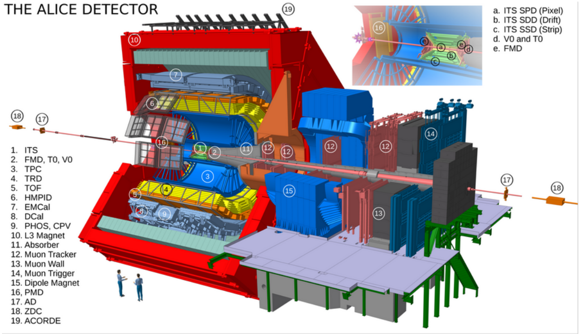
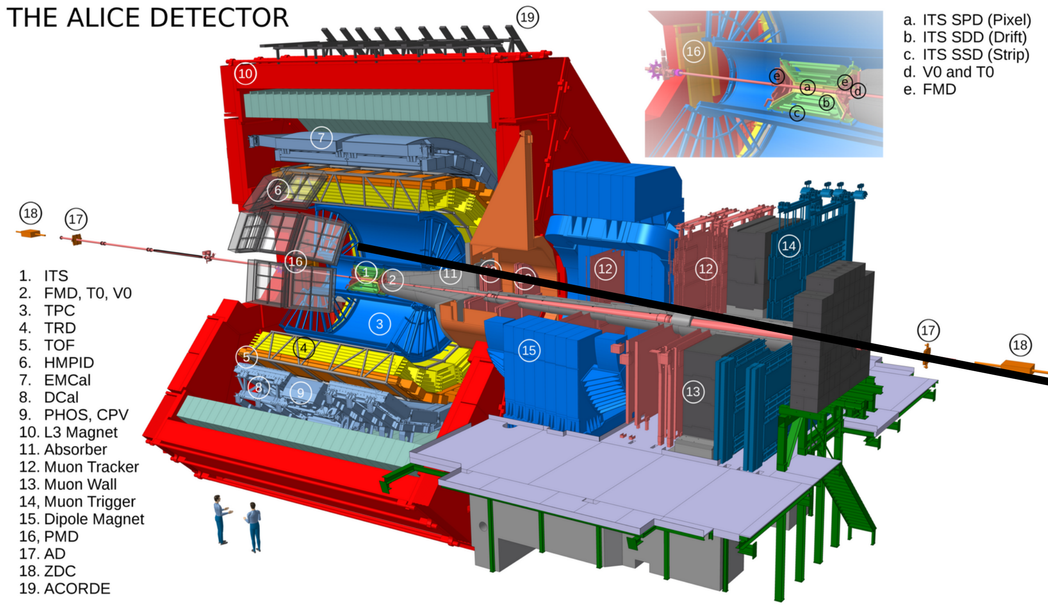
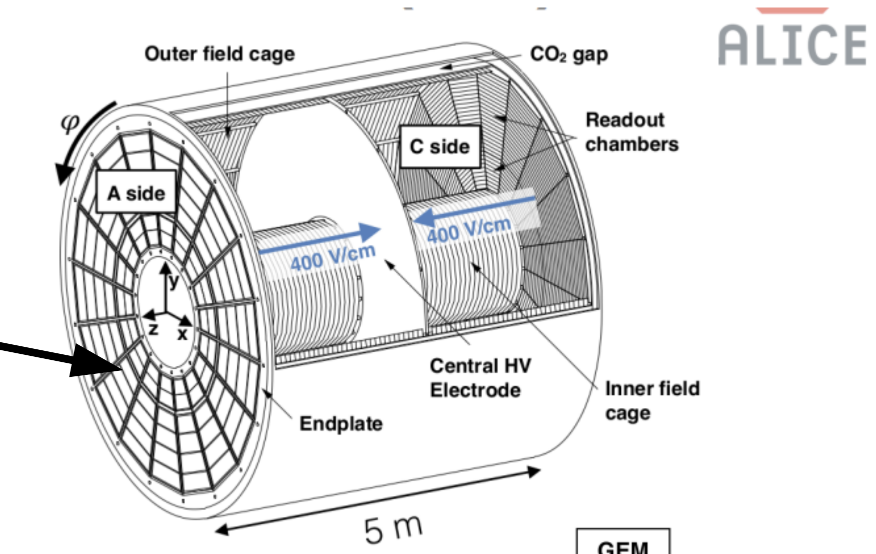
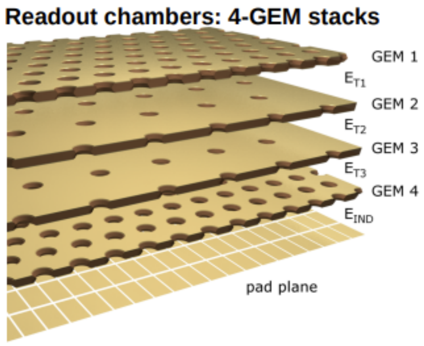


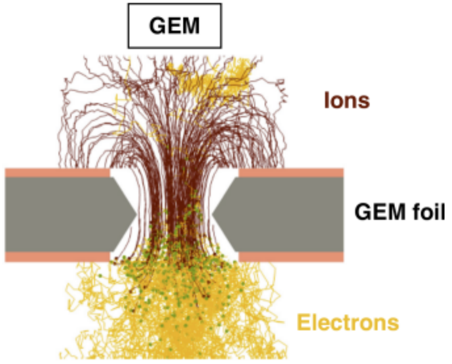
Data-driven machine learning algorithms for the calibration of space-charge distortion fluctuations in the ALICE TPC

ALICE TPC









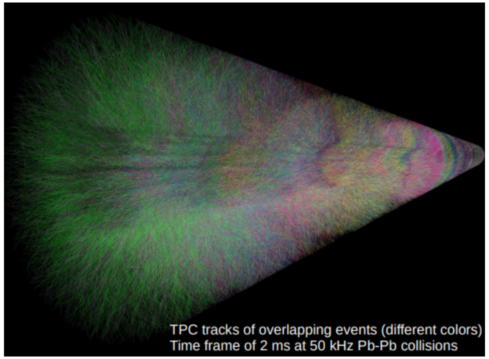
ALICE is one of eight detector experiments at the Large Hadron Collider at CERN

Time Projection Chamber (TPC) is main tracking detector

- gas detector, particle detection via gas ionization
- 2.5 m drift length

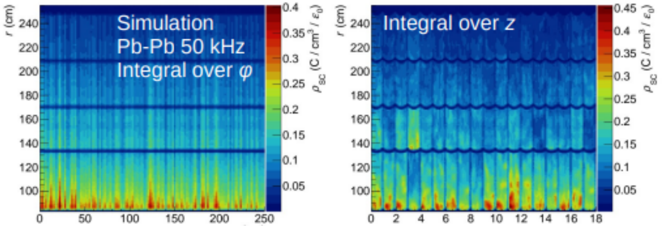
TPC continuous readout at 50 kHz interaction rate in Pb-Pb collisions

- Events overlapping in TPC → substantially higher occupancy (~5 events)



Space charge (SC) inside the TPC drift volume **distorting** trajectories

- Non-uniform space-charge density ρ_{SC} ➔ space-point distortions O(5-15 cm)
- ➔ Space-charge density and distortion fluctuations O(5 %) ~ 0.2 cm
- To be calibrated/corrected to σ ~100 µm with granularity O(10^6) in space and O(5 ms) in time

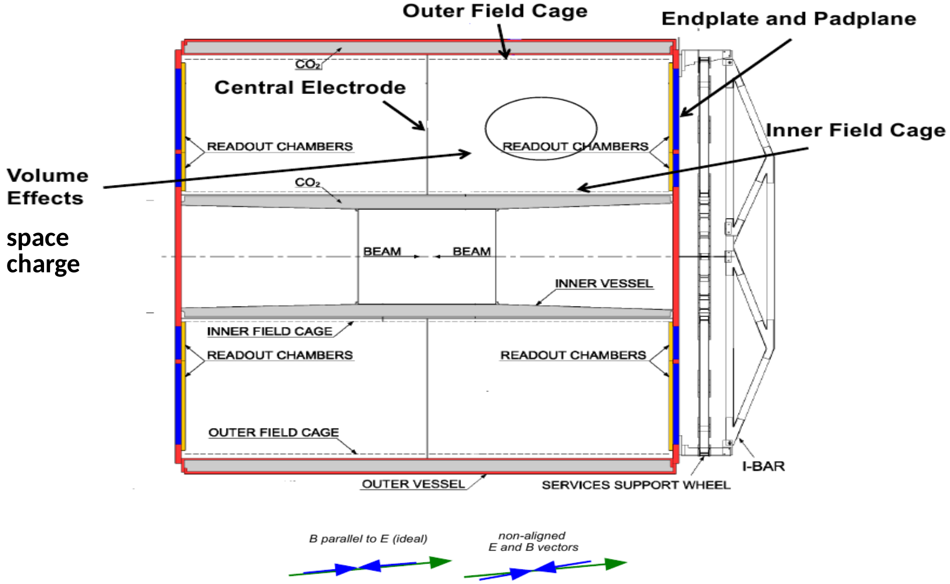


TPC static distortion and surface charging/discharging O(cm)

Space charge density not known- only relative fluctuation of the local density estimated from current measurement

Data-driven machine learning (ML) algorithms for the calibration of space-charge distortion fluctuations needed

Analytical distortion models



Distortion/ Calibration	Effect	Time constant/update frequency	Dist. model space	Dist. model time
static	O(mm)	O(year)	Poisson+LE	
semi static (charging)	O(0-3 cm) Int. rate dependent	Charging - O(min) Discharging - O(s)	Poison+LE	current & indirect current measurement
space charge & **SC** fluctuation	O(0-15cm) Int. rate dependent	Mean charge -rate O(min) Charge fluctuation O(5-10 ms)	Poison+LE	current & indirect current measurement
calibration using tracks		O(min)	all distortion	determined by available statistics
fluctuation using currents		O(5-10ms)	indirect measurement	

Analytical model solving Poisson equation (E-field)+ Langevin equation (LE) for electron and ions drift

Misalignment, E and B field misalignment, charging up of the TPC boundaries (Readout chambers, Field cage, Central electrode) and space charge lead to a non-linear distortion with different temporal variability

Run 1

Static distortions dominant in Run 1, fully calibrated analytically

Space-point distortion approximated as a linear combination of the "partial distortions". **Order of transformation is not important (approximation valid for small distortions with low gradient)**

For big distortion with sharp gradient linear combination of partial E-vectors:

- $\Delta_E = \Sigma\ k_i\ E_i$
- $\Delta\ != \Sigma\ k_i\ \Delta_i$

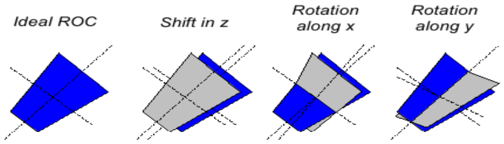
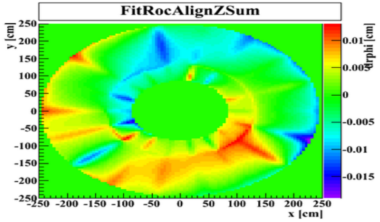


Figure 8: Misalignment scenarios of the ROCs in z

ROC misalignment O(mm)



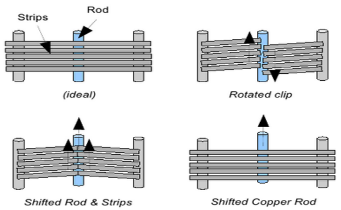
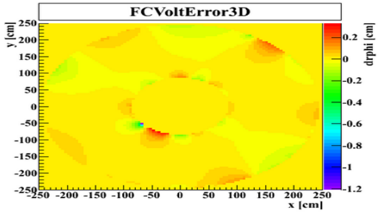
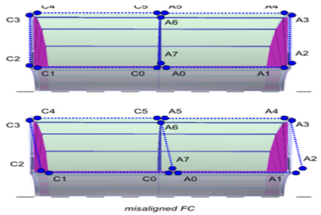


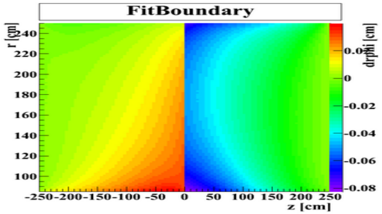
Figure 7: Misalignment scenarios of the FC components at each rod

Field cage/strip misalignment O(cm)

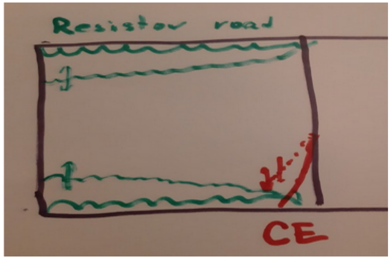




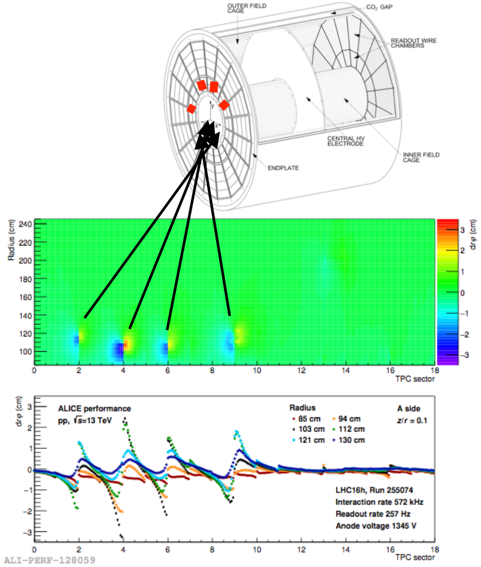
CE/Plane misalignment O(mm)

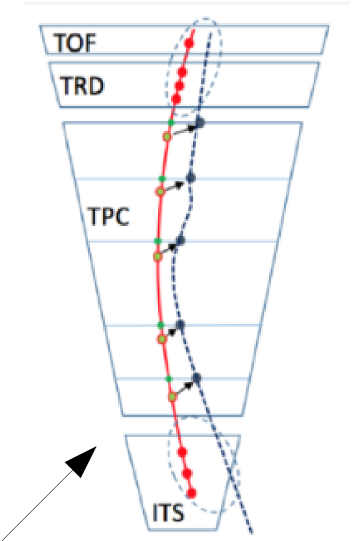


Run 3 - space-charge distortion bigger than local structure



Sharp gradient at sector boundaries. For big distortion in Run3 linearity assumption not full filed, integration along E,B vector following Langevin equation needed





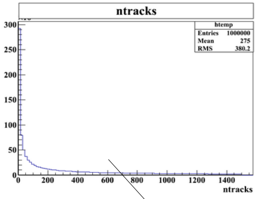
Run 2 TPC calibration (distortion maps + space-charge)

- Time dependent space charge distortion calibration **O(20 minutes)** using stable reference detectors (ITS, TRD, TOF) - mean distortion O(0-3 cm)
- Assumption space charge-distortion are linearly scaling with rate
  - Reference map at low rate to characterize static distortion
  - Local distortion hot-spots characterized by analytical model → line charge model. Most of the volume non affected.
- In Run2 - not enough statistics to calibrate **distortion fluctuation O(5-10 ms)** → instead adding the local distortion fluctuation to track model

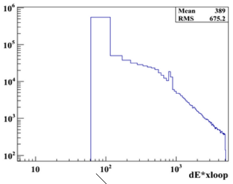
Space-charge distortion in Run 3 bigger O(5-20 cm) and more homogeneous - proper treatment of fluctuation needed

Run 3 - Distortion fluctuation calibration

Event multiplicity fluctuation

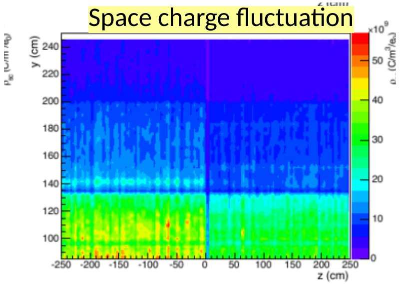


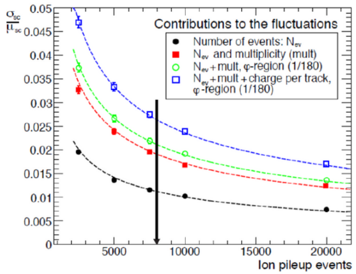
Track charge fluctuation



$$\frac{\sigma_{\rm sc}}{\mu_{\rm sc}} = \frac{1}{\sqrt{N^{\rm ion}_{\rm pileup}}}\sqrt{1+\left(\frac{\sigma_{N_{mult}}}{\mu_{N_{mult}}}\right)^2+\frac{1}{F\mu_{N_{mult}}}\left(1+\left(\frac{\sigma_{Qtrack}}{\mu_{Qtrack}}\right)^2\right)}$$

Space charge fluctuation





Space-charge distortion fluctuation (IR dependent) ~ 2-5 % (0.6-1.0 cm)

- Mean distortion to be calibrated using cluster - ITS-TRD+TOF residual maps O(s)-O(min)
- **Statistics for track based calibration algorithm insufficient to follow fluctuation O(5 ms)**

Fluctuation to be calibrated with time granularity ~ 5 ms ($\sigma_{r\varphi}$<100 μm)

- Readout digital current to estimate space charge density within TPC
  - **2D epsilon map (ρ=kεI) and ion drift velocity to calibrate (changing in time)**

Machine learning and hybrid (analytical/ML) model:

- Analytical solution solving Poisson +Langevin equation to slow →
  - **Convolutional Neural Network** (U-Net implementation) trained - relying on the MC and precise calibration of the (v_{drift},ε)
  - **Data driven calibration** → together with fitting of the (v_{drift},ε) minimizing track residuals

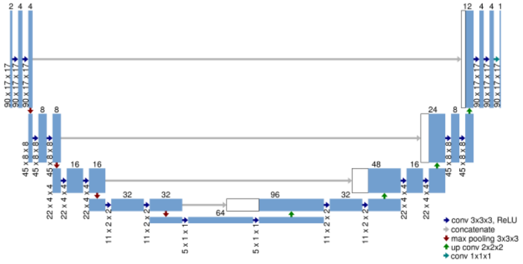
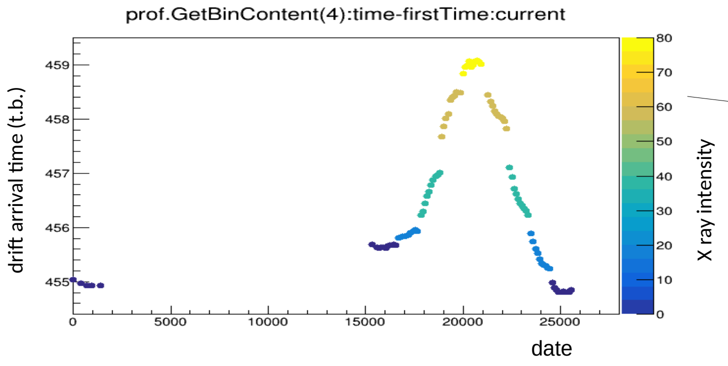


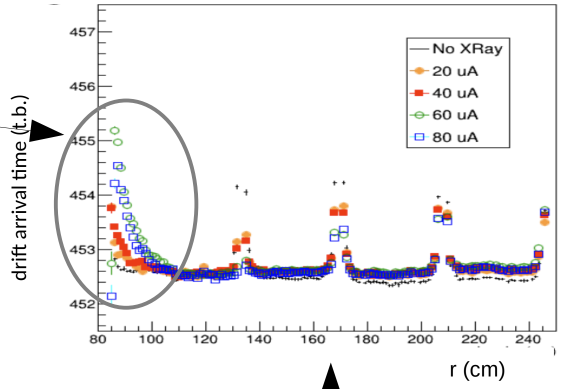
Figure 2. Architecture of the standard implementation of the U-Net.

https://www.epj-conferences.org/articles/epjconf/pdf/2021/05/epjconf_chep2021_03020.pdf

Boundary distortion due to surface charging

Laser calibration scan for Run3





Time constants ~ **O(minute)**

- discharge **O(1s)**

Indication of instability in the inner field cage current (x-ray and current measurement)

Analytical model:

- modifying boundary potential for the Inner filed cage - φ symmetric 1D model

Time profile by field cage current measurement and cluster-track residuals

Distortion in the TPC on the C side close to the Central electrode (R~<100 cm, z~5 cm), ΔR O(cm) and at sector boundaries

→ Local distortions at multiple TPC boundaries, ΔR O(cm)

Mean distortion at R<100 proportional to the flux

Dependence of surface charging on IR differs from space charge

- **O(5-20min) for saturation**

Preferred estimate of the derivative of the distribution for 2 effects separately

Current fluctuation → Density fluctuation → Distortion fluctuation

Digital Currents as a Gaussian white noise

$$i(r, r\phi, t) = \langle i(r, r\phi, t)\rangle + \Delta i(r, r\phi, t) \quad (1)$$

$$i(r, r\phi, t) = \langle i(r, r\phi, t)\rangle + \sum_{N=0} c_n \Phi_n(r, r\phi, t) \quad (2)$$

ΔI - Gaussian white noise vector

- *probability distribution with zero mean and finite variance, and* ***are statistically independent***
- *the* ***covariance matrix*** *R of the FFT components is a* ***diagonal matrix***
- *a Gaussian white noise vector will have a* ***perfectly flat power spectrum****, with $P_i = \sigma^2$ for all i.*

Calibration timings:

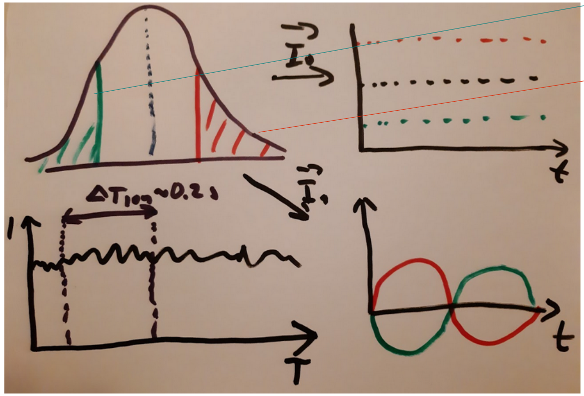
- $T_{calibration}$ ~ O(1 min)
- $T_{ion\ drift}$ ~ O(0.2s)
- $T_{sampling}$ ~O(0.01s)

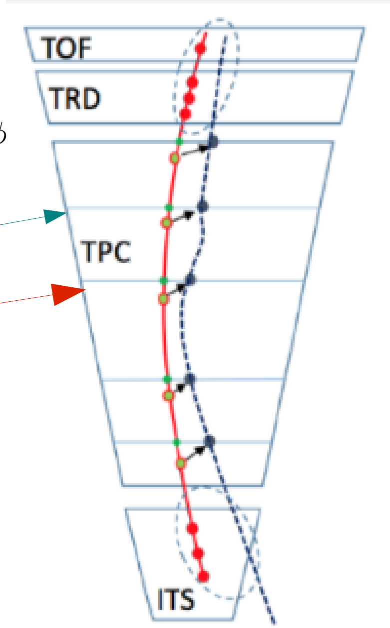
FFT small Δ fluctuation approximation

$$\vec{\Delta}(r, r\phi, z) = \overrightarrow{f_{<i>}}(\langle i(r, r\phi, t)\rangle) + \overrightarrow{f_{\Delta_i}}((r, r\phi, t))$$

$$\vec{\Delta}(r, r\phi, z) = \overrightarrow{f_{<i>}}(\langle i(r, r\phi, t)\rangle) + \sum_{n=0}^{N} c_n \vec{f}_n(\Phi_n(r, r\phi$$

FFT time interval decomposition





The same track based algorithm to calibration mean distortion O(1 min) to be used to calibrate the response to ΔI_k and maps of numerical derivative of distortion in respect to c_k

To reduce processing time and disk space for the calibration approximation using c_0 numerical derivative to be used

Adaptive kernel method - effective number of points

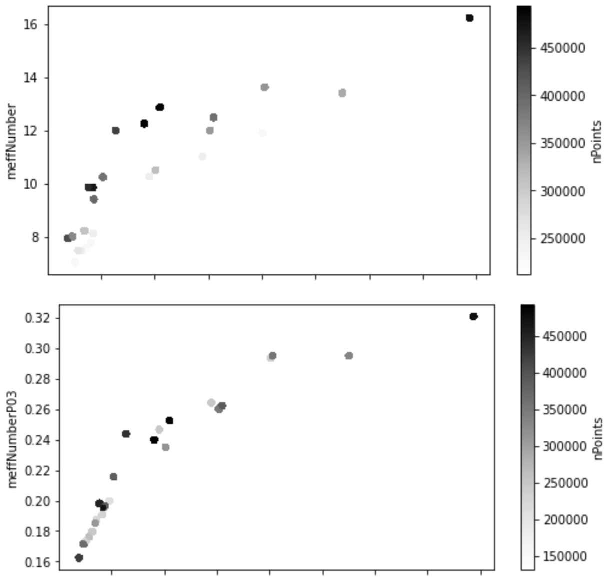
$$f(A,B,C,D) = \mathbf{norm}*A*\sin(\mathbf{n}*2*pi*C) + B*\boldsymbol{\sigma}_{\mathbf{noise}}$$

$$\sigma_{eff} = \frac{\sigma_{ired}}{norm}$$

$$\sqrt{N_{eff}} = \frac{\sigma_{ired}}{\sigma_{red}}$$

$\sigma_{ired}/\sigma_{red}$

$(\sigma_{ired}/\sigma_{red})/nPoints^{0.3}$



σ_{eff}

Parameter scan to emulate statistics requirement

- number of points, function normalization, noise (σ_{ired}), n_{Sin}

Making function variation small in respect to intrinsic noise (σ_{ired}), effective number of points increase → reducible error decrease.

Making regression for delta model (observation - analytical approximation) is preferable

https://indico.ijclab.in2p3.fr/event/5999/contributions/25085/attachments/18750/25200/ATO-563-ErrorAndPDF_MI26042022.pdf

Physical model + ML non parametric model - factorization

Global Linear fit - approximation of the physical model

Input parameters:

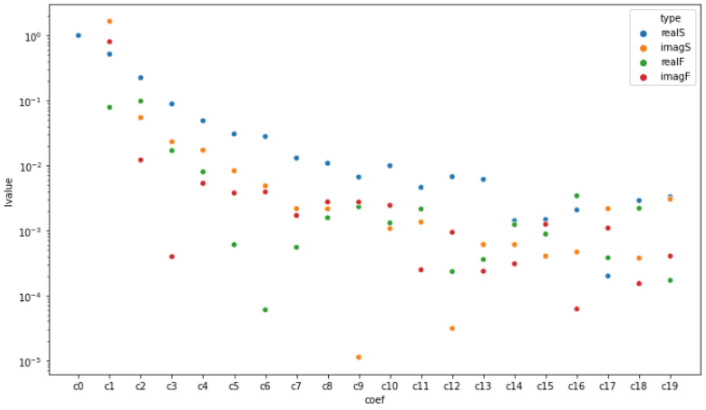
- local derivative of distortion , current in the TPC (ΔI)
- ion current as white noise → individual FFT coefficient independent (μ=0, σ_i=σ)

Output: Δ distortion

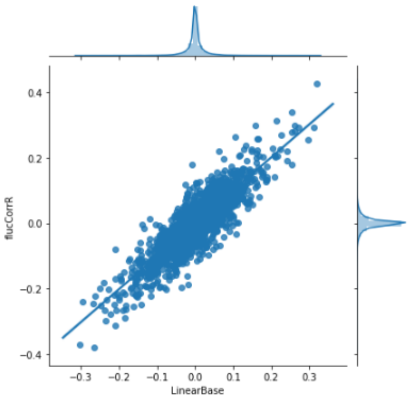
Convolution theorem → approximation of the response to individual FFT current harmonics

- convolution in 3D space → multiplication in FFT space
- Linear fit to approximate convolution kernel
- 1 FFT as a LinearBase , 20 most important FFT

Linear Coefficients

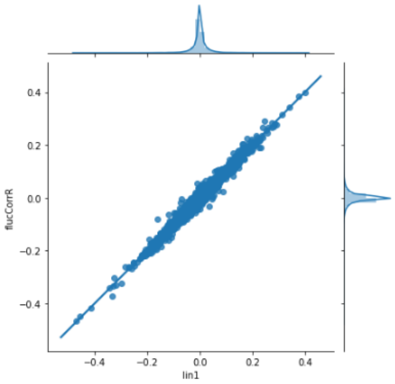


Prediction LinearBase FFT0

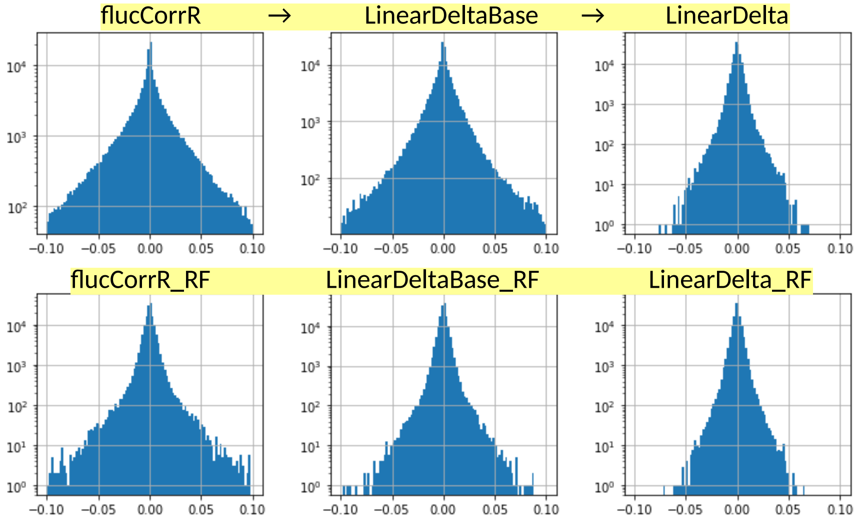


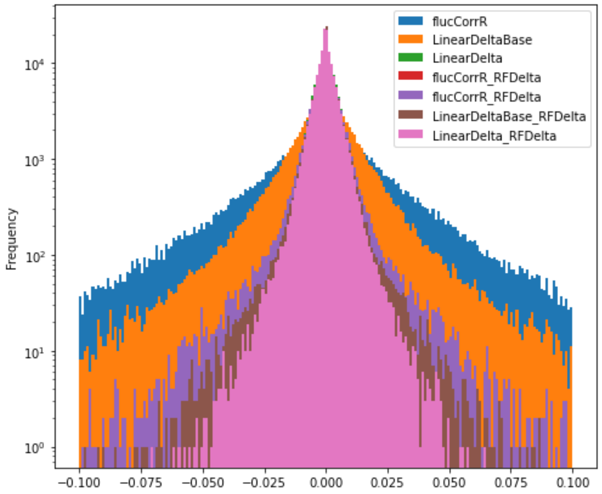
Prediction Linear (20 FFT)

Out[117]: <seaborn.axisgrid.JointGrid at 0x7fb7214a0978>



Physical model + ML non parametric model - factorization





Prediction std:

flucCorrR	0.033161
LinearDeltaBase	0.016588
LinearDelta	0.005755
flucCorrR_RFDelta	0.007754
LinearDeltaBase_RFDelta	0.005938
LinearDelta_RFDelta	0.005011

Random forest and xgboost used with/without physical model as a pre-filter

- Using physics models approximation as pre-filter significantly improves resolution
  - for 10^6 training points ~ 80 microns - 50 microns
- Residual distortion after the LinearFit+RF
  - 3D current fluctuation not used yet in the model

Using experimentally observed derivative of distortion:

- **disentangling surface charging and space charge**
- **Not relying on the MC (epsilon map)**

Conclusion

Hybrid model - analytical approximation, calibration using tracks + machine learning presented

Hybrid model:

- Disentangling surface charging and space charge
- Not relying on the MC (epsilon map)
- Precision of the hybrid model better even for the optimal MC calibration parameters, as expected from the error propagation

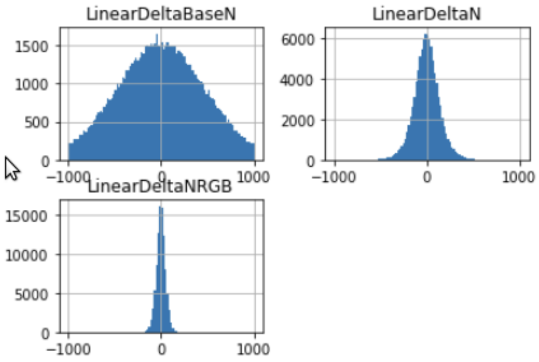
FFT analytical approximation in 1D, further improvement after applying Δ3D current models

- U-Net ?

Backup

Physical model + ML non parametric model - factorization

ΔR at R<95, drift>0.5
Region with biggest fluctuation




```
flucCorrRN          1264.6
LinearDeltaBaseN     509.1
LinearDeltaN         153.4
```

Random forest and xgboost used with/without physical model as a pre-filter

- Using physics models approximation as pre-filter significantly improves resolution
  - for 10^6 training points ~ 80 microns - 40 microns
- Residual distortion after the LinearFit+XGB due 3D current fluctuation not used yet in the model

Using experimentally observed derivative of distortion:

- **disentangling surface charging and space charge**
- **Not relying on the MC (epsilon map)**

Outlook

Distortion analytical models

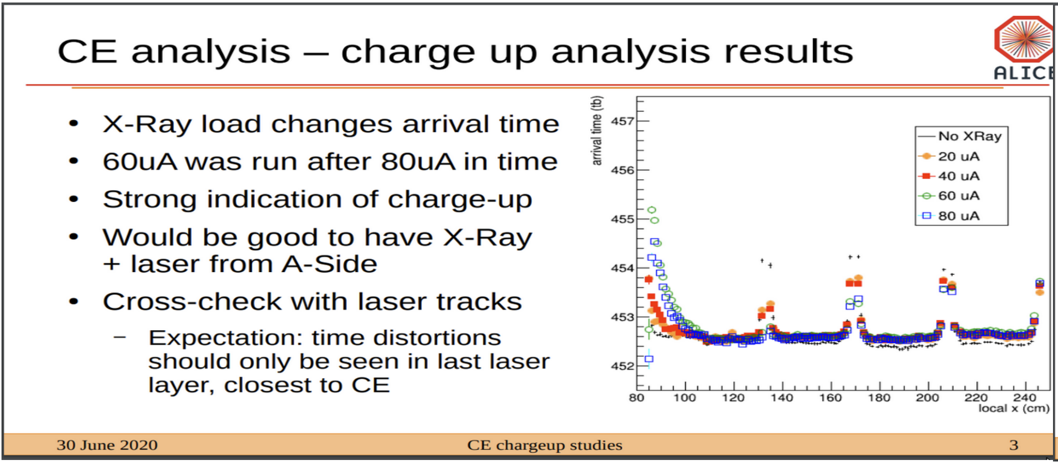
- static distortion, semi-static O(min), space charge O(10 ms)

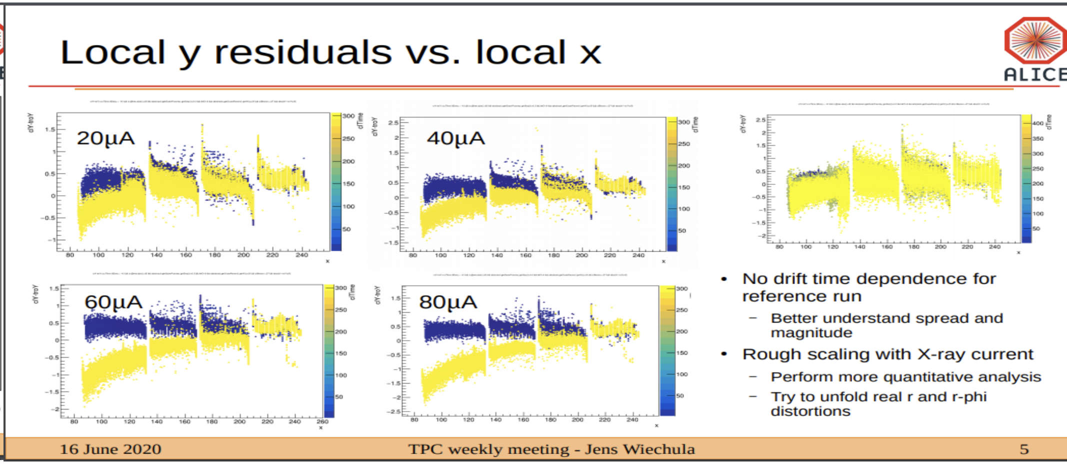
Distortion fluctuation analytical model and calibration

Unet & Data-Driven Machine Learning

- UNet relying on the model and MC parameters
- Data-Driven method:
    - **disentangling between charging up and space charge**
    - **Not relying on the MC and calibration parameters (epsilon map, boundary distortion)**
    - **Calibration parameters extracted from data**

GEM charging up





Distrotion between stack - modification of the arival time and seen also in R and Rφ distortion

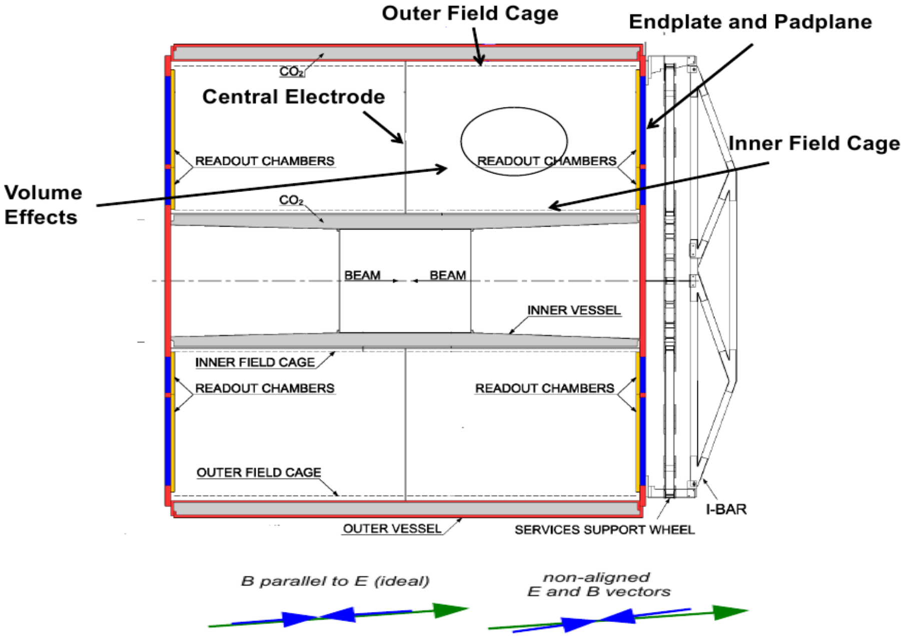
- non perfect E field alignment

Charging up observed ?

- I assume similar as for CE C side

Strong gradient
Time constants ~ O(minute) ?
New in Run3
Template fit (similar to RUN1 type) to be tested - fitting charge

Run 1: Composed correction framework



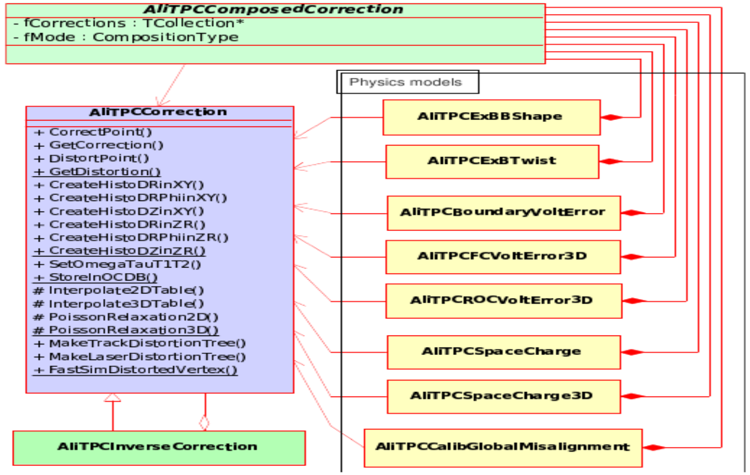
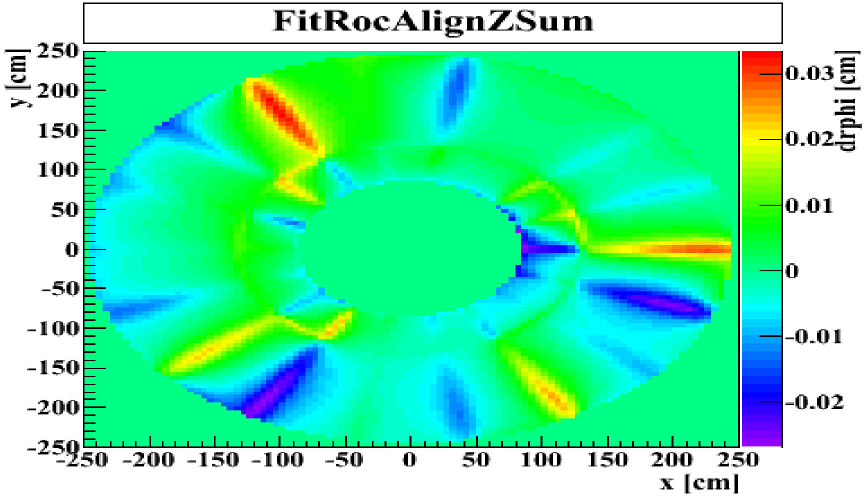
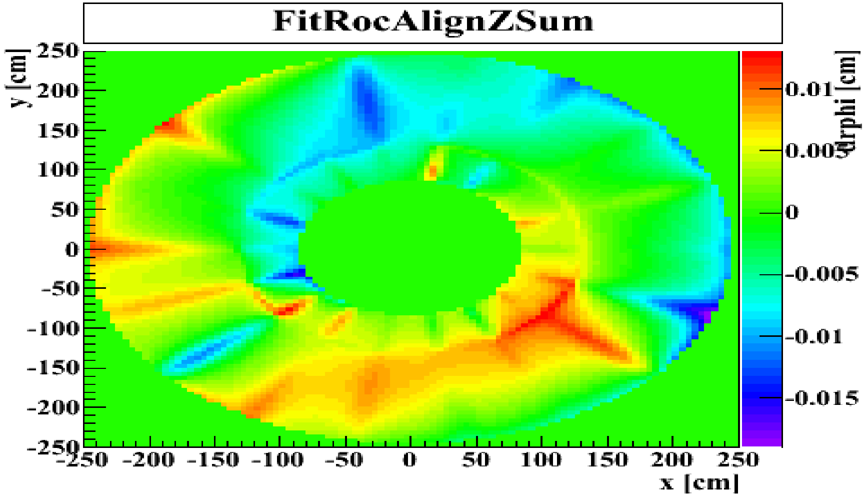


Figure 3: Simplified class diagram showing the inheritance structure and the most general functions

Misalignment, E field misalignment or charging up of the TPC boundaries (ROC,FC, CE) leads to static and semi-static distortion

Run 1 data corrected using set of analytical model (No outer detectors available in that time)
Composed distortion - linear combination of partial distortion template (analytical or measured)





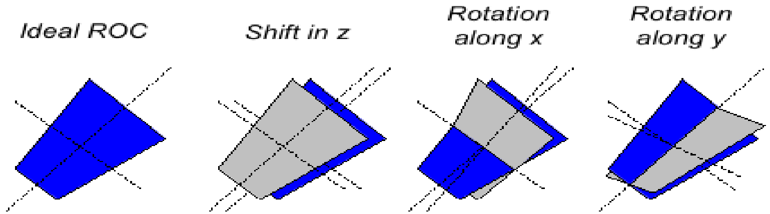
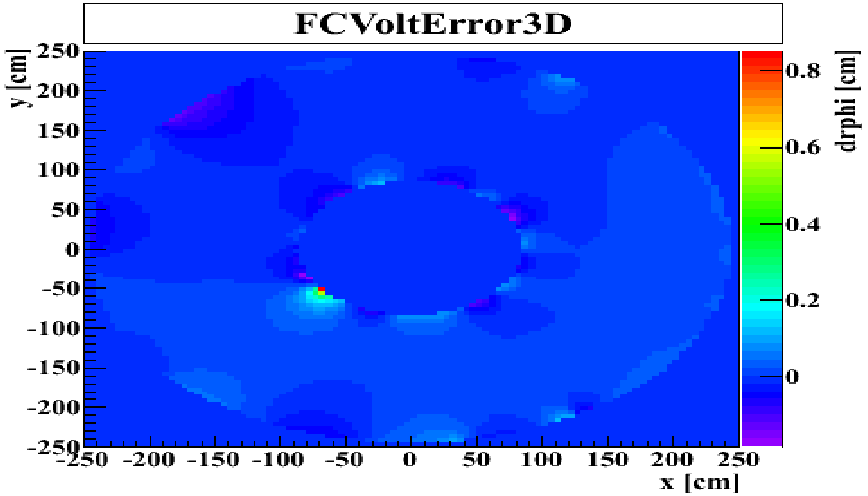
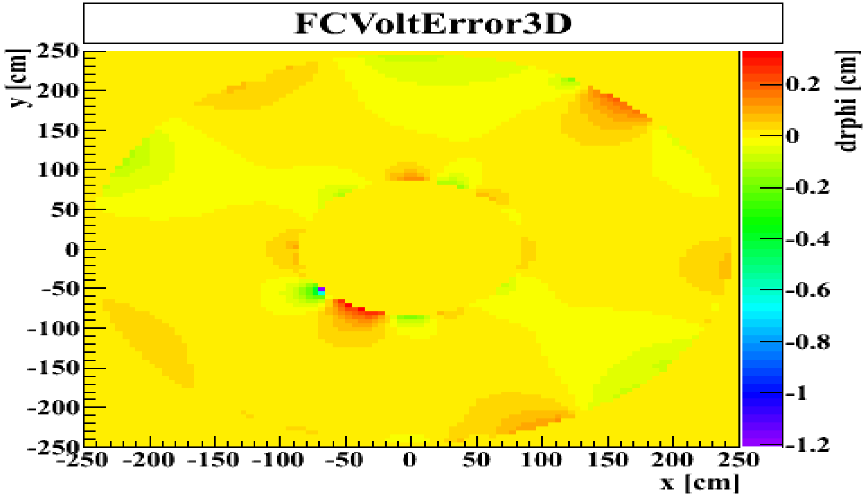


Figure 8: Misalignment scenarios of the ROCs in z

Modification of the E field due misalignment →
Sharp gradient in distortion close to ROC boundaries
Semi-static.
In Run 3 misalignment bigger than in Run1

Field cage and Rod alignment





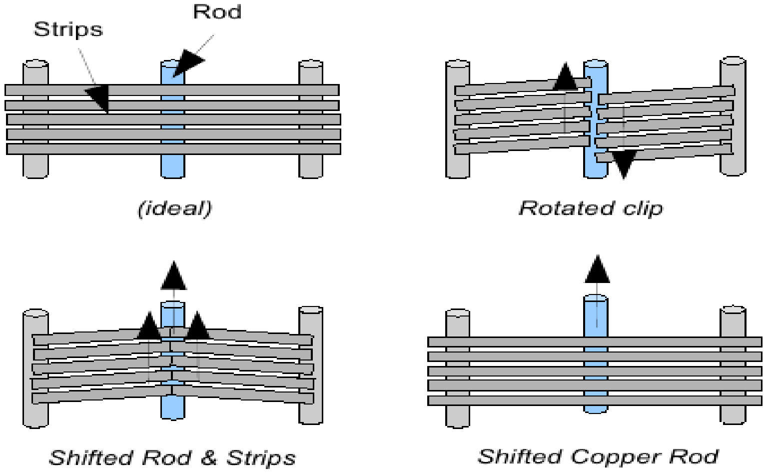


Figure 7: Misalignment scenarios of the FC components at each rod

18 (rods) x 2 (IFC,OFC) x 2 (A side, C-side)

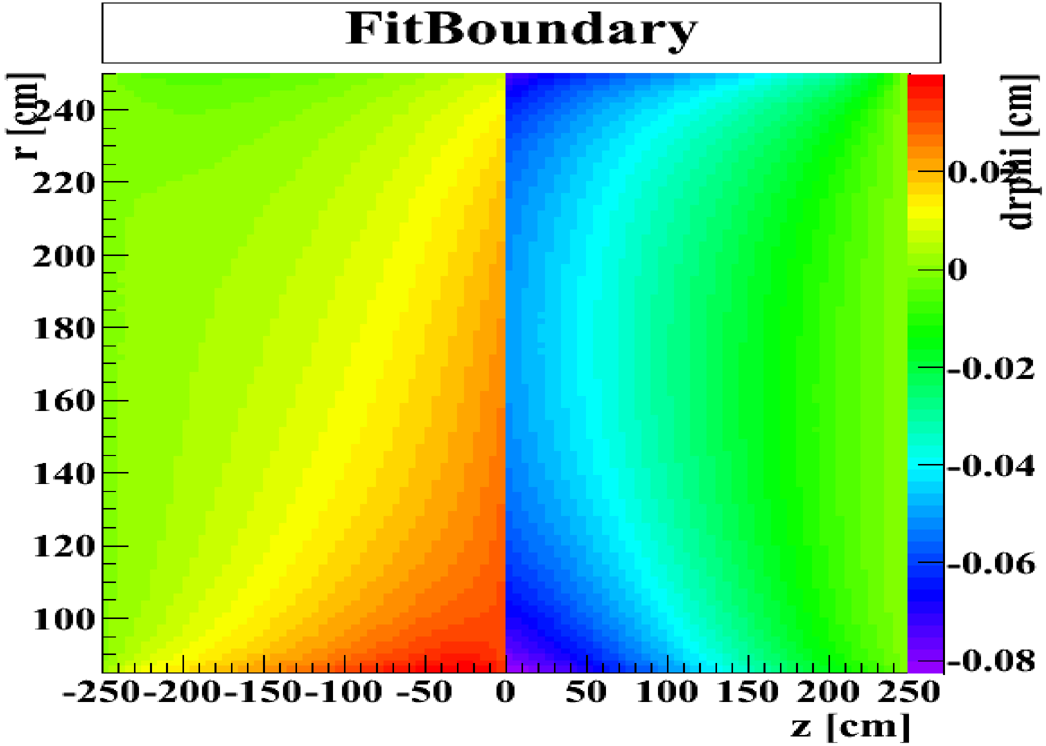
2 rotated clips x 2 (A side, C-side)

B field 0 data used for the alignment/calibration

– Fitting of the distortion maps

Sharp gradient
Rod - semi-static.

Boundary voltage



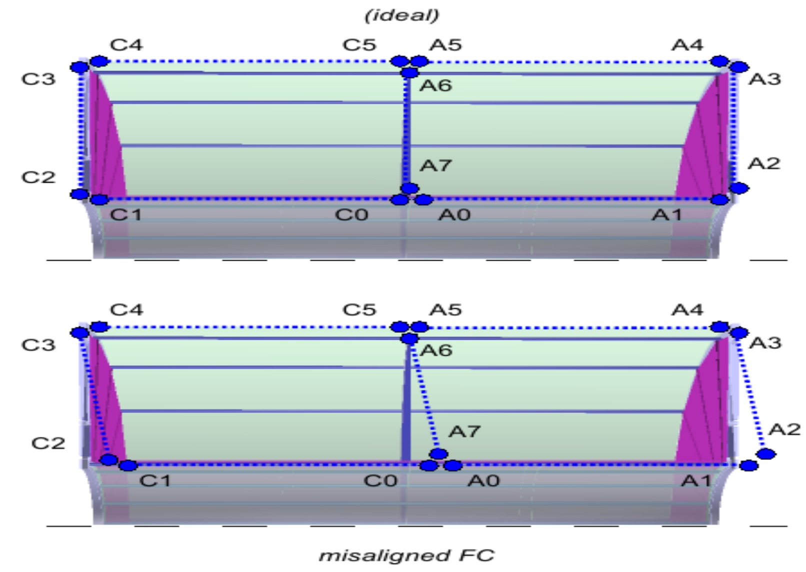


Figure 5: Numbering scheme of the vectors to set the Boundary conditions in **AliTPCBoundaryVoltError**. Top: ideal case, bottom: conical deformation of 1 mm at the IFC (e.g. $A0 = A1 = A2 = A7 = 40V$ and $C0, C1, C2 = -40V$)

Static

No sharp gradient

RUN1: TPC Distortion/Alignment Fitting

Assumptions:

- Space point distortion transformation commute (the order of applying of corrections is not important)
- Space point distortion can be approximated as a linear combination of the "partial distortion" functions with given parameter:
  - $\Delta = \Sigma$ ki Ei
- Space point distortion not directly observed. We define the set of observables O.
  - $\Delta O = \Sigma$ ki Oei
- Under given assumption the analytical (non iterative) global minimization of distortion maps can be performed solving the set of linear equations.
- Assumptions were tested for the typical distortion in the TPC, moreover the assumption were tested also for the fitted parameters.

Distributed computing

Calibration train (Grid) filling of **residual histograms**

Merging

Creation of **distortion maps**

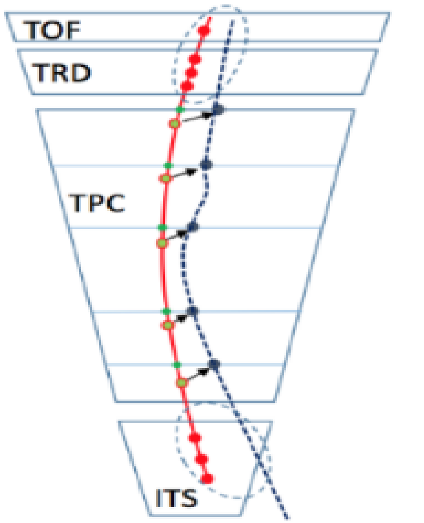
Distortion models Fitting

Distortion calibration (Linear fits using libStat)

- Input data observables and fit models from the tree
- Possibility to add constrains
- Possibility to check differntialy the the fit values (return value of the FitPlaneConstrain)
- Extraction of the partial fits

Run 1 calibration based mostly on the track matching (vertex, external tracks)
In Run 2, Run 3 -calibration simpler - using point - track interpolation residuals
For some type of calibration and calibration QA track/vertex matching will be used

Data driven distortion calibration Δ as function of current i(r,rφ,t)



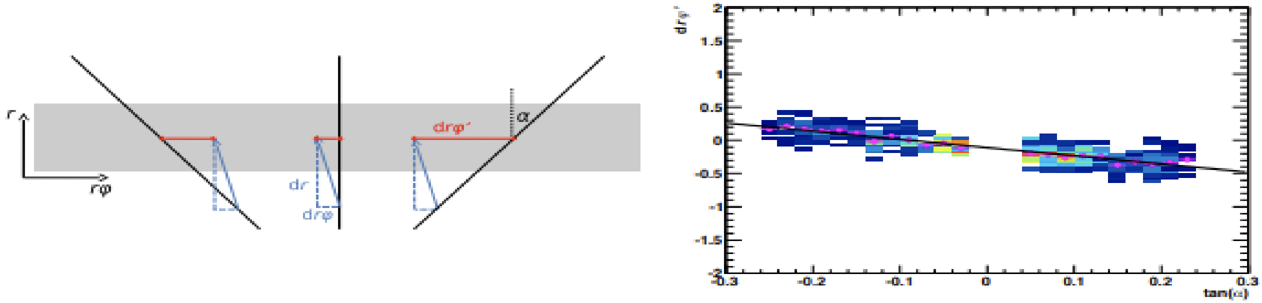
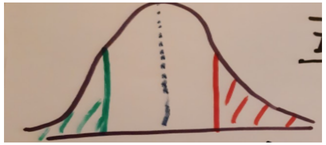


Figure 8.8: (Left) Illustration of the measured $r\varphi$ distortions being composed of the real $r\varphi$ distorions and the radial distortions, shown for three example tracks crossing a pad row (grey area) under different local track inclination angles α. (Right) Measured correlation between $dr\varphi'$ and $\tan(\alpha)$ (see text).



Standard distortion calibration extracted for specially triggered Δ time windows

- percentile of overall statistics used - should be precise enough
- c_n statistic reused

$$\Delta_n(r,r\varphi,z) = f_n(c_n\Phi_j)$$

$$\Delta_n(r,r\varphi,z) = f_n(c_n\Phi_j)$$

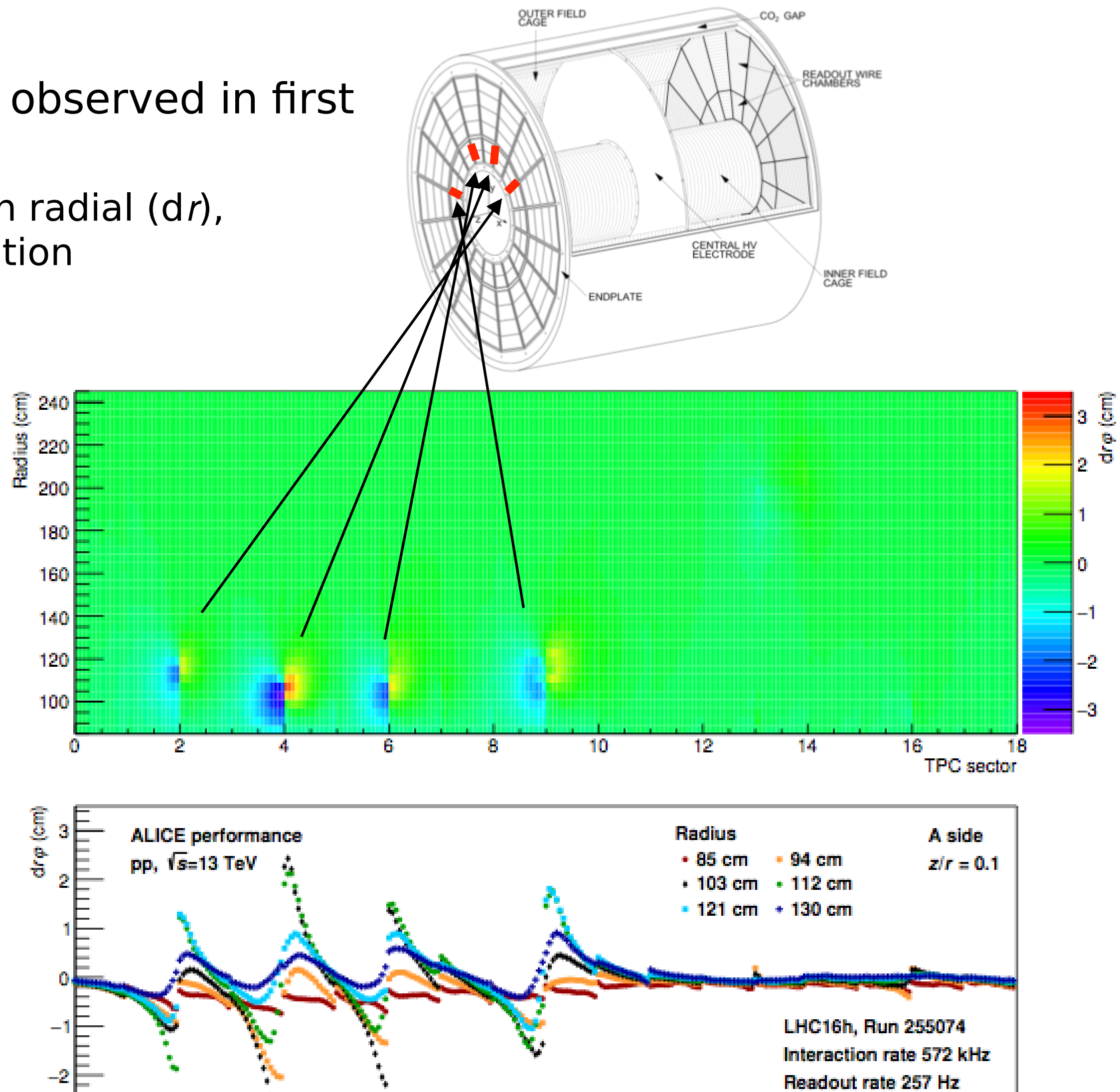
Observed distortions

Large distortions of the drift field observed in first high-luminosity data in RUN 2

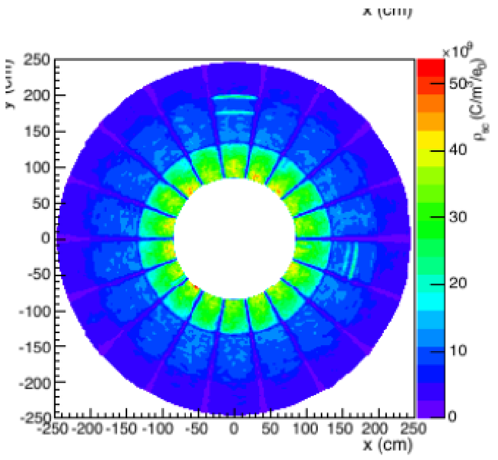
- Deflection of ionization electrons in radial (d*r*), azimuthal (d*rφ*) and drift (d*z*) direction

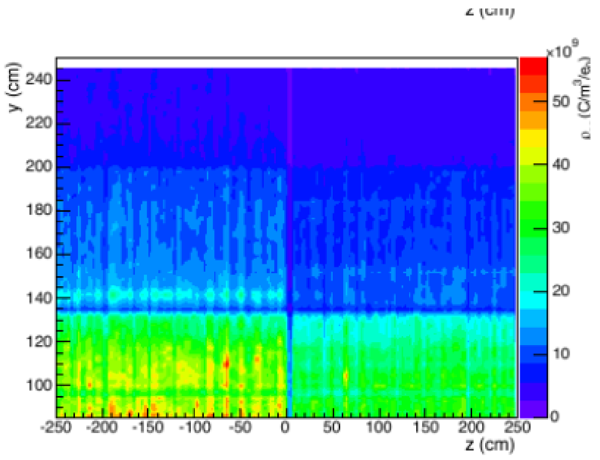
Position of distortion regions well localized in radius (*r*) and azimuth (*rφ*)

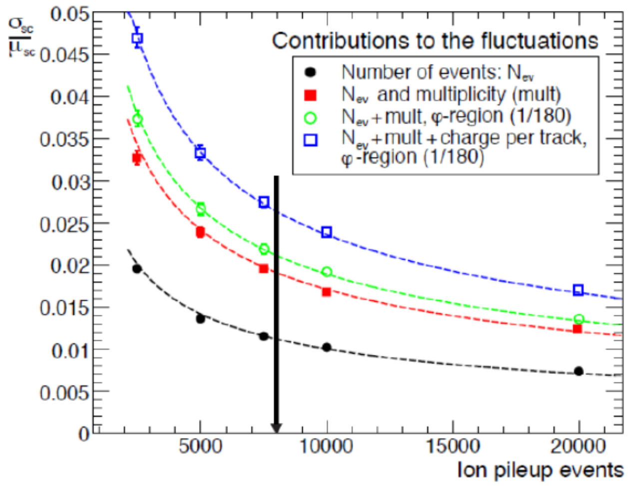
- Boundary of neighboring IROCs
  - Sectors 2, 4, 6, 9, 20, 30
  - Smaller distortions at sectors 7, 16, 31, 35



Distortion fluctuation calibration (Old slide - 2019)







Space charge distortion distortion global and local fluctuation ~ 2-5 % (0.6-1.0 cm)

- Mean distortion to be calibrated using cluster - ITS-TRD+TOF residual maps O(s)-O(min)
- **Calibration algorithm can (not?) follow fluctuation insufficient statistic**

Fluctuation to be calibrated with time granularity ~ 5 ms

- Precise digital current to be used
  - Epsilon maps to be regularly updated
- **Convolutional Neural Network** (U-Net implementation) used in test
- TPC tracklet - track (combined and TPC only) residuals as an QA of the method and as a alternative calibration

Current fluctuation → Density fluctuation → Distortion fluctuation

$$\boxed{i(r, r\phi, t) = \langle i(r, r\phi, t) \rangle + \Delta i(r, r\phi, t)}$$

$$i(r, r\phi, t) = \langle i(r, r\phi, t) \rangle + \Delta i(r, r\phi, t) \tag{1}$$

$$\rho(r, r\phi, z) = \int_{t0}^{t0+\Delta_t} \epsilon(r, r\phi, t) i_{\mathrm{ROC}}(r, r\phi, t) + i_{\mathrm{DRIFT}}(r, r\phi, z, t) \mathrm{d}t \tag{2}$$

$$\vec{\Delta}(r, r\phi, z) = \vec{f}_\rho(\rho(r, r\phi, z)) \tag{3}$$

$$\vec{\Delta}(r, r\phi, z) = \vec{f}_i(i(r, r\phi, t)) \tag{4}$$

1) Ion deposits around mean value **(white noise in time)**

2) Density can be obtained integrating currents along ion drift lines

3) Distortion Δ as function of density ρ (not measured experimentally)

4) Goal: Distortion Δ as function of current i_{ROC}(r,rφ,t)

1) i measured experimentally, i ~ ε i → i >> i

Current fluctuation approximated as (Gausian) white noise

$$i(r, r\phi, t) = \langle i(r, r\phi, t) \rangle + \Delta i(r, r\phi, t) \qquad (1)$$

$$i(r, r\phi, t) = \langle i(r, r\phi, t) \rangle + \sum_{N=0} c_n \Phi_n(r, r\phi, t) \qquad (2)$$

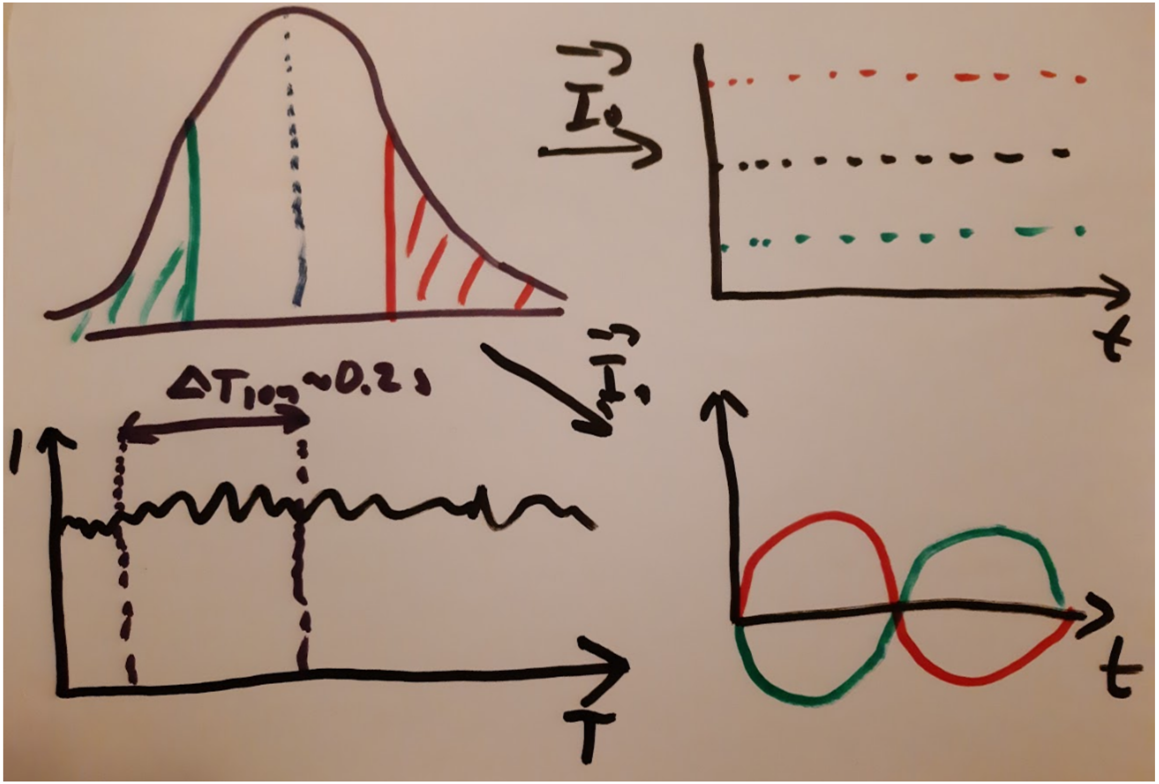
ΔI is a (~Gausian) white noise vector

https://indico.cern.ch/event/932545/contributions/3919813/attachments/2062804/3460835/2020_06_24-ToyStudiesIDCFourierTransform.pdf

A random vector is said to be a white noise vector or white random vector if its components each have a probability distribution with zero mean and finite variance, and are statistically independent

- *the covariance matrix R of the components of a white noise vector w with n elements must be an n by n diagonal matrix*
- *if in addition every variable in w also has a normal distribution with the same variance σ^2, w is said to be a* **Gaussian white noise vector**
- *under most types of discrete Fourier transform, such as FFT and Hartley, the transform W of w will be a Gaussian white noise vector*

Current fluctuation as white noise



Example timings:

$T_{calibration}$ ~ O(1 min)

$T_{ion\ drift}$ ~ O(0.2s)

$T_{sampling}$ ~O(0.01s)

→

Within example calibration time interval:

- O(300) full ion drift
- O(6000) calibration Δ windows

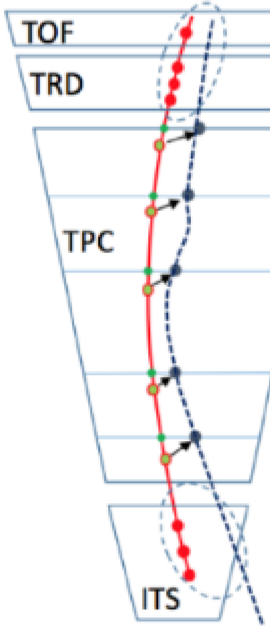
Fourier coefficient c_n extracted for each Δ window

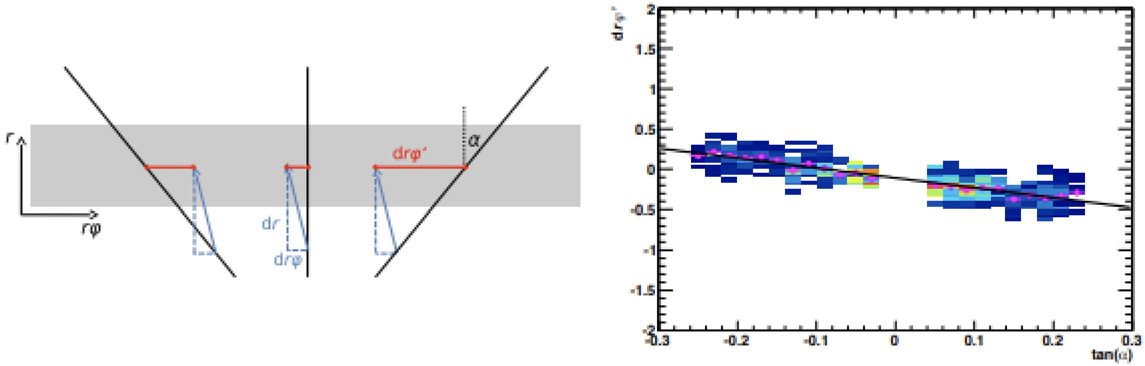
- PDF μ=0, σ
- Fourier coefficient c_n independent

Selecting Δ windows based on c_n percentile - **Upper**/**Middle**/**Lower** (e.g. 20 % percentile)

- averaging over Δ windows → mean currents for given frequency can be selected

Data driven distortion calibration Δ as function of current i(r,rφ,t)





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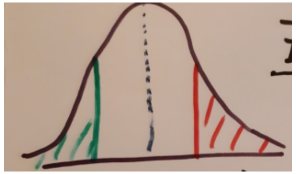


Standard distortion calibration extracted for specially triggered Δ time windows

- percentile of overall statistics used - should be precise enough
- c_n statistic reused

$\Delta_n(r, r\varphi, z) = f_n(c_n \Phi_j)$

$\Delta_n(r, r\varphi, z) = f_n(c_n \Phi_j)$

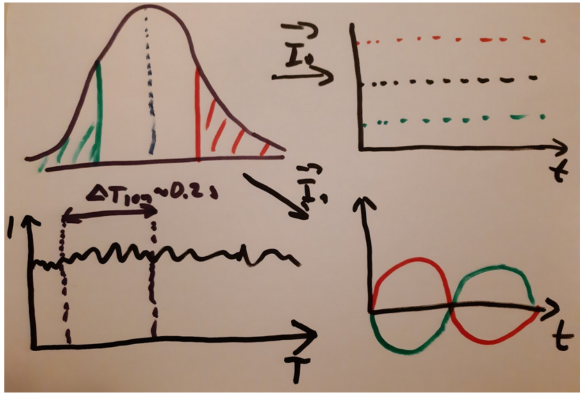
Digital Currents as a white noise

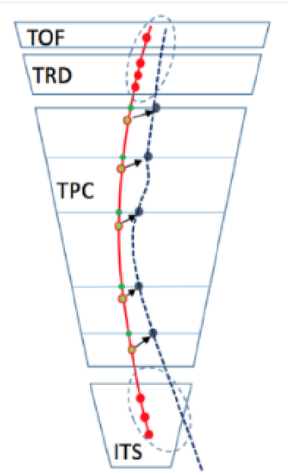
$$i(r, r\phi, t) = \langle i(r, r\phi, t)\rangle + \Delta i(r, r\phi, t) \quad (1)$$

$$i(r, r\phi, t) = \langle i(r, r\phi, t)\rangle + \sum_{N=0} c_n \Phi_n(r, r\phi, t) \quad (2)$$

$$\vec{\Delta}(r, r\phi, z) = \overrightarrow{f_{<i>}}(\langle i(r, r\phi, t)\rangle) + \overrightarrow{f_{\Delta_i}}((r, r\phi, t)) \quad (1)$$

$$\vec{\Delta}(r, r\phi, z) = \overrightarrow{f_{<i>}}(\langle i(r, r\phi, t)\rangle) + \sum_{n=0}^{N} c_n \vec{f_n}(\Phi_n(r, r\phi, t)) \quad (2)$$





ΔI is a (~Gausian) white noise vector

A random vector is said to be a white noise vector if its components each have a probability distribution with zero mean and finite variance, and are statistically independent

- *the covariance matrix R of the components of a white noise vector w with n elements must be an n by n diagonal matrix*
- *Under that definition, a Gaussian white noise vector will have a perfectly* **flat power spectrum,** *with* **$P_i = \sigma^2$** *for all i.*

Example timings:

$T_{calibration}$ ~ O(1 min)
$T_{ion\ drift}$ ~ O(0.2s)
$T_{sampling}$ ~O(0.01s)

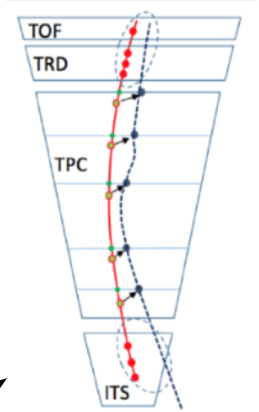
The same track based algorithm to calibration mean distortion to be used to calibrate the response to ΔI_k and maps of **numerical derivative of distortion** in respect to c_k

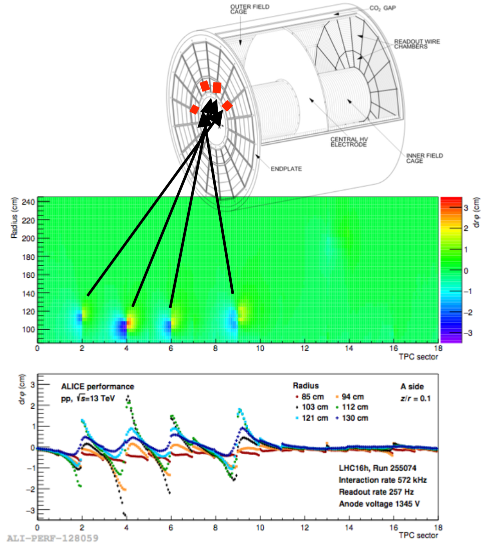
To reduce processing time and disk space for the calibration approximation using c_0 numerical derivative to be used

Distortion calibration. Run1,Run2

Run1 calibration approximation (Analytical static distortion)

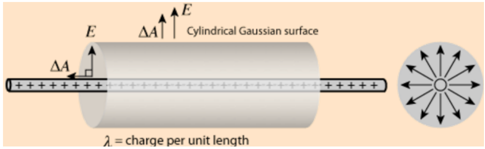
- Space point distortion transformation commute (the order of applying of corrections is not important).
- Space point distortion approximated as a linear combination of the "partial distortion" functions with given parameter:
  - $\Delta = \Sigma\ ki\ Ei$
- Space point distortion not directly observed. We define the set of observables O.
  - $\Delta O = \Sigma\ ki\ Oei$
- Under given assumption the analytical (non iterative) global minimization of distortion maps can be performed solving the set of linear equations.
- Per year





Run2 TPC calibration (distortion maps + space charge)

- Time dependent space charge distortion calibration **O(20 minutes)** using stable reference detectors (ITS, TRD, TOF)
- Assumption space charge distortion are linearly scaling with rate
- Reference map at low rate characterize static distortion
- Local distortion analytical model point hotspots → linear charge model
- Not enough statistics to calibrate **distortion fluctuation O(5-10 ms)** → instead adding the local distortion fluctuation to track model



$$E(r, r\phi) = \sum \frac{Q_i}{\Delta R_i}$$