SC21 Network Research Exhibition: Publishable Abstract

Towards Autonomous Quantum Network Control

Mekena Metcalf*, Huo Chen,
Mariam Kiran, Anastasiia Butko, Gang Huang
Lawrence Berkeley National Laboratory
* mmetcalf@lbl.gov

Quantum networks are going to disrupt how we perceive supercomputing networks. Quantum network testbed programs prompt the development of advanced management and control strategies to distribute entanglement across a multi-node quantum network. Long-distance distribution of quantum information across a network needs preliminary demonstrations and exploration of quantum network applications, but is a challenge due to errors arising from decoherence channels in quantum network components. In this demo, we address these challenges through the development of advanced control routines that improve the Quality of Entanglement (QoE) between network nodes demonstrating a truly distributed quantum network.

Quantum operations on noisy quantum hardware are enhanced by firmware level optimization of microwave and optical control signals. These engineered pulses enhance the fidelity of quantum operations, leading to increased performance capability needed to demonstrate a quantum advantage on current quantum processors. In quantum physics, model-based optimization techniques, however, are insufficient due to the difficulty of modeling quantum systems coupled to decoherence channels. In this demo, we present AI solutions, particularly a Deep Reinforcement Learning (DRL) algorithm, to learn the best pulses to maximize quantum network performance.

Connecting quantum processors across a network requires the conversion of quantum information from microwave photons to optical photons. Challenges for transduction of quantum information arise from the strong coupling needed between the microwave and optical bands. Laser induced heating of intermediary phononic modes that facilitate this coupling significantly reduces the conversion efficiency. To date, optomechanical quantum transduction yields the highest conversion efficiency of 47% [2]. We have developed a digital twin of this experiment and coupled a theoretical model for time-dependent control to generate training data for the DRL algorithm.

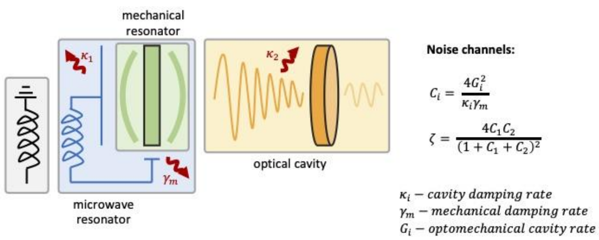
Optomechanical transducers couple a microwave resonator to an optical cavity using a mechanical resonator. Photons from the two cavities are coupled to the mechanical resonator phonons by a radiation pressure force that enables photonic up and down conversion. The second quantized optomechanical transduction Hamiltonian in the laser frame with time -dependent control on the drive amplitudes,

$$H(t) = \omega_m b^\dagger b + \sum_{j=1}^{2} [\Delta_j a_j^\dagger a_j + g_{j,0} (b + b^\dagger) a_j^\dagger a_j + \Omega_j(t)(a_j^\dagger + a_j)],$$

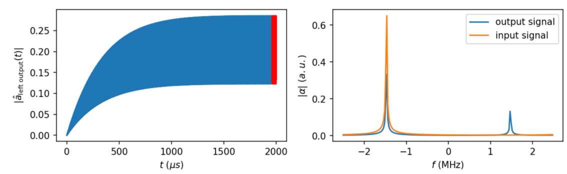
is linearized around the average photon number. The photonic operators a and the phononic operators b are solved for analytically in the Heisenberg picture. With the analytical expressions for the field operators the ABCD - transmission matrix and the scattering matrix (S-matrix) can be obtained,

$$\dot{a} = A(t)a + Ba_{in}$$
$$a_{out} = Ca + Da_{in}$$

The matrices B, C, and D are obtained from the experiment in Ref[1], and the time-dependent A matrix is constructed using our theoretical model with the parameters in Ref[2]. The linear time-varying differential equation is solved numerically to obtain the output signal and the efficiency is calculated as $\eta = a_{out}/a_{in}$. For a time-independent drive we reproduce the experimental results in the frequency domain, Figure 1b. Our simulator is integrated with the DRL algorithm and serves as the environment for the agent.

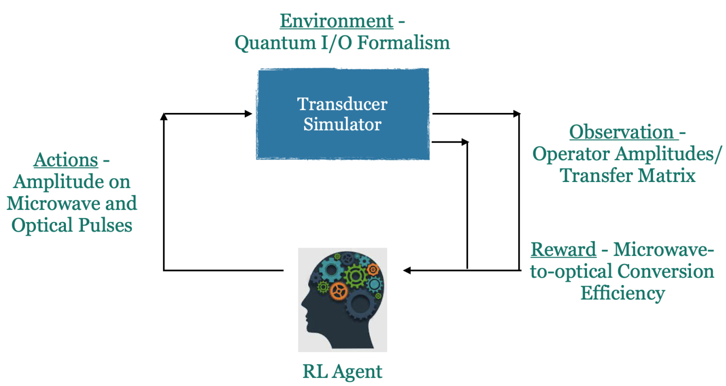


a)

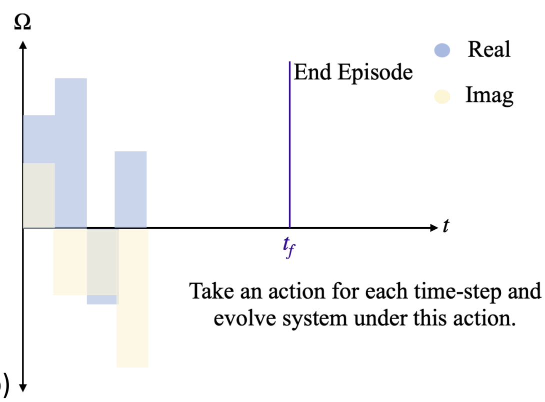


b)

Figure 1. a) Optomechanical Transducer. b) Reproduction of output signal from the transducer.



a)



b)

Figure 2. a) Reinforcement Learning protocol for quantum transducers. b) Example pulse profile generated by the Agent.

We incorporate our simulation as an environment for the DDPG Actor-Critic algorithm. The actions are defined for the real and imaginary pulse components of the optical and microwave drives $A = [A_1, A_2, A_3, A_4] = [Re(\Omega_m), Im(\Omega_m), Re(\Omega_o), Im(\Omega_o)]$ in a multi-discrete action space mapped to the state a of the system using a policy function $\pi_\theta(S, A)$. The agent receives the efficiency of transduction as it's reward $R = \eta(S, A)$ to maximize the efficiency of the transduced signal, Figure 2a. An episode ends when an efficiency threshold is reached or the agent reaches the final time t_f for a transduction experiment.

We will demonstrate our DRL algorithm in action and discuss connecting our automated quantum network control setup using an Arbitrary Waveform Generator (AWG) to interconnected quantum processors.

References.

1. R.W. Andrews, R.W. Peterson, T.P. Purdy, K. Cicak, R.W. Simmons, C.A. Regal, K.W. Lehnert, *"Bidirectional and Efficient Conversion between Microwave and Optical Light,"* Nature Physics (10) 321-326 (2014)
2. A. P. Higginbotham, P. S. Burns, M. D. Urmey, R. W. Peterson, N. S. Kampel, B. M. Brubaker, G. Smith, K. W. Lehnert, and C. A. Regal, *"Harnessing Electro-Optic correlations in an efficient mechanical converter,"* Nature Physics (14) 1038-1042 (2018)