WG:Transition Edge Sensor

Status Report

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ALPS

HELMHOLTZ RESEARCH FOR GRAND CHALLENGES

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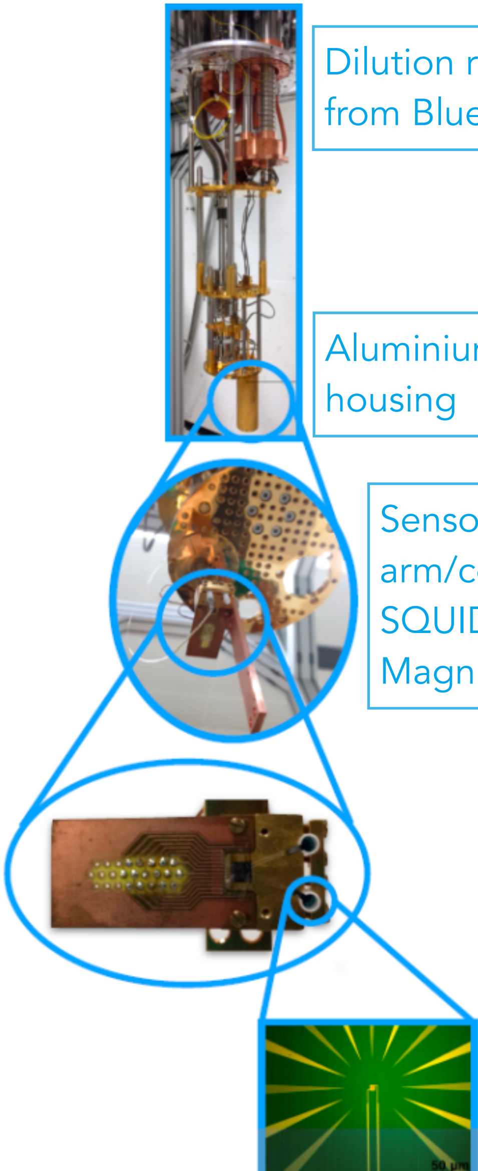
Outline

- Lab and TES Status
- TES Analysis
  - DAQ Setup and workflow
  - Data sets
  - The 3-pronged analysis approach
- TES Room
- TES Lab tests
- Next steps
- Summary

TES in a nutshell



Dilution refrigerator from Bluefors

Aluminium can housing

Sensor module on housing arm/cold finger with attached SQUID electronics (from Magnicon) attached

Sensor module with SQUIDs from PTB and TES from NIST

Photon incidence on TES:

$$\Delta T \approx 100\,\mu K$$

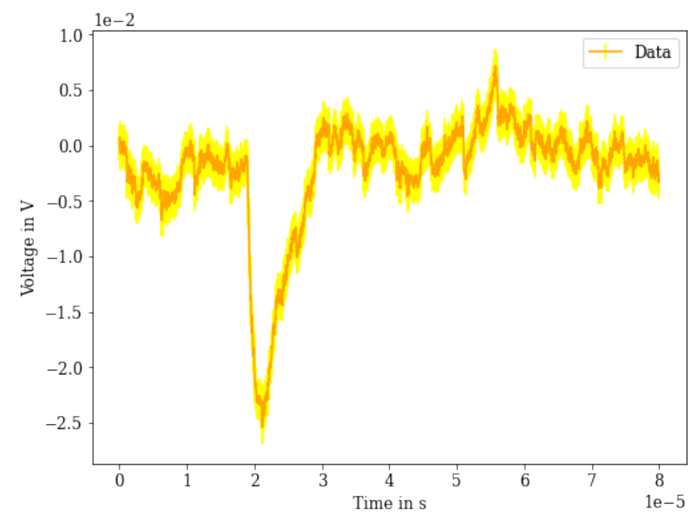
$$\downarrow$$

$$\Delta R \approx 1\,\Omega$$

$$\downarrow$$

$$\Delta I \approx 70\,nA$$

$$\downarrow$$



Example 1064 nm photon event

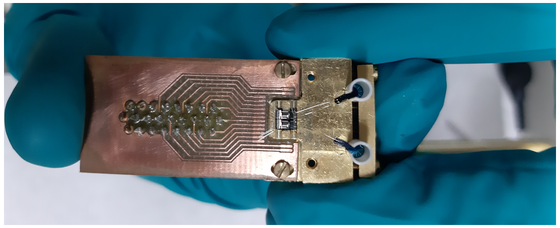
Status

TES Lab, next phase

- Cryostat warmed up, awaiting next round of tests to commence
- Last tests have been done in the first week of March 2020, setup has remained unused since then for about 3.5 months due to coronavirus
- Focus of the work has been shifted to:
    - **Understanding better the TES data**, as we have enough data to streamline the data analysis
    - **Improving TES data analysis** with new methods
    - **Optimisation plans for the TES**
    - Planning **tests for the detection efficiency**, and methods for background suppression

Status

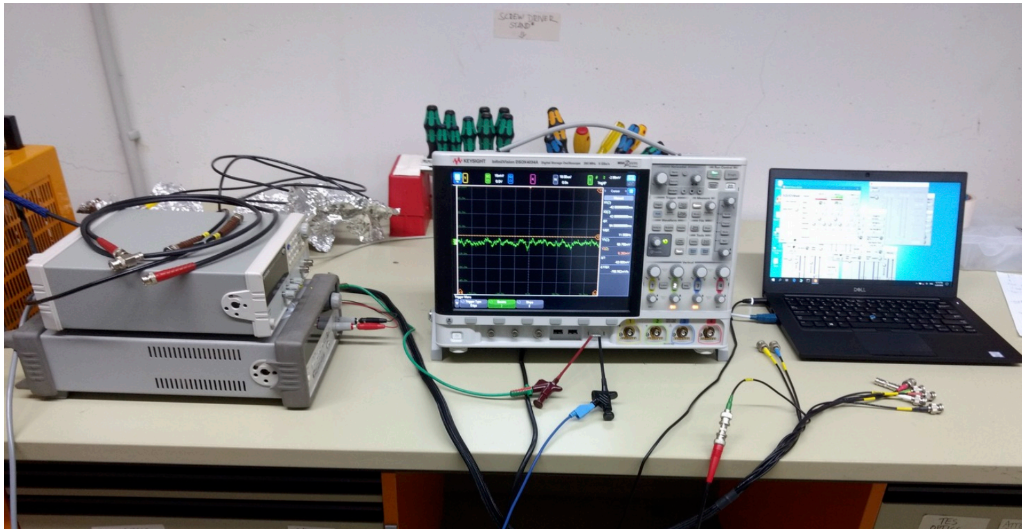
TES Status



- Currently only one of two TES detectors on the sensor module is active
- Heating issues with the SQUIDs persists, even with a bath temperature of ~21 mK
- Optimal SQUID settings heat the TES beyond its operation region
- Using modified SQUID settings to operate the TES:
  - Unstable SQUID working point
  - *Especially sensitive* to any electromagnetic fluctuations in the TES vicinity
- However, data collection from TES is operational for different TES setups
- **Even with non-optimal SQUID settings, we are successfully able to detect 1064 nm photon pulses and background pulses and collect data**
- **Optimisation will be a focus of the restarted lab activities!**

TES DAQ

- TES and SQUIDs are operated and read out by the Magnicon SQUID electronics controlled by a dedicated laptop
- DAQ via another PC with the Alazar card installed, where the output of the SQUID electronics is attached.
- In this setup, also including the cryostat, efforts have succeeded in considerably reducing the noise due to electronic fluctuations and ground loops for a better SNR.



TES DAQ

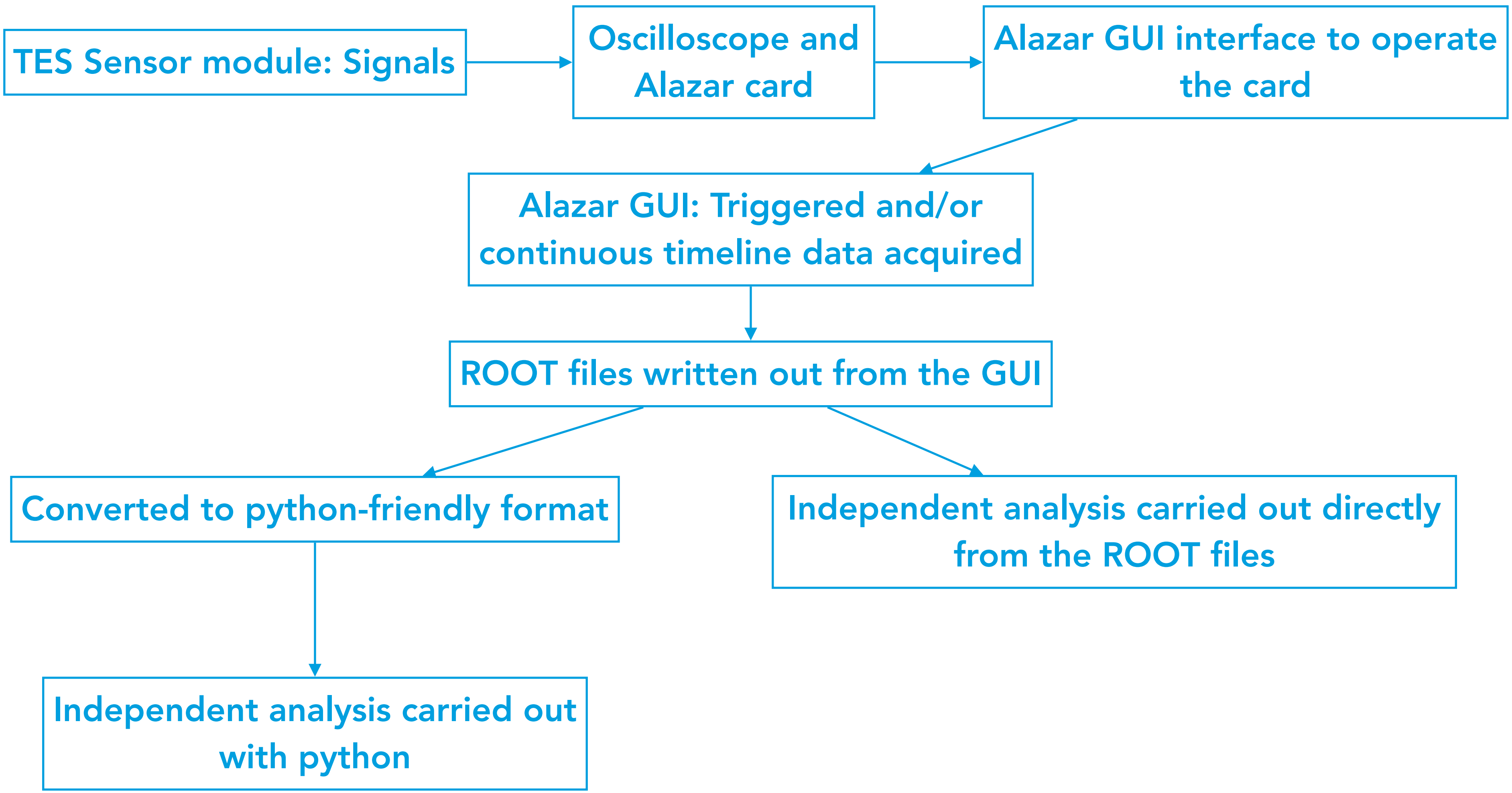
- DAQ and processing done bearing in mind some goals:
  - **Achievement of very low background rates, $\mathcal{O}(10^{-5})\,Hz$,** with optimised background rejection
  - **Identification of different background event types**, whether an optical fiber is attached to the TES or not
  - **Obtaining the best picture possible of the TES response** to a 1064 nm photon, from which TES information can be further extracted

In order to detect (with 50% detector efficiency) a photon with 5σ confidence in a measurement over 20 days,
we need to obtain a dark rate < $7.7 \times 10^{-6}\,Hz$

Value taken from Pg 5, Transition Edge Sensor, ALPS II - Design requirement document, Document number v3, *Jan Hendrik Põld and Hartmut Grote*

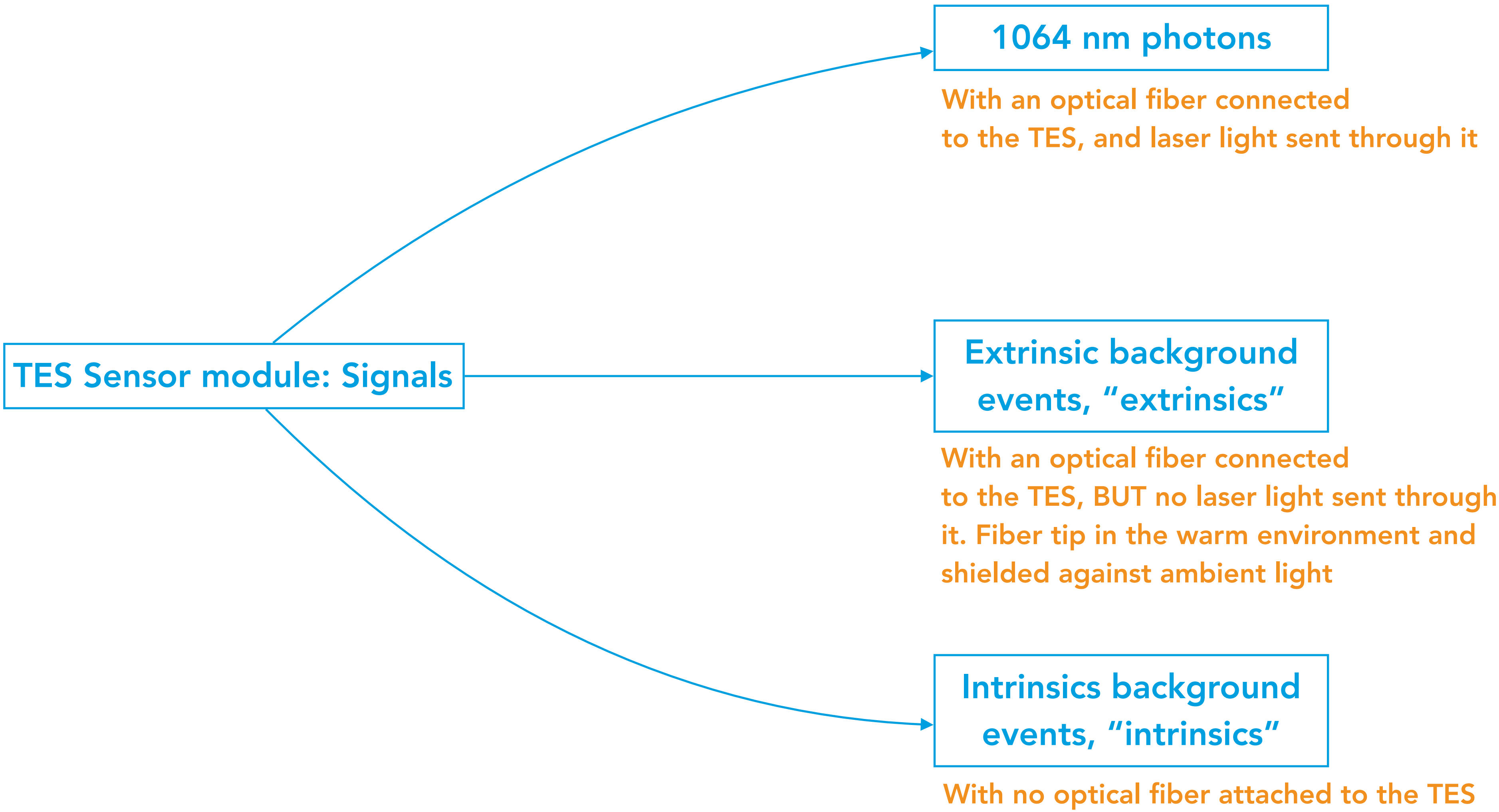
TES DAQ

Workflow



TES DAQ

Data types



TES DAQ

Data types

TES Sensor module: Signals

- Data for pulse characterisation only
  - **1064 nm photons**
    With an optical fiber connected to the TES, and laser light sent through it
- **Extrinsic background events, "extrinsics"**
  With an optical fiber connected to the TES, BUT no laser light sent through it. Fiber tip in the warm environment and shielded against ambient light
- No optical connections to TES at all
  - **Intrinsics background events, "intrinsics"**
    With no optical fiber attached to the TES

TES Pulse Analysis

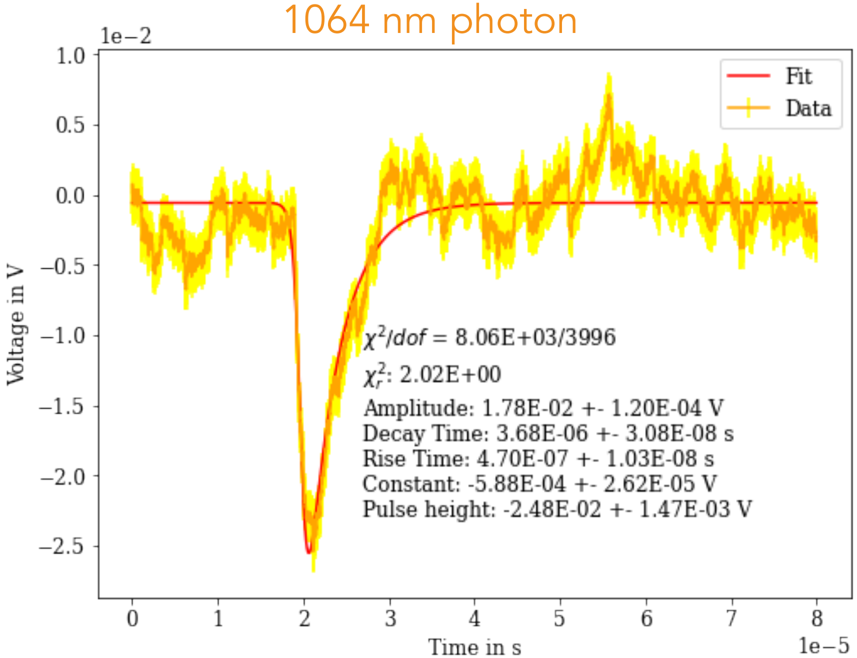
- TES Pulse analysis adopts a three pronged approach currently:
  - Backbone of the analysis: **Fitting the pulses** and selecting based on fit parameters
- In addition, we study the scope of using:
  - **Machine learning** techniques
  - **Principal component analysis**

TES Pulse Analysis

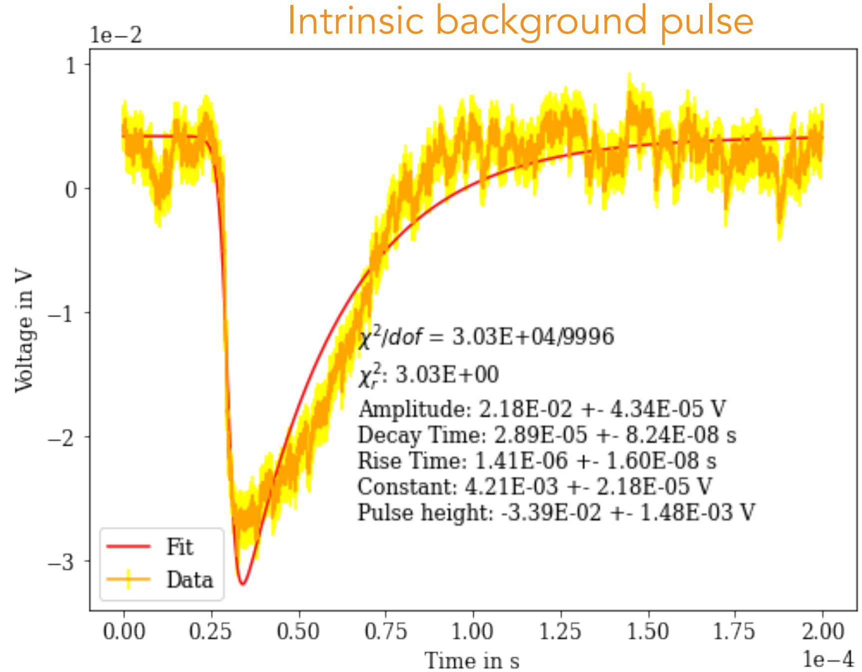
Fitting

- Fitting TES pulses performed via a classical approach which models the TES pulses and can be used for suppression of backgrounds and extraction of TES information.
- Has been done with independent approaches with python and ROOT, implemented separately
- **The fitting procedure works extremely stably for all kinds of pulses**

1064 nm photon



Intrinsic background pulse

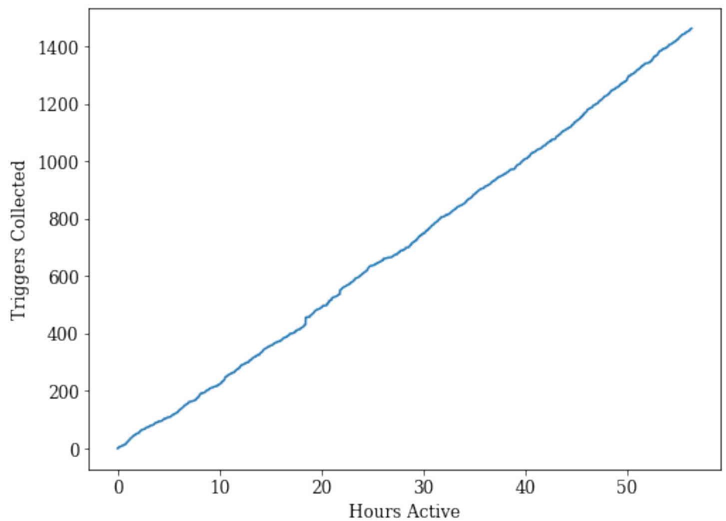


TES Pulse Analysis

Fitting

- The fitting parameters from the 1064 nm photon pulses are used to define cuts
- To select eligible photons in background data sets, the cuts ensure for 1064 nm pulses:
    - ~90% of the pulses remain after the cuts
    - An Energy resolution 7- 11% is obtained

Intrinsics Data Set '7 day'



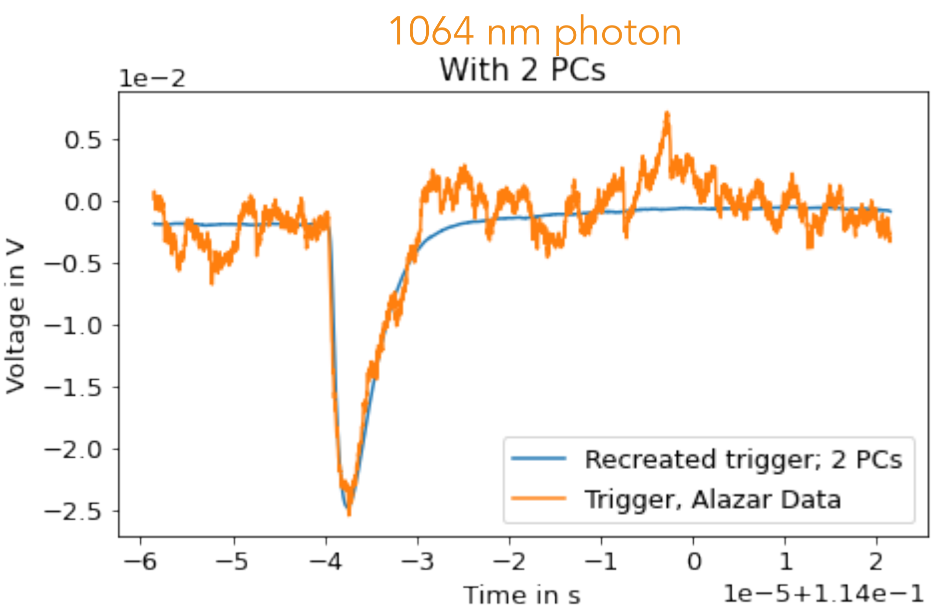
For an intrinsic background data set with active data taking time of 54.8 hours, we select no photon pulses with the cuts!
The limit obtained on the (intrinsic) dark rate is $1.86 \times 10^{-5}\, Hz$ at 95% CL

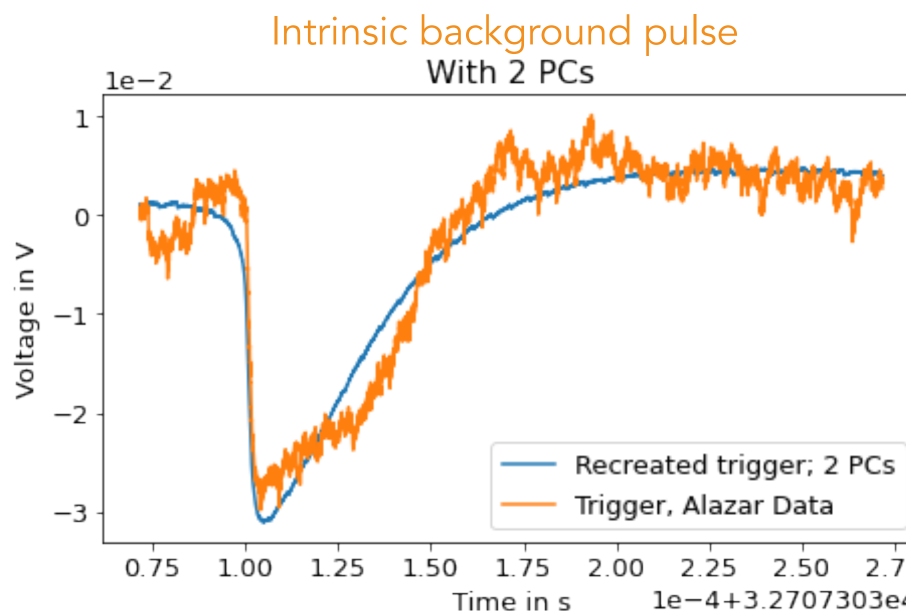
TES can fulfil the specs required for the dark rate (with no optical connections to the TES)

TES Pulse Analysis

Principal Component Analysis PCA

- The PCA approach has been used to improve energy resolution, hope to use it for our data.
  Tomography of photon-number resolving continuous-output detectors, *Peter C Humphreys et al 2015 New J. Phys. 17 103044;*
  Photon-number-resolving transition-edge sensors for the metrology of photonic microstructures based on semiconductor quantum dots, *M. Schmidt et al, Journal of Low Temperature Physics volume 193, pages 1243–1250(2018)*
- Idea is to reduce the raw pulse to a couple of meaningful, information-heavy 'components' per pulse (Akin to fit parameters per trigger)
- **Works stably for the data sets available, large datasets processed in seconds**
- **Background rates comparable to those from fitting procedure**





TES Pulse Analysis

Machine Learning by Manuel Meyer

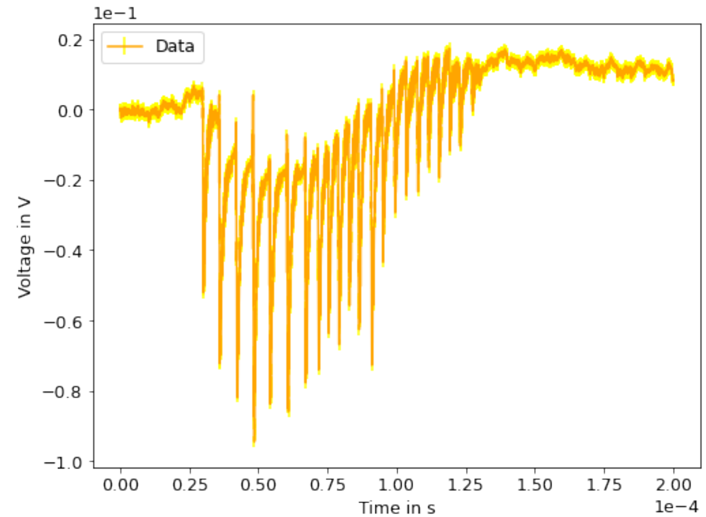
- First steps towards implementing machine learning algorithms to better our photon selection using the parameters from pulse fitting
- Using out-of-the-box algorithms like Decision Trees (DTs), Boosted Decision Trees (BDTs) and Random Forests (RFs).
- Working on few data samples collected with non-optimal system
- **Background rejection performance already comparable to pulse fitting approach**
- **Optimistic about improvement with more data samples, and with the PCA**

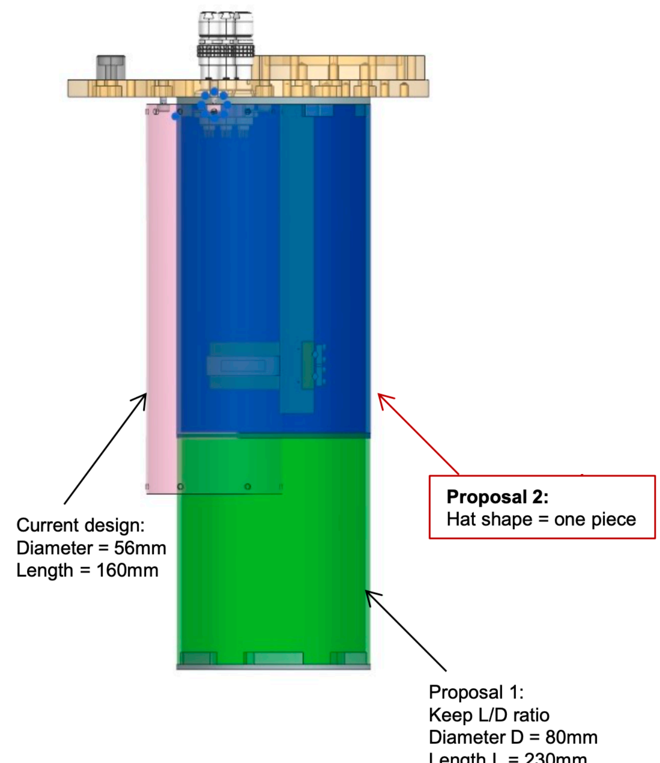
Method Used	Intrinsic dark rate achieved, in Hz
Decision tree	$2.463 \times 10^{-5} \pm 5.51 \times 10^{-6}$
Boosted Decision Tree	$2.463 \times 10^{-5} \pm 5.51 \times 10^{-6}$
Random forest	1.86×10^{-5} at 95% CL
Cut-based selection	1.86×10^{-5} at 95% CL

Magnetic Shielding Tests

TES Lab

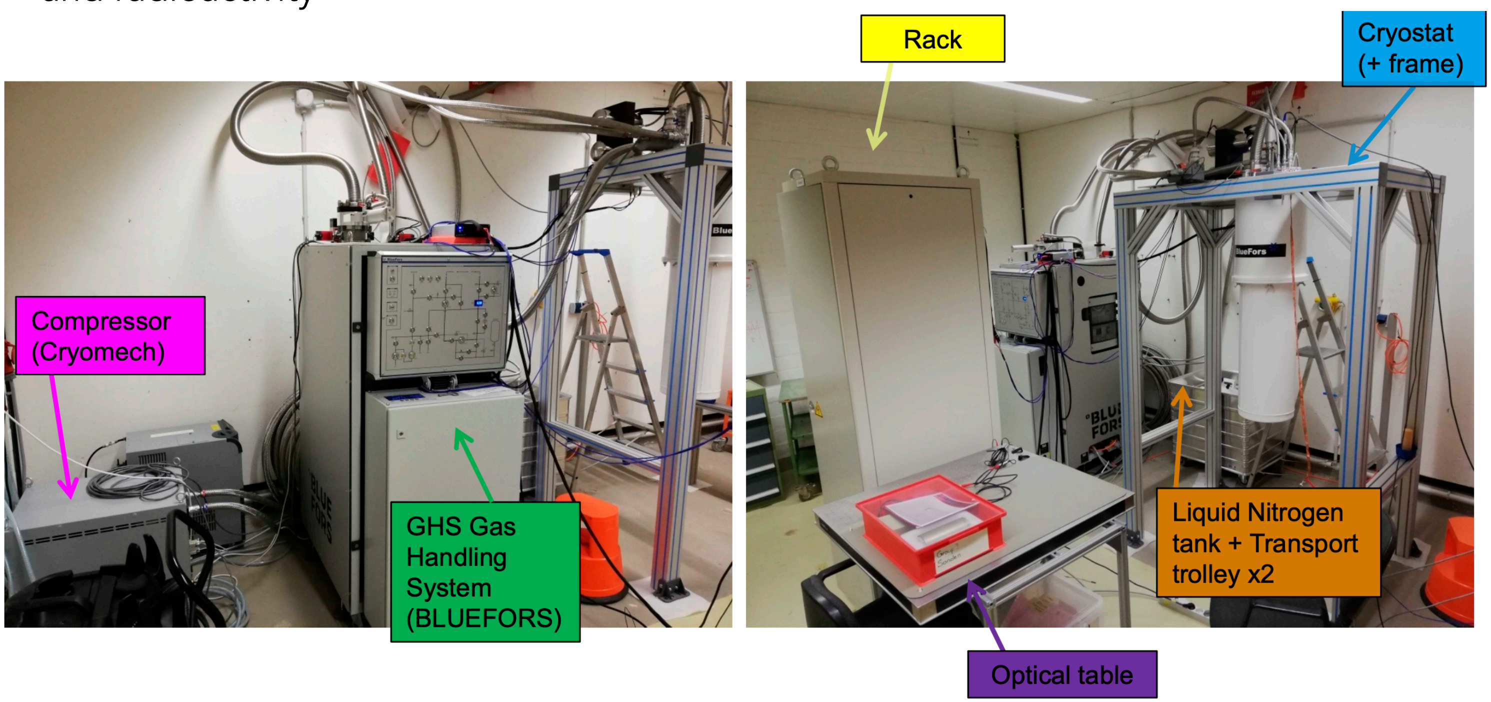
- Non-optimal SQUID settings used result in SQUIDs losing lock with EM interference, TES being overloaded with EM pulses
- Need to understand the extent of magnetic shielding due to the cryostat vacuum, the inner μ metal shielding, and the aluminium can housing the TES
- Could also install a redesigned aluminium can to house the TES, which is also needed to accommodate the updated sensor module
- **Tests planned with warmed up and vented cryostat this week**



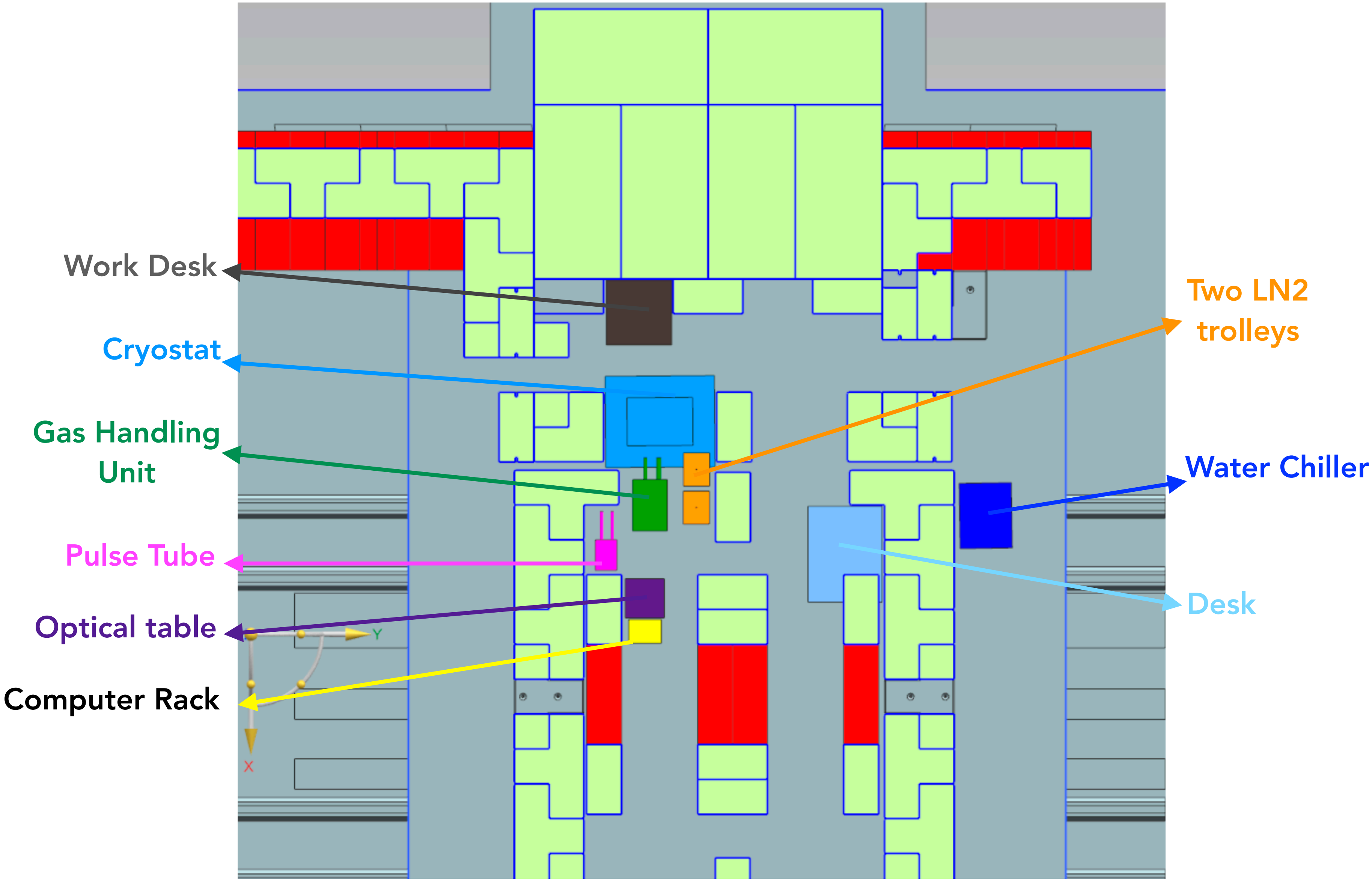


TES Room Layout

- New layout for proposed TES Room under the bridge
- Another proposed candidate for the TES Room is on Floor 6 near the main power supply for the magnets
- Can be considered viable only after
    - Tests for EM interference
    - Tests with a much longer optical fiber, to check for increased backgrounds also due to cosmics and radioactivity



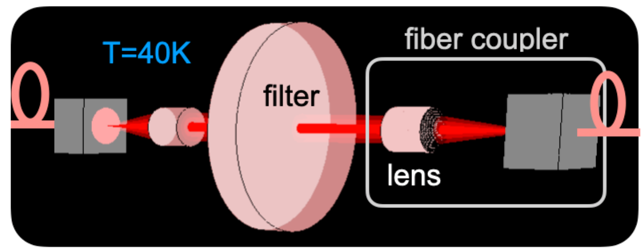
TES Room Layout

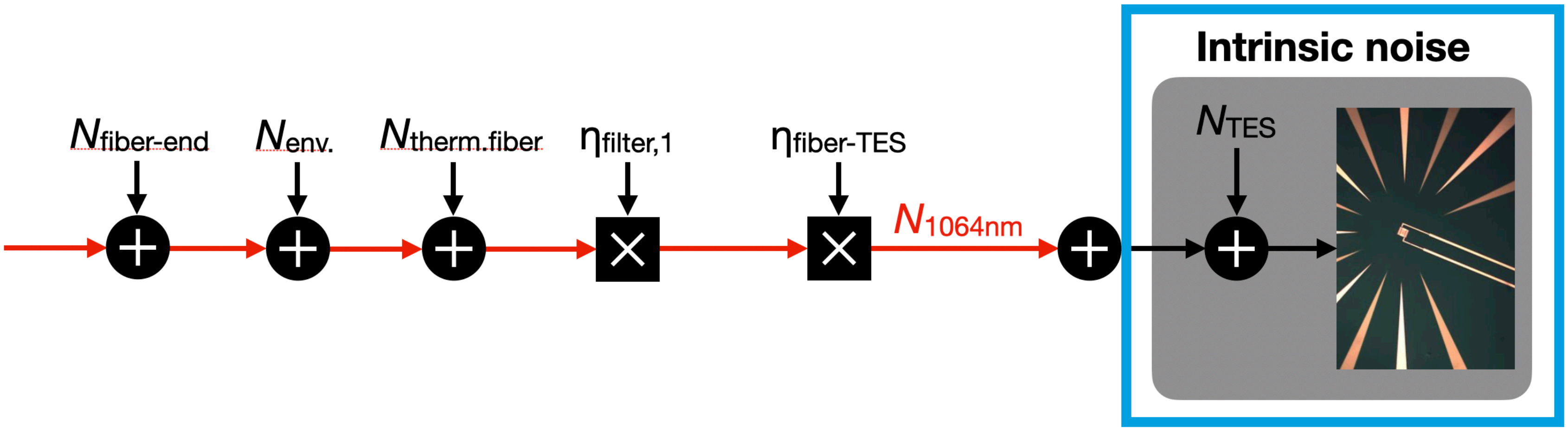


TES Optics

- Effects of adding and making optical connections to the TES
- To understand the make up of the extrinsic background
- Studies to reduce suspected black body pile up
- Optimisation of filter bench and investigating fiber curling
- Single photon source to calibrate the TES
- Design of setup to measure TES efficiency

Filter bench (IfoCAD model)





Next steps

- Restarting lab work!
- Optimising TES working point, and possible updates to sensor module
- Investigate extrinsic background and methods to reduce it (fiber curling, filter bench)
- Longer data taking runs for intrinsic background level (currently limits only!)
- Efficiency measurements and optimisation
- Need to understand the source of the the background pulses for the full setup
- Magnetic shielding tests
- Tests on dark counts with a long optical fiber for TES room
- Analysis optimisation
- Expansion of R&D efforts with the UK proposal

Summary

- “No-lab” time has been very well utilised for data understanding and streamlining DAQ response
- Data collection and analysis is very stable and robust even with suboptimal setup
- Successful analysis of the data with baseline fitting
- ML and PCA analysis in place, results consistent with baseline analysis, could possibly improve efficiency and energy resolution
- The intrinsic background level of the TES is reaching ALPS II specs (no events remaining after cuts for a 54.8 hour run)
- Two possibilities for a TES Room in HERA North
- Next steps will focus primarily on working point optimisation, longer intrinsic background runs to see rate (and not only limit) and measurement of efficiency of the setup

Backup

TES Pulse Analysis

Fitting functions

- TES Pulse analysis adopts a three pronged approach currently: **Fitting the pulses** and selecting based on fit parameters, using **machine learning** techniques and using **principal component analysis**.
- Fitting TES pulses can be done via:
    - TES Small-Signal-Theory response : Analytical solution to the response of the TES to an incident photon.
    - Photon flare function: Models the TES pulses very accurately, adapted from astrophysical gamma flare analyses.

$$V(t) = C - \frac{A}{\chi} \cdot \left(\exp\left(-\frac{(t-t_0)}{t_r} \right) + \exp\left(-\frac{(t-t_0)}{t_d} \right) \right),$$

$$\text{with } \chi = \left(\frac{t_d}{t_r} \right)^{\frac{td}{t_r - t_d}} - \left(\frac{t_d}{t_r} \right)^{\frac{tr}{t_r - t_d}}, t > t_0$$

TES SST Response

$$V(t) = C - \frac{2A}{\exp\left(-(t-t_0)/t_r\right) + \exp\left(-(t-t_0)/t_d\right)}$$

Photon flare

TES Pulse Analysis

Fitting functions: Choices

TES SST Response

- Fitting in general is time consuming and does not always work too well
- Can be used at best to extract TES info from a well defined pulse

Photon flare

- Fitting in general consumes lesser time and fits all kinds of pulses well
- Can be used to model photon pulses very well and distinguish between 1064 nm photon pulses and background pulses
- Best used for background analyses

Best bargain approach:

Fit all pulses with the flare function and use it discriminate between photon and background pulses

Fit the average of the photon flare fits with the TES SST response and extract TES information

TES Pulse Analysis

Fitting functions: Examples

$$V(t) = C - \frac{A}{\chi} \cdot \left(\exp\left(-\frac{(t-t_0)}{t_r} \right) + \exp\left(-\frac{(t-t_0)}{t_d} \right) \right),$$
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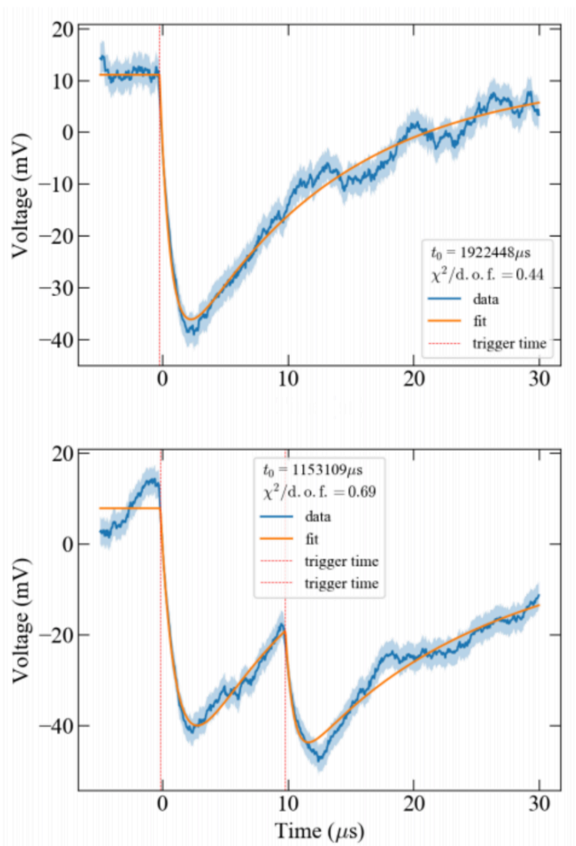
TES SST Response



Photon flare

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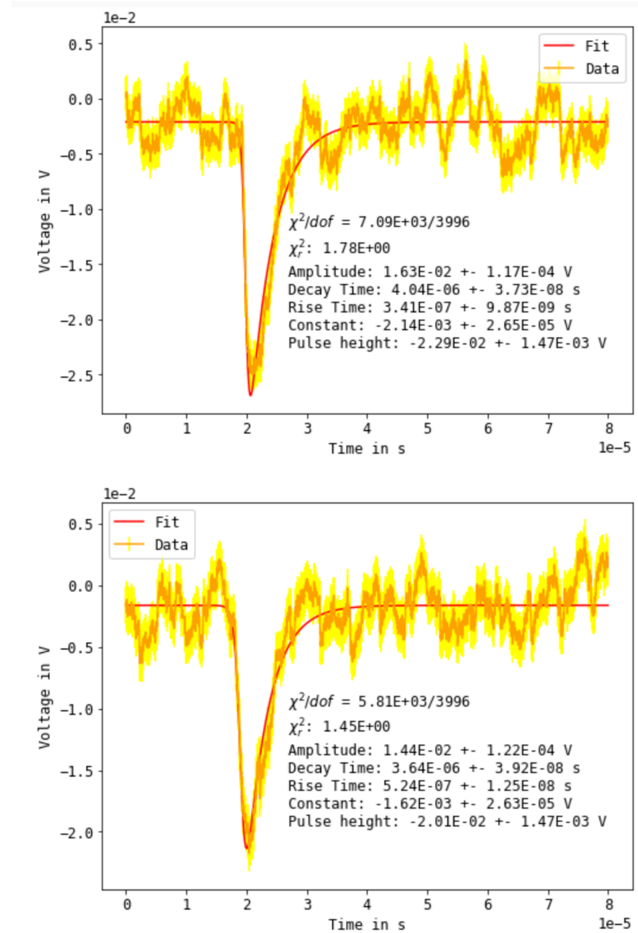

PCA: Principal Components

Uses and Pros

- Attempt to find linear combinations of features in the original high dimensional data matrix, i.e. interrelations in the data / measurement breaking up the data set into its most useful components

- V is the set of all triggered signals where each column is a trigger

- For any data sample with T triggers of M data points each, the dataset is thus a matrix with dimensions (M x T):

  Dataset $V = \left(\text{trigger } 1 \,|\, \text{trigger } 2 \,|\, \text{trigger } 3 \,|\, \ldots \,|\, \text{trigger } T\right)_{M \times T}$

- Each *trigger* (a column) can then be further decomposed into $\{v_i(t)\}$, where V is an array of M values

- Each v_i can be represented as $v_i = \sum s_{ij} w_j(t) \implies v_1 = s_{11}w_1 + s_{12}w_2 + \ldots + s_{1T}w_T$

  - where v_i is the measured voltage at a time t (within the trigger)

  - s_{ij} are the mixing factors, or coefficients, and w_j are the Principal Components.

PCA: Principal Components

Uses and Pros

- Each measured voltage value in any trigger is the linear sum of all w_j . What we hope to is to go from
- $$v_i = \sum_j^M s_{ij} w_j(t) \implies v_1 = s_{11}w_1 + s_{12}w_2 + \ldots + s_{1T}w_T$$

to

$$v_i = \sum_j^N s_{ij} w_j(t) \implies v_1 = s_{11}w_1 + \ldots + s_{1N}w_N\,,$$

- Here only N principal components are used and typically N << T.
- We use PCA because the lion's share of the information is then captured in the first few PCs.

  This means reducing the dimensionality of the original dataset.

How to: PCs calculation

- For a dataset, we can calculate $W =$ eigenvectors $(V^T V)$, where $V^T V$ is the covariance matrix for V
- The matrix W (of the principal components) is the matrix corresponding to each trigger in the original dataset V.
- If N is number of chosen principal components for the analysis:

$$V = (\text{trigger } 1|\text{trigger } 2|\text{trigger } 3|\dots|\text{trigger } T)_{M\times T}$$
$$\implies W = (\text{Column of N PCs for trigger 1}|\dots|\text{Column of N PCs for trigger T}|)_{N\times T}$$

- To express the dataset V in terms of W, we use $V = S \cdot W$, and calculate the coefficient matrix S using $S = V \cdot W^T$:
- $$\begin{pmatrix} s_{11} & s_{12} & \dots & s_{1N} \\ \dots & & & \\ s_{M1} & & \dots & s_{MN} \end{pmatrix}_{M\times N}$$
- For the **reduced dataset $V' = S \cdot W$, which has then the same dimensions as V,** but each measured v_i has lesser noisy information
  ….we hope: **most (useful) information is captured in the PCs used**

How to: PCs calculation

- For a dataset, we can calculate $W =$ eigenvectors $(V^T V)$, where $V^T V$ is the covariance matrix for V
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$$\implies W = (\underbrace{\text{Column of N PCs for trigger 1}|\ldots|}_{\text{Each row is the array of PCs}}\text{Column of N PCs for trigger T})_{\boxed{N \times T}}$$

Reduction in dimensions: Each trigger can be understood as a few PCs, like it was the few fit parameters.

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-
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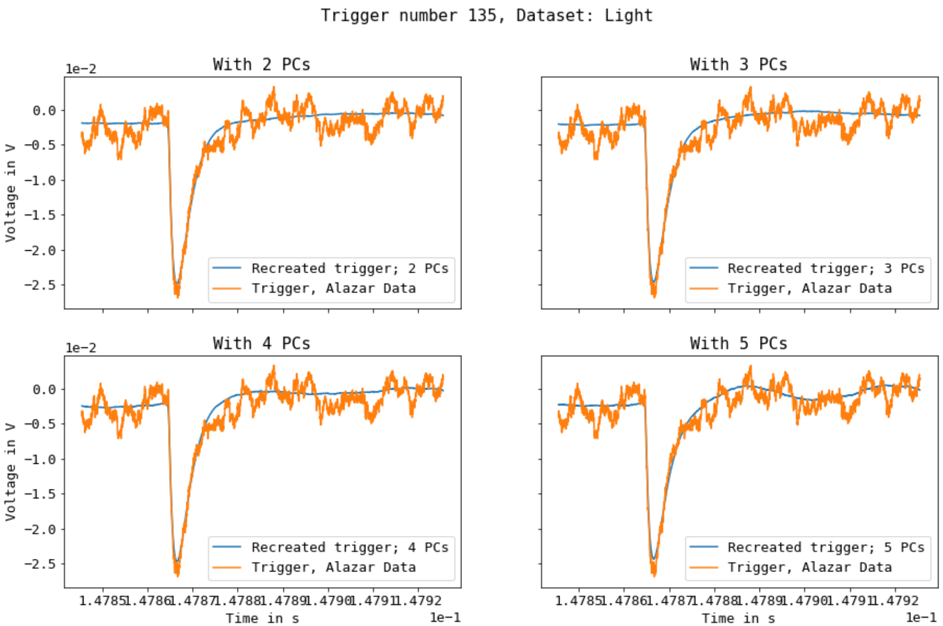
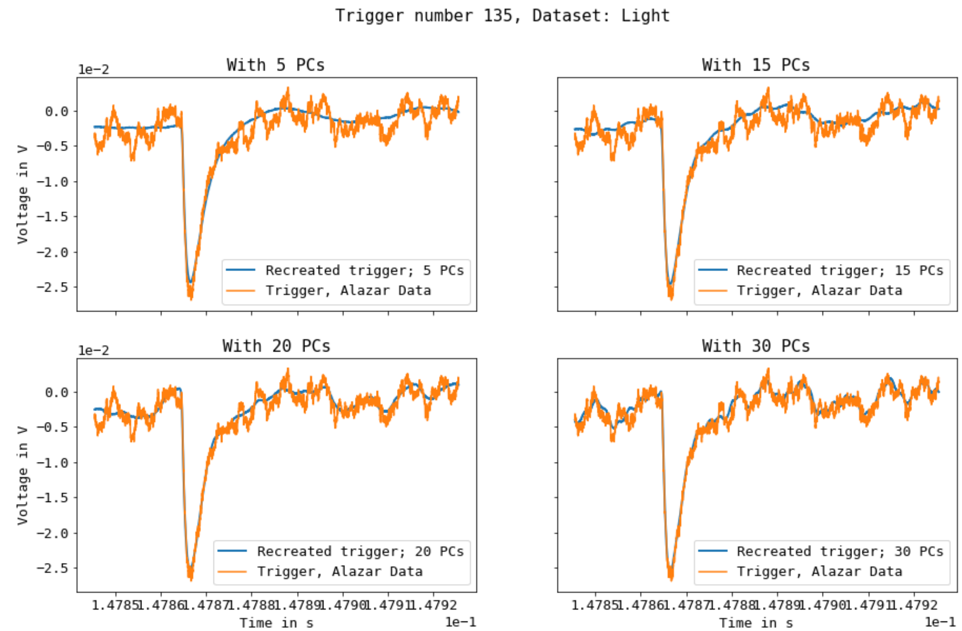
Recreating Pulses

Choice of PCs





1. Taking a look at the 1064 nm pulse, 2 PCs do the trick
2. From 5 PC onwards, we see that the noise fluctuation starts to creep in.