Improving Single Qubit Gates by Automated Closed-loop Optimization

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1 Introduction

The goal of the Q-CTRL challenge[1] was to optimize the implementation of Single Qubit gates on a cloud-based superconducting computing or a simulation thereof using the Boulder Opal[2] Package from Q-CTRL. Boulder Opal offers three ways of optimizing quantum control: Optimal, Robust and Learning Control. Optimal control requires detailed knowledge of the system Hamiltonian and the sources of all error which can be very difficult to determine, while Robust Control is employed when one has partial knowledge of the system such as information amplitude damping and dephasing errors. In order to implement a simple but highly general approach, our team used the Learning Control for optimization. Since, the X gate and the H gate are important parts of a universal gate set[3], the challenge focused on obtaining an optimal pulse to implement these on a superconducting qubit.

2 Learning Control

The basic idea behind learning control[4] is to treat the quantum computer as a black box instead of modelling its Hamiltonian.Starting with a given pulse, one evaluates a cost function based on the output of projective measurement and then creates a new pulse based on minimizing the cost function. This pulse is again fed to the quantum computer and results are used to create and even better pulse. This process is repeated till error is comparable to State Preparation and Measurement (SPAM) error.

3 Cost Function

Since we only had access to projective measurements a simple way to define cost function was to use the square of difference between the probabilities that were obtained and the probabilities expected from the gate operation on the initial state $|0\rangle$. For the X gate this cost function is

$$c_X^2 = p_0^2 + (1 - p_1)^2 + p_2^2 \tag{1}$$

while it is

$$c_H^2 = \left(\frac{1}{2} - p_0\right)^2 + \left(\frac{1}{2} - p_1\right)^2 + p_2^2 \tag{2}$$

for the H gate.

4 Optimized Pulses for Quantum Control

For our initial test points, we used values with complex phase of 45 degrees and 225 degrees at varying amplitudes. Using the pulses designed by a Learning Control system that used a Gaussian Function Minimizer[5], we were able to obtain a control pulse for X gate that resulted in $\text{Prob}(|1\rangle) = 0.97$, while the pulse for H gate lead to $\text{Prob}(|0\rangle) = 0.51$, $\text{Prob}(|1\rangle) = 0.48$, and $\text{Prob}(|2\rangle) = 0.01$. To obtain these, we kept the pulse duration at a constant 100ns, and we varied the segment count and the shot count in the optimizer.

The optimized pulses for the X gate and the H gate are illustrated below:

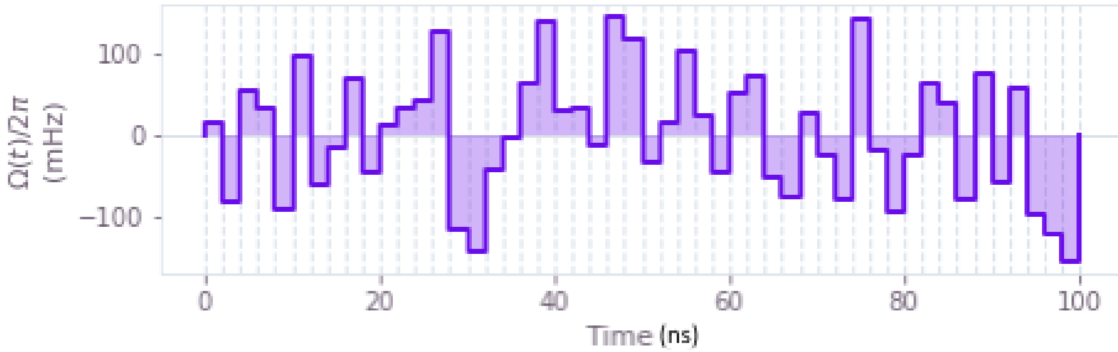

Figure 1: Control Pulse to implement X gate

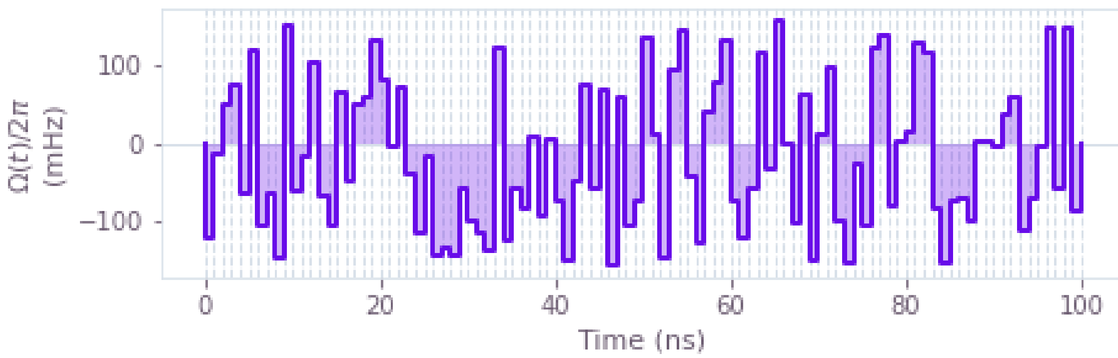

Figure 2: Control Pulse to implement H gate

5 Conclusion

As illustrated above we conclude that an automated learning based optimization of control pulses can be used to obtain high fidelity single qubit gates. Since we treated the quantum computer as a black box, this method is very general and can be used to obtain control pulses for all computing platforms; whether it is super-conducting, trapped-ion or photonic quantum computing.

References

[1] Q-CTRL. *Q-CTRL QCHack challenge*. https://docs.q-ctrl.com/boulder-opal/user-guides/automate-closed-loop-hardware-optimization-of-quantum-devices.

[2] Q-CTRL. *Q-CTRL Boulder Opal*. https://app.q-ctrl.com/boulder-opal/launchPad.

[3] Michael A. Nielsen and Isaac L. Chuang. *Quantum Computation and Quantum Information*. Cambridge University Press, 2000.

[4] Q-CTRL. *Automate closed-loop hardware optimization of quantum devices*. https://docs.q-ctrl.com/boulder-opal/user-guides/automate-closed-loop-hardware-optimization-of-quantum-devices.

[5] Jorge Nocedal. *Numerical Optimization (Springer Series in Operations Research and Financial Engineering)*. Springer, Apr. 2000. ISBN: 0387987932. URL: https://www.xarg.org/ref/a/0387987932/.