Energy Reconstruction with Recurrent Neural Networks

IN2P3/IRFU Machine Learning workshop

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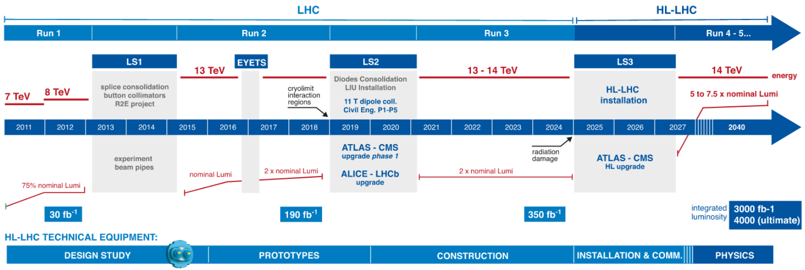
16.03.2021

Content

The Phase-II Upgrade of the LHC

Upgrade of the ATLAS experiment

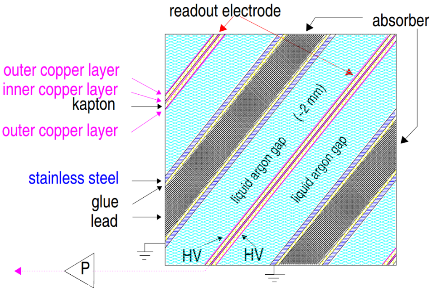


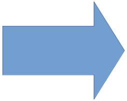
- The High Luminosity LHC (HL-LHC) is a important milestone for particle physics
  - Increase the luminosity to study rare processes
  - Increase the collision rate to up to 200 simultaneous p-p collisions (pileup) per bunch crossing (BC)
- The detectors will be upgraded to cope with the high collision rate at the HL-LHC
  - In particular the ATLAS calorimeter readout electronics will be completely replaced

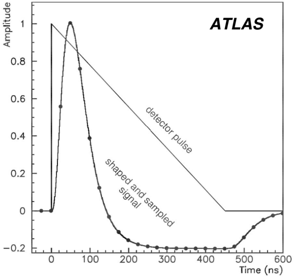
Liquid Argon Calorimeter

Energy reconstruction in the LAr calorimeter

- Liquid Argon Calorimeter (LAr) mainly measures the energy deposited by electromagnetically interacting particles
  - Consisting of ≈ 180 000 calorimeter cells
- Passing particles ionize the material
  - Bipolar pulse shape with total length of up to 750 ns (30 BCs)
  - Pulse is sampled and digitized at 40MHz
- Energy reconstruction is done real-time and used in triggering decision
  - Using the digitized samples from the pulse





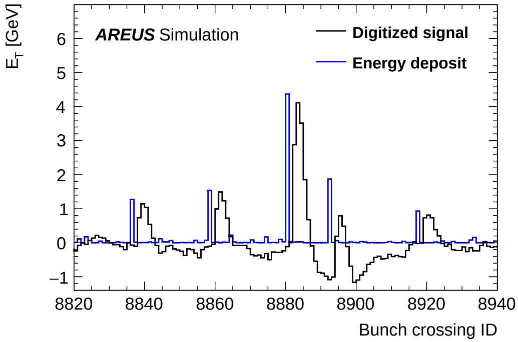


Energy Reconstruction

Energy reconstruction in the LAr calorimeter

- Current energy reconstruction uses optimal filtering algorithm with maximum finder (OFMax)
  - Using five samples around pulse shape peak
  - Assuming perfect pulse shape
- High pileup leads to higher rate of overlapping pulse shapes
  - Distorted bipolar shape → significantly decreased performance of OFMax

- Energy is computed real-time at 40MHz
  - Need to use electronic boards based on FPGAs
- Phase-II electronics with high-end FPGAs
  - Increased computing capacity
  - Improved online energy reconstruction using machine learning based methods
- Constraints from running on FPGAs
  - Latency, frequency and occupancy
  - See next presentation by Etienne Fortin



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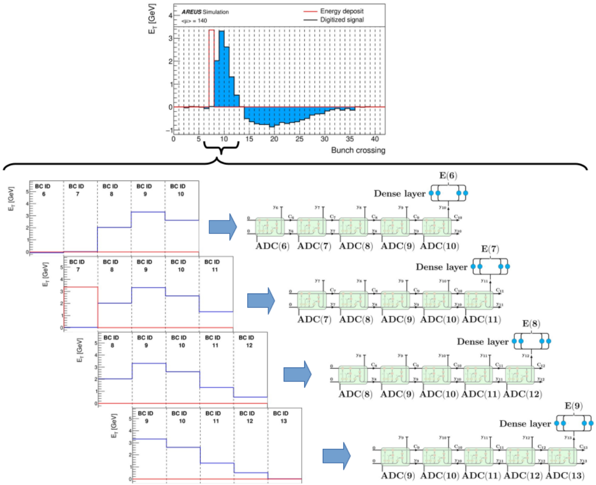
LSTM Network

Using a many-to-one network for energy reconstruction

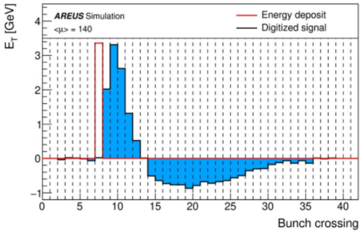
- Recurrent Neural Networks (RNNs) are designed to process time series data
    - Long Short-Term Memory (LSTM) network for efficiently handling past information
    - LSTM consists of neural network layers that process the new time input combined with past processed state
- Use digitized samples as inputs for the recurrent network
- Full sequence split into overlapping subsequences with a sliding window
- One energy prediction per subsequence

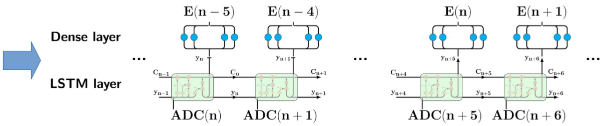


LSTM Network Without State Resets

Using a many-to-many network for continuous energy reconstruction

- Use the LSTM cell to process all digitized samples in one continuous chain instead of a sliding window
- Apply the same LSTM operation for each bunchcrossing combining the past state and new ADC value
- Use each intermediate state for energy reconstruction
- No state resets (stateful in Keras)
- Reduces the computational requirements when each prediction requires only one iteration of the cell





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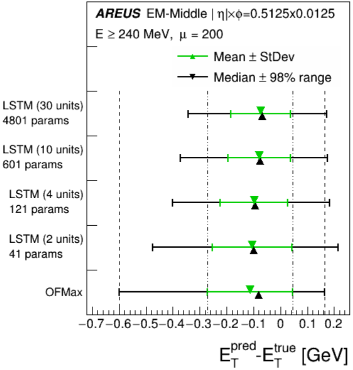
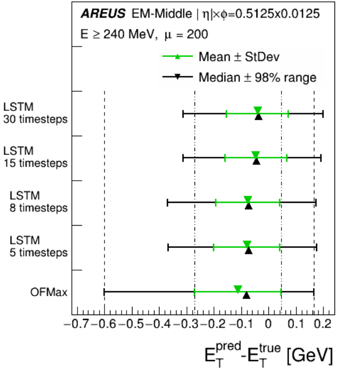
LSTM Network Optimization

Find the smallest well performing network, example for sliding window LSTM

- Use standard deviation and 98% range to compare energy resolution
  - Non-gaussian distribution of the energy resolution
- Optimization of the energy resolution while keeping the network size under control
  - Vary the network parameters: internal dimension (units), sliding window size (timesteps)
  - Network trained with simulated data of a single LAr calorimeter cell using the AREUS software

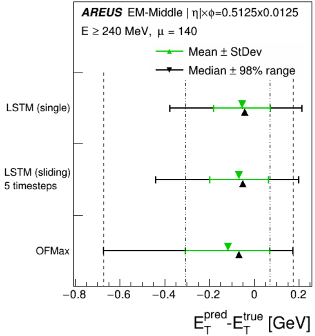


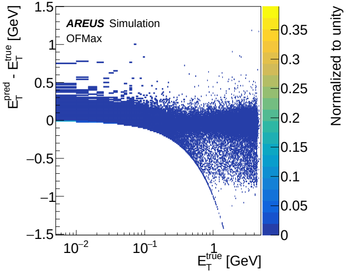


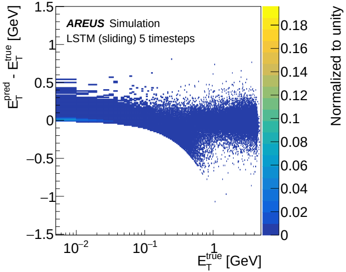
LSTM Performance

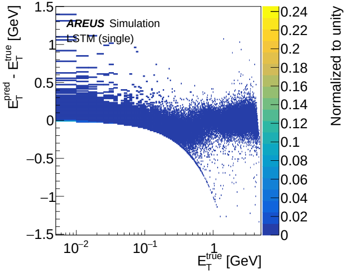
Energy resolution in comparison to OFMax

- Both LSTM architectures perform better than OFMax
- LSTM with sliding window is more resilient to outliers and focuses on the peak
- Stateful LSTM performs slightly better overall with better correction of long range effects but has a wavy feature





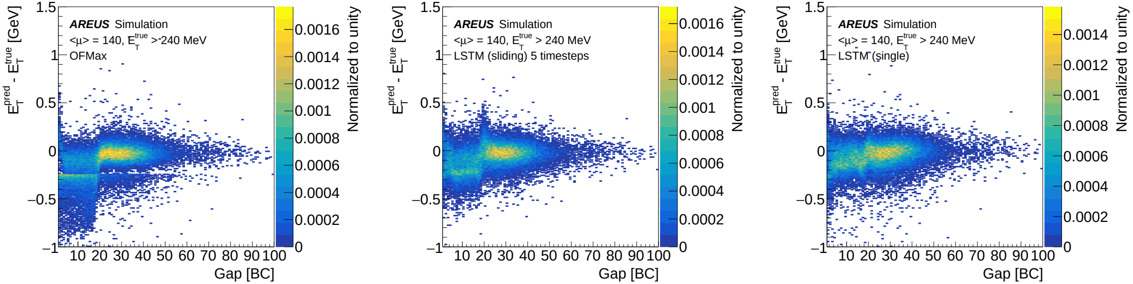




LSTM Performance

Resolution as a function of gap to previous energy deposit in BCs

- Clear performance decrease with OFMax at low gap
- LSTM with sliding window showing slight underestimation of energy at low gap and overestimates at around a gap of 20 BC
  - Increasing the amount of timesteps removes both effects
- Single cell LSTM handles long range effects better



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Conclusion

Energy reconstruction using recurrent neural networks

- Energy reconstruction with LSTM overperforms legacy algorithms in Phase-II conditions
  - Better energy resolution overall
  - Better recovery of energy resolution with overlapping signals
- Strict resource and latency constraints limit the size of the networks
  - Energy resolution optimized while keeping the network size small
- FPGA implementation of LSTM presented next by Etienne Fortin
- Next steps:
  - Using other RNN architectures (Vanilla RNN and GRU)
  - Quantization aware training using QKeras (better adapted to FPGA implementation)
  - Continue studies of the robustness against HL-LHC conditions (bunch train structure, varying instantaneous luminosity, ...)