Differentiable Digital Twins for Automated Characterisation of Quantum Computers

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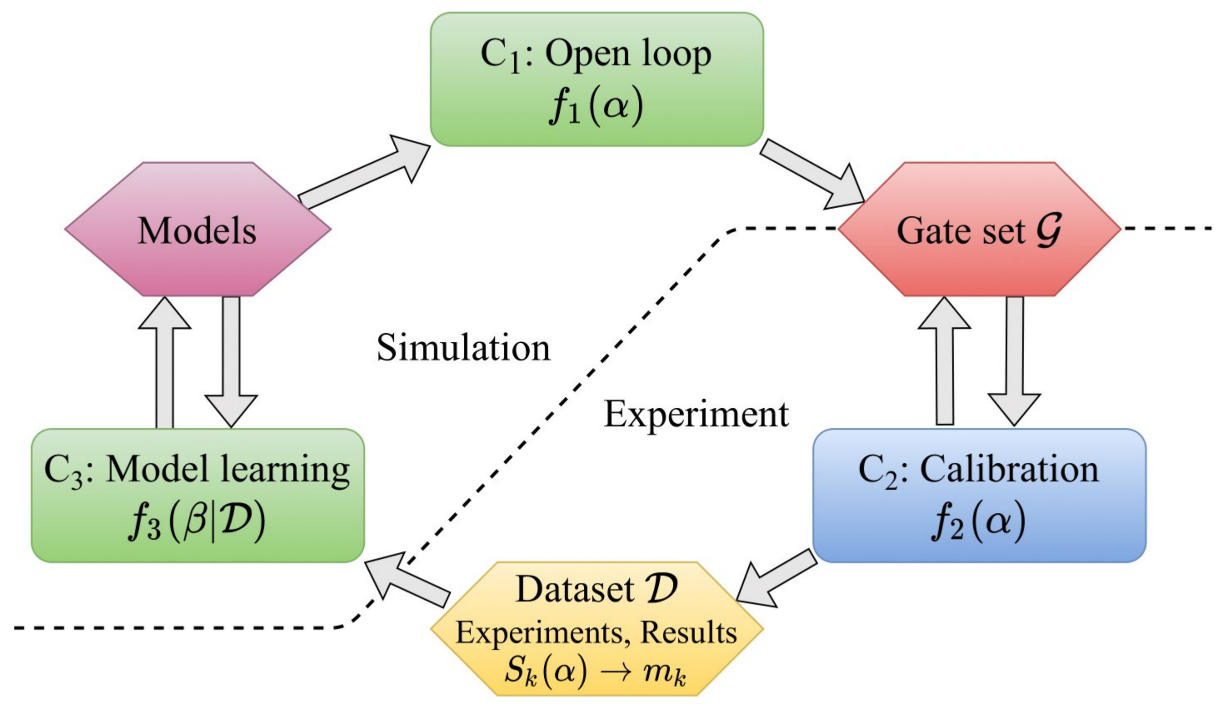
The principal limiting factor for scaling NISQ devices is not the number of qubits but the entangling gate infidelity. Qruise helps rectify this issue with our integrated tool-set for Control, Calibration and Characterization, capable of open-loop pulse optimization, model-free calibration, model fitting and refinement. We present a methodology to combine these tools to find a quantitatively accurate system model, high-fidelity gates and an approximate error budget, all based on a high-performance, feature-rich, differentiable simulator.

Control, Calibration and Characterization



The Simulated Device

We simulate a two superconducting qubit experimental device (Hamiltonian below) including dephasing and relaxation Lindblad operators, a transfer function, finite operating temperature for state preparation and dynamics, misclassification errors.

$$\frac{H}{\hbar} = \sum_{i=A,B} \left[\omega_i b_i^\dagger b_i - \frac{\delta_i}{2}\left(b_i^\dagger b_i - 1\right) b_i^\dagger b_i\right] + g\left(b_A + b_A^\dagger\right)\left(b_B + b_B^\dagger\right) + \sum_{i=A,B} c_i(t)\left(b_i + b_i^\dagger\right)$$

The Models

We assume very limited information about the device: all model parameters are only known to rough accuracy (e.g., frequency error is around 1MHz). Initially we'll think of the qubits as perfect and uncoupled, then we'll refine the model to include all characteristics of the device, progressing through these models:

1. **Simple model:** Two uncoupled qubits, closed system dynamics
2. **Intermediate model:** Two coupled qubits, closed system dynamics
3. **Full model:** Two coupled qubits, open system, with SPAM errors

Open Loop Optimal Control

We optimize a gate-set G of $\pi/2$ rotations with DRAG pulses.

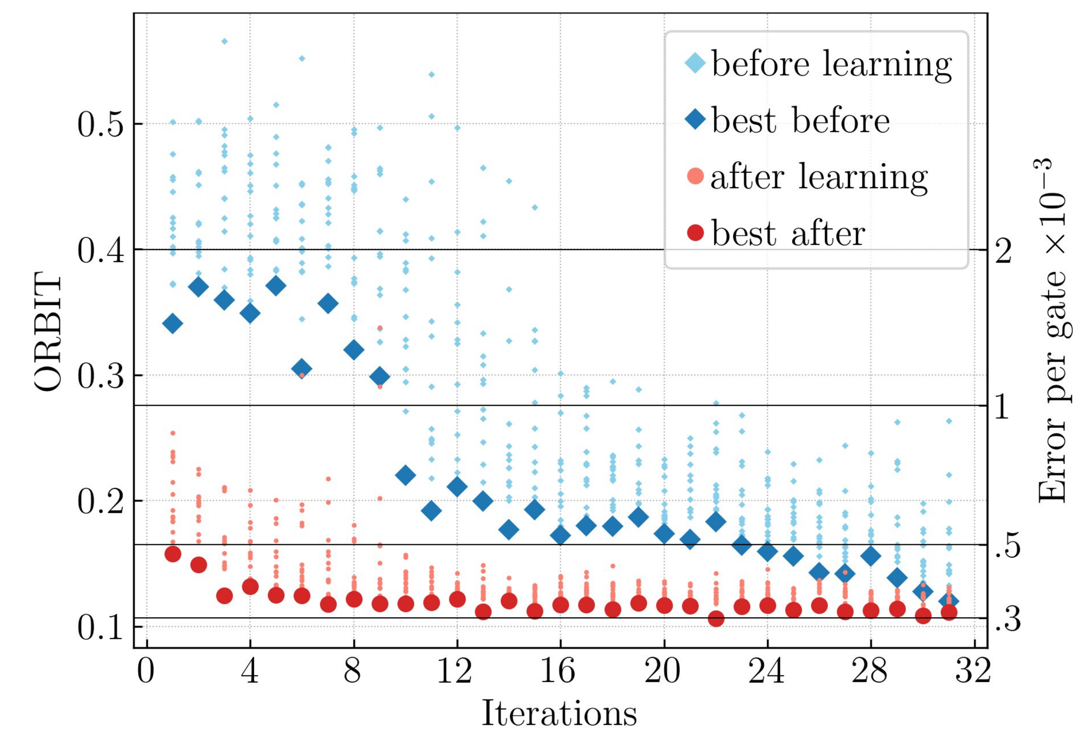
Using TensorFlow, we numerically calculate the gradient of the gate-set infidelity with respect to the control parameters α, and search for the minima with the L-BFGS algorithm:

$$f_1(\alpha) = 1 - \frac{1}{|G|}\sum_{U \in G} f_a(U(\alpha)) \to \text{TensorFlow} \to \partial_\alpha f_1(\alpha)$$

We test the obtained pulses on the device by performing an RB experiment for each qubit and find a discrepancy in performance: the gate infidelities are 6.6E-4, 4.9E-4 and 2.4E-3 and 1.5E-3 on the device, for qubit A (B).

Closed Loop Calibration on Hardware

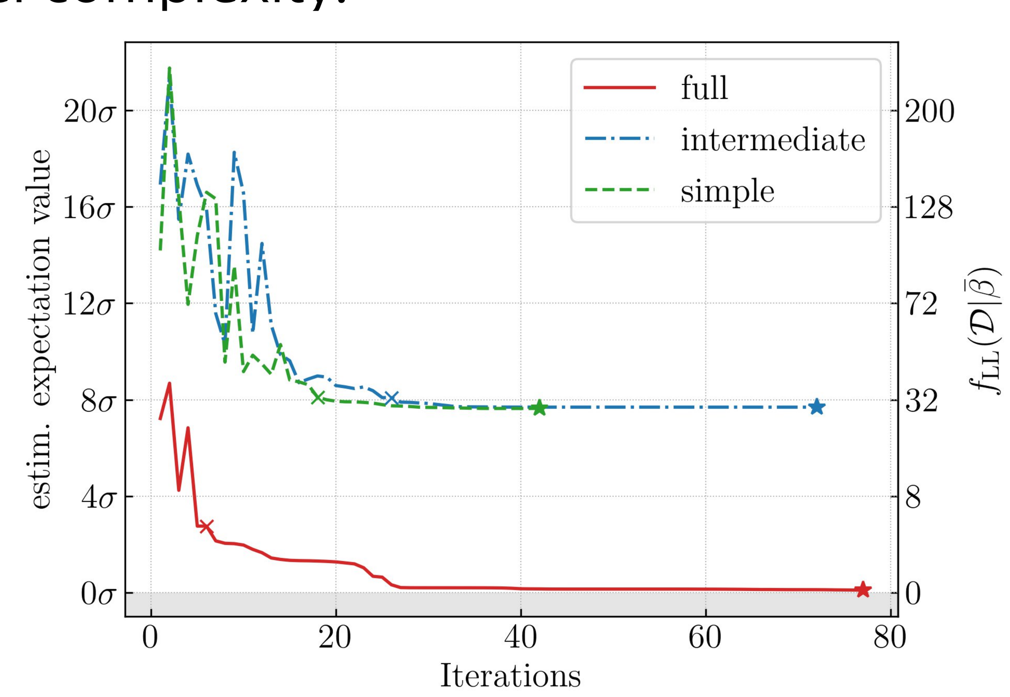
We calibrate the gate-sets (qubit B shown below) on the device by performing a gradient-free search (CMA-ES) over the ORBIT (single length RB sequences) survival probability.



The light blue diamonds (light red dots) represent the values of the ORBIT goal function for varying pulse parameters α as chosen by the search algorithm. The larger blue diamonds (larger red dots) highlight the best of 25 points generated and sampled at each iteration. Both calibrations achieve the same final fidelity, however the optimal gates derived from the learned model provide a better initial guess.

Characterization & System Identification

During calibration we record all experiment/result pairs, including information about the pulse parameters used α, the sequences performed, and the resulting outcomes measured m_k. We then reproduce the experiments in simulation and obtain new outcomes m_k. Using TensorFlow we update the model parameters B to minimize the difference between m_k and updated m_k, using a combination of CMA-ES and L-BFGS searchers. Once converged to the optimal model parameters B, if the match is not satisfactory, we increase model complexity.



The outcome of the procedure is a model that correctly simulates the behavior of the system requiring little to no calibration.

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