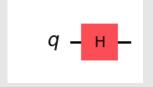
# Workshop: A Quantum Engineer's Guide to the Quantum Optimal Control Suite (QuOCS)

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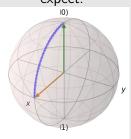
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# The problem with quantum control

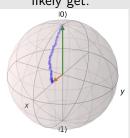
What we theoretically want:



What we ideally expect:



What we will most likely get:



## Quantum Optimal Control

Loose definition: Tuning variables in the system dynamics to achieve a certain goal.

## The control landscape:

- System dynamics.
- Cost function or figure of merit.
- Control space restriction.

## Traversing the control landscape: QOC search methods

## Type 1: Gradient-based

- Gradient Ascent Pulse Engineering (GRAPE).
- Krotov's method.
- Gradient Optimization Using Parameterization (GROUP).
- Gradient Optimization of Analytic Controls (GOAT).

## Type 2: Gradient-free

- Chopped Random Basis (CRAB).
- Dressed Chopped Random Basis (dCRAB).

[Rembold et al., AVS Quantum Sci. 2, 024701 (2020).]

# The Dressed Chopped Random Basis (dCRAB) Algorithm

- Set superiteration s = 1.
- Expand control using a **chopped basis**  $\{f_k^s\}$  with randomized basis parameters  $\beta_k^s$ :

$$f^s(t) = \sum_{k=1}^{N_c} a_k^s f_k^s (\beta_k^s; t)$$

- Numerically optimize  $a_k^s$  using algorithms such as the Nelder-Mead (NM) simplex or Covariance Matrix Adaptation Evolution Strategy (CMA-ES).
- Carry the optimized pulse in superiteration s = 1 over to superiteration s = 2. Repeat optimization.

$$f^{s}(t) = a_{0}^{s} f^{s-1}(t) + \sum_{k=1}^{N_{c}} a_{k}^{s} f_{k}^{s}(\beta_{k}^{s}; t)$$

Rinse and repeat.



## Scaling function

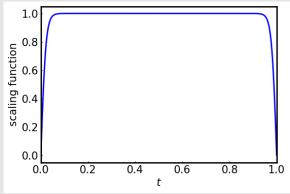
Multiplies the pulse; useful to hold the end-values at zero.

$$\Lambda(t) = \tanh\left[\sigma\sin\left(\frac{\pi t}{2T}\right)\right] \tanh\left[-\sigma\sin\left(\frac{\pi(t-T)}{2T}\right)\right]$$

where

 $\sigma$  : ramp steepness.

T : pulse duration.



# Optimization hyperparameters

#### General:

- Initial guess.
- Stopping criteria and tolerances of search methods.

#### dCRAB-specific:

$$f^{s}(t) = a_{0}^{s} f^{s-1}(t) + \sum_{k=1}^{N_{c}} a_{k}^{s} f_{k}^{s}(\beta_{k}^{s}; t)$$

- Number  $N_c$  of basis per superiteration.
- Variation of amplitude  $a_k^s$  between iterations.
- The basis {f<sub>k</sub><sup>s</sup>} used.
- Sampling interval  $[\beta_{\min}, \beta_{\max}]$  of the randomized basis parameters  $\beta_k^s$ .

#### **Experiments:**

- Drift compensation.
- Pulse re-evaluation.



# The Quantum Optimal Control Suite (QuOCS)



## Why use QuOCS?

- Open source and actively maintained.
- Informative logging.
- Provides popular QOC algorithms (dCRAB, GRAPE, etc.).
- Easy to use with simple syntax.
- Highly modular and customizable, even allowing users to add customized algorithms and bases.



# Using QuOCS

- Set up the optimization parameters in the optimization dictionary.
- 2 Create the appropriate Figure of Merit object.
- 3 Create the optimizer object and run the optimization.

# Example problem: The Ising Chain

## System dynamics:

$$\hat{H} = -J \sum_{k=0}^{N-1} \hat{\sigma}_k^z \hat{\sigma}_{k+1}^z + u(t) \cdot \sum_{k=0}^{N-1} \hat{\sigma}_k^x, \qquad \hat{\sigma}_{N-1}^z = \hat{\sigma}_0^z$$

#### **Cost function:**

$$|\psi_i\rangle = \bigotimes_{k=0}^{N-1} |0\rangle_k, \qquad |\psi_{\text{target}}\rangle = \bigotimes_{k=0}^{N-1} |1\rangle_k$$

$$J = 1 - F(|\psi_f\rangle, |\psi_{\text{target}}\rangle) = 1 - |\langle\psi_f|\psi_{\text{target}}\rangle|$$

## **Control space restrictions:**

$$|u(t)| \leq 10$$



# Further reading

- QuOCS' article: 10.1016/j.cpc.2023.108782 or arXiv:2212.11144
- QuOCS' repository on GitHub
- A review on QOC for NV center systems by Rembold et al.: 10.1116/5.0006785
- A great textbook on QOC theory by D'Alessandro: 10.1201/9781003051268