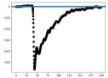
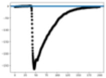
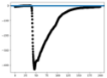
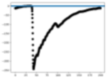
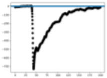
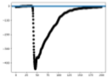
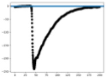
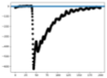
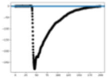
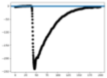
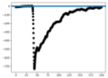
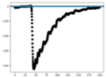
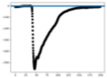
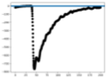
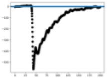
LXe scintillation model

December 5, 2019

Game plan

- Use averaged PMT signals from several data sets to find parameters that best fit models.
- Compare fits of different models to find which model is more likely.

	Cs source to the lab	Cs source to the door	Co source to the lab	Co source to the door	Background
PMT 0					
PMT 1					
PMT 19					

Averaged PMT signal as model tester

$$WF_{i,a} = \frac{dx}{\sqrt{2\pi}\sigma_a}\left[\langle N_a\rangle * \left(\langle spe_a\rangle * e^{-T_0^2/2\sigma_a^2}\right)\right]$$

$$\underbrace{\langle N\rangle_{t=i,PMT=a}}_{\text{Average number of pes detected by PMT a at time t.}} = \underbrace{\langle PEs\rangle}_{\text{Dataset average of photons emitted per event.}} \overbrace{Q_a}^{\text{LCE}} \underbrace{P(t,\theta_a,\phi_a)}_{\text{Scintillation model}} \quad (1)$$

Parameters to fit:

- Model parameters:...
- Dataset parameters: $\langle PEs\rangle$, $\hat{z}$.
- PMT parameters: $Q, T_0, \sigma, \theta, \phi$.

Models to compare

The standard scintillation model:

$$
\begin{aligned}
P(t,\theta,\phi) =& P_0(t) = \frac{F}{4\pi\tau_f}e^{-t/\tau_f} + \frac{1-F}{4\pi\tau_s}e^{-t/\tau_s} \\
&0 < F < 1, \quad \tau_f \sim 5\ ns, \quad \tau_s \sim 45\ ns
\end{aligned}
\tag{2}
$$

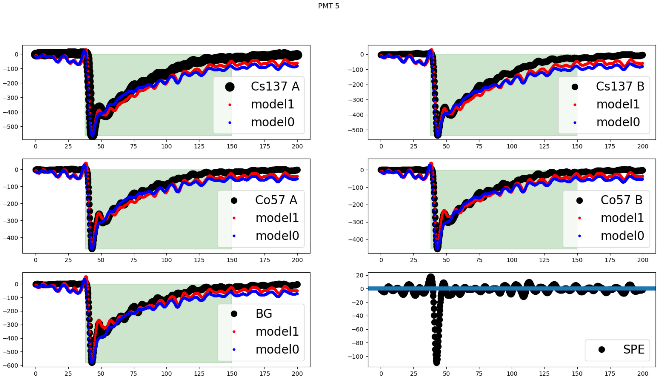
The proposed scintillation model:

$$
\begin{aligned}
P(t,\theta,\phi) =& R_0 R(\theta,\phi)\delta(t) + (1-R_0)P_0(t) \\
&0 < R_0 < 1, \quad \int R(\theta,\phi)d\Omega = 1 \\
R(\theta,\phi) =& \frac{e^{-(cos\theta-1)^2/2\zeta^2} + e^{-(cos\theta+1)^2/2\zeta^2}}{4\pi\sqrt{2}\zeta erf(\sqrt{2}/\zeta)}
\end{aligned}
\tag{3}
$$

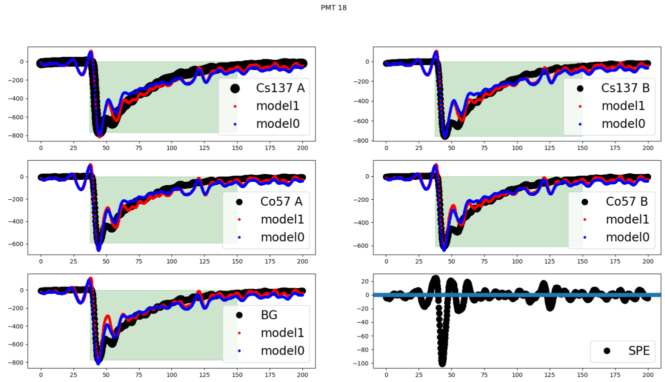
Parameters to fit

- Model parameters: $\overbrace{R_0, \zeta, F}^{\text{Maybe energy dependent}}, \tau_f, \tau_s$.
- Dataset parameters: $\langle PEs \rangle$, $\hat{z}$.
- PMT parameters: $Q, T_0, \sigma, \theta, \phi$.

PMT 5

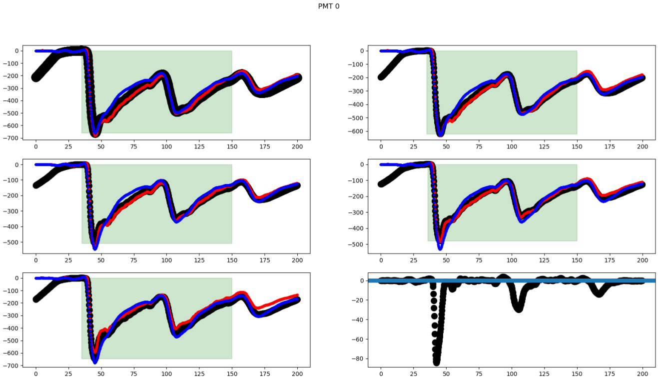

PMT 5
Cs137 A
model1
model0
Cs137 B
model1
model0
Co57 A
model1
model0
Co57 B
model1
model0
BG
model1
model0
SPE

PMT 18

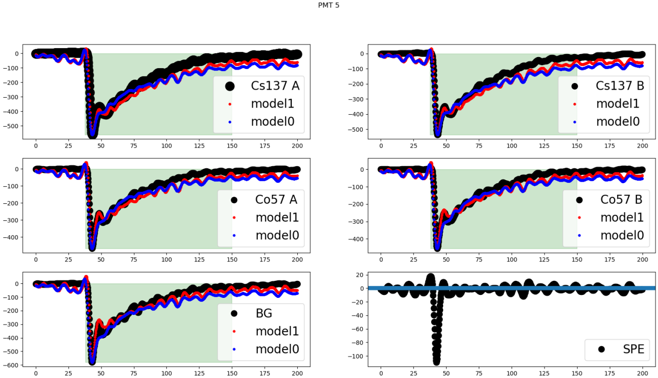


PMT 18
Cs137 A
model1
model0
Cs137 B
model1
model0
Co57 A
model1
model0
Co57 B
model1
model0
BG
model1
model0
SPE

PMT 0

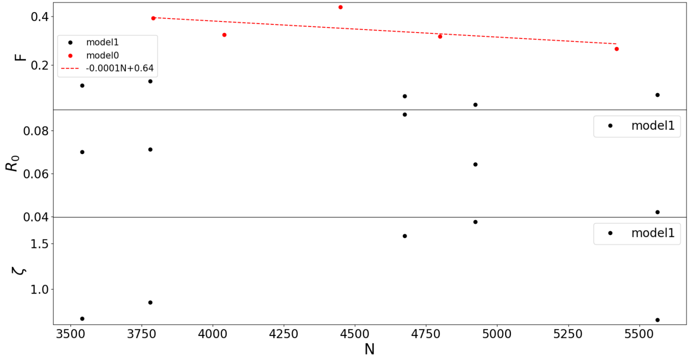


PMT 5


PMT 5
Cs137 A
model1
model0
Cs137 B
model1
model0
Co57 A
model1
model0
Co57 B
model1
model0
BG
model1
model0
SPE

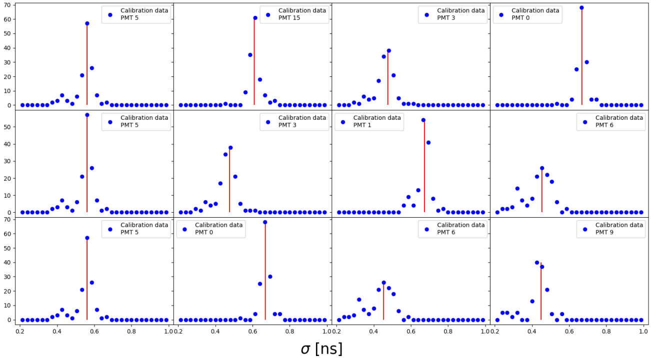
Results - model parameters

	model 0	model 1
$\sqrt{\langle\chi^2\rangle}$	6.48	4.69
τ_f [ns]	16.38	15.5
τ_s [ns]	69.3	58.5



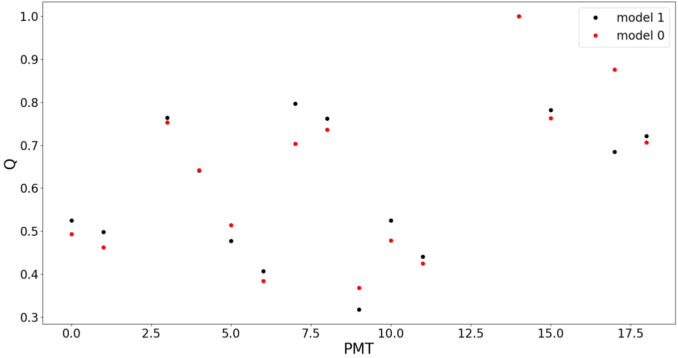
(Model 1 and 0: CoA, CoB, BG, CsB, CsA)

Results - PMT parameters - σ



$$\sigma_i = 0.5\sqrt{\sigma_{ij}^2 + \sigma_{ik}^2 - \sigma_{jk}^2} \tag{4}$$

Results - PMT parameters - Q



Waveform generator

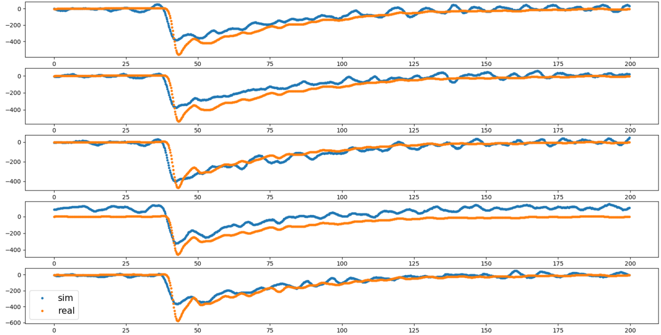
Create average waveform from a given model:

- Create N waveforms.
- Average them with a shift which drawn from Normal$(0, \sigma)$.

Create single waveform:

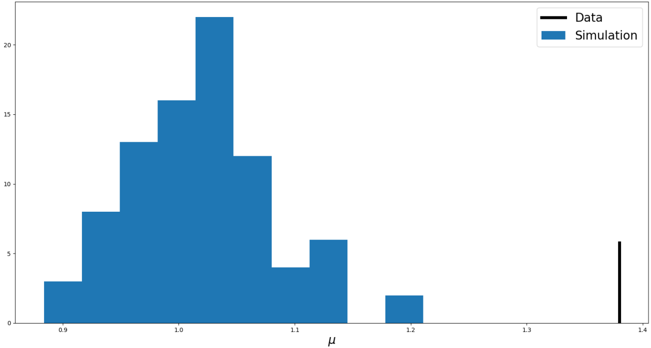
- Iterate through the 1000 digitized points (i) and draw a number of photons to generate $n_i \sim \text{Binom}(\text{Poission}(P_{i,\theta,\phi}), Q)$
- For each generated photon draw an SPE waveform from the calibration data.
- Add the SPE signal to the waveform at a point j which is drawn from Normal(i, σ).

Simulated waveforms



Significance

- Generate datasets with the parameters that best fit model-0 in the real data.
- Fit it to model-0 and model-1.
- Compute $\mu = \chi_0^2/\chi_1^2$.



Detector sensitivity

- For each value of R_0, ζ generate large number of datasets drawn from model-1.
- Compute in which fraction (ρ) of datasets there is a detection over model-0.
- Put R_0, ζ in the ρ'th CL band.

Upgrades before next run