Machine Learning Techniques for Quantum Gate Engineering

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Introduction

First proposed in the 1980's by Feynman, quantum computers have been proven to be exponentially more efficient than any classical algorithm for the simulation of many-particle systems that are described by non-relativistic quantum mechanics. A comprehensive solution of the many-nucleon problem remains an outstanding challenge, in particular, nuclear reactions.
Nascent demonstrations using a minimal discrete gate set on superconducting quantum devices have shown promise for simulating quantum systems.
We use a control-based paradigm and try to improve its efficiency

Quantum Computing basics

- **Qubit**: unit of quantum information: n-level quantum-mechanical system ($n \geq 2$).
- **Quatum Gate**: circuit that performs basic operations on few qubits.
- **Quantum Computer**: a machine that takes an input state $|\psi\rangle$ and returns (and measure) a new state $|\psi'\rangle = U\,|\psi\rangle$, where U is some **unitary transformation**.

Controls Optimization

The full Hamiltonian for a 3D transmon (a superconducting charge qubit device) coupled to a readout cavity is:

$$H_d = \hbar\omega_T a_T^\dagger a_T + \hbar\omega_R a_R^\dagger a_R - E_J\left[cos(\phi) + \frac{\phi^2}{2}\right]$$

where $\omega_T(R)$ and $a_T^\dagger$ (a_T) are respectively the bare frequency and creation (annihilation) operators of the transmon (readout), E_J is the Josephson energy and ϕ is the phase across the junction. We have N quantum states as shown in Fig. (2).

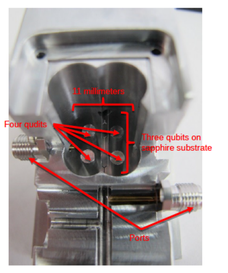

Figure 1: Physical realization of the qubit

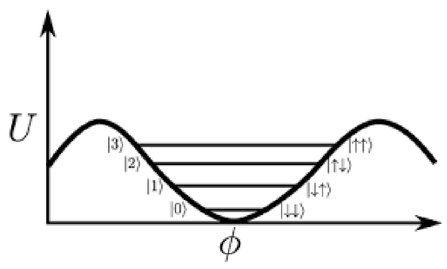

Figure 2: Energy landscape

Given the time-dependent drive H_c that describe the interaction between the transmon and an electric field,

$$H_c = \hbar\epsilon_I(t)(a^\dagger + a) + i\,\hbar\,\epsilon_Q(t)(a^\dagger - a)$$

we use a numerical optimization to find a particular control sequences $\epsilon_I(t), \epsilon_Q(t)$ that satisfies, within an acceptable error, the equality

$$U = T\ \exp\left[-\frac{i}{\hbar}\int_0^{T_{machine}} (H_d + \ H_c(t))\,d\tau\right]$$

where the U represents the unitary operator we want to simulate in the QC.

References

"Optimal Control for the Quantum Simulation of Nuclear Dynamics", *Holland, Wendt, Kravvaris, Wu, Ormand, DuBois, Quaglioni, Pederiva*

Controls Reconstruction

We describe the dynamics between nuclear particles with the LO Hamiltonian of Chirial EFT:

$$H(r) = T + V_{OPE}(r)\,[1 - \delta_{R_0}(r)] + [C_0 + C_1\sigma_1\cdot\sigma_2]\,\delta_{R_0}(r)$$

In our tests, we have considered a system of two neutrons in a coprocessing framework. The spins dynamics is computed with the quantum computer while the spatial part with a classical computer.

Controls Reconstruction:
The optimization algorithm is slow and, since the Hamiltonian depends on the positions of the neutrons, we need to compute the controls at every time-step.
In order to overcome this limitations, we try to find a mathematical relation that allows to reconstruct the controls, corresponding to a given relative position of the neutrons, without using the optimization algorithm. See Fig. (3).
Implementation of this idea are:

- Fourier Transform Method
- Neural Network Method

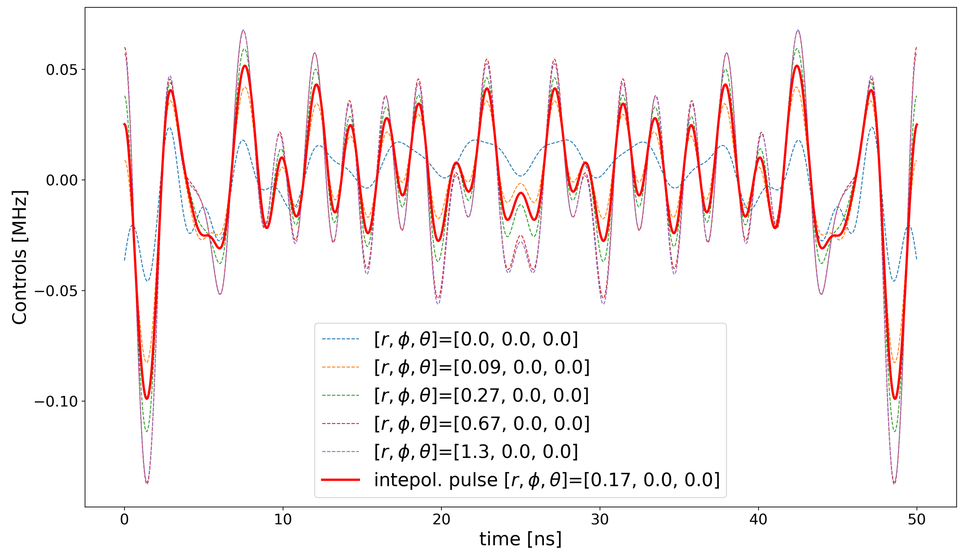

Figure 3: (Dashed lines): Set of different controls corresponding to different values of the neutron-neutron relative position. (Solid red line): Reconstructed control.

Results:
The methods gives good result in reconstructing the controls with good fidelity. In Fig. (4) we compare the exact simulation of the spins dynamics with the same evolution obtained with the reconstructed controls.

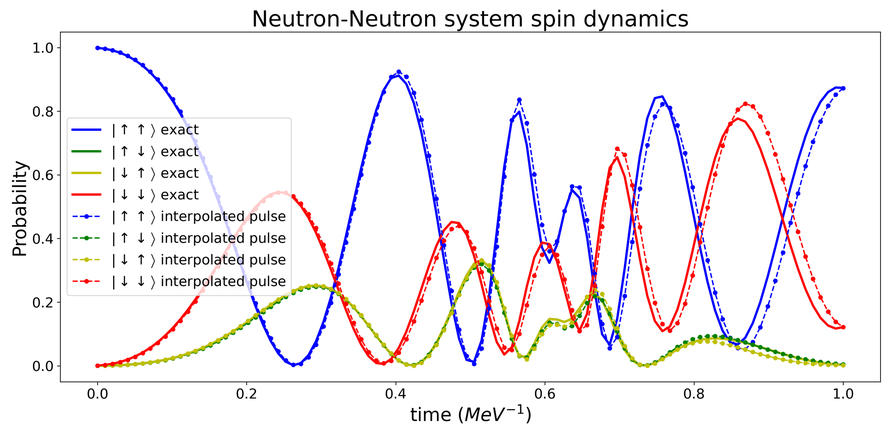

Figure 4: Simulation of the spin dynamics of the neutron-neutron system along a spatial trajectory