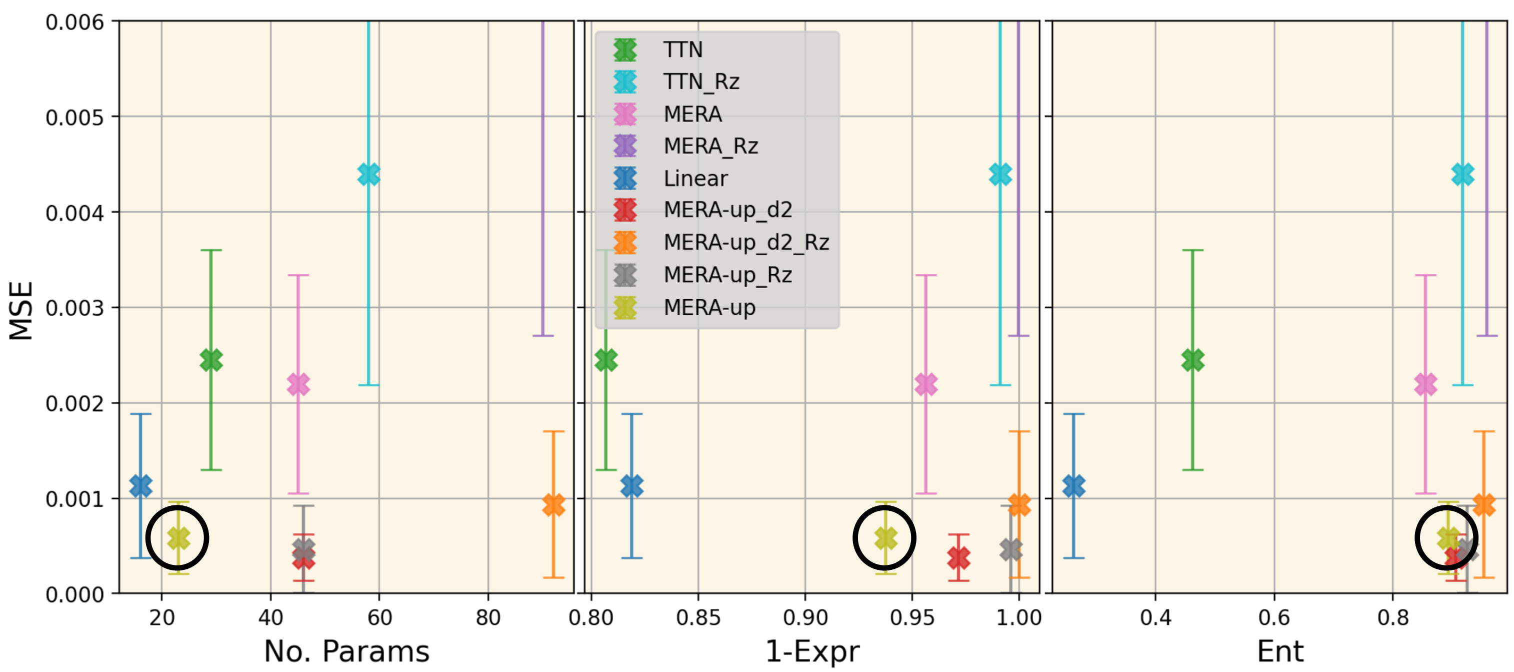
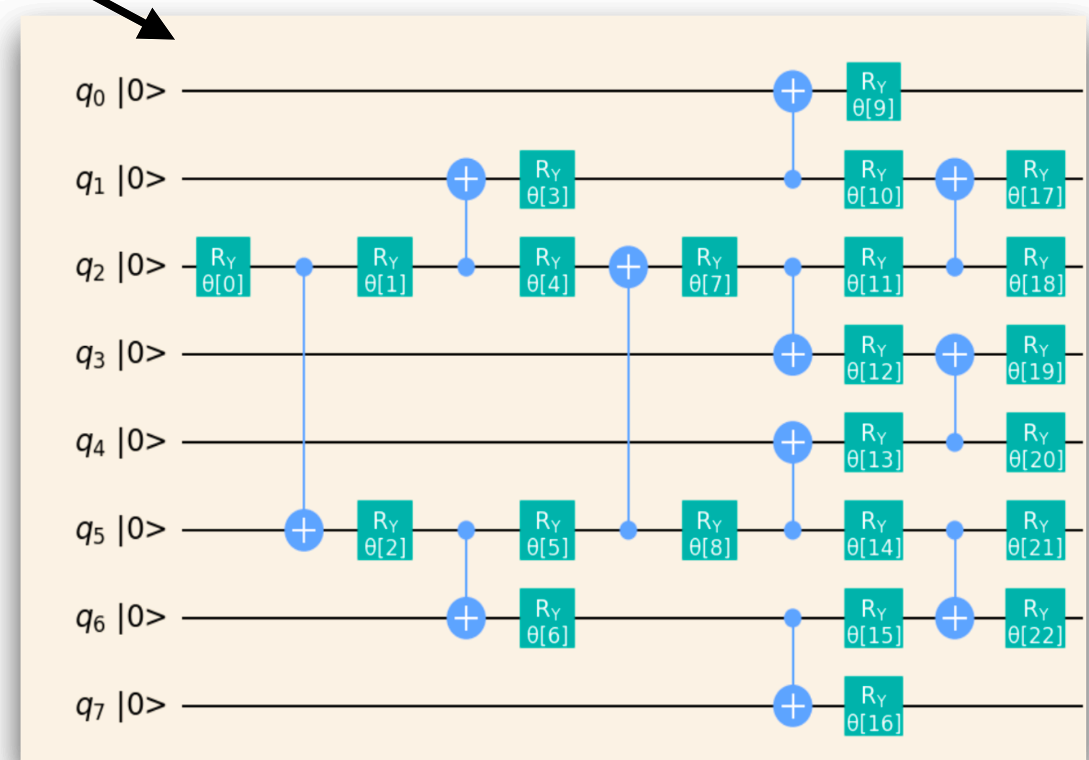
Architecture Selection

[1]G. Evenbly, G. Vidal [arXiv:1109.5334]

- Need for an architecture with good performance and limited number of gates
- We take inspiration from **MERA**[1] for the topology of the quantum circuit
- With a limited number of qubits, our "**MERA-up**" architecture is favoured





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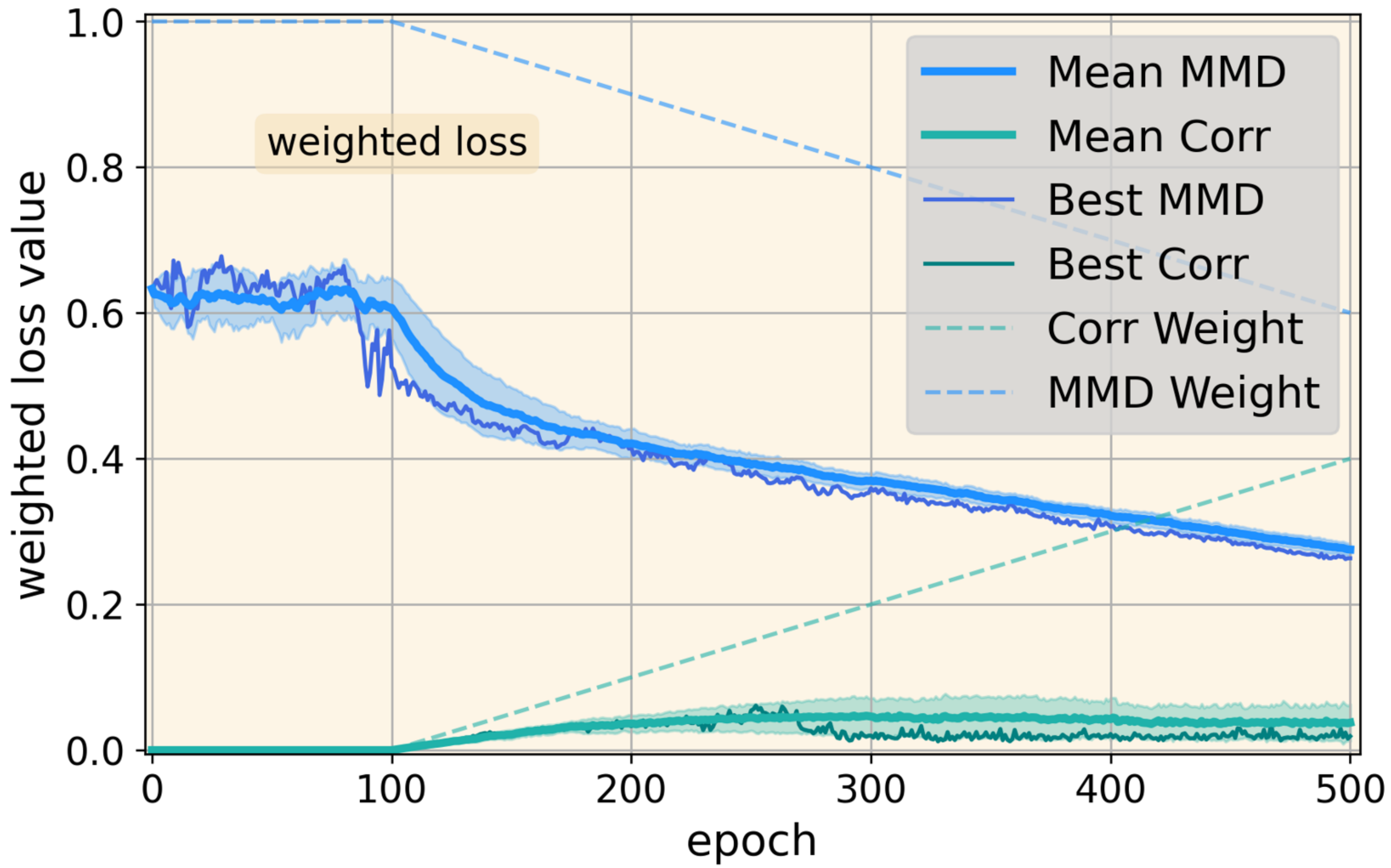
Training Setup

- The Mean Maximum Discrepancy (**MMD**)[1] and a correlation (**Corr**) loss[2] were used in combination as loss functions
- Simultaneous Perturbation Stochastic Approximation **(SPSA)** used as optimiser for training

[1]Gretton et al. [jmlr:gretton12a]
[2]Corr loss = MSE (between G4/QAG) of the pixel-pixel correlation



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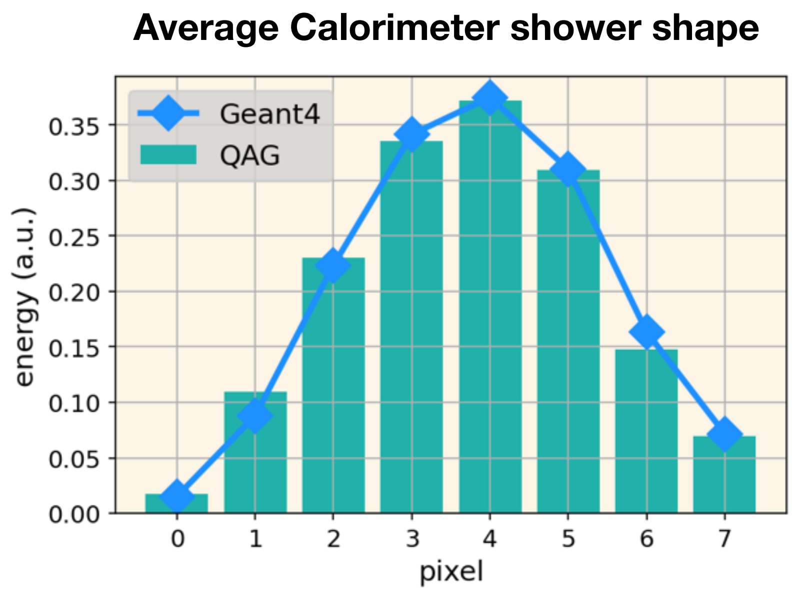
QAG compared to Geant4

- The QAG model results are **compared against Geant4 test data**



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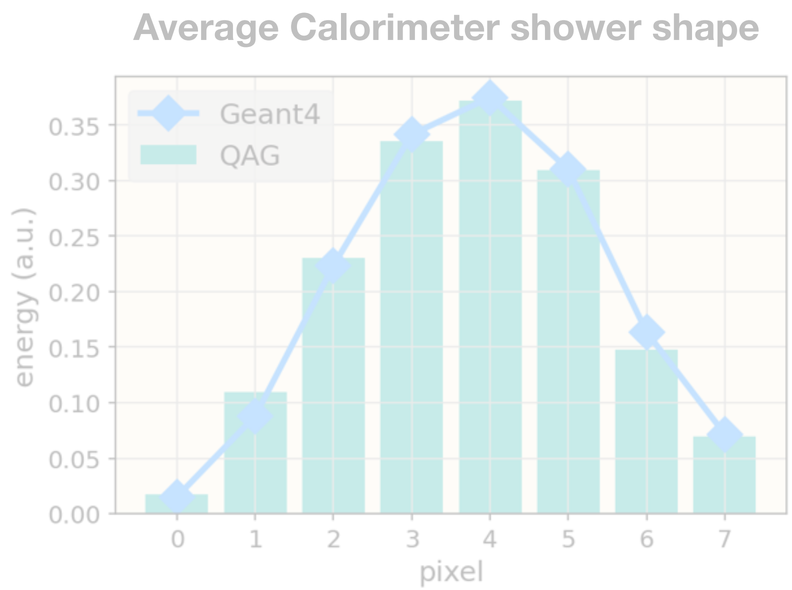

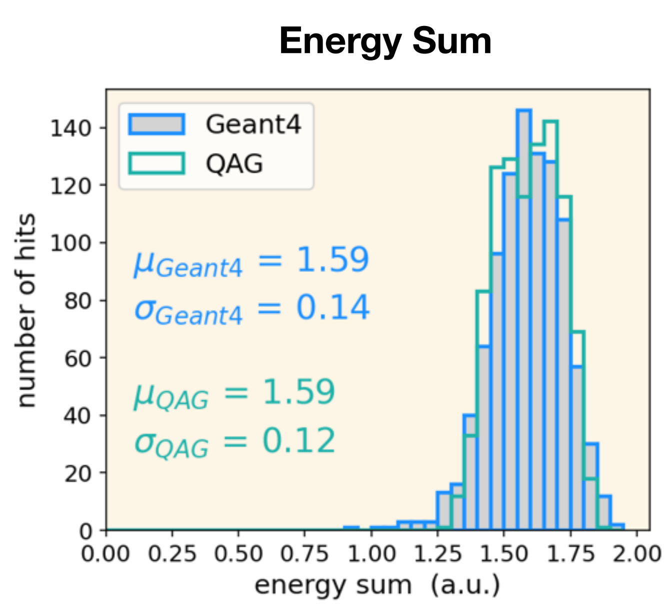

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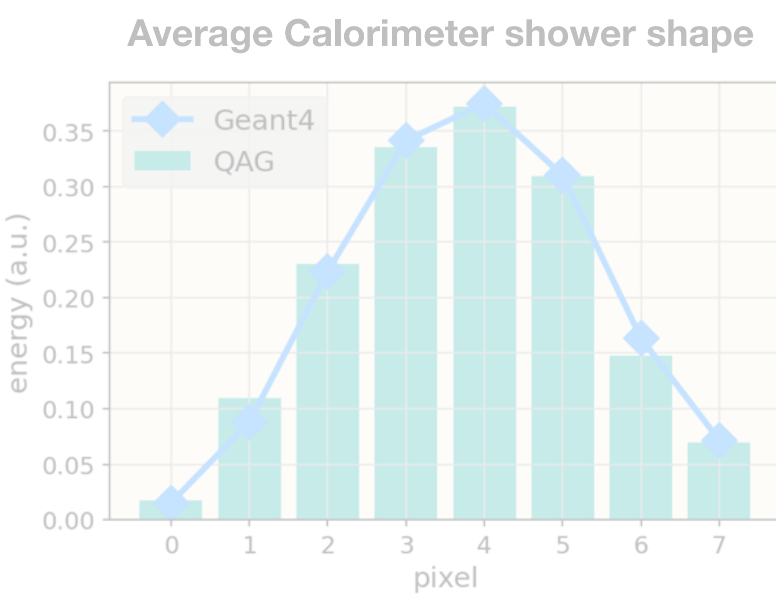

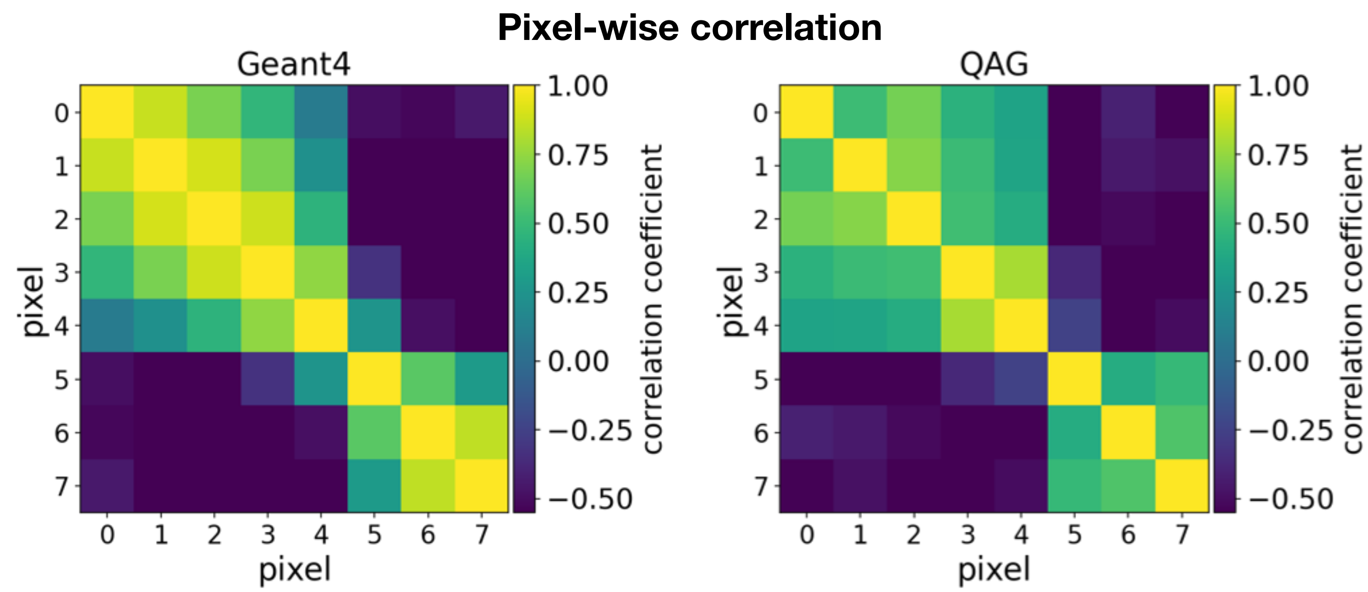

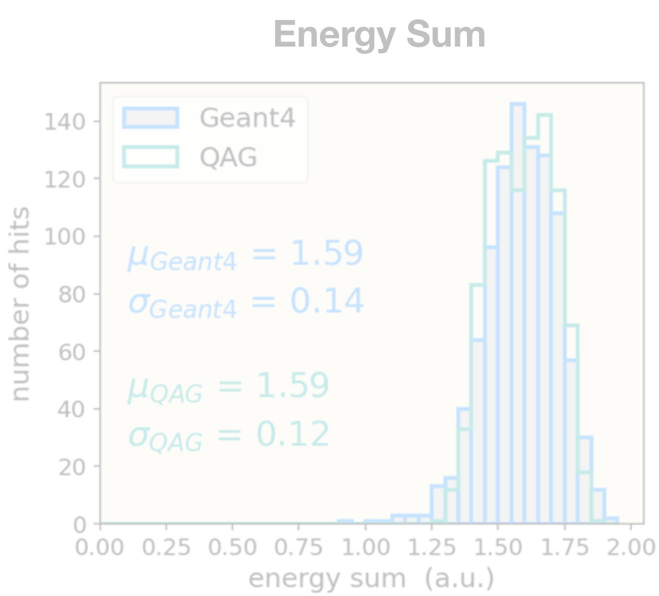

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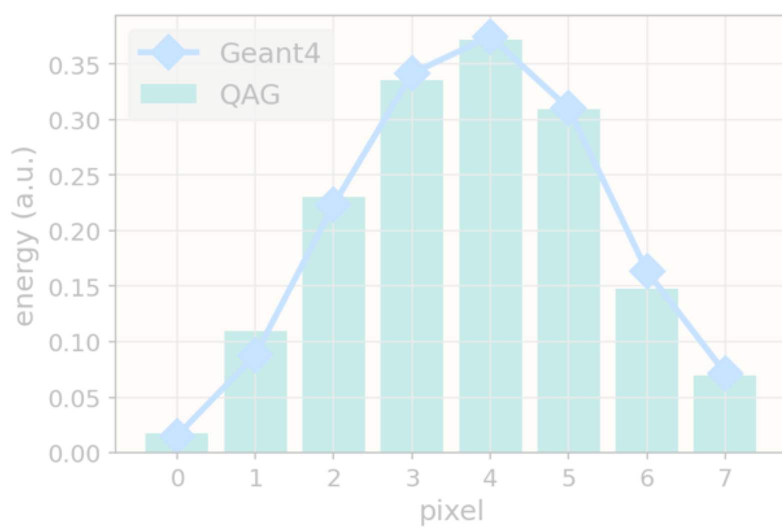
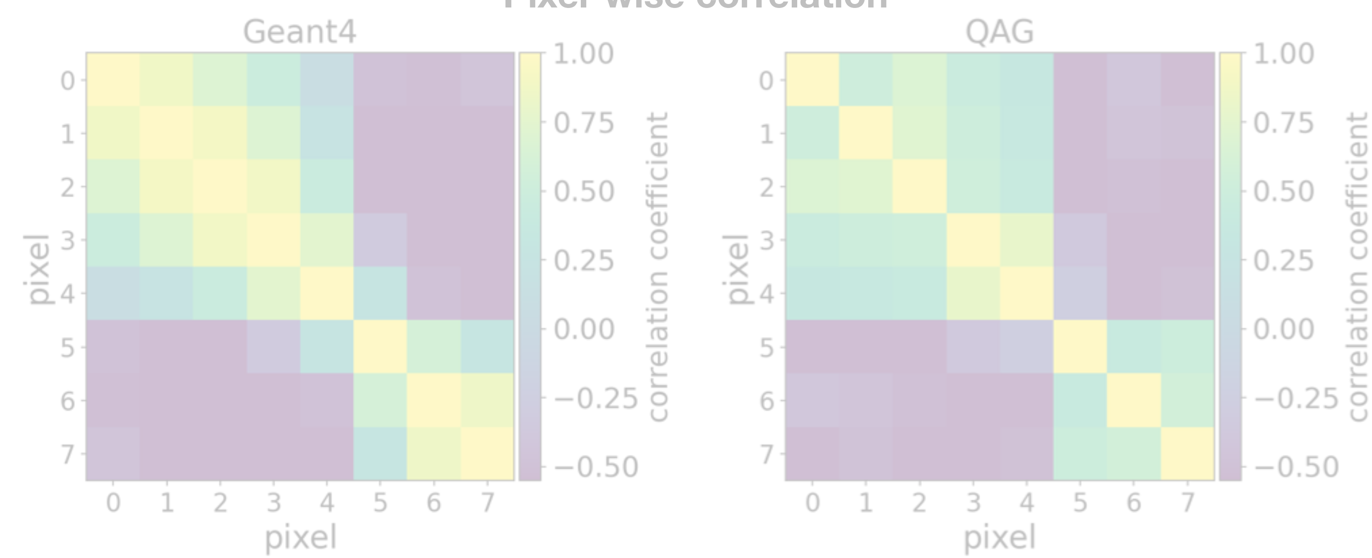
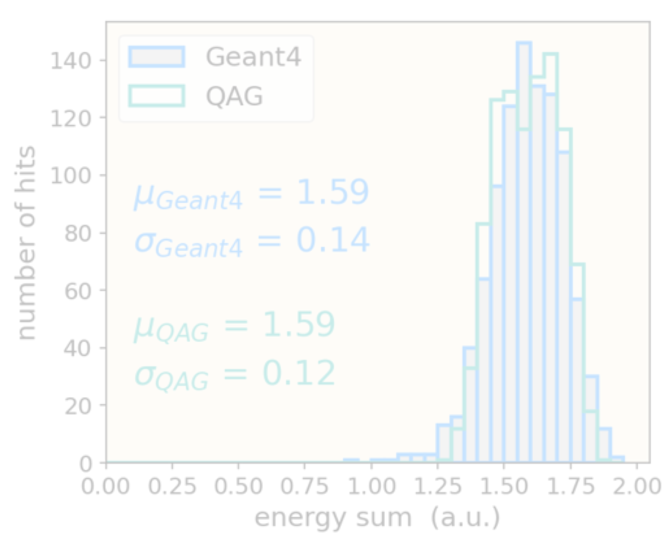
Average Calorimeter shower shape



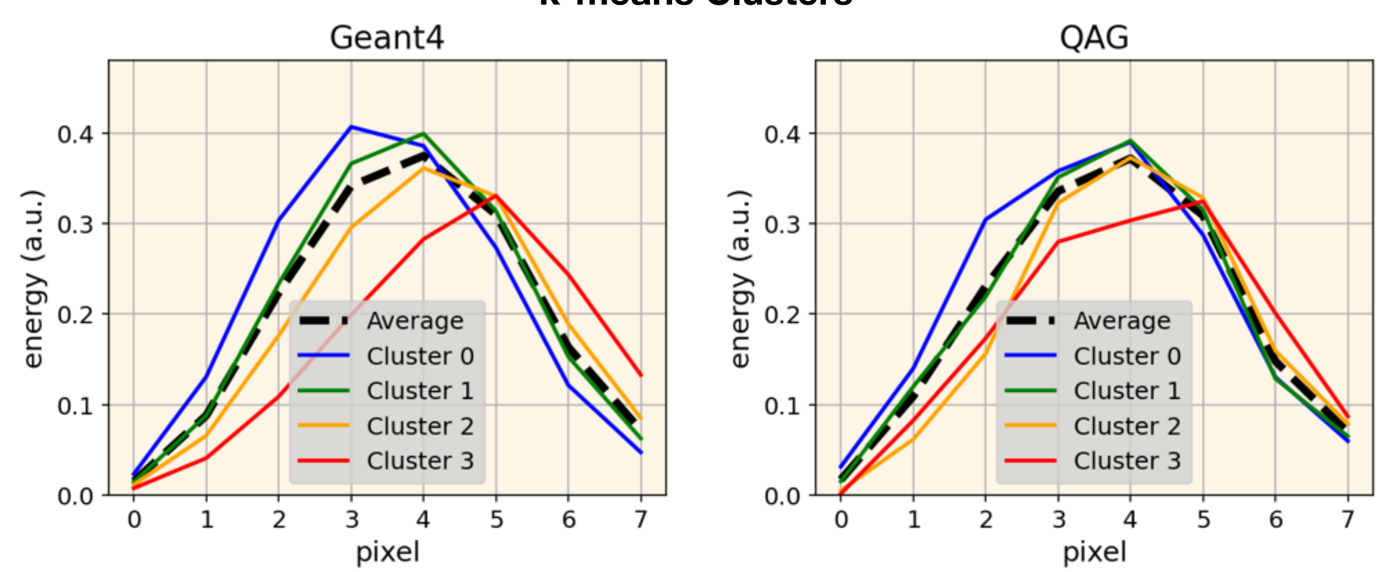
Pixel-wise correlation



Energy Sum



k-means Clusters



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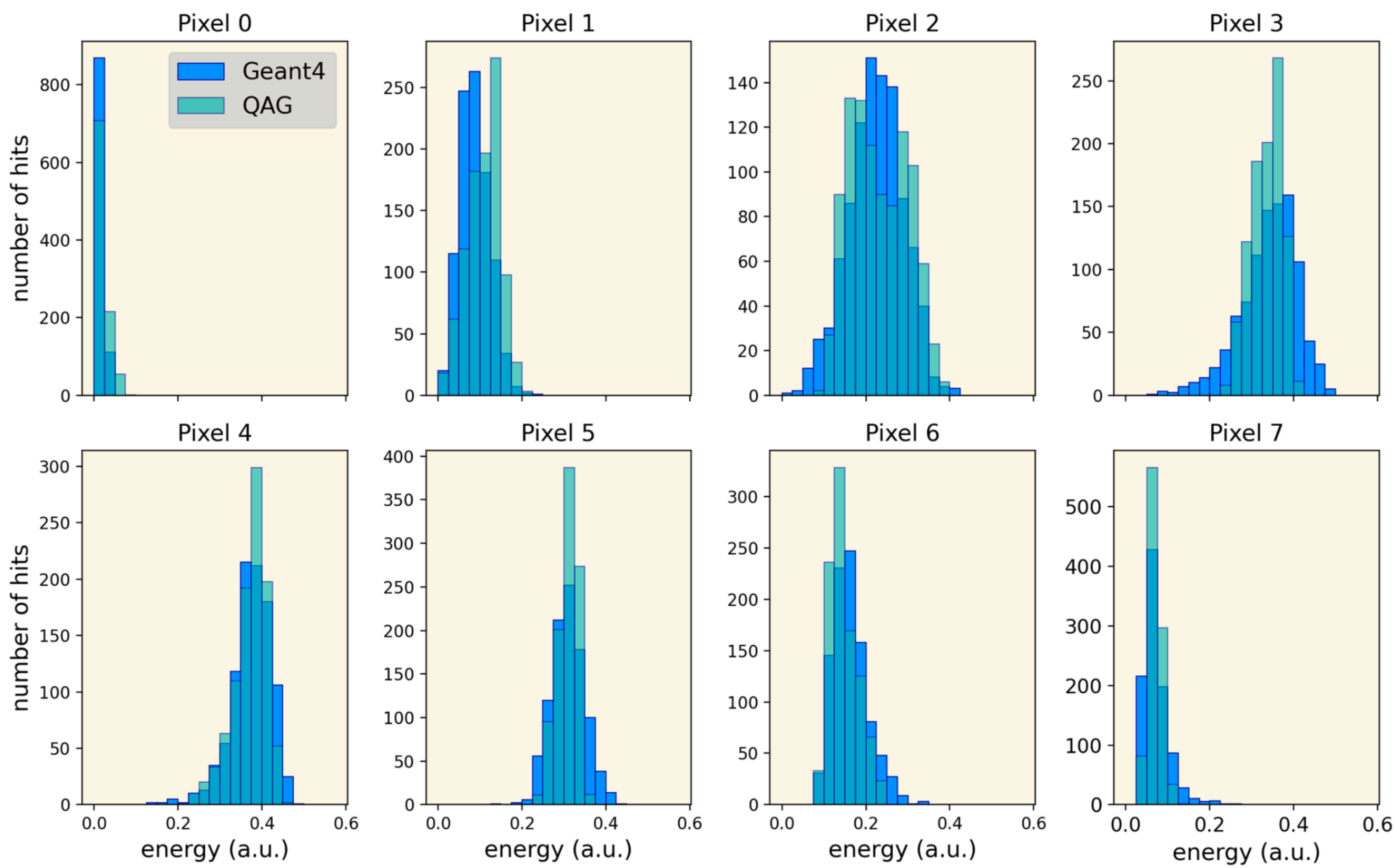
QAG compared to Geant4

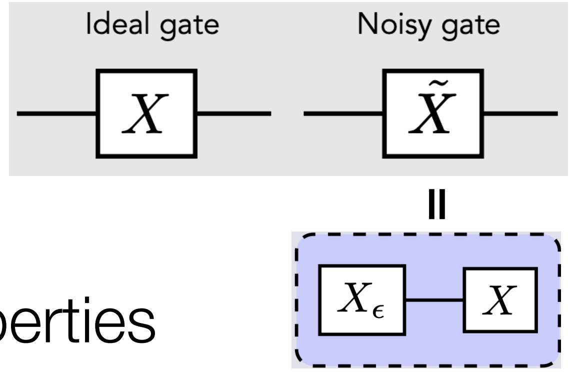
- Pixel-wise energy distribution



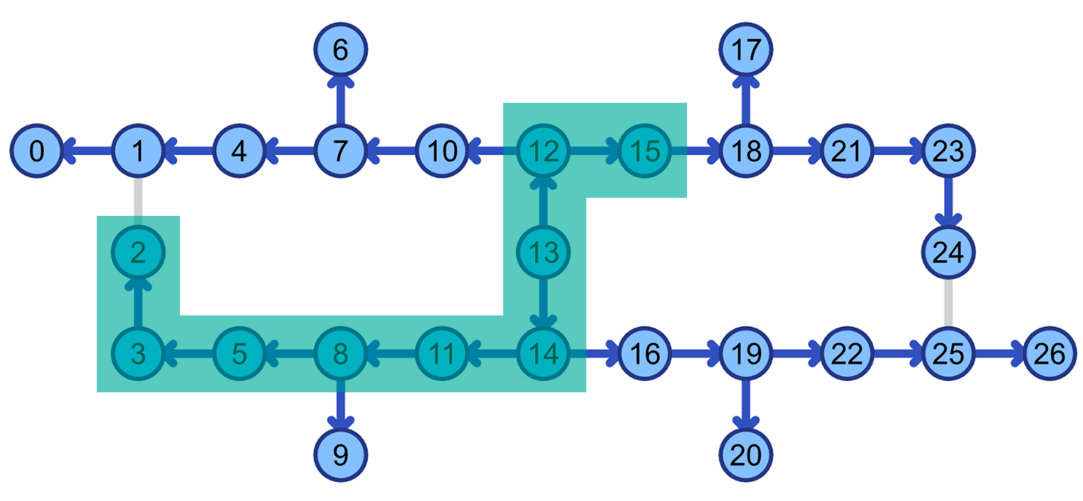
Quantum Noise Study

Models of noise

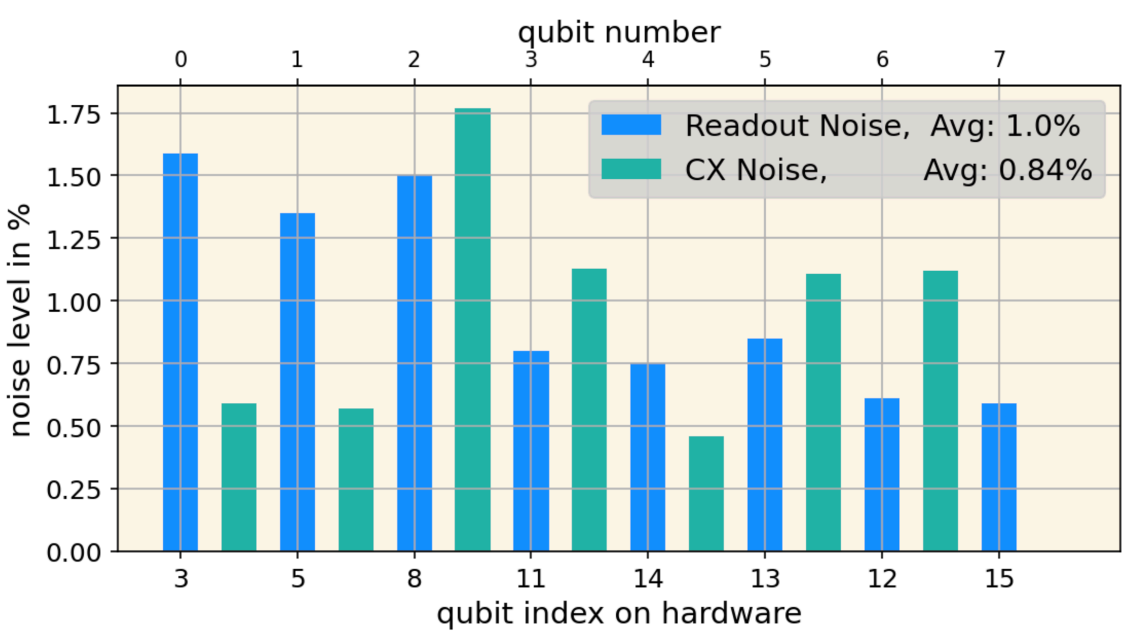
1. **Fake**: Qubits are treated identically
   - Single-qubit readout errors (read out)
   - Two-qubit gate errors (CNOT)
2. **Simulated**: Calibration information from backend properties
   - Gate error probabilities
   - Readout error probabilities



3. **Real Hardware:**



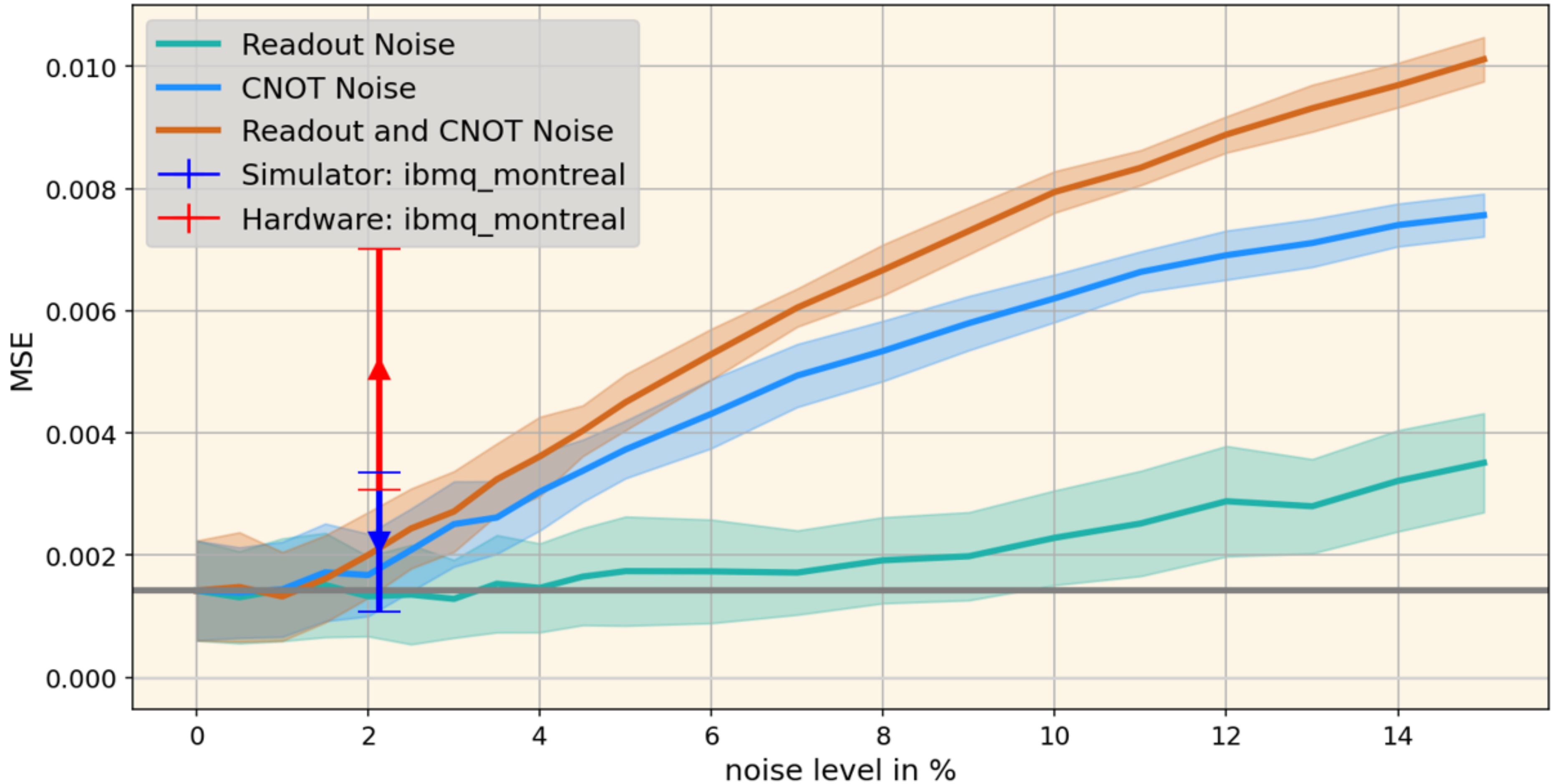
ibm_montreal machine



Quantum Noise Study

Inference

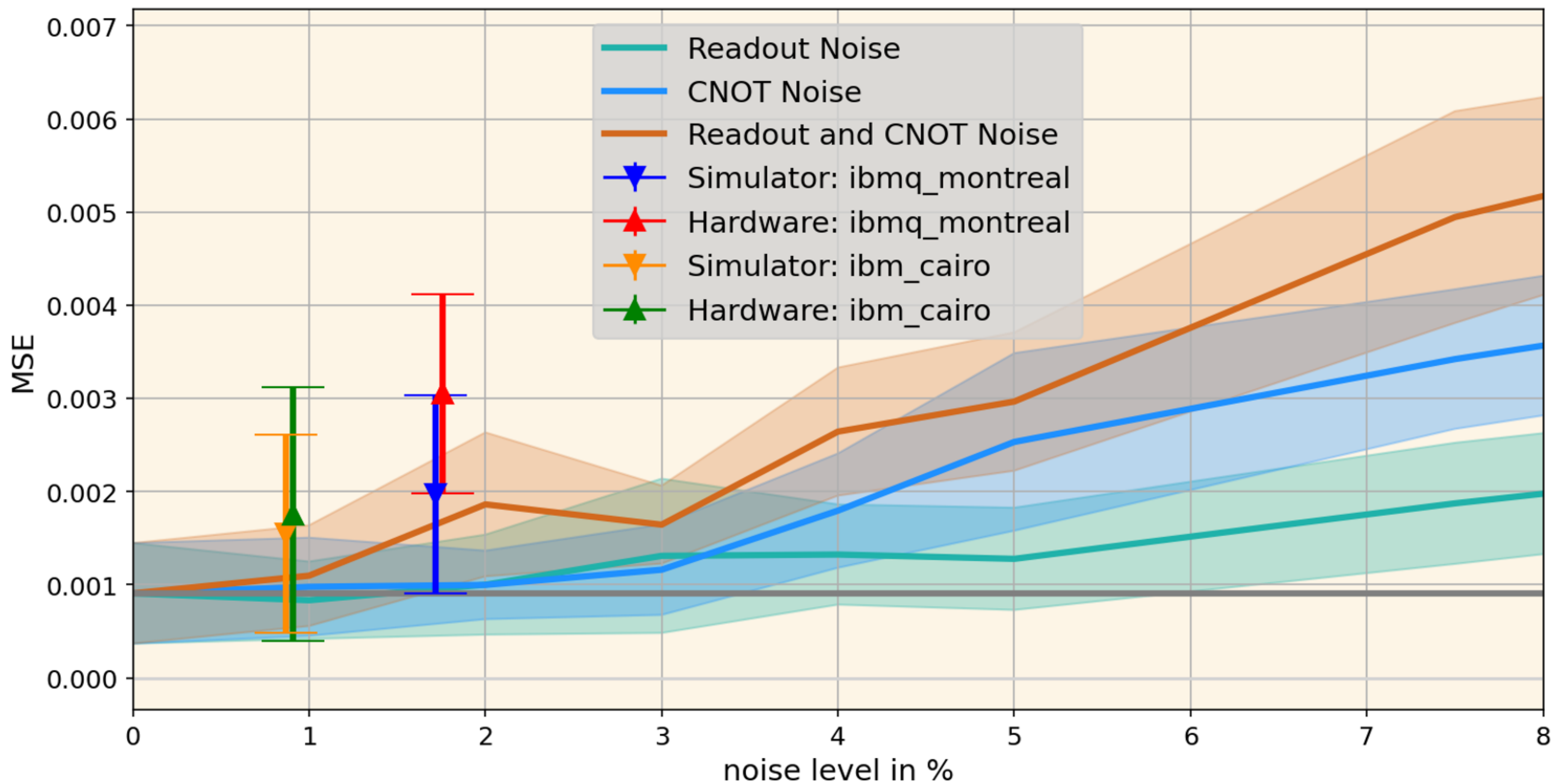
- Quantum noise applied only when doing inference, using the QAG baseline model trained without noise
- The grey line is the noise-free simulation
- The fake noise sources are shown at different error levels
- The device used is the ***ibmq_montreal*** *simulator* and real hardware



Quantum Noise Study

Training

- Quantum noise is applied during training to compare with inference-only results
- The training and analysis are conducted using ***ibmq_montreal*** and ***ibmq_cairo***
- Training the model with noise makes the QAG model more robust
- For low hardware noise levels, the simulated and real hardware outcomes behave similarly



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Conclusion

1. The **QAG model** is capable of generating calorimeter showers within the limits of the current hardware
2. The **MERA-up quantum circuit architecture** performs well
3. Including quantum hardware **noise** during inference the **results are** still **stable** in the expected noise level regime
4. **Training on noisy hardware** makes the QAG model **more robust** to noise and increases performance