

Designing Minimalistic Quantum Reservoir Computing in Practice

Grecia Castelazo^{a,b}, Zihang Wang^b, Dirk Bouwmeester^{b,c}

^a*Department of Computer Science, University of California Santa Barbara, Santa Barbara, California 93106, USA*

^b*Department of Physics, University of California Santa Barbara, Santa Barbara, California 93106, USA*

^c*Huygens-Kamerlingh Onnes Laboratory, Leiden University, P.O. Box 9504, 2300 RA Leiden, The Netherlands*

Keywords: Experimental/Hardware QML, Brain-Inspired QML

In this work, we explore the potential of existing quantum systems such as cold atoms in optical cavities or quantum dots to perform complex computational tasks through the Quantum Reservoir Computing (QRC) paradigm under some of the key constraints of the Noisy Intermediate Scale Quantum (NISQ) era, such as: moderate hardware size, and non-negligible levels of noise. QRC is a relatively novel machine learning framework and a candidate for showing quantum advantage with respect to its classical counterparts; and at the same time is known to circumvent the cost and training bottlenecks of conventional QML based on variational quantum circuits.

Reservoir Computing (RC) was motivated by the robustness of input- and hardware-noise-tolerant neural circuits in the brain [1, 2] and QRC by the idea of exploiting the analogue dynamics of engineered and controllable many-body quantum systems for computations beyond the digital circuit architecture. In reservoir computing, there are three different layers: the input layer, the reservoir layer, and the output layer. In QRC, increasing the number of physical sites exponentially increases the number of quantum basis states, hence the number of hidden nodes within the quantum neural network. This exponential scaling yields rich complex and nonlinear dynamics. Quantum reservoir computers are built up on ensembles of quantum emitters with fixed interactions –the reservoir layer is not trainable by definition–, which internally reshape its connections to mimic the dynamics of the presented input dataset and can demonstrate learning by exploiting the quantum evolutions of the system.

One of the main engineering challenges of these platforms are the often destructive measurements of the quantum system to extract readout information. Building on the Quantum Reservoir Computing framework of [3], made up of a few atoms in a single-mode optical cavity, combined with the continuous quantum measurement method proposed, we discuss the feasibility of implementing such measurement schemes based on individual quantum dots emitters and homodyne detection techniques developed in the group [4]. We present the stages of bridging a proposal from the algorithm formulation to the experimental deployment. We work out the relaxation of some core assumptions in [3] for continuous quantum measurement, such as taking the deterministic limit in the stochastic master equation assuming infinite shots and zero-mean Gaussian Wiener increments. In our study, we keep the full stochastic master equation throughout and introduce fine-sample estimators, and work out the error propagation for more accurate simulations. Our results are benchmarked against classical Echo-State Networks (ESNs). Moreover, we attempt to extend the prediction learning tasks beyond the Mackey-Glass smooth attractors to biological tasks with a small number of atoms.

References

- [1] Danijela Marković and Julie Grollier. “Quantum neuromorphic computing”. In: *Applied physics letters* 117.15 (2020).
- [2] Rodrigo Araiza Bravo et al. “Quantum reservoir computing using arrays of Rydberg atoms”. In: *PRX Quantum* 3.3 (2022), p. 030325.
- [3] Chuanzhou Zhu et al. “Minimalistic and scalable quantum reservoir computing enhanced with feedback”. In: *npj Quantum Information* (2025).
- [4] Morten P Bakker et al. “Homodyne detection of coherence and phase shift of a quantum dot in a cavity”. In: *Optics Letters* 40.13 (2015), pp. 3173–3176.