

Simultaneous Calibrations for Liquid Noble Detectors

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Introduction: Familiar Problems

- How many of you can name every calibration fit performed by EXO-200?
- How many can do so for your own experiment?
- Can you rank the calibrations from best to worst?
- Our calibration methodology is crucial for results, but details are often hidden in internal tech notes or dissertations. The longest published form of a calibration may be a four paragraph summary of four years of work.
- Does your analysis have variables like “z”, “z_corr”, “E_pe”, “E_keV”, “E_keV_corr”?
- Is an important calibration parameter based on a one-off analysis conducted years ago?

These are consequences of the “waterfall” calibration approach

The amount of scintillation light collected by the APDs depends on the location of the energy deposition. This variation is caused by differences in the solid angle covered by the APDs and by their gain differences. Three-dimensional correction functions are used to account for this position dependence. Such correction functions are generated from ^{220}Th calibration runs with the source placed at the two anodes and three positions around the cathode plane. The detector volume is divided into 1352 spatial voxels (13 radial bins, 8 azimuthal bins, and 13 Z bins). The bin widths are chosen to ensure adequate statistics, and to optimally map the response in the regions with a high light-collection gradient.

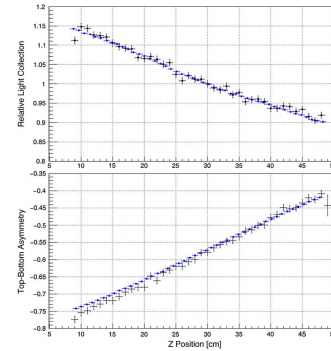
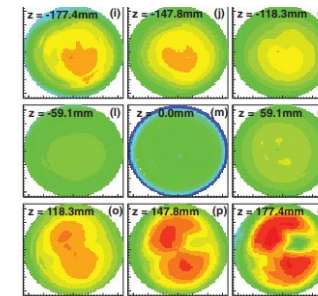
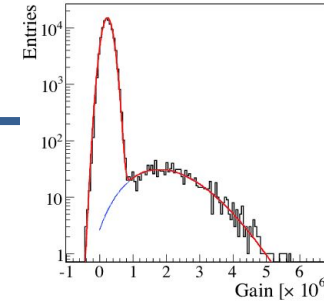
The light map is normalized such that the mean response is 1. A continuous correction function, $f(r, \phi, z)$, is created with a trilinear interpolation between the centers of the voxels in the light map.

Because maintenance was performed on the APD front-end boards in the middle of Run 2a, two light maps are used for this data. The first light map covers the period from October 1, 2011, until February 20, 2012, and the second covers the period from February 20, 2012, until April 15, 2012. Some representative sections of the first light map are shown in Fig. 11.

For a SS event, the correction function is applied by multiplying the sum of the two APD plane signals by $1/f(r, \phi, z)$, while for a MS event, a correction factor is deduced by taking the appropriate charge-cluster energy-weighted sum. The light-map correction function improves the scintillation-only energy resolution at 2045 keV from 7.9% to 6.0% for SS events and from 8.1% to 6.3% for MS events, respectively. The largest correction factor within the fiducial volume is ~15% (the fiducial cut near the cathode eliminates the region of the detector that sees the largest gradient in the correction function).

Waterfall Calibration

1. Fit channel gains using, e.g., single photoelectron
 2. Fit simple position parameters (e.g. drift velocity)
 3. Fit simple position-dependent light/charge collection function (drift lifetime, light map)
 4. Fit more complex position reconstruction (distorted field effects)
 5. Fit signal amplitude \rightarrow KeV_{EE} relationship using gamma lines
 6. Fit PSD/S1:S2/Single-site:Multi-site behavior
 7. Fit $\text{keV}_{EE} \rightarrow \text{keV}_{NR}$
- etc, etc...



Each fit uses the **subset** of the available data that can be fit with a simple model

Simultaneous Calibration: Response Function

Write down the entire detector response function first
(just a sketch here)

Expectation value of signal in channel c :

$$\vec{c}(E, p, t, \vec{x}) = f(\vec{x}) \cdot Y(E, p) \cdot \vec{g}(t) + noise$$

Light/charge yield Y , position-dependent factor f :

$$f(\vec{x}) = e^{-z/d} \cdot LRF(x, y)$$

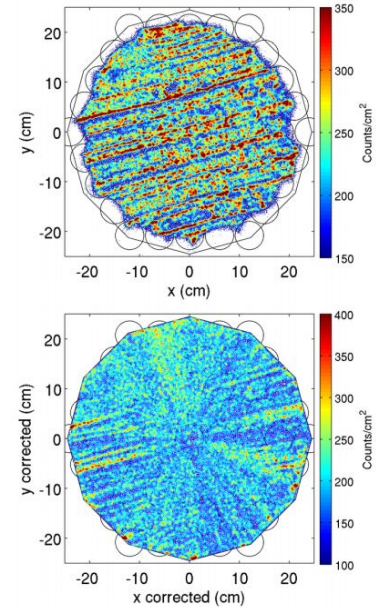
Lots of free parameters: drift lifetime d , gain g , yield curves, light response function has many bins in (x, y) .

~100 parameters per channel, per time (if time-varying) = ~1e6 - 1e7 free parameters

Traditional minimizers can't handle 1e7 parameters, but that's nothing to a deep learning minimizer

Fitting the parameters

- Response function + Monte Carlo predicts spectrum of observables in your calibration data
- Some data sets are degenerate in some parameters: not easy to use a uniform source to calibrate position reconstruction and recover uniformity
- But entire calibration data set is clearly sufficient to pin down every parameter
- **Simultaneously fit all $1e7$ parameters against all calibration events**
- **All** events.
 - Not just full-energy peaks.
 - No quality cuts: include hard-to-reconstruct events, etc.
 - All sources (simultaneously fit separate datasets)
 - Over all time (simultaneously fit different time periods, using time-varying free params)



Insist that every event observed is consistent with your calibration

Dealing with a few objections

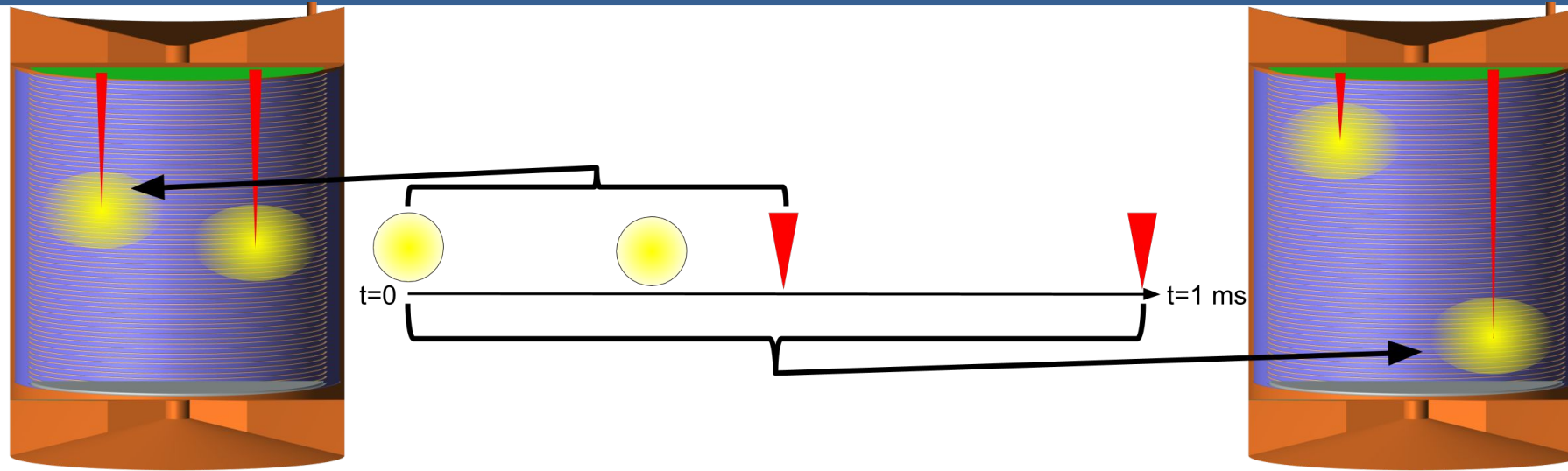
- “Monte Carlo is never that accurate”
 - Can always apply systematic errors to parts of the MC model that you don’t want constraining the fit
 - Better approach: identify discrepancies and add nuisance parameters to resolve them
 - Those nuisance parameters then can be used in physics analysis to show impact of MC systematics on final result
 - If your MC has issues you can’t resolve, you should at least know where they are
- “The detector response function isn’t so obvious”
 - Yes, collaborations spend person-decades figuring out the nuances of their detector response
 - Those nuances often show up when something doesn’t fit as well as it should, especially off-peak
 - Doing the calibration only on the cleanest data hides nuances for later
 - Potential for “first light panic” if big fit doesn’t converge on day 1, but we’re not running first-gen experiments any more

OK, but why?

- A single, unified calibration
 - Replicable: one piece of analysis that can reproduce every parameter; no “side projects”
 - Response function is documentation of the method
 - Systematics (and mistakes) show up as discrepancies in the fit; visible to whole collaboration
- As detectors get bigger, calibration data becomes precious
 - Penetrating with energetic sources is harder
 - More spatial bins, fewer events per bin
 - Longer for dissolved source mixing
 - For precision measurements, noise / low quality events become the calibration data

No more calibration mysteries. No wasted data.

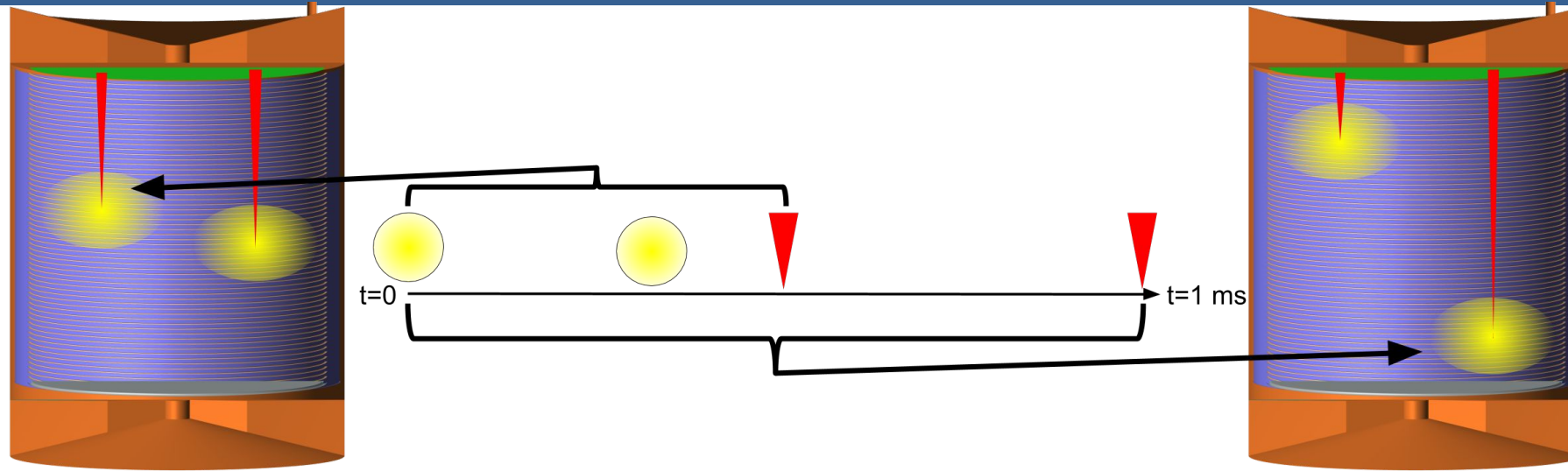
Example: Pileup During Intense External Source Calibration



- kBq of Th calibration source needed to calibrate full nEXO volume in reasonable time
- Which charge pulse goes with the first light pulse?
- Waterfall approach:
 - Calibrate rough light map using no-pileup events
 - Use rough light map to guess XY position for light pulses (hope it's single-site!)
 - Use XY to pair charge/light
 - Use salvaged pairs to improve light map/drift lifetime calibration

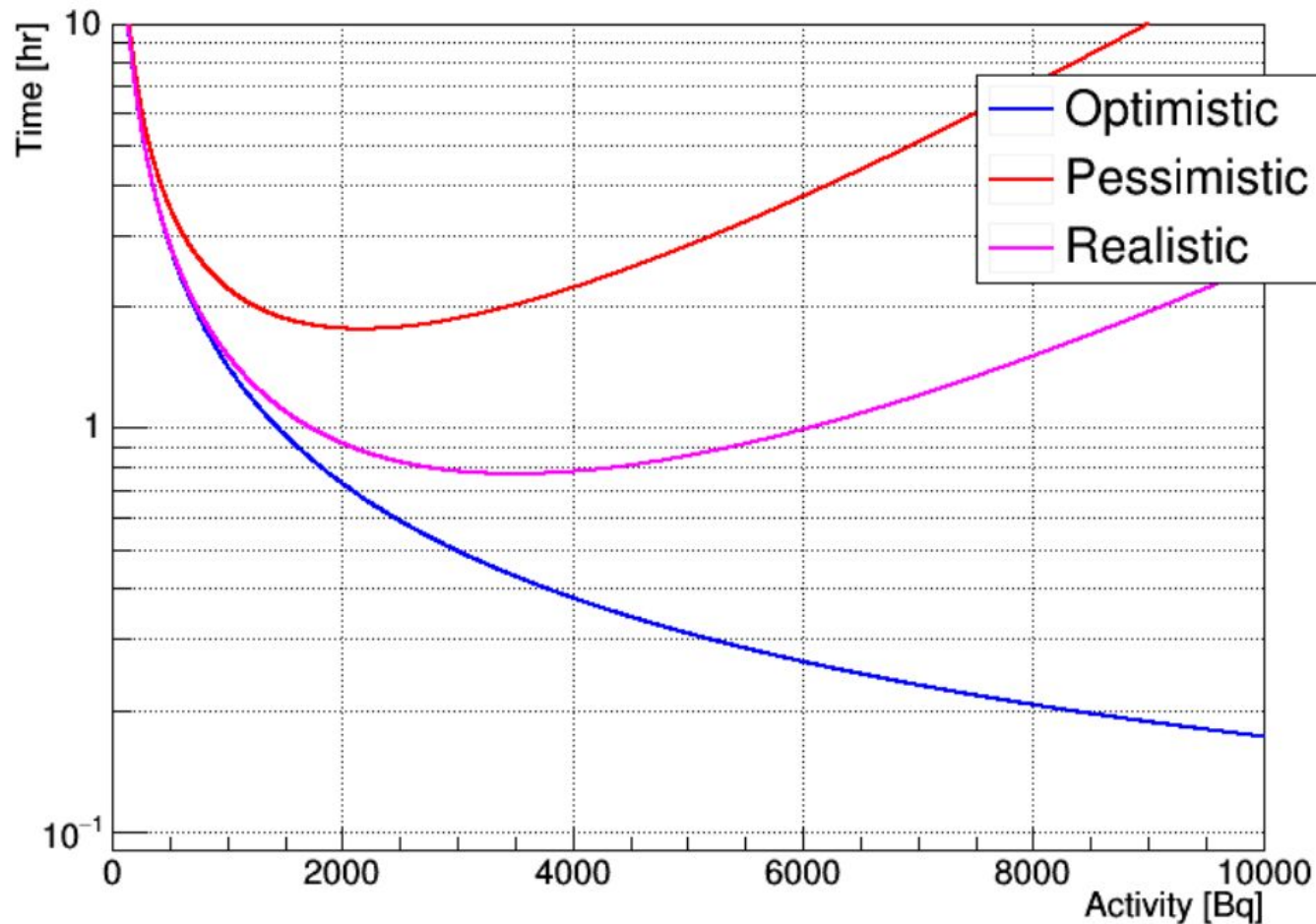
Reminder:
Kr-83m is
below
threshold
for nEXO

Example: Pileup During Intense External Source Calibration



- Simultaneous approach:
 - 2,3,etc. pileup events go into additional histograms
 - Fit every histogram simultaneously, with light map, drift lifetime, charge/light yields, E-scale, etc.
 - Pileup events constrain fit nearly as well as no-pileup events, since less ambiguity when considering light map
 - Not single site? No problem--still constrains fit

Example: Pileup During Intense External Source Calibration



Time for 100 usable events in inner tonne of nEXO (from nEXO pre-CDR)

- **Realistic:** Waterfall approach, with decent scintillation-only XY recon
- **Optimistic:** Waterfall approach, with great scintillation-only XY recon
- **Pessimistic:** What the waterfall approach has to work with to develop that XY-recon
- Simultaneous better than optimistic
- Large reduction in calibration time = 6% livetime improvement

How do we do it?

- Response function:
 - Develop abstract form by iteration by collaboration, same as standard analysis
 - How to represent in code? As callable functions? As histograms/PDFs?
- Simulation:
 - G4 for radiation, lots of tools for photon/charge transport, custom for signal sim
 - How can we implement nuisance parameters so the simulation is “always right?”
- Minimization:
 - If we need to batch data, can we do better than random batches?
 - The response function may have an analytic gradient in all or most parameters
 - What specific data science tools fit our needs?



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