Machine Learning For Real-Time Processing of ATLAS Liquid Argon Calorimeter signal with FPGAs





## INTRODUCTION

- High-luminosity phase of LHC (HL-LHC) is an important milestone for particles physics
  - Expect to increase instantaneous luminosity by 5-7
- Upgrade of the ATLAS LAr calorimeter off-detector system to meet physics requirement
  - > Improvement of computing capacity with Stratix-10 FPGAs
     > Energy reconstruction made by real-time artificial intelligence algorithm

## ENERGY RECONSTRUCTION IN LAr CALORIMETER

- Measure the energy of electromagnetic showers of photons/electrons thanks to the ionization signal by the Liquid-Argon (LAr) Calorimeters
  - Calorimeter with ~182.468 cells
- Bipolar pulse shape (total length of up to 600 ns, 25 Bcs).
  - Sampled and digitized at 40 MHz
- ATLAS level-1 calorimeter trigger (L1Calo) data processing uses Optimal

- Trigger frequency : 1MHz
- Simultaneous proton-proton collisions (pileup) every 25 ns : 140-200 per Bunch crossing (Bc)
- Process 256 or 384 LAr
  calorimeter cells by each FPGA

Filter (OF) algorithm (readout path) with maximum finder (trigger path)

- > Use four to fives samples around pulse shape peak
- Assume perfect pulse shape

• High pileup leads to overlapping pulse shapes



Sample sequence (black) simulated by AREUS, together with the true transverse energy deposits (yellow) shifted by five BC to improve the plot visibility







Recurrent Neural Network (RNN)

• Process data series input with previous calculated state

# Network Performance

- Reconstruction of the energy
- Two format :
  - Sliding window (Vanilla, LSTM)
  - Single cell (LSTM)



RNNs with sliding window

# Convolutional Neural Network (CNN)

- Process energy through two stages :
  - Pulse tagging with 2 layers
    (Energy detection above noise and sigmoid activation)
  - \* Energy reconstruction with 1-2



#### from LAr cells with NNs is better than OF with maximum finder





	3-Conv	6	344	337 ns	390	0,8% / 1,5 %
	4-Conv	6	334	258 ns	352	0,7% / 1,7%
	Vanilla (HLS)*	15	640	200 ns	576	2,6 % / 0,6%
	Vanilla (VHDL) **	11	595	150 ns	465	2,4% / 0,7%

Characteristics of the NN implementation on a Stratix-10 FPGA

- 3-Conv CNN and Vanilla RNN fits for 384 channels but 4-Conv CNN only fits for 256 channels but use a lot of logic
- Vanilla with HLS reports are good but when we add it multiple times with Quartus, the ALM resource usage explode and the frequency decrease a lot
- Placement optimization reduces the randomness of a compilation with better results



Relative deviation of firmware and software results Ressource usage

	Multiplexing	Nb Channels	Frequency	DSP/ALM
Vanilla (HLS)	15	390 (3 FEB)	425	68,6% / 74,5 %
Vanilla (VHDL) No placement	11	385 (3 FEB)	433	82,6 % / 20,6 %
Vanilla (VHDL) With placement	11	385 (3 FEB)	484	82,6 % / 18,7 %

#### Background rejection and signal efficiency of CNN compared to OF with maximum finder

### Conv CNN, LSTM (single), Vanilla RNN (sliding)

for OF with maximum finder, 3-

#### Implementation of RNN on FPGA with Quartus

[2] Nico MADYSA. A software framework for atlas readout

electronics upgrade simulation (areus). CHEP 2018, 2019.

\* : Resource estimated by HLS report \*\* : Test of a VHDL implementation of a Vanilla NN made after the article

#### References

[1] W.E Cleland E.G. Stern. Signal processing considerations for liquid ionization calorimeters in a high environment. NIM A Volume 338, 467-497, 1994.

[3] Aad, G., Berthold, AS., Calvet, T. et al. Artificial Neural Networks on FPGAs for Real-Time Energy Reconstruction of the ATLAS LAr Calorimeters. Comput Softw Big Sci 5, 19 (2021).

Robert FAURE on behalf of the ATLAS Liquid Argon Calorimeter Group CPPM, Aix-Marseille Université, CNRS/IN2P3 (FR)

