Machine Learning-aided Optimal Control of a Noisy Qubit

Riccardo Cantone[1], Shreyasi Mukherjee[1], Luigi Giannelli[1,2], Elisabetta Paladino[1,2,3], Giuseppe A. Falci[1,2,3]

1. Università di Catania, Dipartimento di Fisica e Astronomia "Ettore Majorana", Via S. Sofia 64, 95123 Catania, Italy

2. INFN, Sezione di Catania, 95123 Catania, Italy

3. CNR-IMM, Via S. Sofia 64, 95123 Catania, Italy

Abstract: We present a transformer-based graybox machine-learning framework for modeling and controlling a qubit under non-Markovian and Markovian noise, achieving gate fidelities above 99% for the lowest considered noise coupling and above 90% for the highest.

Quantum optimal control is essential for high-fidelity quantum operations [1], yet designing robust protocols remains challenging under complex, possibly non-Markovian, noise. We develop an enhanced *graybox* framework [2,3] combining physics-informed layers (*whitebox*) with a lightweight transformer neural network (*blackbox*) to emulate and control a driven qubit subject to classical dephasing noise.

We consider a qubit driven by Gaussian pulses along x and y, with dephasing noise along z: $H(t) = f_x(t)\,\sigma_x + f_y(t)\,\sigma_y + g\,\beta(t)\,\sigma_z$, where g is the coupling strength and $\beta(t)$ a stochastic process [2]. We benchmark Random Telegraph Noise (RTN), a non-Gaussian process relevant for superconducting qubits [4], and Ornstein-Uhlenbeck (OU) noise, its Gaussian counterpart with matching power spectrum.

The whitebox layers enforce quantum mechanics: they construct the control Hamiltonian, compute the unitary U_{ctrl}, assemble the noise-encoding operator V_O [2], and reconstruct the process matrix from a tomographically complete set of expectation values [5]. The blackbox, a self-attention encoder [6], learns the four real parameters of V_O encapsulating all noise effects. The model is trained on simulated data, minimizing the mean squared errors of the process-matrix fidelities for a universal gate set $\{I, X, Y, Z, H, R_X(\pi/4)\}$.

After training, the model serves as a fast emulator for gradient-based optimal control. We minimize the infidelity $J = 1 - \mathcal{F}$ via BFGS to find pulse sequences implementing each target gate. As shown in Fig. 1, at $g = 0.1\,\mathrm{MHz}$ all gates achieve fidelities above 99%; at $g = 0.5\,\mathrm{MHz}$ fidelities remain above 90%. The non-Gaussian character of RTN does not appreciably alter performance compared to OU noise, demonstrating robustness across noise statistics and suggesting extensions to multiqubit systems.

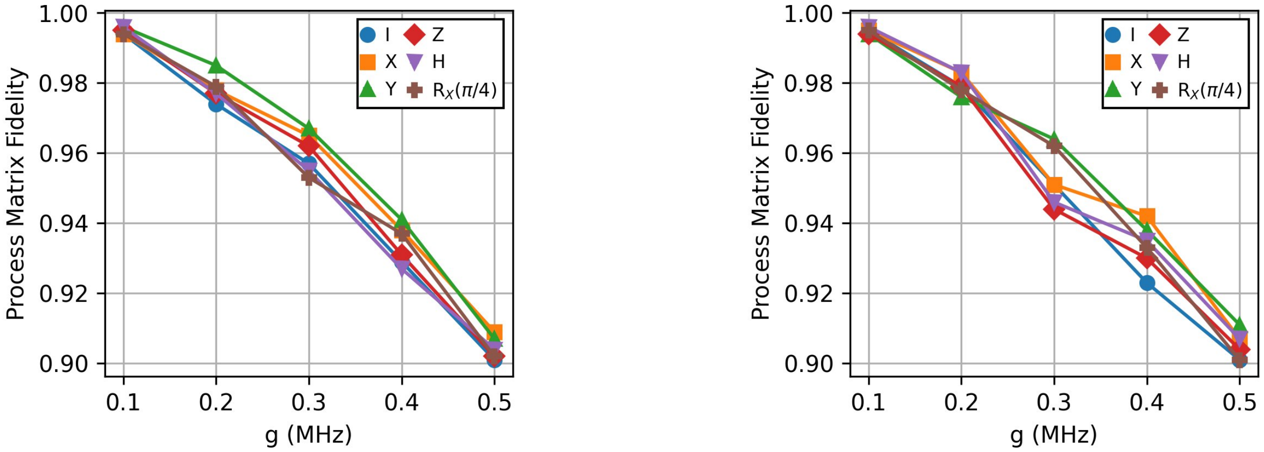

Figure 1: Process matrix fidelity vs. noise coupling strength g for each gate in the universal set. Left: RTN. Right: OU noise.

References

[1] L. Giannelli *et al.*, "A tutorial on optimal control and reinforcement learning methods for quantum technologies," Phys. Lett. A **434**, 128054 (2022).

[2] A. Youssry *et al.*, "Characterization and control of open quantum systems beyond quantum noise spectroscopy," npj Quantum Inf. **6**, 95 (2020).

[3] A. Youssry *et al.*, "Multi-axis control of a qubit in the presence of unknown non-Markovian quantum noise," npj Quantum Inf. **10**, 55 (2024).

[4] E. Paladino *et al.*, "1/f noise: Implications for solid-state quantum information," Rev. Mod. Phys. **86**, 361 (2014).

[5] M. Luo and X. Wang, "Universal quantum computation with qudits," Phys. Rev. A **87**, 022301 (2013).

[6] A. Vaswani *et al.*, "Attention is all you need," in *Adv. Neural Inf. Process. Syst. 30* (2017).