Prediction of electromagnetic fraction in a hadronic shower using deep neural network

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1. Motivation and goal
2. Simulations and preprocessing
3. DNN model and training
4. Preliminary results

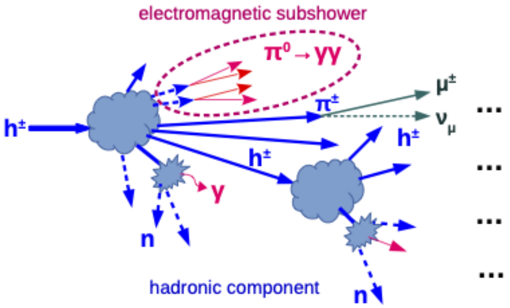
Motivation and goal

Percent-level precision of jet energy measurements is important for future collider experiments aimed at searches for New Physics beyond SM

- **modern trend**: particle flow (PF) reconstruction based on highly granular calorimeter systems and high-precision tracking
- **bottleneck for jet resolution**: contribution from neutral hadrons

Hadronic energy resolution

- complex structure of hadronic showers results in significant fluctuations of energy deposition due to fluctuations of electromagnetic fraction (with dominated contribution from π^0s)
- possible solutions for improvement:
  - hardware compensation (compensating calorimeters, e.g. ZEUS)
  - software compensation algorithms, e.g. in *[JINST 7 (2012) P09017]*



In this talk: software compensation using predictions of electromagnetic fraction by DNN

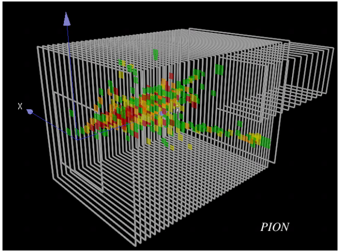
Machine-learning-based approach for software compensation

Software compensation (SC)

means event-by-event energy correction during reconstruction

Previous and ongoing studies:

- parameterised local (hit-based) and global (observables-based), up to 15% improvement in stochastic term for single pions for both data and MC
- Graph neural network trained on MC samples - considers hadronic shower as image (work in progress by CALICE)



Simulated 80-GeV pion shower in highly granular calorimeter

A novel approach proposed in this study

DNN training and optimisation on MC

- inputs: global calorimetric observables
- target: true electromagnetic fraction $f_{\mathrm{em}} = \sum_{over \pi^0 s} E_{\pi^0} / E_{\mathrm{initial}}$
- supervised learning

Inference (event-by-event)

- calculation of calorimetric observables
- prediction of f_{em} from DNN trained
- correction of event energy

Simulations, detector model and event selection

Simulations with Geant4 version 10.3

- **single negative pions @ 10–80 GeV**, about 500 kevt / energy point (raw samples centrally produced by CALICE DESY group)
- model of **highly granular analog hadron calorimeter AHCAL** (scintillator-SiPM, steel absorber, long. depth: ~4.3 nucl. int. length, transverse size: 72×72 cm^2)
- Physics lists: **FTFP_BERT_HP** and **QGSP_BERT_HP**
  HP (High Precision) – precise neutron models and cross sections below 20 MeV

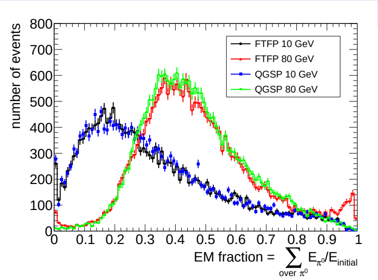
Calibration and digitisation

- MIP calibration with MC muons
- light collection and photon detection by SiPM, pixelisation and saturation are emulated in digitisation
- digitisation tuned with MC-to-Data comparisons for muons and electrons
- EM calibration factor, $C_{\mathrm{em}} = 0.0233$ GeV/MIP

Reconstruction chain and event selection

- cell signals above 0.5 MIP threshold — hits
- shower start finder algorithm tuned on MC
  for analysis: only events with found shower start at 3–6 AHCAL layers
- conversion factor to hadron energy scale: $C_{\mathrm{had}} = 1.2$

Event energy reconstruction



Standard hadron energy reconstruction

$$E^{\text{em}}_{\text{reco}} = C_{\text{em}} \cdot \sum_{i=1}^{N_{\text{hits}}} e_i , \qquad E^{\text{had}}_{\text{reco}} = C_{\text{had}} \cdot E^{\text{em}}_{\text{reco}}$$

where e_i - hit energy in MIP, N_{hits} - total number of hits

Energy reconstruction with correction from known electromagnetic fraction

$$E_{\text{measured}} = \langle em \rangle \cdot E_{\text{initial}} \cdot f_{\text{em}} + \langle h \rangle \cdot E_{\text{initial}} \cdot (1 - f_{\text{em}})$$

where $\langle em \rangle$ and $\langle h \rangle$ are mean reconstruction efficiencies for electromagnetic and hadronic subshowers and are assumed to be energy independent: $\langle em \rangle = 1$ for electromagnetic calibration and $\langle h \rangle$ can be estimated empirically for particular calorimeter ($\langle h \rangle \approx$ 0.7–0.75 for AHCAL)

In MC, f_{em} can be extracted as a sum of π^0 energies in event, and one can correct for f_{em} fluctuations:

$$E^{\text{cor}}_{\text{reco}} = \frac{E^{\text{em}}_{\text{reco}}}{f_{\text{em}} + \langle h \rangle \cdot (1 - f_{\text{em}})},$$

where $\langle h \rangle$ accounts also for C_{had}

f_{em} is not accessible in data but can be predicted by DNN from calorimetric observables!

Calorimetric observables for DNN input — 29 variables

Counting observables

- **Number of isolated hits**, $N_{\rm iso}$ [isolation – 0 neighbours in a cube of 3×3×3 cells around the hit]
- **Number of track hits**, $N_{\rm trk}$ [defined as having two in-line neighbours and MIP-like deposition]

Amplitude observables

- **Mean shower hit energy**, $\langle e_{\rm hit}\rangle$
- **Shower radius** $R_{\rm sh} = \frac{\sum_{i=1}^{N_{\rm sh}} e_i \cdot r_i}{\sum_{i=1}^{N_{\rm sh}} e_i}$, $r_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}$ - hit rad. dist. from sh. axis (x_0,y_0)
- **Longitudinal shower centre of gravity** $Z_{\rm CoG} = \frac{\sum_{i=1}^{N_{\rm sh}} e_i \cdot (z_i - z_{\rm start})}{\sum_{i=1}^{N_{\rm sh}} e_i}$,

  e_i - energy of hit with coordinates x_i, y_i, z_i; $N_{\rm sh}$ - number of shower hits
  z_i - hit longitudinal coordinate, $z_{\rm start}$ - longitudinal coordinate of shower start

Additional "ring" observables (integrated over longitudinal depth)

3-cm wide rings around shower axis, consistent with cell transverse size; 12 rings in total

- **number of isolated hits in a ring**, $N_{\rm iso}^{\rm ring}$
- **energy fraction in a ring**, $f_{\rm enr}^{\rm ring}$, w.r.t total energy sum

Deep Neural Network model, architecture and training

Target: electromagnetic fraction in event as a ratio of a sum of π^0 energies to the initial energy

Regression model with MSE loss function

$$L_i = (Y_i^{\text{predicted}} - Y_i^{\text{true}})^2 \quad \text{Loss} = \frac{1}{N} \cdot \sum_{i=1}^{N} W_i \cdot L_i$$

N - number of events for training

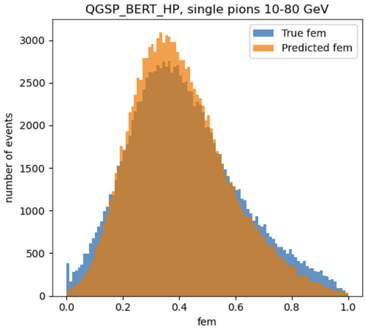
$\mathrm{W_i}$ – event weights from density-based weighting

Training, validation and test subsamples

- mixed sample for 10-80 GeV
- after selections: ∼130 kevt/ phys.list
- train:valid:test ≈ 60%:20%:20%

Example DNN architecture and output

- number of layers: 1 input, 6 hidden, 1 output
- number of neurons: 29/80/40/20/16/32/64/1
- activation function: ReLU $= \max(0, x)$ for hidden, linear $(\mathrm{f(y) = y})$ for output
- bias neurons and weighted loss
- number of training epochs: about 15
- **supervised learning**

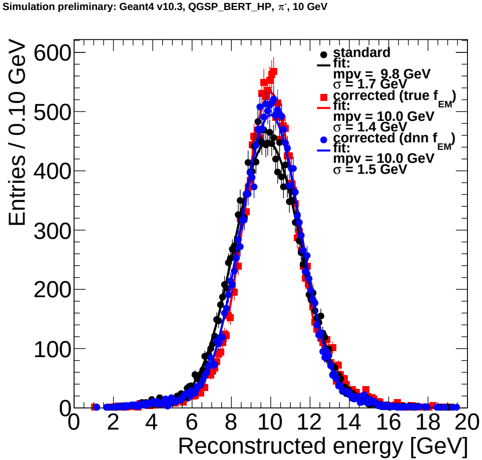


Tools: TensorFlow library, Keras framework, scikit-learn package

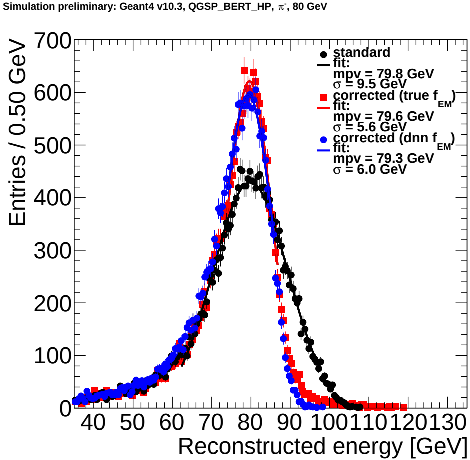
Example of corrected energy distributions for QGSP_BERT_HP

DNN trained on mixed sample of QGSP_BERT_HP and applied to QGSP_BERT_HP

10 GeV



80 GeV

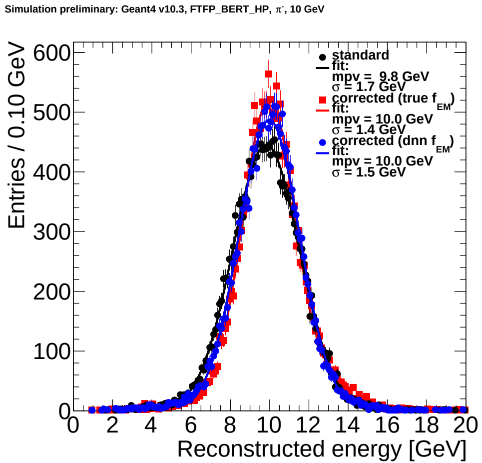


Comparable improvement by true and predicted f_{em} with $\langle h \rangle = 0.72$ and $\langle h \rangle = 0.75$.

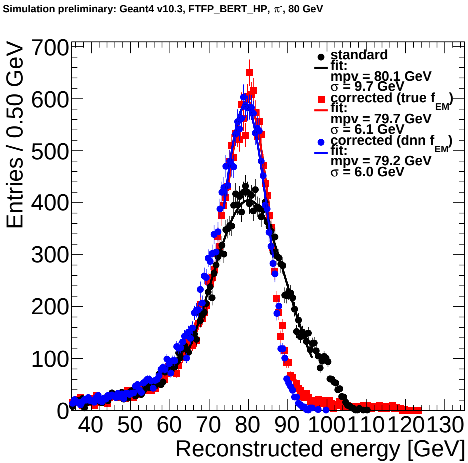
Example of corrected energy distributions for FTFP_BERT_HP

DNN trained on mixed sample of QGSP_BERT_HP and applied to FTFP_BERT_HP

10 GeV



80 GeV

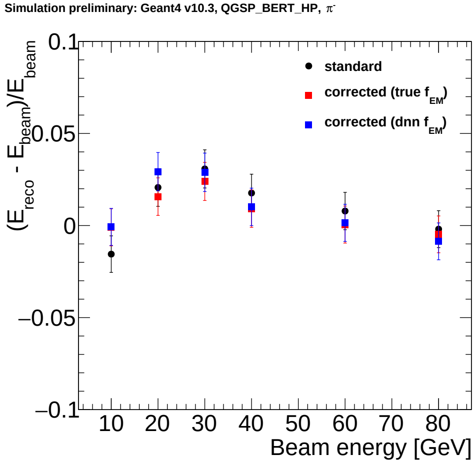


Comparable improvement by true and predicted f_{em} with $\langle h \rangle = 0.72$ and $\langle h \rangle = 0.75$.

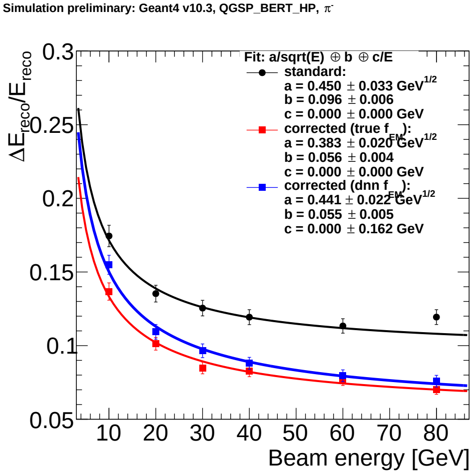
Energy correction using f_{em}

DNN trained on mixed sample QGSP_BERT_HP and applied to QGSP_BERT_HP

Linearity



Relative resolution

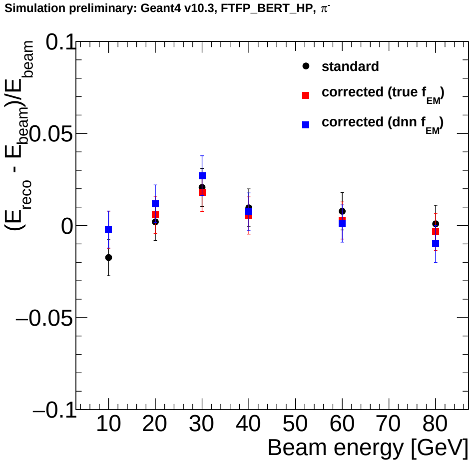


Better linearity and resolution with true f_{em}. Significant improvement in rel. resol. with predicted f_{em}.

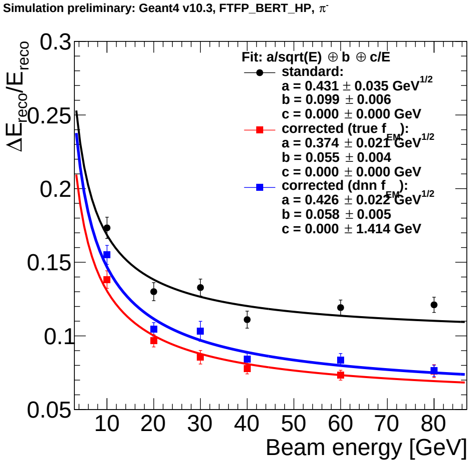
Energy correction using true and predicted f_{em}

DNN trained on mixed sample QGSP_BERT_HP and applied to FTFP_BERT_HP

Linearity



Relative resolution



Better linearity and resolution with true f_{em}. Significant improvement in rel. resol. with predicted f_{em}.

Summary

Prediction of em fraction in hadronic showers

tested on simulations with QGSP_BERT_HP and FTFP_BERT_HP physics lists from Geant4 v10.3

- **Technique:** regression model in Deep Neural Network trained using supervised learning
- **Inputs:** 29 calorimetric observables from a highly granular calorimeter
- **Target:** electromagnetic fraction in a hadronic shower
- **Preliminary results for single pion-induced showers**
  - DNN trained on mixed samples (10-80 GeV)
  - reasonable performance in event-by-event prediction of electromagnetic fraction

Application

- predicted em fraction was used to correct energy event-by-event
- **comparable correction effects are achieved with true and predicted em fraction**

Plans

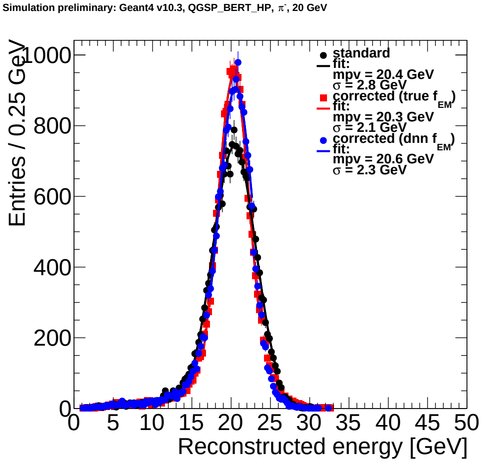
- optimise DNN hyperparameters to improve performance
- **apply trained model to data**

Backup slides

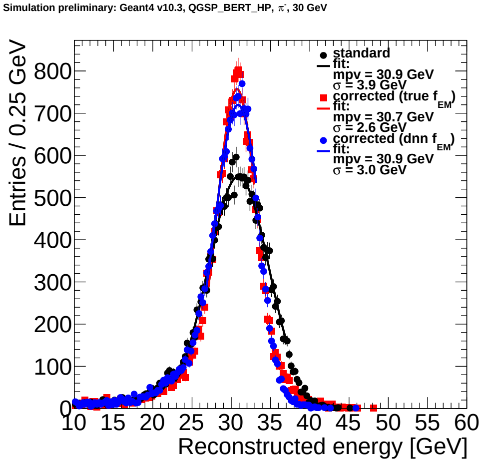
Example of corrected energy distributions for QGSP_BERT_HP

DNN trained on mixed sample of QGSP_BERT_HP and applied to QGSP_BERT_HP

20 GeV



30 GeV



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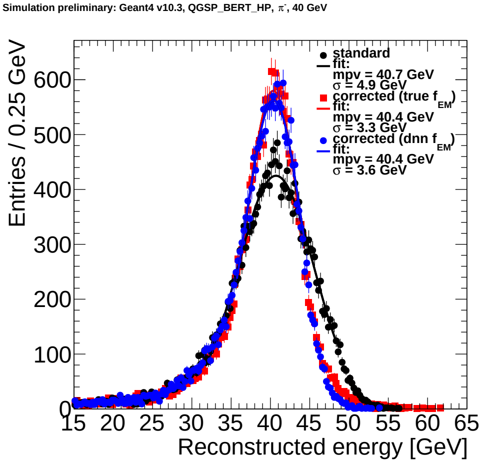
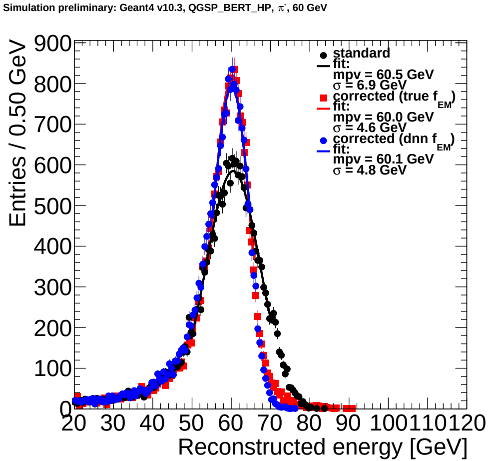


60 GeV



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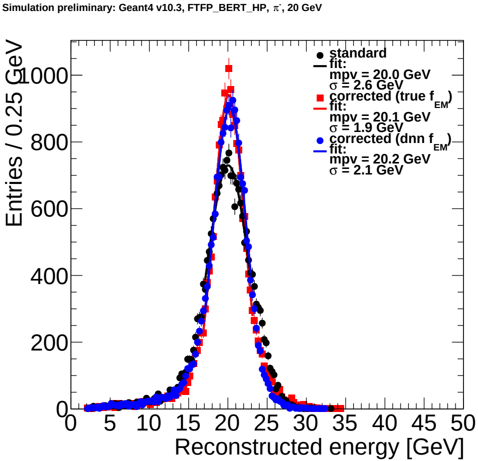
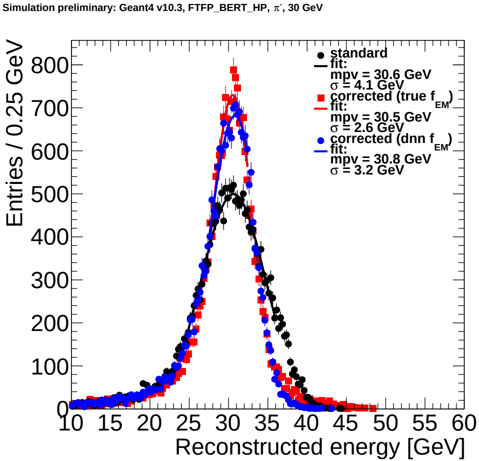
20 GeV



30 GeV



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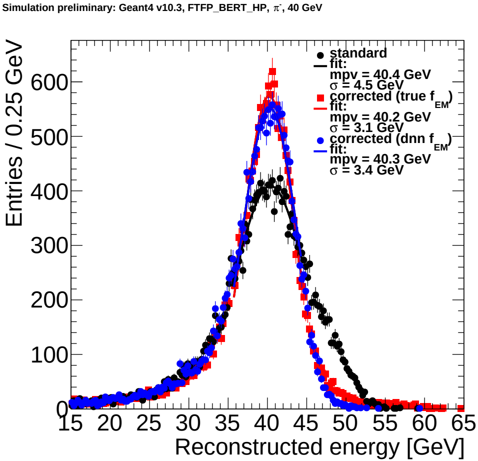
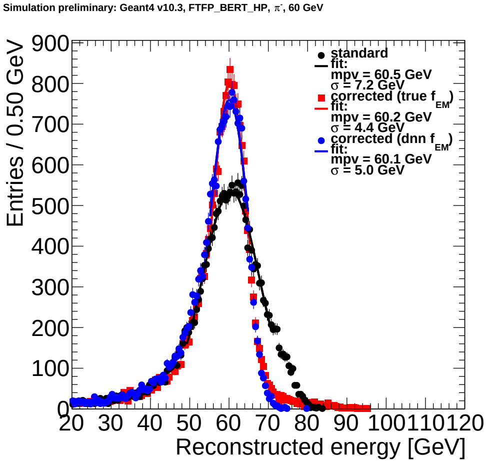


60 GeV



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