Automating Rabi & Ramsey Measurements via ML

Rachel Roberts[1], David van Zanten[2] , College of Dupage - CCI Intern

FERMILAB-POSTER-24-0244-STUDENT

Introduction & Motivation

- Similar to bits (1 or 0), quantum computers run on qubits (1, 0, or a superposition).
- Quantum computers utilize digital gates, which require precise knowledge of qubit parameters found through qubit tune-up.

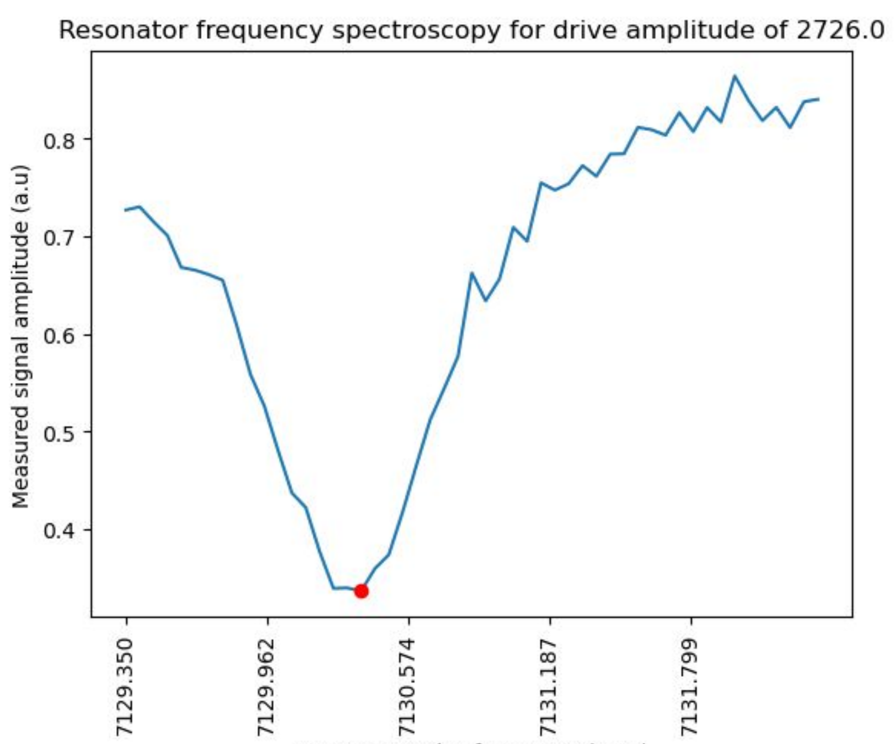

Fig. 1: Resonator spectroscopy, first step of tune-up

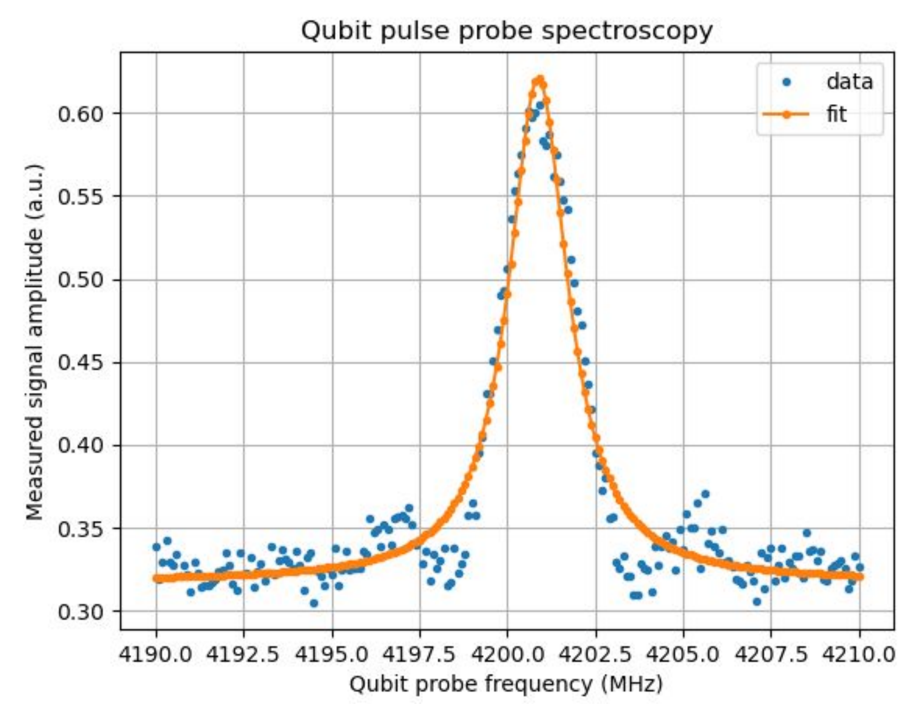

Fig. 2: Qubit spectroscopy, second step of tune-up

- Rabi and Ramsey cycle is used to fine tune qubit frequency by repeating these steps over and over.

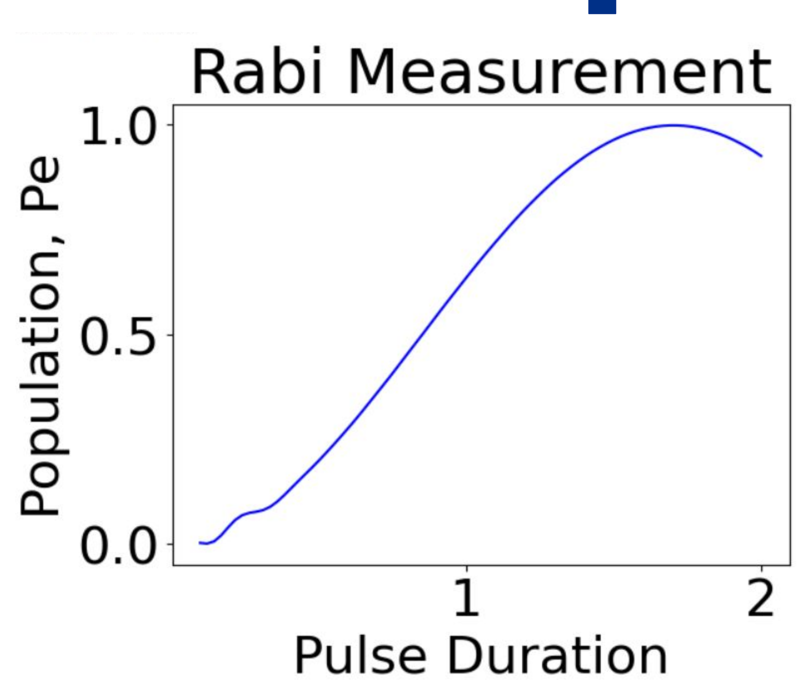

Fig. 3: Example Rabi measurement from simulation. π/2 pulse from this data is 0.8575

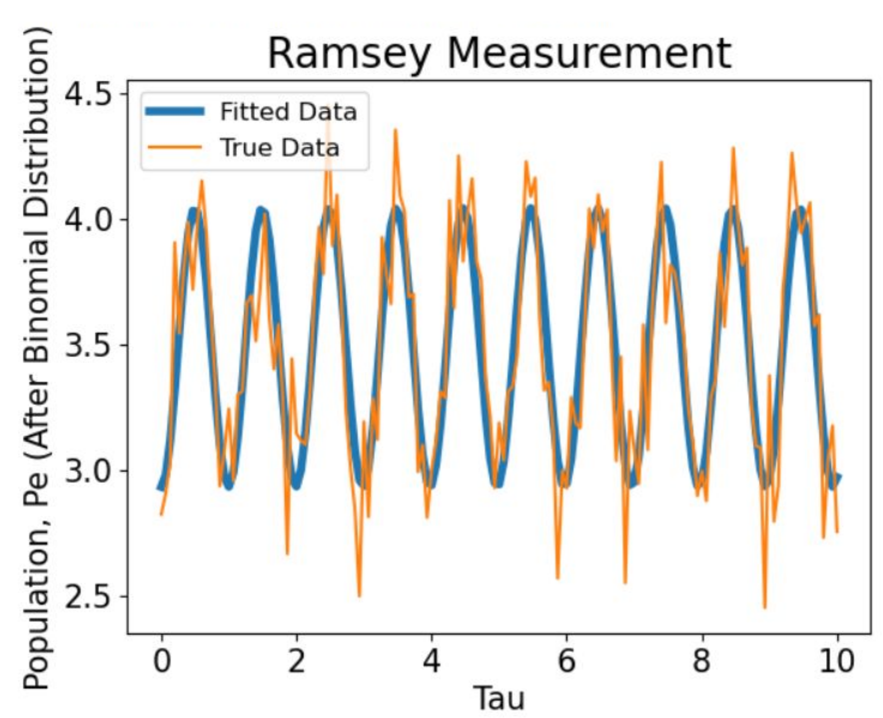

Fig. 4: Example Ramsey measurement from simulation.

- Tune up is repetitive to complete manually, and hard to code procedurally.

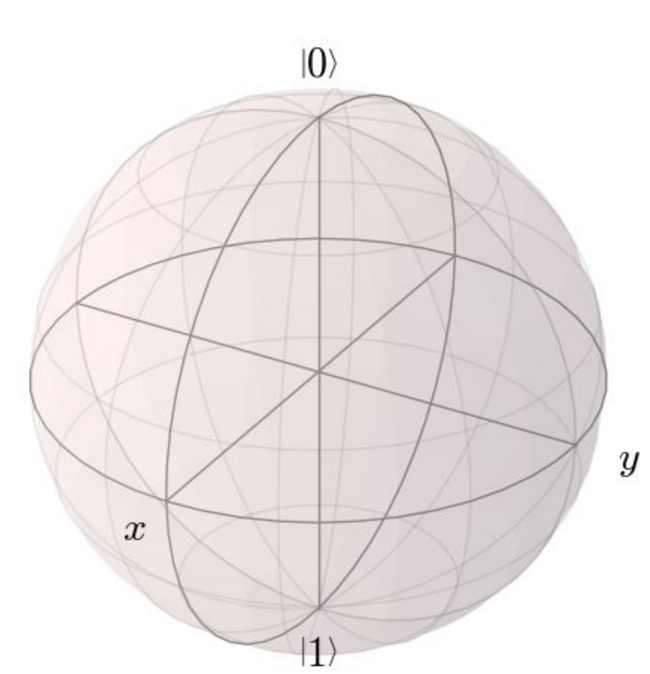

Fig. 5: Bloch Sphere from qutip simulation

Methods

- Automated using LSTM machine learning model. Designed for forecasting.

- Created training data using qutip simulations.

$$\Delta = \omega r - \omega fit \quad (1)$$
$$\omega d' = \omega d + \Delta \quad (2)$$

- Binomial and gaussian distributions were used to simulate noise in state measurement.
- Fourier Transform and least-square fitting were used to find the ramsey oscillation frequency

$$A * cos(\omega\tau + \phi) + B$$

- Generated data was clean with only a few outliers.

Results

- Final training loss and validation loss are almost the same. Model is learning at a good rate and isn't overfitting.

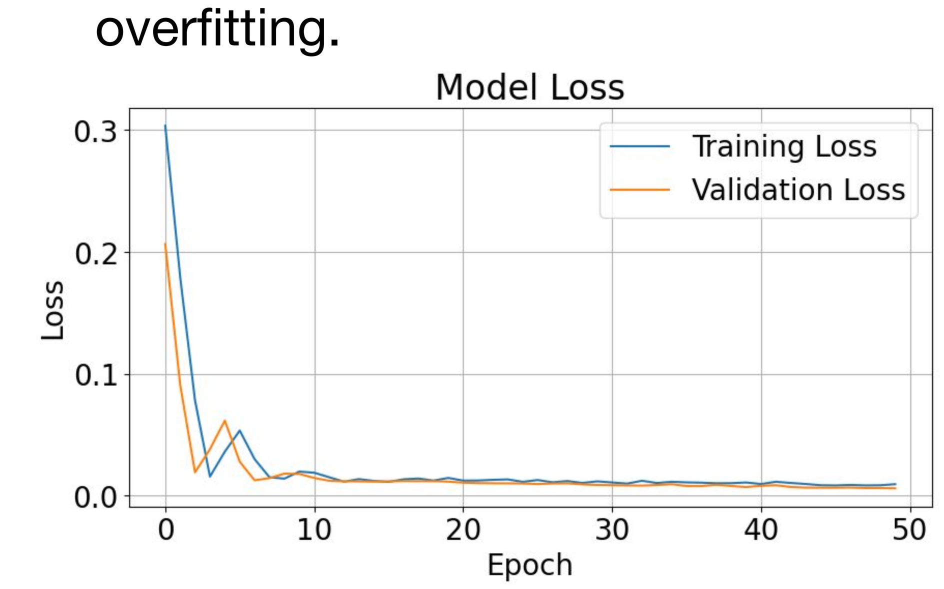

Fig 6: Graph showing model loss. Representation of how well the model is learning.

- Trained the model using 2 batches of data I collected (93 time series, 10 timesteps each)

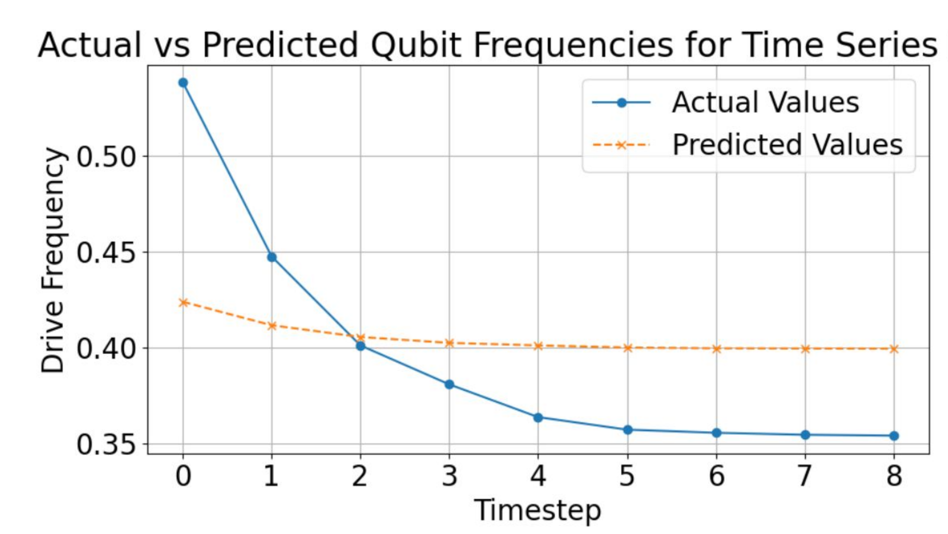

Fig.7: Example of the models prediction vs test values.

- Mean squared error after first batch of data: 0.04039351923326499
- Mean squared error after second batch of data: 0.004615815333339588

Limitations

- Percent error remains larger than experimental values

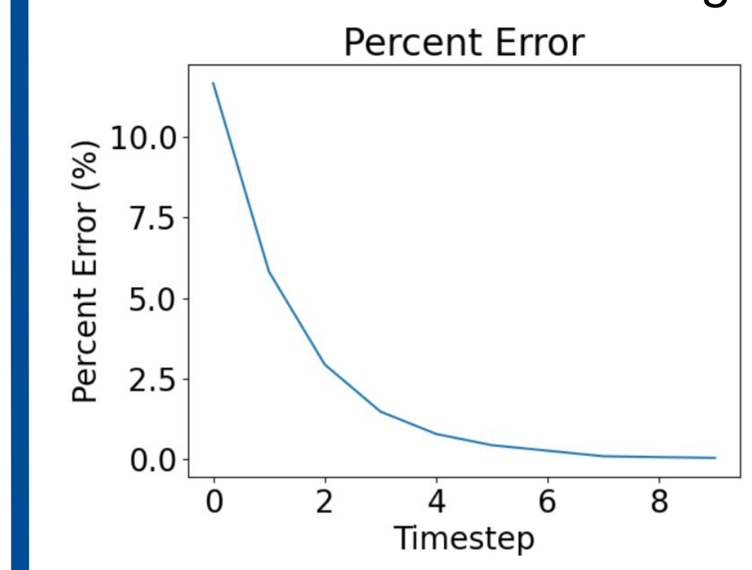

Fig. 8: Example graph from simulation of the error of wd exponentially decreasing. The percent error should be ~0 by the 3rd or 4th timestep.

- Only simulates one type of noise. Typically the curve is represented by a decaying cosine, however mine doesn't decay.

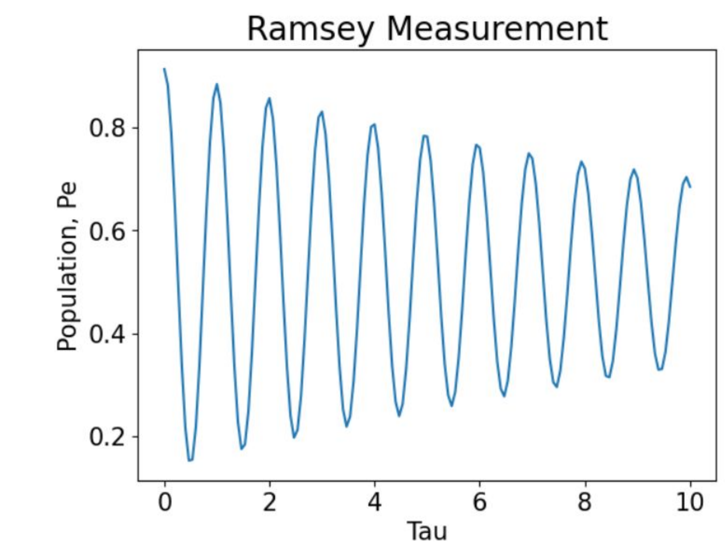

Fig.9: Example of the ramsey that decays due to atom and cavity dissipation.

- Reinforcement Learning or reservoir computing may have been better choices than the LSTM model.

Conclusions

I believe forecasting could be a valid technique to automate tune-up in the future. Instead of predicting the just the qubit frequency, it could be expandible to predicting every necessary tune-up parameter. However, future researchers should ensure the simulation has $\leq 1.0^{-8}\%$ error.

Another topic I was unable to research is the possibility of a model which can predict the final qubit frequency only using the initial rough qubit frequency, without the need to run through every timestep to get there.

Lastly, ensure enough data to properly train the model is obtained. Thousands of data points are required. I recommend starting with clean simulation data, adding multiple types of noise, and then finally using experimental data.

This manuscript has been authored by Fermi Research Alliance, LLC under Contract No. DE-AC02-07CH11359 with the U.S. Department of Energy, Office of Science, Office of High Energy Physics.

This work was supported in part by the U.S. Department of Energy, Office of Science, Office of Workforce Development for Teachers and Scientists (WDTS) under the Community College Internship (CCI)