Development of an open-source calibration framework for superconducting qubits

Master's degree in Physics

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QC, what is for?

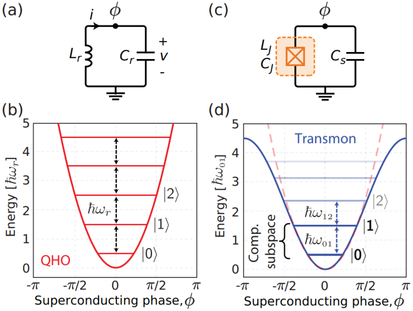
- **Simulation of quantum system:**
  "Nature isn't classical, dammit, and if you want to make a simulation of nature, you'd better make it quantum mechanical, and by golly it's a wonderful problem, because it doesn't look so easy"
  - Richard Feynman, 1982, Simulating Physics with Computers
- Optimization and modeling (chemistry, finance, traffic, weather...), eg. VQE, QAOA
- Quantum Algorithms
- Quantum Machine Learning

Superconducting qubits

Artificial atoms

Qubit: two level system

Superconducting qubits: use Josephson Junctions to build anharmonic oscillators



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Qubit control

Electromagnetic pulse applied to the qubit

$$V_d(t) = A\varepsilon(t)\sin\left(\omega_d t + \alpha\right)$$

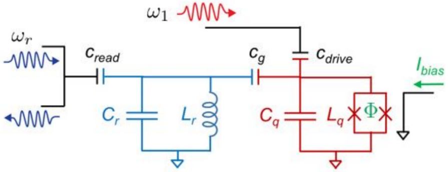
Qubit - electric field Hamiltonian (RWA)

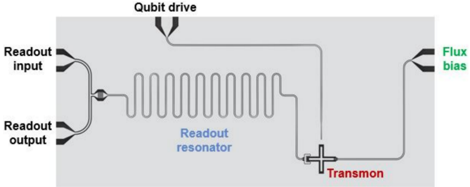
$$\hat{H} = -\frac{\hbar(\omega_q - \omega_d)}{2}\hat{\sigma}_z + \frac{\hbar\Omega}{2}\varepsilon(t)\left(\hat{\sigma}_x\cos\alpha + \hat{\sigma}_y\sin\alpha\right)$$

Qubit evolution under electromagnetic pulse:

$$R_{\hat{n}(\alpha)}(\theta) = e^{-\frac{i}{2}\hat{n}(\alpha)\cdot\vec{\sigma}\theta} = e^{-\frac{i}{2}(\hat{\sigma}_x\cos\alpha + \hat{\sigma}_y\sin\alpha)\theta}$$

where $\theta = \Omega\int_0^{+\infty}\varepsilon(t')dt'$





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State readout

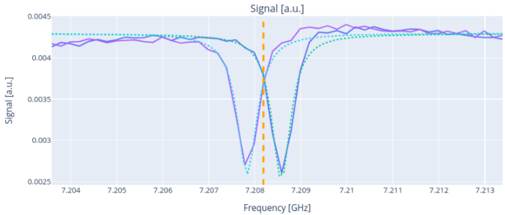
Qubit - resonator Hamiltonian:

$$\hat{H} = \hbar\omega_r \hat{a}\hat{a}^\dagger - \frac{\hbar\omega_{01}}{2}\hat{\sigma}_z + \hbar g(\hat{\sigma}^+\hat{a} + \hat{\sigma}^-\hat{a}^\dagger)$$

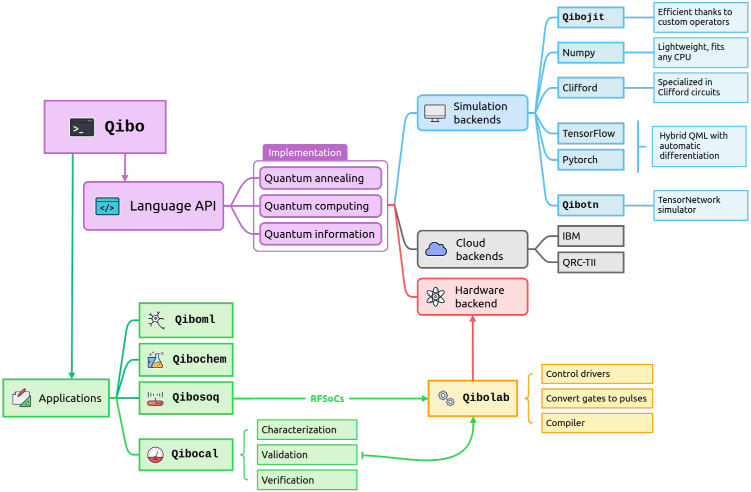
Dispersive regime ($g \ll \omega_q - \omega_r$):

$$\hat{H}_{disp} = \hbar(\omega_r - \chi\hat{\sigma}_z)\hat{a}^\dagger\hat{a} - \frac{\hbar}{2}(\omega_{01} + \chi)\hat{\sigma}_z$$

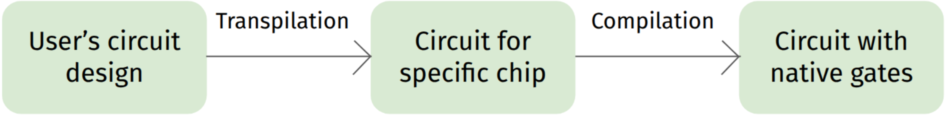
dispersive shift: $\chi = \frac{g^2}{\Delta}$,
$\Delta = \omega_q - \omega_r$



Qibo framework



Superconducting qubit calibration



We need to calibrate *only* native gates

Native single qubit gates on superconducting qubits: $R_X(\pi)$, $R_X(\frac{\pi}{2})$, $R_Z(\theta)$

For each pulse we calibrate frequency, duration, power, shape

Average Clifford gate fidelity optimization

Randomized Benchmarking

Randomized benchmarking estimates average gate fidelity by applying random sequences of Clifford gates followed by an inverting gate.

Randomization with Clifford gates provides a depolarized noise channel:
$\rho \rightarrow d\frac{\mathbb{I}}{2} + (1-d)\rho$

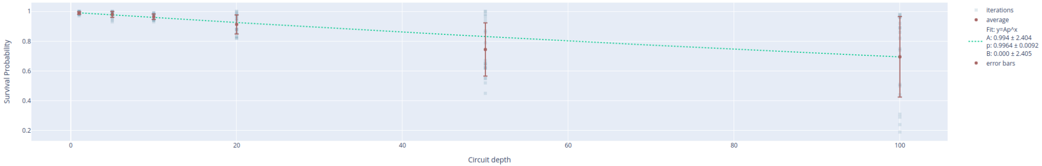
Randomized Benchmarking protocol:

1. Initialize the system in the ground state
2. For each sequence length m draw a sequence of Clifford group elements
3. Calculate the inverse gate
4. Measure complete sequence
5. Repeat the process for multiple sequences of the same length while varying the length

Randomized Benchmarking

The survival probability decays exponentially with the number of Clifford gates $F(m) = Ap^m + B$ where $1 - p$ is the depolarization rate.

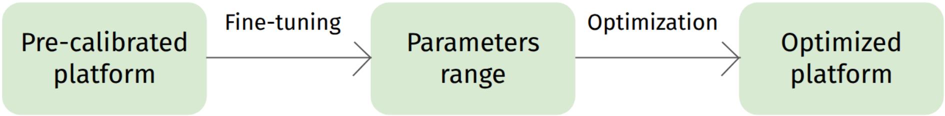
From p we can extract the average error per Clifford gate.



Can we optimize the average Clifford gate fidelity to automate $R_X(\pi)$ gate recalibration?

RB optimization [Kelly et al. 2014]

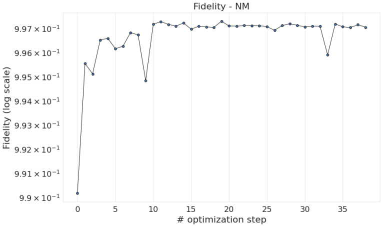
Test closed-loop optimization with modern optimization libraries

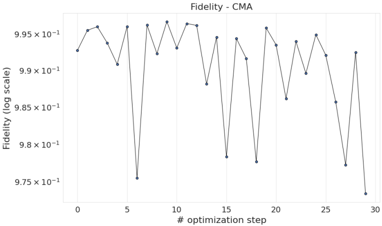


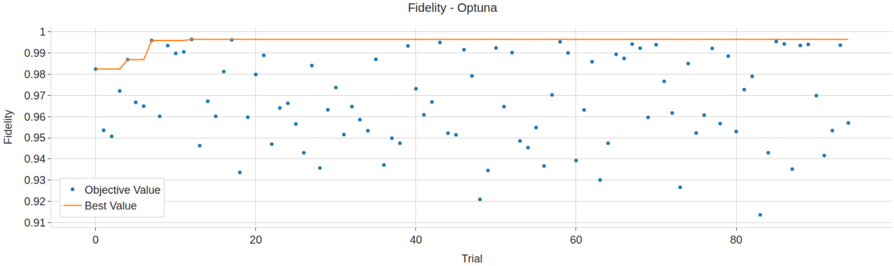
Optimization parameters:

- Pulse amplitude
- Pulse frequency
- Pulse shape (through β DRAG parameter)

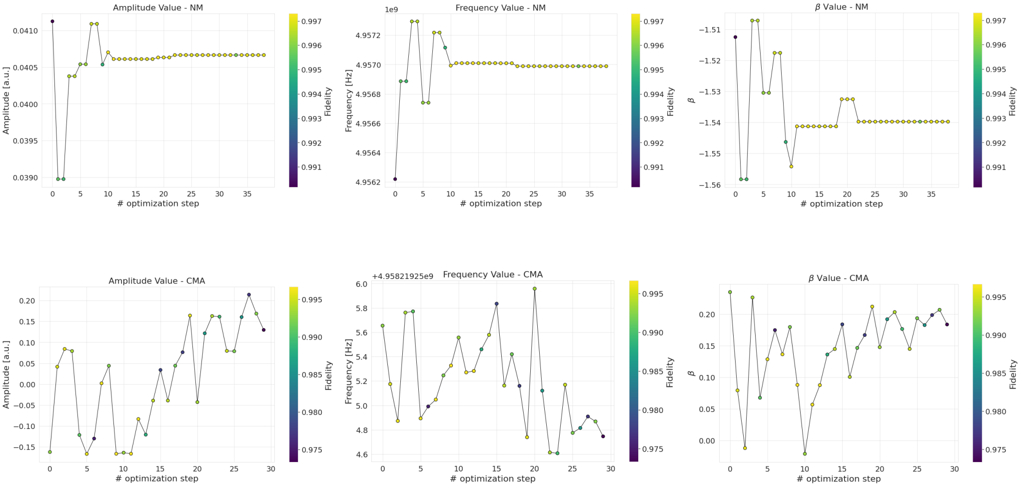
Average Clifford gate Fidelity







Parameters evolution



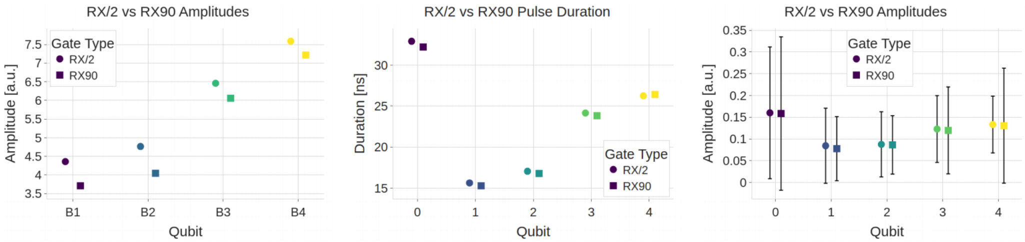
Library additions

Native RX90

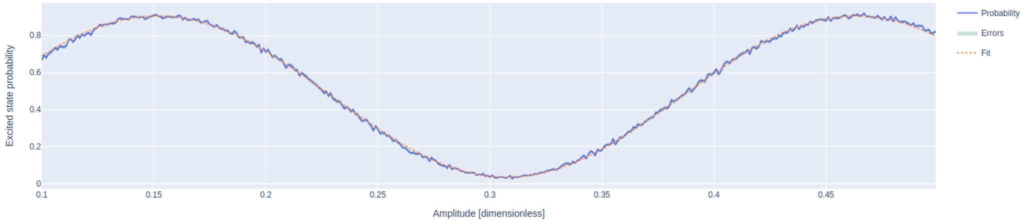
Qibolab single-qubit native gates are $R_X(\pi)$ and MZ

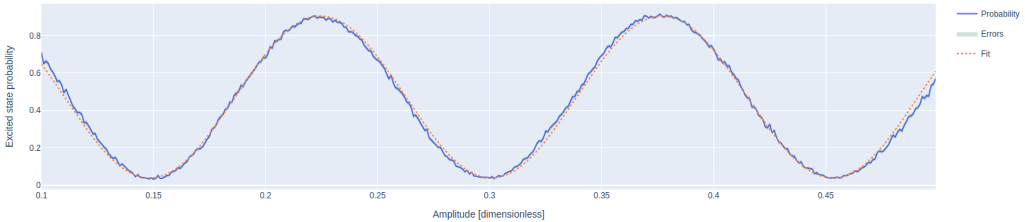
$R_X(\frac{\pi}{2})$ gate is implemented by halving the calibrated values for $R_X(\pi)$

Add native $R_X(\frac{\pi}{2})$ for more precise gates implementation



Rabi amplitude experiment





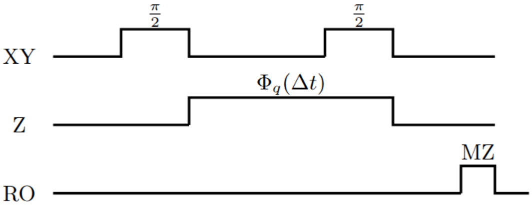
Flux pulse reconstruction [Rol et al. 2020]

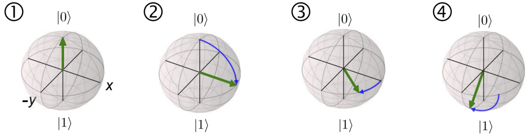
Transmon frquency dependence on magnetic flux:

$$f_q(\Phi_q) \approx \left(\sqrt{8E_J E_C \left|\cos\left(\pi \frac{\Phi_q}{\Phi_0}\right)\right|}\right)$$

Detuning as function of the flux pulse:

$$\Delta f_q = \frac{\varphi_{\tau+\Delta\tau} - \varphi_\tau}{2\pi} \approx \frac{1}{\Delta\tau}\int_\tau^{\tau+\Delta\tau} \Delta f_q(\Phi_{q,\tau+\Delta\tau}(t))$$





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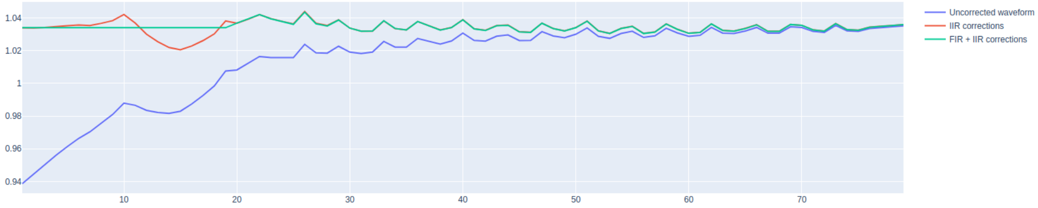
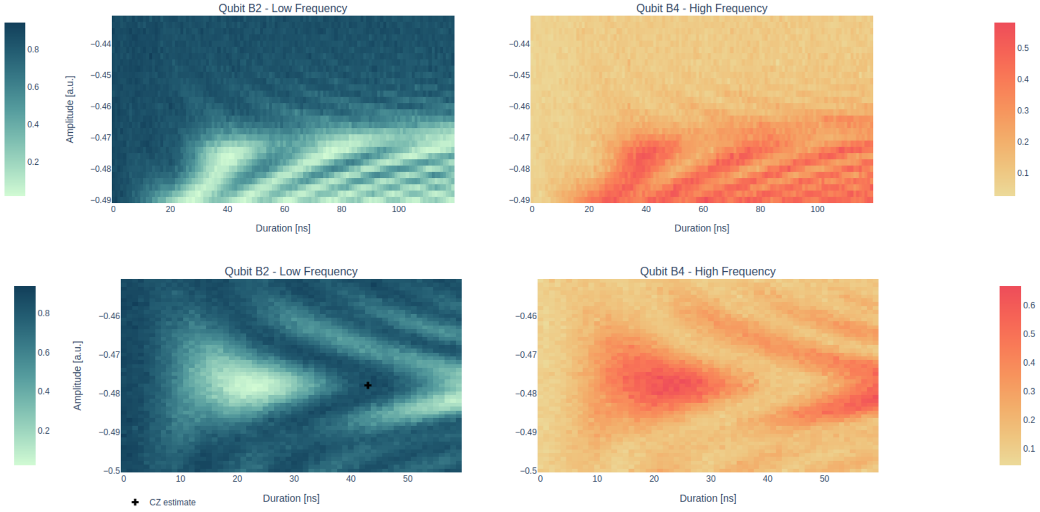
Filter determination



1. Determine exponential correction
2. Obtain coefficients for the Infinite Impulse Response from exponential correction
3. Determine Finite Impulse Response coefficients
4. Obtain coefficients for real-time correction

Impact of correction on chevron plots



Cryoscope routine

Qibocal · v0.2.2

Search

`relaxation_time: float`

Wait time for the qubit to decohere back to the *gnd* state.

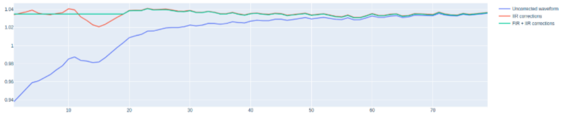
Example

A possible runcard to launch a Cryoscope experiment could be the following:

```
- id: cryoscope

  operation: cryoscope
  parameters:
    duration_max: 80
    duration_min: 1
    duration_step: 1
    flux_pulse_amplitude: 0.7
    relaxation_time: 50000
```

The expected output is the following:



✎ Note

In the case where there are no filters the protocol will compute the FIR and the IIR filters. If the filters are already present the computation of the filters will be skipped and only the reconstructed waveform will be shown.

Requirements

- Single Shot Experiments

Conclusions & Outlooks

Gate recalibration by RB optimization

✓ We can always find parameters configuration with average Clifford gate fidelity $> 99.5\%$

✓ Does not rely on manual tuning by an operator

✗ RB evaluation is computationally expensive ($\sim$ 30 minutes)

✗ More stable methods (eg. Nelder-Mead) require many cost function evaluation

✗ Parameters drift makes optimization unstable

Possible future work: optimize RB parameters to allow a faster and more reliable optimization

Library additions

- ✓ Extended Qibolab and Qibocal libraries to support native $R_X(\pi/2)$ gates with dedicated calibration routines
- ✓ Implemented and added the Cryoscope calibration experiment to Qibocal library to correct flux-pulse distortions (average NMSE improvement $\sim 70\%$)
- ✗ Study long-time distortions of the flux-pulse

Possible future extensions:

- Readout optimization protocols
- Active qubit reset schemes
- Implement leakage mitigation strategies

Thank you

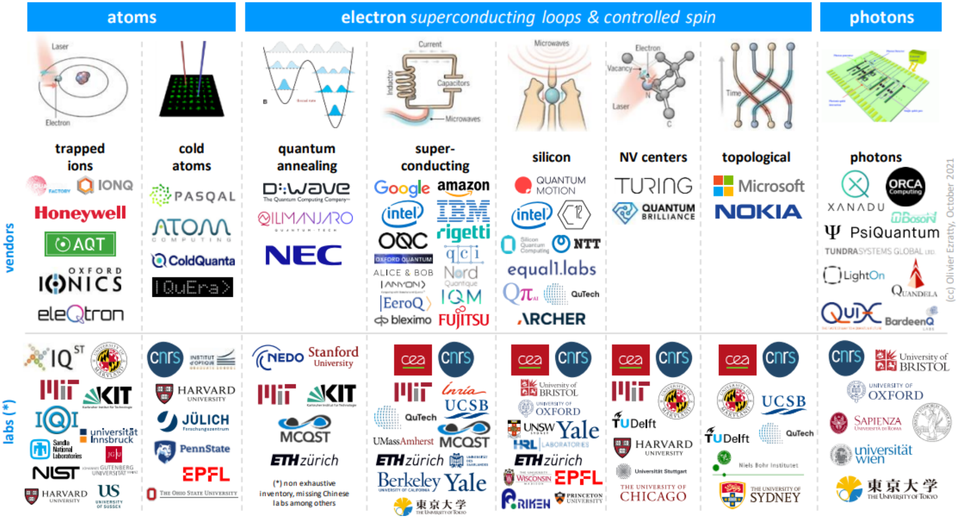
References

Kelly, J. et al. (June 2014). **"Optimal Quantum Control Using Randomized Benchmarking".** en. In: *Physical Review Letters* 112.24, p. 240504. ISSN: 0031-9007, 1079-7114. DOI: 10.1103/PhysRevLett.112.240504. URL: https://link.aps.org/doi/10.1103/PhysRevLett.112.240504 (visited on 02/24/2025).

Rol, M. A. et al. (Feb. 2020). **"Time-domain characterization and correction of on-chip distortion of control pulses in a quantum processor".** en. In: *Applied Physics Letters* 116.5. arXiv:1907.04818 [quant-ph], p. 054001. ISSN: 0003-6951, 1077-3118. DOI: 10.1063/1.5133894. URL: http://arxiv.org/abs/1907.04818 (visited on 02/24/2025).

Backup slides

Qubit platforms



Calibration workflow & assessment

Procedure:

1. Resonator characterization
2. Qubit characterization
3. Gate calibration
4. Gate set characterization

Metrics example:

- readout & assignment fidelity
- relaxation time T_1
- decoherence time $T_2 2$
- gate fidelity

Calibration workflow & assessment

Main steps:

1. Resonator characterization
2. Qubit characterization
3. Gate calibration
4. Gate set characterization

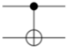
Calibration quality metrics:

- readout & assignment fidelity
- relaxation time T_1
- decoherence time T_22
- gate fidelity

Qubit	**Readout Fidelity**	**Assignment Fidelity**	**T1** [μs]	**T2** [μs]	**Gate infidelity** ($\cdot 10^{-3}$)
D1	0.876	0.938	26.4 ± 0.4	13.0 ± 2.0	27.0 ± 21.0
D2	0.945	0.973	14.9 ± 0.1	18.0 ± 10.0	20.5 ± 6.2
D3	0.905	0.952	23.6 ± 0.3	28.0 ± 12.0	7.0 ± 18
D4	0.929	0.964	20.6 ± 0.2	38.0 ± 5.2	4.4 ± 4.8
B2	0.902	0.951	17.5 ± 0.2	27.5 ± 5.2	18.0 ± 16

Clifford gates

- Special subset of quantum gates that map Pauli operators to Pauli operators under conjugation
- Clifford gates group is generated by H, S, $(CNOT)$ gates
- Quantum circuits that consist of only Clifford gates can be efficiently simulated with a classical computer (Gottesman–Knill theorem)

Hadamard (H)		$\frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix}$
Phase (S, P)		$\begin{bmatrix}1 & 0\\ 0 & i\end{bmatrix}$
Controlled Not (CNOT, CX)		$\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 1\\ 0 & 0 & 1 & 0\end{bmatrix}$

RB optimization summary

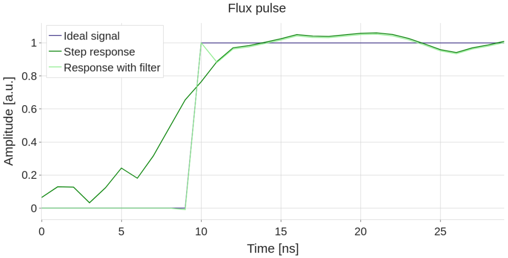
Analysis Name	Iterations	Time [s]	Fidelity Best	Amplitude Best [a.u.]	Frequency Best [$\times 10^9$ Hz]	β Best
Nelder_Mead	40	2892	0.99731	0.04063	4.95701	-1.53253
init_simplex_1	40	3096	0.99533	0.04069	4.95820	-
init_simplex_2	40	3128	0.99564	0.04131	4.95817	-
init_simplex_3	40	3190	0.99554	0.04058	4.95819	-
SLSQP	15	3873	0.99518	0.04058	4.95822	-0.00115
CMA-ES	30	4536	0.99665	-0.16634	4.95822	0.08802
optuna_30	30	763	0.99583	0.28059	4.95601	2.75519
optuna_100	100	2257	0.99645	0.29026	4.955279	-1.46504
optuna_1000	1000	21811	0.99847	-0.00051	4.961836	0.2222
optuna no β	1000	21820	0.99846	0.04104	4.957374	-

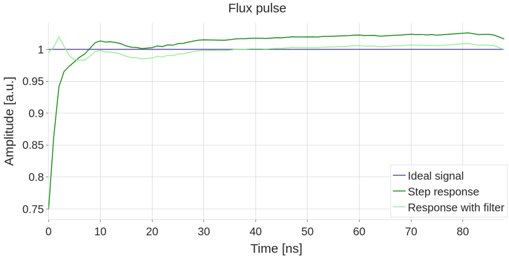
Filter determination details

Compensate distortion using a digital IIR filter based on an inverted exponential model

$$s_{\text{corr}}(t) = \frac{s(t)}{g(1 - Ae^{-t/\tau})}$$

parameters g, A, and τ are estimated via least-squares minimization using `scipy.optimize`





Filter determination details

Digital IIR filter implemented in control hardware using discretized coefficients.

$$a_0 y[n] = \sum_{i=0}^{N} b_i x[n-i] - \sum_{i=1}^{M} a_i y[n-i],$$

Filter coefficients derived from fitted parameters (1st order IIR):

$$\begin{aligned} a_0 &= 1, \\ a_1 &= -(1-\alpha), \\ b_0 &= 1 - k + k\alpha, \\ b_1 &= -(1-k)(1-\alpha), \end{aligned}$$

where $\alpha = 1 - \exp\left(-\frac{1}{f_s \cdot \tau(1+A)}\right)$ and

$$k = \begin{cases} \frac{A}{(1+A)(1-\alpha)}, & \text{if } A < 0, \\ \frac{A}{1+A-\alpha}, & \text{if } A \geq 0, \end{cases}$$

FIR filters:

$$y[n] = \sum_{i=0}^{N} b_i x[n-i],$$

FIR filter coefficients are optimized using CMA-ES to minimize the average relative deviation between the FIR-filtered IIR-corrected signal and the ideal step response.