

Introduction to Hadronic Final State Reconstruction in Collider Experiments (Part XI)

Peter Loch
University of Arizona
Tucson, Arizona
USA



General cluster features

Motivated by shower reconstruction

No bias in signal definition towards reconstruction of a certain, possibly very specific, physics signal object like a jet

Clusters have shapes and location information

Spatial cell energy distributions and their correlations drive longitudinal and lateral extensions

Density and energy sharing measures

Signal center of gravity and (directional) barycenter

Shapes are sensitive to shower nature

At least for a reasonable clustering algorithm

Local (cluster) calibration strategy

First reconstruct truly deposited energy at cluster location...

e/h, mostly

...then correct for other energy losses in the vicinity of signal cluster

Dead material energy losses and signal losses due to noise suppression

Calibration input

Reconstructed cluster shapes represent shower shapes

E.g., dense and compact clusters indicate electromagnetic shower activity anywhere in the calorimeter

Can be intrinsic to a hadronic shower!

Calibration functions can exploit the cluster shapes to apply the corrections for $e/h \neq 1$ dynamically

Location of cluster together with shape

E.g., dense and compact clusters located in electromagnetic calorimeter indicate electron or photon as particle originating the signal

Cluster not (part of) hadronic shower signal!

Clusters can be classified before calibration

Electron/photon clusters need different calibration than dense clusters from hadronic showers!

Cluster calibration extensions

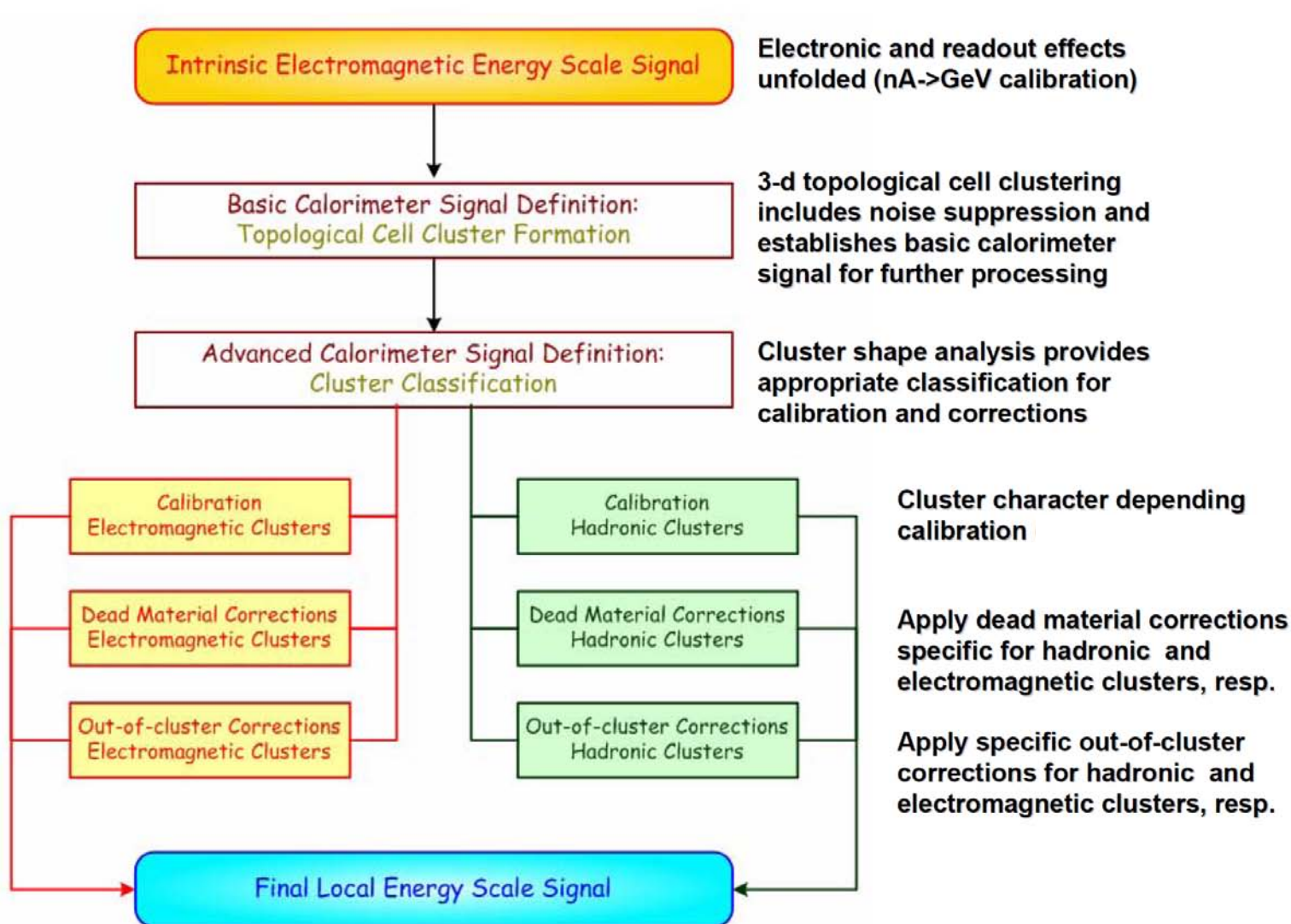
Shapes, location and size also indicate possible energy losses around the cluster

Some correlations between energy losses in inactive material in front or inside of clusters

Cluster size and signal neighbourhood sensitive to lost true signal in noise suppression algorithm

Out-of-cluster corrections





Quality of True Deposited Energy Estimate



Phase-space pion counting method

Classify clusters using the correlation of

Shower shape variables in single π^\pm MC events

λ_{cluster} = cluster center of gravity depth in calorimeter

$$\bar{\rho}_{\text{cluster}} = \frac{1}{E_{0,\text{cluster}}} \sum_{\text{cells in cluster}} E_{0,\text{cell}} \cdot \rho_{\text{cell}}$$

Electromagnetic fraction estimator in bin of shower shape variables:

$$F \equiv \frac{\varepsilon(\pi^0)}{\varepsilon(\pi^0) + 2\varepsilon(\pi^-)}$$

$$\varepsilon(X) = \frac{N(X) \text{ producing a cluster in a given } (\eta, E_{0,\text{cluster}}, \lambda_{\text{cluster}}, \bar{\rho}_{\text{cluster}})}{N(X) \text{ total}}$$

Implementation

keep F in bins of η , E , λ , ρ of clusters for a given cluster

If $E < 0$, then classify as unknown

Lookup F from the observables $|\eta|$, E , λ , ρ

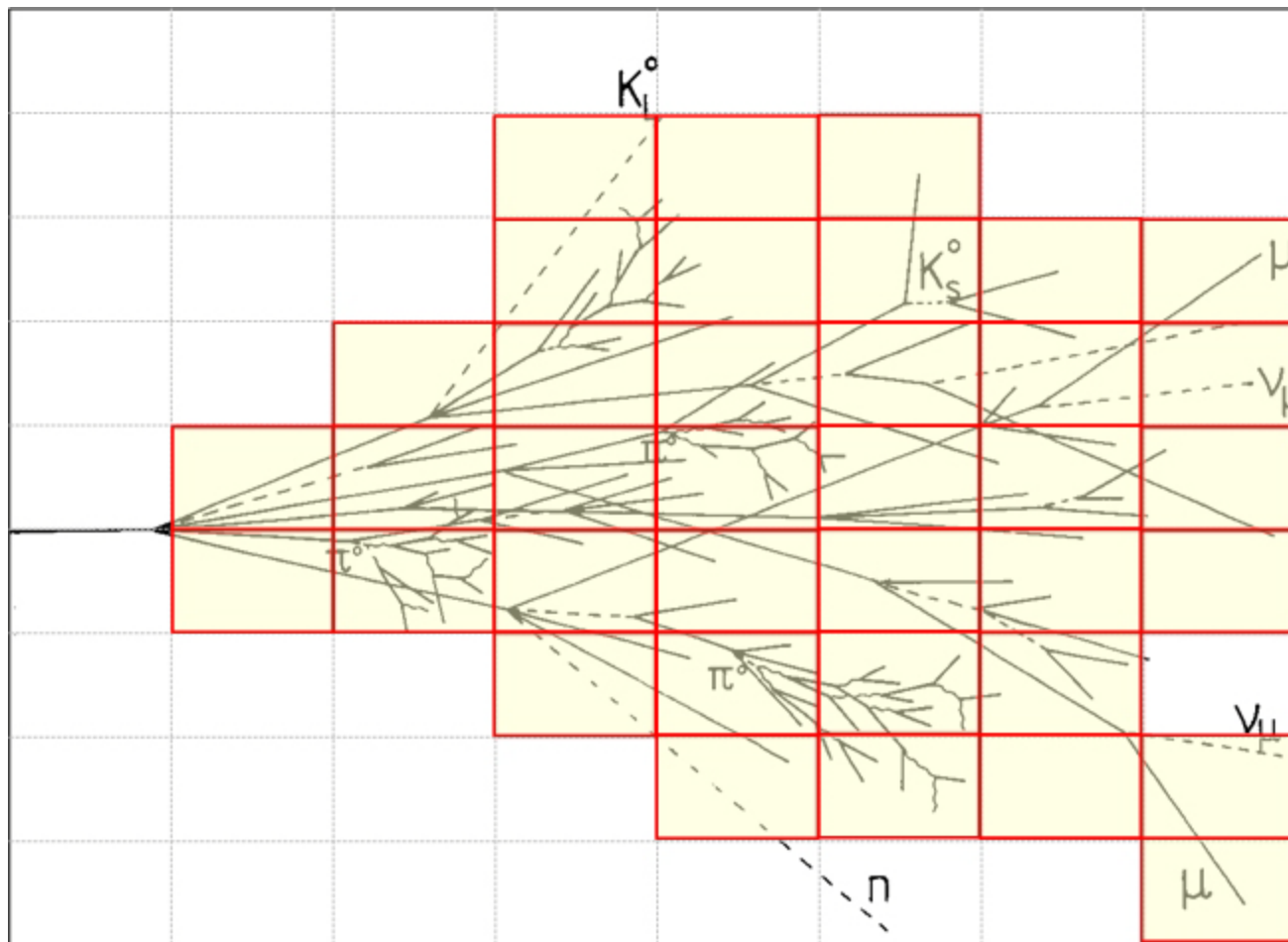
Cluster is EM if $F > 50\%$, hadronic otherwise



Calibration with cell signal weights

Idea is to compensate for lack of pion response in each cell

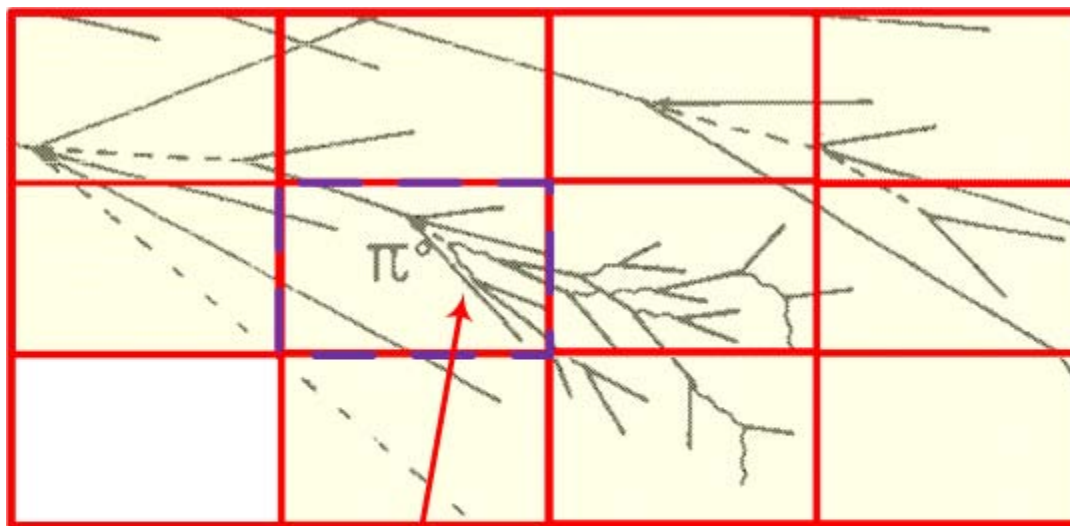
Pioneered in CDHS and applied in H1



Calibration with cell signal weights

Idea is to compensate for lack of pion response in each cell

Pioneered in CDHS and applied in H1



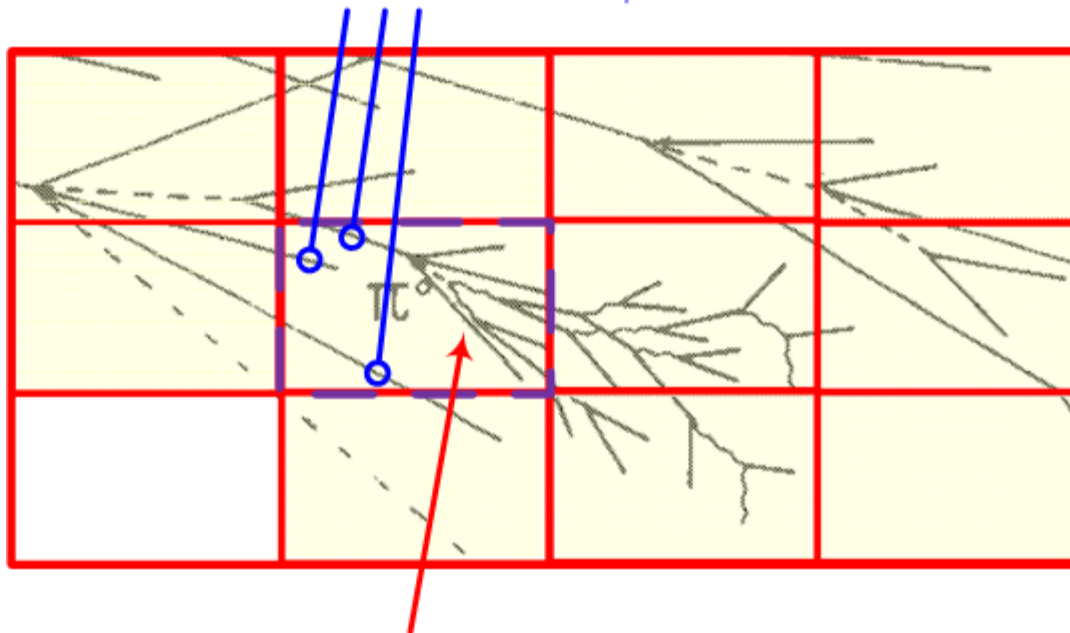
$$E_{\text{cell}}^{\text{em}} = [E_{\text{cell}}^{\text{em}}]_{\text{active}} + [E_{\text{cell}}^{\text{em}}]_{\text{passive}}$$

Calibration with cell signal weights

Idea is to compensate for lack of pion response in each cell

Pioneered in CDHS and applied in H1

$$E_{\text{cell}}^{\text{ion}} = \left[E_{\text{cell}}^{\text{ion}} \right]_{\text{active}} + \left[E_{\text{cell}}^{\text{ion}} \right]_{\text{passive}}$$

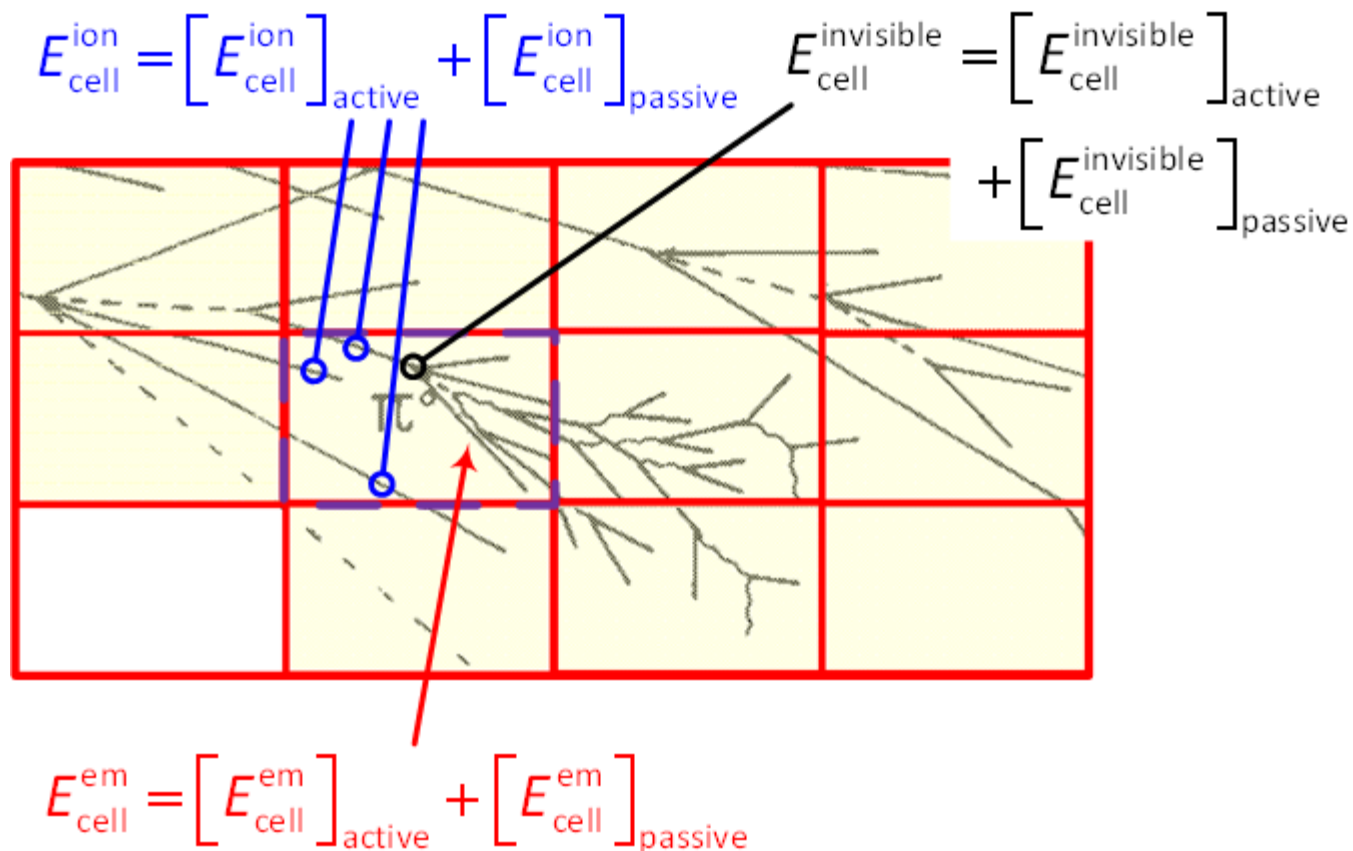


$$E_{\text{cell}}^{\text{em}} = \left[E_{\text{cell}}^{\text{em}} \right]_{\text{active}} + \left[E_{\text{cell}}^{\text{em}} \right]_{\text{passive}}$$

Calibration with cell signal weights

Idea is to compensate for lack of pion response in each cell

Pioneered in CDHS and applied in H1



Calibration with cell signal weights

Idea is to compensate for lack of pion response in each cell

Pioneered in CDHS and applied in H1

Uses deposited energies in cells

Deposit can be in active or passive medium of calorimeter!

$$w_{\text{cell,cluster}}^{\text{calib}} = \left\langle \frac{E_{\text{deposited,cell}} = E_{\text{cell}}^{\text{em}} + E_{\text{cell}}^{\text{ion}} + E_{\text{cell}}^{\text{invisible}} + E_{\text{cell}}^{\text{escaped}}}{\text{"deposited" energy anywhere within cell boundaries}} \right\rangle$$

$$E_{0,\text{cell}} = c_{\text{em}} \cdot A \left(\underbrace{\left[E_{\text{cell}}^{\text{em}} \oplus E_{\text{cell}}^{\text{ion}} \right]_{\text{active}}}_{\text{reconstructed em scale signal}}, t, \vec{X}, \dots \right)$$

($E_{\text{cell}}^{\text{escaped}}$ is the energy escaping the calorimeter, i.e. carried by neutrinos - it is often assigned to the cell in which the neutrino vertex is located)



Calibration with cell signal weights

Idea is to compensate for lack of pion response in each cell

Pioneered in CDHS and applied in H1

Uses deposited energies in cells

Deposit can be in active or passive medium of calorimeter!

$$w_{\text{cell,cluster}}^{\text{calib}} = \left\langle \frac{E_{\text{deposited,cell}} = E_{\text{cell}}^{\text{em}} + E_{\text{cell}}^{\text{ion}} + E_{\text{cell}}^{\text{invisible}} + E_{\text{cell}}^{\text{escaped}}}{\text{"deposited" energy anywhere within cell boundaries}} \right\rangle$$

$$E_{0,\text{cell}} = c_{\text{em}} \cdot A \left(\left[E_{\text{cell}}^{\text{em}} \oplus E_{\text{cell}}^{\text{ion}} \right]_{\text{active}}, t, \vec{X}, \dots \right)$$

reconstructed em scale signal

Only signal contribution from energy deposited by electromagnetic sub-showers and through ionization by charged particles!



Calibration with cell signal weights

Idea is to compensate for lack of pion response in each cell

Pioneered in CDHS and applied in H1

Uses deposited energies in cells

Deposit can be in active or passive medium of calorimeter!

Energy deposited in cell not available in experiment

Use of detector simulations

Deposited energy and signal available

Use “unit cell” volume concept to collect invisible energies

Shower model dependent!

Use single pion testbeam data

Develop model for weights in cells

Fit parameters of model using cells testbeam

Minimize resolution with beam energy constraint

Statistical – does not necessarily produce the correct weights!



Basic idea

Use a dynamically self-adjusting calibration weight

High cell signal density →
electromagnetic deposit

Low cell signal density → hadronic
deposit

Principal weighting function characteristics

Depends on cell energy density

Depends on cell location

Accidental application to electron signals
should yield correct energy as well

Extraction of weighting functions

Minimize resolution in (pion) testbeam data

Fitting function model

May not produce the correct weights –
may even be unphysical!

Use simulation

Deterministic approach relates signal to
deposited energy within cell volume – no
fitting!

May depend on details of (hadronic)
shower modeling

$$E_{\text{rec,cell}} = w_{\text{cell}}(\dots) \cdot E_{0,\text{cell}} = E_{\text{deposited,cell}}$$



Basic idea

Use a dynamically self-adjusting calibration weight

High cell signal density \rightarrow
electromagnetic deposit

Low cell signal density \rightarrow hadronic
deposit

Principal weighting function characteristics

Depends on cell energy density

Depends on cell location

Accidental application to electron signals
should yield correct energy as well

$$E_{\text{rec,cell}} = w_{\text{cell}}(\dots) \cdot E_{0,\text{cell}} = E_{\text{deposited,cell}}$$

$$w_{\text{cell}}(\dots) = w(\rho_{\text{cell}} = E_{0,\text{cell}}/V_{\text{cell}}, \vec{X}, \dots)$$

Extraction of weighting functions

Minimize resolution in (pion) testbeam data

Fitting function model

May not produce the correct weights –
may even be unphysical!

Use simulation

Deterministic approach relates signal to
deposited energy within cell volume – no
fitting!

May depend on details of (hadronic)
shower modeling



Basic idea

Use a dynamically self-adjusting calibration weight

High cell signal density \rightarrow
electromagnetic deposit

Low cell signal density \rightarrow hadronic
deposit

Principal weighting function characteristics

Depends on cell energy density

Depends on cell location

Accidental application to electron signals
should yield correct energy as well

Extraction of weighting functions

Minimize resolution in (pion) testbeam data

Fitting function model

May not produce the correct weights –
may even be unphysical!

Use simulation

Deterministic approach relates signal to
deposited energy within cell volume – no
fitting!

May depend on details of (hadronic)
shower modeling

$$E_{\text{rec,cell}} = w_{\text{cell}}(\dots) \cdot E_{0,\text{cell}} = E_{\text{deposited,cell}}$$

$$w_{\text{cell}}(\dots) = w(\rho_{\text{cell}} = E_{0,\text{cell}}/V_{\text{cell}}, \vec{x}, \dots)$$

e.g. in H1:

$$E_{\text{rec,cell}} = \underbrace{\left(1 + \alpha(\vec{x}, \dots) \cdot e^{-\beta(\vec{x}, \dots) \cdot \rho_{\text{cell}}}\right)}_{=w(\rho_{\text{cell}}, \vec{x}, \dots)} \cdot E_{0,\text{cell}},$$

with $\lim_{\rho_{\text{cell}} \rightarrow \infty} E_{\text{rec,cell}} = E_{0,\text{cell}}$



Basic idea

Use a dynamically self-adjusting calibration weight

High cell signal density →
electromagnetic deposit

Low cell signal density → hadronic
deposit

Principal weighting function characteristics

Depends on cell energy density

Depends on cell location

Accidental application to electron signals
should yield correct energy as well

Extraction of weighting functions

Minimize resolution in (pion) testbeam data

Fitting function model

May not produce the correct weights –
may even be unphysical!

Use simulation

Deterministic approach relates signal to
deposited energy within cell volume – no
fitting!

May depend on details of (hadronic)
shower modeling

Fit $\alpha(\vec{x}, \dots), \beta(\vec{x}, \dots)$ with

$$\chi^2 = \sum_{\text{events}} \frac{(E_{\text{rec, cell}} - E_{\text{beam}})^2}{\sigma^2} = \min$$

i.e.:

$$\frac{\partial \chi^2}{\partial \alpha} = 0 \quad \text{and} \quad \frac{\partial \chi^2}{\partial \beta} = 0$$



Basic idea

Use a dynamically self-adjusting calibration weight

High cell signal density \rightarrow
electromagnetic deposit

Low cell signal density \rightarrow hadronic
deposit

Principal weighting function characteristics

Depends on cell energy density

Depends on cell location

Accidental application to electron signals
should yield correct energy as well

Extraction of weighting functions

Minimize resolution in (pion) testbeam data

Fitting function model

May not produce the correct weights –
may even be unphysical!

Use simulation

Deterministic approach relates signal to
deposited energy within cell volume – no
fitting!

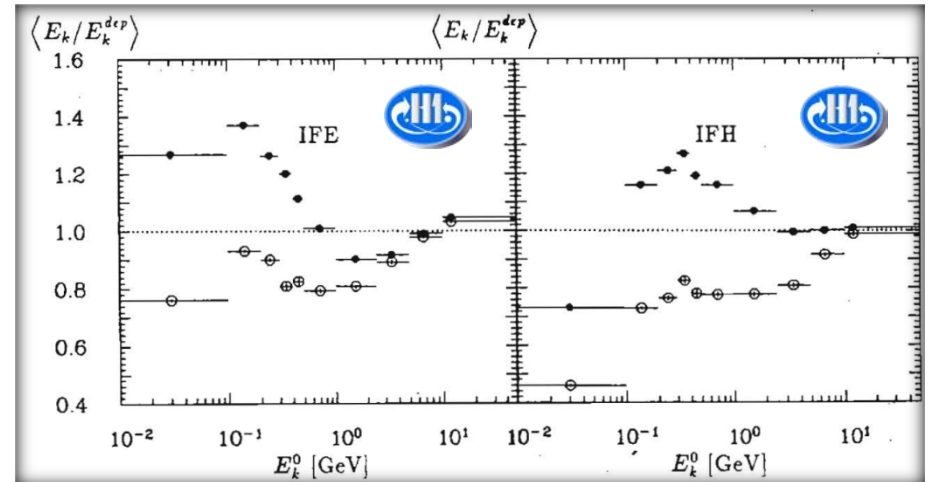
May depend on details of (hadronic)
shower modeling

Fit $\alpha(\vec{x}, \dots), \beta(\vec{x}, \dots)$ with

$$\chi^2 = \sum_{\text{events}} \frac{(E_{\text{rec,cell}} - E_{\text{beam}})^2}{\sigma^2} = \min$$

i.e.:

$$\frac{\partial \chi^2}{\partial \alpha} = 0 \quad \text{and} \quad \frac{\partial \chi^2}{\partial \beta} = 0$$



$$\circ \quad \frac{E_{\text{rec,cell}}}{E_{0,\text{cell}}} \quad \bullet \quad \frac{E_{\text{deposited,cell}}}{E_{0,\text{cell}}}$$



Basic idea

Use a dynamically self-adjusting calibration weight

High cell signal density \rightarrow
electromagnetic deposit

Low cell signal density \rightarrow hadronic
deposit

Principal weighting function characteristics

Depends on cell energy density

Depends on cell location

Accidental application to electron signals
should yield correct energy as well

Extraction of weighting functions

Minimize resolution in (pion) testbeam data

Fitting function model

May not produce the correct weights –
may even be unphysical!

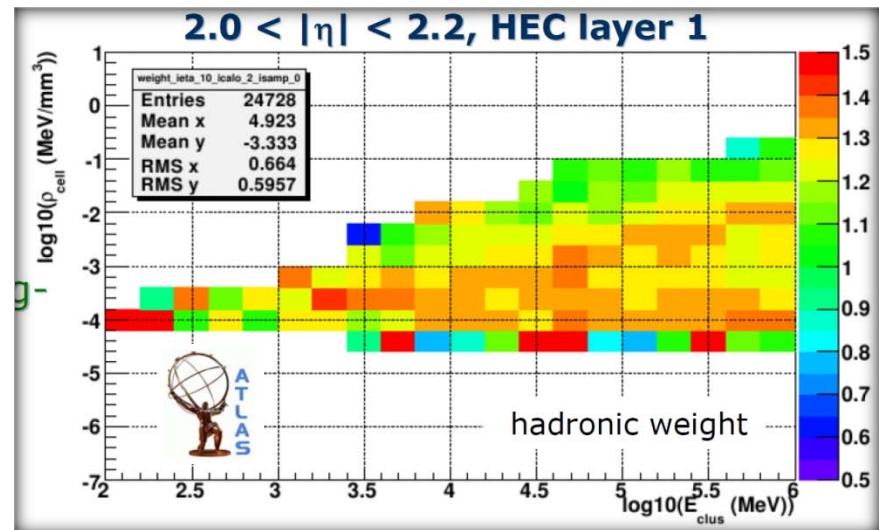
Use simulation

Deterministic approach relates signal to
deposited energy within cell volume – no
fitting!

May depend on details of (hadronic)
shower modeling

ATLAS cluster-based approach:

1. Use only cells in hadronic clusters
2. Cluster sets global energy scale as a reference for densities
3. Calculate $E_{\text{deposited,cell}}/E_{0,\text{cell}}$ from **single pion simulations** in bins of cluster energy, cell energy density, cluster direction, and calorimeter sampling layer
4. Store $[E_{\text{deposited,cell}}/E_{0,\text{cell}}]^{-1}$ in look-up tables



Basic idea

Use a dynamically self-adjusting calibration weight

High cell signal density \rightarrow
electromagnetic deposit

Low cell signal density \rightarrow hadronic
deposit

Principal weighting function characteristics

Depends on cell energy density

Depends on cell location

Accidental application to electron signals
should yield correct energy as well

Extraction of weighting functions

Minimize resolution in (pion) testbeam data

Fitting function model

May not produce the correct weights –
may even be unphysical!

Use simulation

Deterministic approach relates signal to
deposited energy within cell volume – no
fitting!

May depend on details of (hadronic)
shower modeling

ATLAS cluster-based approach:

1. Use only cells in hadronic clusters
2. Cluster sets global energy scale as a reference for densities
3. Calculate $E_{\text{deposited,cell}}/E_{0,\text{cell}}$ from **single pion simulations** in bins of cluster energy, cell energy density, cluster direction, and calorimeter sampling layer
4. Store $[E_{\text{deposited,cell}}/E_{0,\text{cell}}]^{-1}$ in look-up tables
5. Retrieve weights for any cell in any cluster from look-up table to reconstruct cell and cluster energies

$$E_{\text{rec,cluster}}^{\text{calib}} = \sum_{\text{cells in cluster}} E_{\text{rec,cell}} = \sum_{\text{cells in cluster}} w_{\text{cell,cluster}}^{\text{calib}} (E_{0,\text{cluster}}, \eta_{\text{cluster}}, S_{\text{cell}}, \rho_{\text{cell}}) \cdot E_{0,\text{cell}}$$



Dead material

Energy losses not directly measurable

Signal distribution in vicinity can help

Introduces need for signal corrections up to O(10%)

Exclusive use of signal features

Corrections depend on electromagnetic or hadronic energy deposit

Major contributions

Upstream materials

Material between LArG and Tile (central)

Cracks

dominant sources for signal losses

$|\eta| \approx 1.4-1.5$

$|\eta| \approx 3.2$

Clearly affects detection efficiency for particles and jets

Already in trigger!

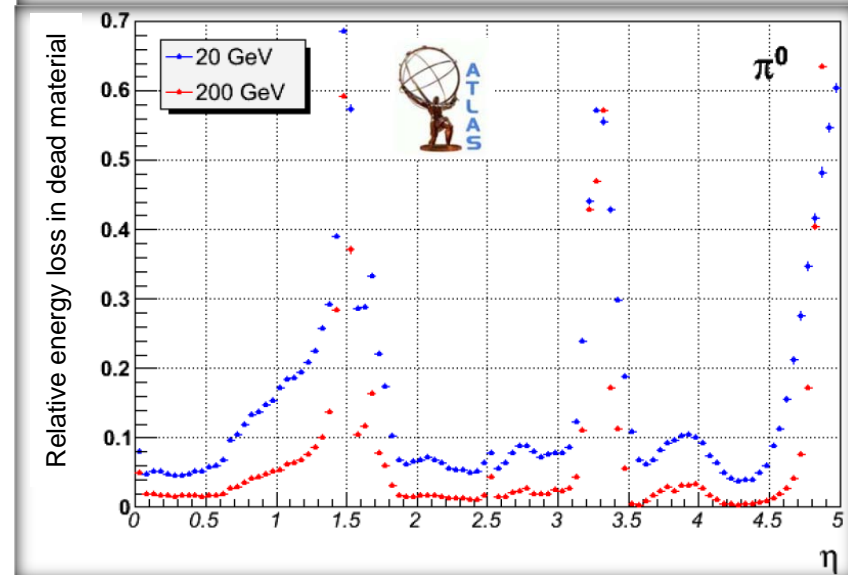
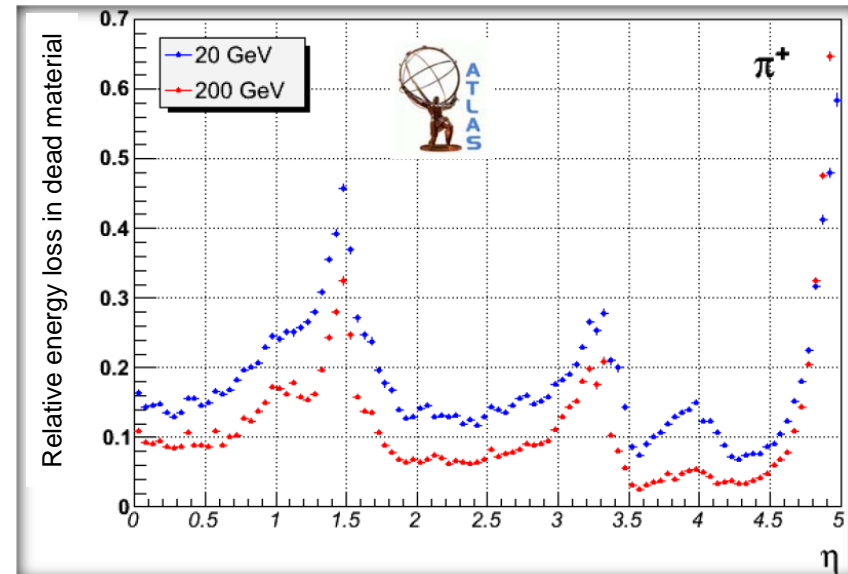
Hard to recover jet reconstruction inefficiencies

Generate fake missing E_t contribution

Topology dependence of missing E_t reconstruction quality

Additive correction:

$$E_{\text{rec,cluster}}^{\text{calib+DM}} = E_{\text{rec,cluster}}^{\text{calib}} + E_{\text{rec,cluster}}^{\text{DM}}(\vec{x}_{\text{cluster}}, \dots)$$



Compensate loss of true signal

Limited efficiency of noise suppression scheme

Discard cells with small true energy not close to a primary or secondary seed

Accidental acceptance of a pure noise cell

Can be significant for isolated pions

10% at low energy

Correction derived from single pions

Compensates the isolated particle loss

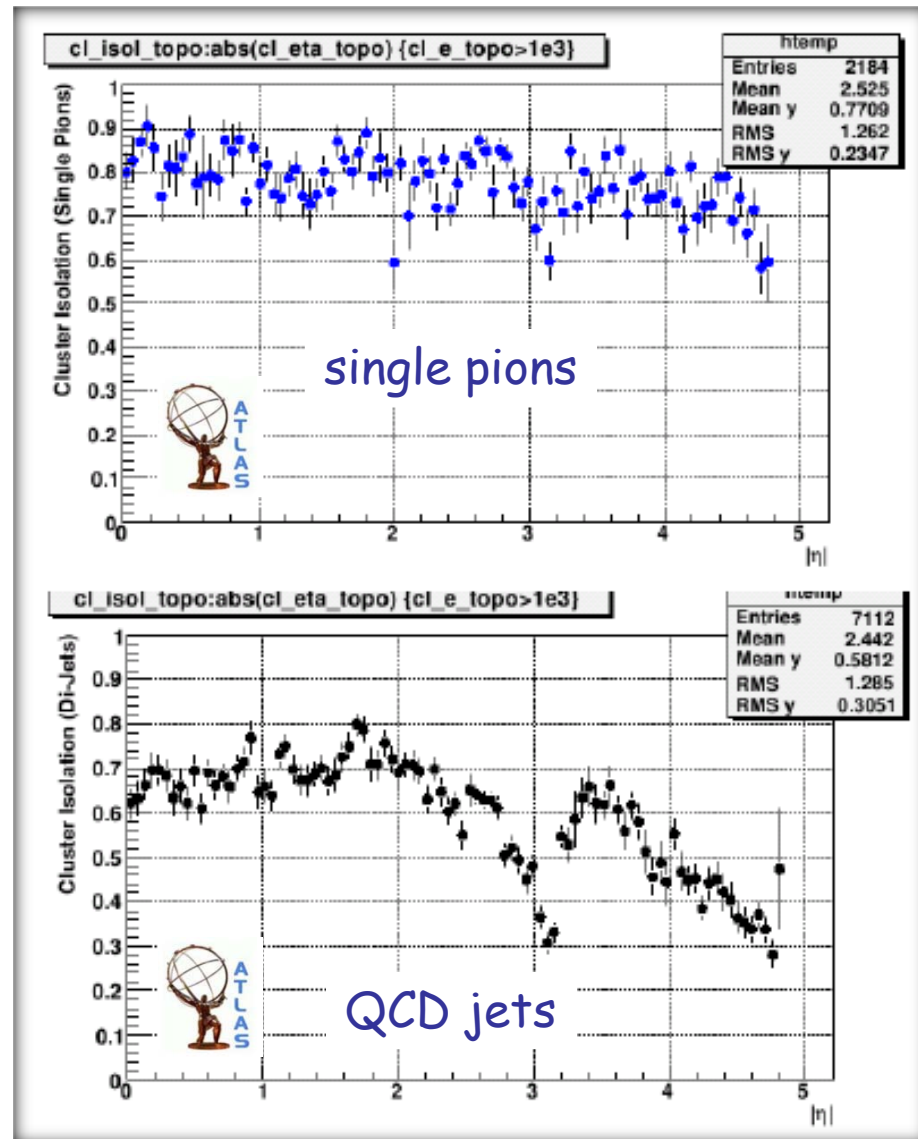
But in jets neighboring clusters can pick up lost energy

Use isolation moment to measure effective “free surface” of each cluster

Scale single pion correction with this moment (0...1)

Additive correction:

$$\begin{aligned}
 E_{\text{rec,cluster}}^{\text{calib+DM+OOC}} &= E_{\text{rec,cluster}} \\
 &= E_{\text{rec,cluster}}^{\text{calib+DM}} + E_{\text{rec,cluster}}^{\text{OOC}}(\vec{x}_{\text{cluster}}, m_{\text{isol}}, E_{0,\text{cluster}}, \dots)
 \end{aligned}$$



Attempt to calibrate hadronic calorimeter signals in smallest possible signal context

Topological clustering implements noise suppression with least bias signal feature extraction

Residual concerns about infrared safety!

No bias towards a certain physics analysis

Calibration driven by calorimeter signal features without further assumption

Good common signal base for all hadronic final state objects

Jets, missing E_t , taus

Factorization of cluster calibration

Cluster classification largely avoids application of hadronic calibration to Electromagnetic signal objects

Low energy regime challenging

Signal weights for hadronic calibration are functions of cluster and cell parameters and variables

Cluster energy and direction

Cell signal density and location (sampling layer)

Dead material and out of cluster corrections are independently applicable

Factorized calibration scheme

Local calibration does not reproduce jet energy

Energy losses not correlated with cluster signals can not be corrected

Magnetic field losses

Dead material losses

Needs additional jet energy scale corrections

Use specific jet context to derive those

Only applicable to cluster jets!

$$E_{true}^{jet} = E_{dep}^{calo} + E_{mag}^{loss} + E_{low}^{loss} + E_{leak}^{loss} + E_{out}^{loss} - E_{UE\otimes PU}^{gain} - E_{env}^{gain}$$

E_{dep}^{calo} energy deposited in the calorimeter within signal definition

E_{mag}^{loss} charged particle energy lost in solenoid field

E_{low}^{loss} particle energy lost in dead material

E_{leak}^{loss} energy lost due to longitudinal leakage

E_{out}^{loss} energy lost due to jet algorithm/calorimeter signal definition

$E_{UE\otimes PU}^{gain}$ energy added by underlying event and/or pile-up

E_{env}^{gain} energy added by response from other nearby particles/jets

only source of signal!



Use jet context for cell calibration

Determine cell weights using jet energy constraints

Same principle idea as for local cell weighting, but different global energy scale

Needs jet truth reference

Jet context relevant

Supports assumption of hadronic signal activity

Has enhanced electromagnetic component contributing to the weighting function
 parameterizations of all cells – larger (volume/area) context than topological clustering

May be biased with respect to calorimeter signal definition and jet algorithms

Jet energy references for calorimeter jets

Simulation

Matching particle level jet (same jet definition) energy

Experiment

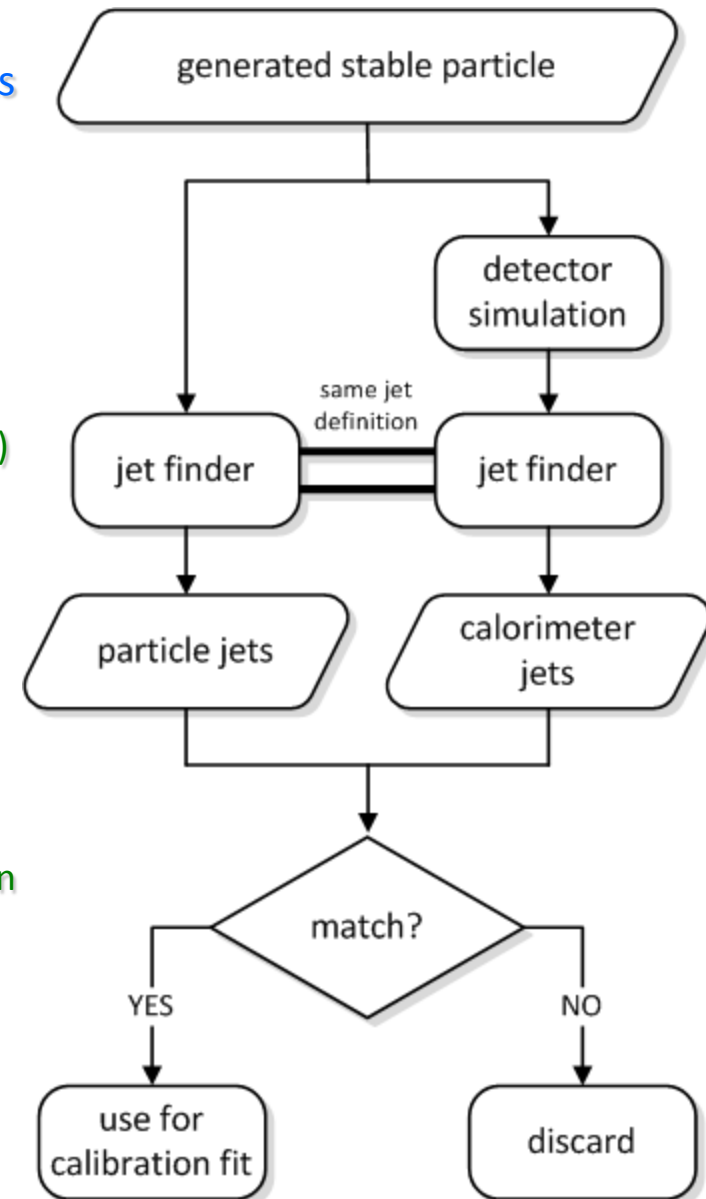
pT balance with electromagnetic system like photon or Z-boson

W mass spectroscopy

Sampling energy based jet calibration

Coarser than cell signals but less numerical complexity

Fewer function parameters



Simulated particle jets

Establish “true” energy reference to constrain calibration function fits for calorimeter jets

Attempt to reconstruct true jet energy

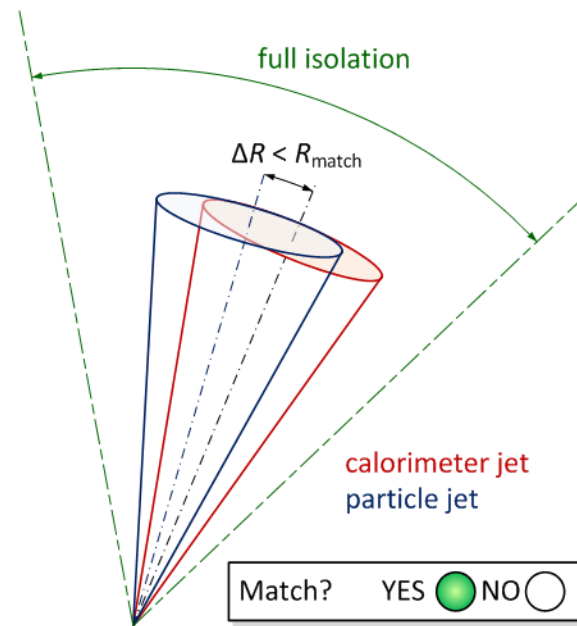
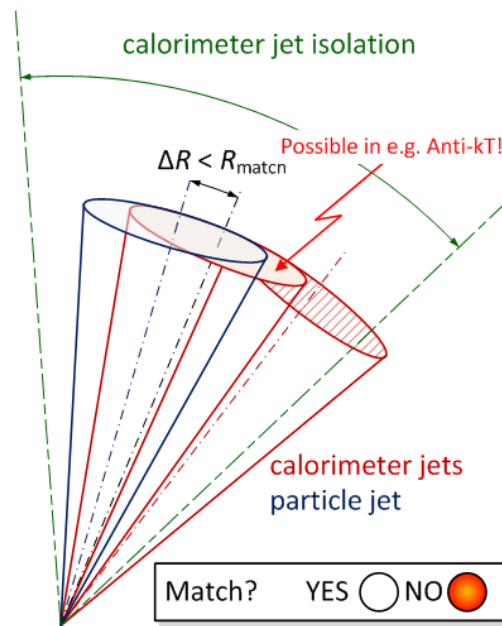
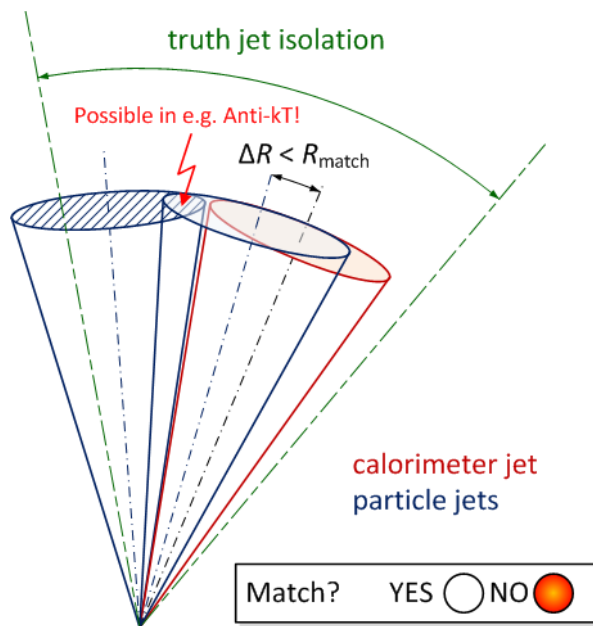
Need matching definition

Geometrical distance

Isolation and unique 1-to-1 jet matching

$$\Delta R =$$

$$\sqrt{(\eta_{\text{particle,jet}} - \eta_{\text{rec,jet}})^2 + (\phi_{\text{particle,jet}} - \phi_{\text{rec,jet}})^2}$$



Select matched jet pair

Typically small matching radius

$$R_{\text{match}} = 0.2 - 0.3$$

Restrict jet directions to regions with good calorimeter response

No excessive dead material

Away from cracks and complex transition geometries

Calibration functions

Cell signal weighting

Large weights for low density signals

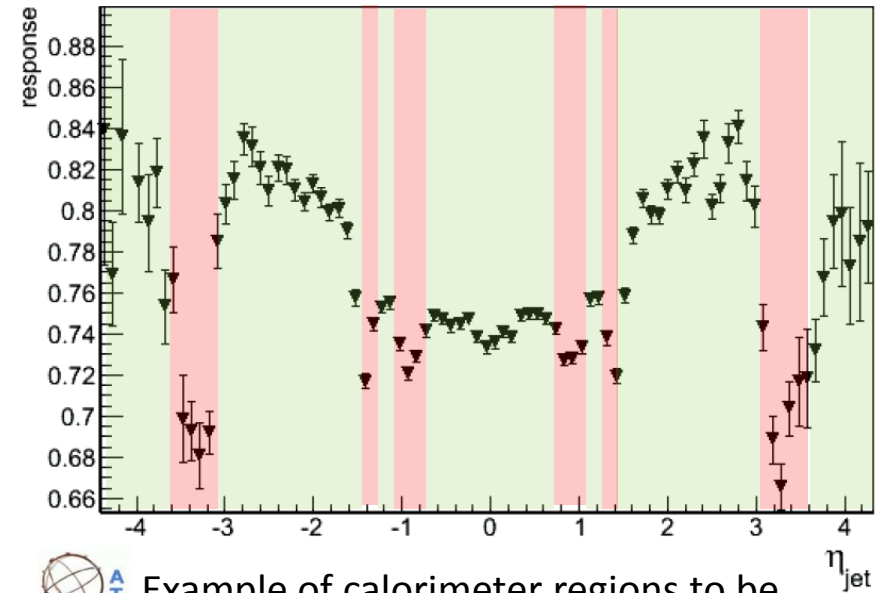
Small weights for high density signals

Sampling layer signal weighting

Weights determined by longitudinal energy sharing in calorimeter jet

Functions can be complex

Often highly non-linear systems



Example of calorimeter regions to be considered for jet calibration fits in ATLAS (tinted green). The red tinted regions indicate calorimeter cracks and transitions. The points show the simulated jet response on electromagnetic energy scale, as function of the jet pseudorapidity. (figure for illustration purposes only!)



Select matched jet pair

Typically small matching radius

$$R_{\text{match}} = 0.2 - 0.3$$

Restrict jet directions to regions with good calorimeter response

No excessive dead material

Away from cracks and complex transition geometries

Calibration functions

Cell signal weighting

Large weights for low density signals

Small weights for high density signals

Sampling layer signal weighting

Weights determined by longitudinal energy sharing in calorimeter jet

Functions can be complex

Often highly non-linear systems

$$E_{\text{rec,cell}} = w_{\text{cell}}(\rho_{\text{cell}}, \dots) \cdot E_{0,\text{cell}}$$

$$w_{\text{cell}}(\rho_{\text{cell}}, \dots) \begin{cases} \nearrow \text{for } \rho_{\text{cell}} \uparrow \\ \searrow \text{for } \rho_{\text{cell}} \downarrow \end{cases}$$

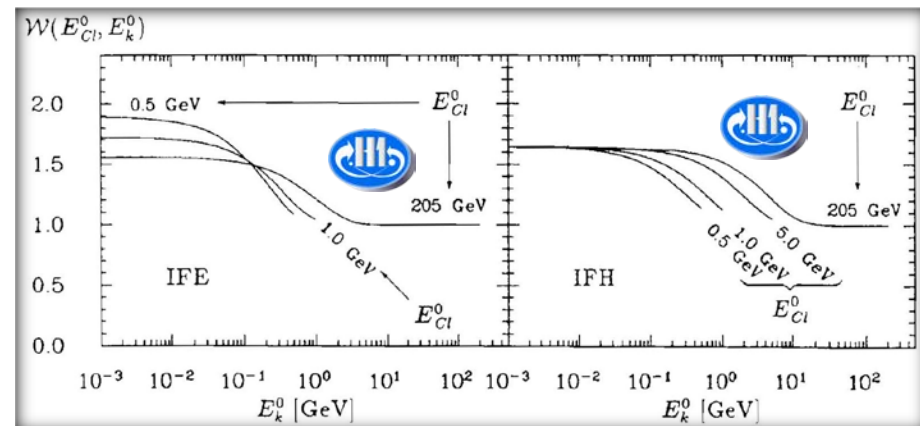
Typical boundary conditions:

$$\max(w_{\text{cell}}(\rho_{\text{cell}}, \dots)) \approx 1.5 - 3.0$$

(avoid boosting noise!)

$$\min(w_{\text{cell}}(\rho_{\text{cell}}, \dots)) = 1.0$$

(avoid suppressing em response!)



Example: cell signal weights \mathcal{W} , parameterized as function of the cell energy E_k^0 and the cluster energy E_{cl}^0



Select matched jet pair

Typically small matching radius

$$R_{\text{match}} = 0.2 - 0.3$$

Restrict jet directions to regions with good calorimeter response

No excessive dead material

Away from cracks and complex transition geometries

Calibration functions

Cell signal weighting

Large weights for low density signals

Small weights for high density signals

Sampling layer signal weighting

Weights determined by longitudinal energy sharing in calorimeter jet

Functions can be complex

Often highly non-linear systems

$$E_{\text{rec,cell}} = w_{\text{cell}}(\rho_{\text{cell}}, \dots) \cdot E_{0,\text{cell}}$$

$$w_{\text{cell}}(\rho_{\text{cell}}, \dots) \begin{cases} \nearrow \text{for } \rho_{\text{cell}} \uparrow \\ \searrow \text{for } \rho_{\text{cell}} \downarrow \end{cases}$$

Typical boundary conditions:

$$\max(w_{\text{cell}}(\rho_{\text{cell}}, \dots)) \approx 1.5 - 3.0$$

(avoid boosting noise!)

$$\min(w_{\text{cell}}(\rho_{\text{cell}}, \dots)) = 1.0$$

(avoid suppressing em response!)

Example for non-algebraic functional form:

(similar in ATLAS)

$$w_{\text{cell}}(\rho_{\text{cell}}, \mathfrak{R}_{\text{cell}}) = \omega_{ij} \text{ for } \begin{cases} \log(\rho)_i \leq \log(\rho_{\text{cell}}) < \log(\rho)_{i+1} \\ \mathfrak{R}_{\text{cell}} \in \mathfrak{R}_j \end{cases}$$

$\mathfrak{R}_{\text{cell}}$ is a region descriptor for a given cell,

$$\text{like } \mathfrak{R}_{\text{cell}} = \underbrace{\{M_{\text{cell}}, S_{\text{cell}}\}}_{\substack{\text{calorimeter module id,} \\ \text{sampling id}}}$$



Select matched jet pair

Typically small matching radius

$$R_{\text{match}} = 0.2 - 0.3$$

Restrict jet directions to regions with good calorimeter response

No excessive dead material

Away from cracks and complex transition geometries

Calibration functions

Cell signal weighting

Large weights for low density signals

Small weights for high density signals

Sampling layer signal weighting

Weights determined by longitudinal energy sharing in calorimeter jet

Functions can be complex

Often highly non-linear systems

$$E_{\text{rec},S} = w_S E_{0,S} = w_S \cdot \sum_{\text{cells in sampling } S} E_{0,\text{cell}}$$

Possible parameterizations:

$$w_S = w_S(f_{\text{EMC}}), \text{ with } f_{\text{EMC}} = \frac{\sum_{\text{jet cells in EMC}} E_{0,\text{cell}}}{\sum_{\text{all jet cells}} E_{0,\text{cell}}}$$

Example for non-algebraic functional form:

$$w_S(f_{\text{EMC}}) = \omega_{S,i} \text{ for } F_{\text{EMC},i} \leq f_{\text{EMC}} < F_{\text{EMC},i+1}$$



Fitting

Possible constraints

Resolution optimization

Signal linearity

Combination of both

Regularization of calibration functions

Try to linearize function ansatz

Use polynomials

Can reduce fits to solving system of linear equations

Non-linear function fitting

Use numerical approaches to find (local) minimum for multi-dimensional test functions (e.g., software like MINUIT etc.)

Reconstructed jet energy with cell calibration:

$$E_{\text{rec,jet}} = \sum_{\text{cells in jet}} w_{\text{cell}}(\rho_{\text{cell}}, \mathcal{R}_{\text{cell}}) \cdot E_{0,\text{cell}}$$

Fit $\{\omega_{ij}\}$ such that...

$$\chi^2 = \sum_{\text{matching jet pairs}} \frac{(E_{\text{rec,jet}} - E_{\text{particle,jet}})^2}{\sigma_{\text{rec,jet}}^2 + \sigma_{\text{particle,jet}}^2} = \min$$

Reconstructed jet energy with sampling calibration:

$$E_{\text{rec,jet}} = \sum_{S \text{ in jet}} w_S(f_{\text{EMC}}) \cdot E_{0,S}$$

Fit $\{\omega_{i,S}\}$ using the same χ^2 test function!

Note that $\sigma_{\text{rec,jet}}^2 \sim E_{\text{rec,jet}}^{-1}$!



Attempted de-convolution of signal contributions

Normalization choice convolutes various jet response features

E.g., cell weights correct for dead material and magnetic field induced energy losses, etc.

Limited de-convolution

Fit corrections for energy losses in material between calorimeter modules with different functional form
 Separation in terms, but still a correlated parameter fit

Reconstructed jet energy with cell calibration:

$$E_{\text{rec,jet}} = \sum_{\text{cells in jet}} w_{\text{cell}}(\rho_{\text{cell}}, \mathcal{R}_{\text{cell}}) \cdot E_{0,\text{cell}} + E_{\text{DM,jet}}$$

Use χ^2 test function such that...

$$\begin{aligned} \chi^2 &= \sum_{\text{matching jet pairs}} \frac{(E_{\text{rec,jet}} - E_{\text{particle,jet}})^2}{\sigma_{\text{rec,jet}}^2 + \sigma_{\text{particle,jet}}^2} \\ &= \sum_{\text{matching jet pairs}} \frac{\left(\left[\sum_{\text{cells in jet}} w_{\text{cell}}(\rho_{\text{cell}}, \mathcal{R}_{\text{cell}}) \cdot E_{0,\text{cell}} + \alpha \cdot \sqrt{E_{0,S=\text{before}}} \cdot E_{0,S=\text{behind}} \right] - E_{\text{particle,jet}} \right)^2}{\sigma_{\text{rec,jet}}^2 + \sigma_{\text{particle,jet}}^2} \\ &= \min \end{aligned}$$



with empirically motivated ansatz for $E_{\text{DM,jet}}$ for dead material between sampling layers $S = \text{before}$ and $S = \text{behind}$, in a combined fit of $(\{w_{\text{cell}}\}, \alpha)$



Attempted de-convolution of signal contributions

Normalization choice convolutes various jet response features

E.g., cell weights correct for dead material and magnetic field induced energy losses, etc.

Limited de-convolution

Fit corrections for energy losses in material between calorimeter modules with different functional form
 Separation in terms, but still a correlated parameter fit

Reconstructed jet energy with cell calibration:

$$E_{\text{rec,jet}} = \sum_{\text{cells in jet}} w_{\text{cell}}(\rho_{\text{cell}}, \mathcal{R}_{\text{cell}}) \cdot E_{0,\text{cell}} + E_{\text{DM,jet}}$$

Use χ^2 test function such that...

$$\chi^2 = \sum_{\text{matching jet pairs}} \frac{(E_{\text{rec,jet}} - E_{\text{particle,jet}})^2}{\sigma_{\text{rec,jet}}^2 + \sigma_{\text{particle,jet}}^2}$$

$$= \sum_{\text{matching jet pairs}} \frac{\left(\left[\sum_{\text{cells in jet}} w_{\text{cell}}(\rho_{\text{cell}}, \mathcal{R}_{\text{cell}}) \cdot E_{0,\text{cell}} + \alpha \cdot \sqrt{E_{0,S=\text{before}} \cdot E_{0,S=\text{behind}}} \right] - E_{\text{particle,jet}} \right)^2}{\sigma_{\text{rec,jet}}^2 + \sigma_{\text{particle,jet}}^2}$$

= min

with empirically motivated ansatz for $E_{\text{DM,jet}}$ for dead material between sampling layers $S = \text{before}$ and $S = \text{behind}$, in a combined fit of $(\{w_{\text{cell}}\}, \alpha)$

Relatively low level of factorization in this particular approach with correlated (by combined fit) parameters!

