1 Introduction

Team HASAA has attempted to implement both the Optimal Control and Automated closed-loop approach for solving the challenge. Ultimately, we settled on using the Automated closed-loop approach, however it was a valuable experience for our team to delve deeper into the physics outlined in the application notes that were given in the challenge documentation. We thoroughly enjoyed the challenge. We begin this document by outlining some of the physics of superconducting qubits.

$$\frac{H_{ideal}(t)}{\hbar} = \frac{1}{2}\Omega(t)b + \frac{1}{2}\Omega^*(t)b^\dagger \tag{1}$$

In equation 1, we show the *ideal* qubit Hamiltonian with no error processes under the action of a microwave pulse. We use this as the basis for of our mathematical model and then we consider further error terms.

$$H(t) = \frac{\Omega(t)}{2}\left(\sigma_x + Q_{\text{unknown}}\right) \tag{2}$$

$$= H_{ideal}(t) + \frac{\Omega(t)}{2}Q_{\text{unknown}} \tag{3}$$

In equation 2, $\Omega(t)$ is the control pulse Rabi rate and $Q_{unknown}$ is the unknown error operator, combining all the error terms. This Hamiltonian represents a more realistic model of the qubit, albeit not detailed. In order to optimize these pulses to achieve a high fidelity *NOT*-gate and *H*-gate, we estimate the errors.
There are some leading source of errors for a superconducting qubit like dephasing errors, SPAM error, amplitude errors etc. Dephasing causes decoherence and this error can be addressed with the optimization of bandlimited pulses. State preparations and measurements are also error-prone, that is known as SPAM errors.
@Sakib : talk about general error terms. Dephasing, SPAM errors, amplitude errors

2 Optimal Control

Optimal control involves constructing a system Hamiltonian for the qubit, with appropriate error terms and specific parameters. One must have a detailed model of the system in order to use this approach, as such we expanded on the model for our *more realistic superconducting qubit*. However, in practice restructuring the code for a new Hamiltonian became a big challenge and we eventually decided that Optimal Control would require more time than we had, so we opted to switch to the automated closed-loop approach, since the other half of our team has achieved more promising results in the time frame. Our approach would have been as follows:

1. Create an accurate model of the "more realistic superconducting qubit" using the system identification method outlined in the application notes and parametrising the error channels in the Hamiltonian. Trial sent pulses to the local qubit to optimize our system.

2. Create an accurate model of the "qubit in the cloud". Use the system identification method on one of the templates that we prepared based on the finding that we made in step 1 to characterise the control lines and identify the constant terms of the Hamiltonian.

3. Use the model derived in step 2 and optimize it using one of the worked examples described in Optimize control user guide.

The main outcome from having attempted to work with Optimal Control has been the invaluable learning experience of the physics and mathematics of the quantum systems that we would not have been able to get if we decided to only stick with the Machine Learning approach due to the way how machine learning models deprecate the need to exactly model the qubit Hamiltonian error terms.

3 Closed-loop automated control

The idea behind the closed-loop automated control is that we use BOULDER OPAL's toolkit to enable a closed feedback loop, optimising the parameters of the control pulse. This is easier to implement because the

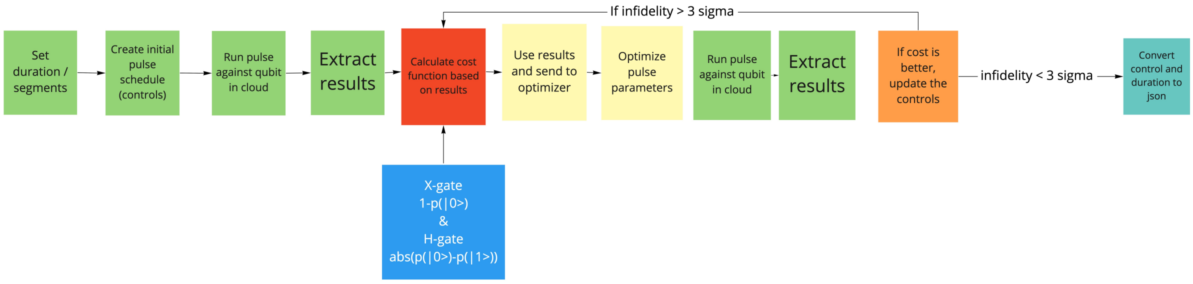

Figure 1: This is a miro board explaining the algorithm flow. Here we show the how the cost function is minimized by executing a for loop until the $< 3\sigma$ condition is satisfied. For the **NOT-gate** & **H-gate**, the cost function is calculated based on the results from the cloud qubit. Then the simulation results are optimized with gaussian processing to obtain new pulse parameters. This process is looped and is contingent on the cost function decreasing.

machine learning model erases the need to characterise the control lines and identify the constant terms of the Hamiltonian. As in equation 2, we can see the error terms in the Hamiltonian are left undefined and the machine learning model is powerful enough to converge even without knowing anything about the system. We have successfully deployed the closed-loop control method and we outline it with the following miro board:
Internally we organise the results into a proper input format and then call the automated closed-loop optimiser and obtain the next set of test points. Afterwards, we are going to record the best results after every round of experiments. We then export to json the best results. Ideally, we will observe that we have chosen the right numbers for duration and segmentation. This will provide us with an optimisation loop that will obtain the functioning gate. In our work we have implemented a function that is going to get infidelities, we have made it functional for both the H gate and Not gate. As specified earlier, we are going to repeat the process of running the pulse against the qubit in the cloud and extracting the results. We will describe the processes and challenges that we had in our loop in more detail below:

3.1 Sending pulses to the qubit in the cloud

After creating an initial pulse with obtaining testing points we planned to send these pulses to the cloud qubit. Hence, using Equation (3) we tried to minimize the cost function for *NOT gate*. Then the attained results are sent to the optimizer by using optimize pulse parameters. Then, we run this pulse against the cloud qubit to extract the results and if the cost is better than the within 3 standard deviation i.e. (cost function $> 3\sigma$) then the process stops.

3.2 Duration altering for NOT gate

Duration was firstly set as $t_{init} = \frac{\pi}{\Omega}$, where Ω is the Rabi rate obtained from our previous work on the noisy simulated qubit. We then adjusted the duration to minimise it without exceeding the rabi rate maximum value. To probe other durations, it was initialized to 300ns, since it was the maximum duration given by the mentors. We then proceeded to lower the duration by 50 until we arrived in the range of 50-100. Once we reached that range we used finer adjustments to reach an optimal duration of 60ns. We have also tried using different segments and made attempts to pass it as a function of the duration, we found that shorter segments worked better for us than longer segments, so we probed starting from 20 until we have gone down to 8 segments.
For t_{init} the training time of the machine learning model exceeded time scales. Hence to get the proper piecewise constant segment we ended up with 60ns and we found that this *Duration* plots a quite good pulse that has low infidelity. For **NOT-gate** we used a cost function of

$$\text{Cost function} = 1 - p\left(|1\rangle\right) \tag{4}$$

where $p\left(|1\rangle\right)$ is the probability of the state being in the excited state.
Using the NOT gate multiple times will allow the error to be more accurately minimised. This is because the error scales with the amount of gates applied. We ran 9 repetitions to obtain a higher error rate and then optimized using equation 4.

3.3 H gate

The Hadamard gate is a single qubit gate which when applied on $|0\rangle$ gives the $|+\rangle$. In order to implement this, we created the cost function by assuming that the ideal state is when the difference between the populations of the ground and excited state are minimised. So, the formula of : Cost function $= \frac{\|p(|0\rangle)-p(|1\rangle)\|}{\text{shot count}}$. Nevertheless, by minimizing this cost function, we would be optimizing for *any* superposition state. Therefore, we would not be able to tell if we specifically had the $|+\rangle$.

We got it to a superposition, however we are not sure if it is the $|+\rangle$ state. Therefore if we were to continue this project we would apply our supposed H gate and then our controlled NOT gate to check if it is in exactly the $|+\rangle$ state, as the $|+\rangle$ state is an eigenstate of the NOT gate.

Going forward, we would consider using the pulse calibration method outlined in the Q-CTRL guidelines to obtain a better approximation to the Ω of the simulated qubit. We would then tackle using robust control to infer the state trajectory. We started this process however found difficulty with configuring the notebook to connect to the cloud qubit instead of an IBM machine.