Novel Approach to Multivariate Forecasting with Quantum Reservoirs

D. A. Aranda[1,†], J. Ballesteros[3], J. Bonilla[1,†], Elías F. Combarro[2,†], N. Monrio[1,†], S. Ranilla-Cortina[2,†] and J. Ranilla[2,†]

[1] *IAQ Orbital, ARQUIMEA Research Center (Spain)*
[2] *Computer Science Department, University of Oviedo (Spain)*
[3] *Instituto Tecnológico y de Energías Renovables (Spain)*

Abstract

We investigate a quantum reservoir computing (QRC) architecture based on a fully connected transverse-field Ising model for time series forecasting. Preliminary results on univariate financial data demonstrate that QRC-enhanced models achieve improved predictive accuracy compared to a classical linear baseline. We outline planned extensions to multivariable time series forecasting using multi-qubit and compact encoding strategies, and propose future evaluations on both synthetic and real-world datasets.

Keywords

Quantum reservoir computing, time series forecasting, multivariate prediction, quantum machine learning

1. Introduction

Reservoir computing (RC) is a neural-network paradigm in which a fixed, high-dimensional dynamical system, the reservoir, projects time-series inputs into a nonlinear feature space, while learning is restricted to a linear readout layer [1]. Quantum reservoir computing (QRC) extends this idea by harnessing the intrinsic complexity of quantum dynamics to generate expressive feature representations without requiring internal parameter optimization [2].

While QRC has demonstrated strong performance in classification and univariate forecasting tasks [3], its potential for multivariable time series forecasting, where multiple interdependent signals evolve jointly, remains largely unexplored. Yet, such multivariable settings are typical of real-world use cases in finance, climate modeling, energy systems, and biomedicine.

In this work, we present preliminary results using QRC-enhanced models for univariate time series forecasting, demonstrating improved predictive accuracy over a classical linear baseline. These early findings motivate the development of QRC architectures for multivariable scenarios, where quantum reservoirs may provide efficient and scalable mechanisms for modeling inter-channel dependencies. We outline our planned extensions, including alternative encoding schemes, architectural variations, and evaluations on both synthetic and real-world multivariate datasets.

2. Fully-Connected Quantum Ising Model

We implement a quantum reservoir (QR) based on a fully-connected transverse-field Ising model, following the protocol in [3]. The system is simulated using the open-source package QuTiP [4].

In contrast to [3], where the reservoir was initialized in a maximally mixed state, we initialize our reservoir in the pure product state $\rho_0 = |+\rangle^{\otimes N} \langle +|^{\otimes N}$, with $|+\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$. This choice provides

AIQxQIA 2025: International Workshop on AI for Quantum and Quantum for AI | co-located with ECAI 2025, Bologna, Italy

† These authors contributed equally.

daranda@arquimea.com (D. A. Aranda); jballesteros@iter.es (J. Ballesteros); jbonilla@arquimea.com (J. Bonilla); efernandezca@uniovi.es (E. F. Combarro); ext.nmonrio@arquimea.com (N. Monrio); ranillasandra@uniovi.es (S. Ranilla-Cortina); ranilla@uniovi.es (J. Ranilla)

0000-0002-8603-3000 (D. A. Aranda); 0000-0001-7621-0248 (J. Bonilla); 0000-0003-3808-4273 (E. F. Combarro); 0009-0002-9680-0370 (N. Monrio); 0000-0002-5326-5657 (S. Ranilla-Cortina); 0000-0003-2941-3741 (J. Ranilla)

a clean and symmetric initial condition, placing the system in a coherent superposition across the computational basis while retaining a product structure, and in our experiments, it led to more stable dynamics and improved forecasting performance.

At each forecasting step, a normalized scalar input x_l is sequentially encoded into the quantum reservoir by preparing the first qubit ($i = 0$) in the pure state $|\psi(x_l)\rangle = \sqrt{1 - x_l}\,|0\rangle + \sqrt{x_l}\,|1\rangle$, via amplitude encoding. The rest of the system remains unchanged. This updated local state is then tensored with the reduced density matrix of the remaining system, $\rho \mapsto |\psi(x_l)\rangle\langle\psi(x_l)| \otimes \mathrm{Tr}_0[\rho]$, effectively overwriting only the first qubit at each step.

The system subsequently evolves under the time-independent Hamiltonian

$$H = \sum_{i<j} J_{i,j} X_i X_j + \sum_i h_i Z_i, \tag{1}$$

where X_i and Z_i are Pauli operators acting on qubit i. The coefficients $J_{i,j}$ represent inter-qubit couplings, and h_i correspond to local transverse magnetic fields. In our implementation, the local fields are sampled from a uniform distribution $\mathcal{U}[0.1, 1.0]$, while all inter-qubit couplings are fixed to $J_{i,j} = 0.5$ for $i \neq j$, with $J_{i,i} = 0$.

This homogeneous configuration simplifies the reservoir architecture while preserving the fully connected topology required for rich dynamics. Although [3] explores both random and engineered coupling patterns such as $J_{i,j}^{(k)} \propto (i+j)^k$, we found that the uniform setup offers favorable performance and reproducibility for forecasting tasks. The random sampling of local fields introduces sufficient variability into the quantum dynamics, helping to break symmetries and enrich the internal state evolution without requiring disorder in the coupling matrix.

The quantum state evolves over V equally spaced time intervals (virtual nodes), during which the observables $\langle Z_i(t_k)\rangle = \mathrm{Tr}[Z_i \rho(t_k)]$ are extracted across all qubits. The resulting set of measurements forms a high-dimensional feature vector for each input. After processing a full input window, the linear readout weights are trained using the Moore–Penrose pseudoinverse solution to minimize the mean square error between predictions and targets.

3. Preliminary Results

We evaluated the performance of the quantum reservoir model on the S&P 500 aggregated daily closing values time series [5], using a setup inspired by the one considered in [3]. Specifically, we employed a reservoir of $N = 6$ qubits with $V = 2$ virtual nodes and a Hamiltonian evolution time step of $\Delta t = 0.3$.

To construct the input for the linear readout, we aggregated the reservoir features corresponding to the last four input injections, $(x_{i-3}, x_{i-2}, x_{i-1}, x_i)$. The resulting high-dimensional feature vector was then used to predict the next 25 values of the time series, $[x_{i+1}, \ldots, x_{i+25}]$. We evaluated the model for each time index $i \in [1100, 1199]$, using all data up to x_i for training and the subsequent 25 points for testing.

The mean absolute error (MAE) was computed over the full prediction window for each value of i, and the final score was obtained by averaging the MAE across all 100 indices. This averaging mitigates the sensitivity of the MAE to the particular choice of i, which can significantly affect forecasting performance in financial time series [3].

To assess the added value of the quantum reservoir, we compared the full QRC pipeline to a baseline model where a linear readout was trained directly on the raw input values, without reservoir transformation. Each experiment was repeated across 200 independent quantum reservoir initializations to ensure statistical robustness. The average MAE results, shown in Fig. 1, demonstrate a consistent improvement of the QRC-enhanced model over the baseline, particularly at longer prediction horizons.

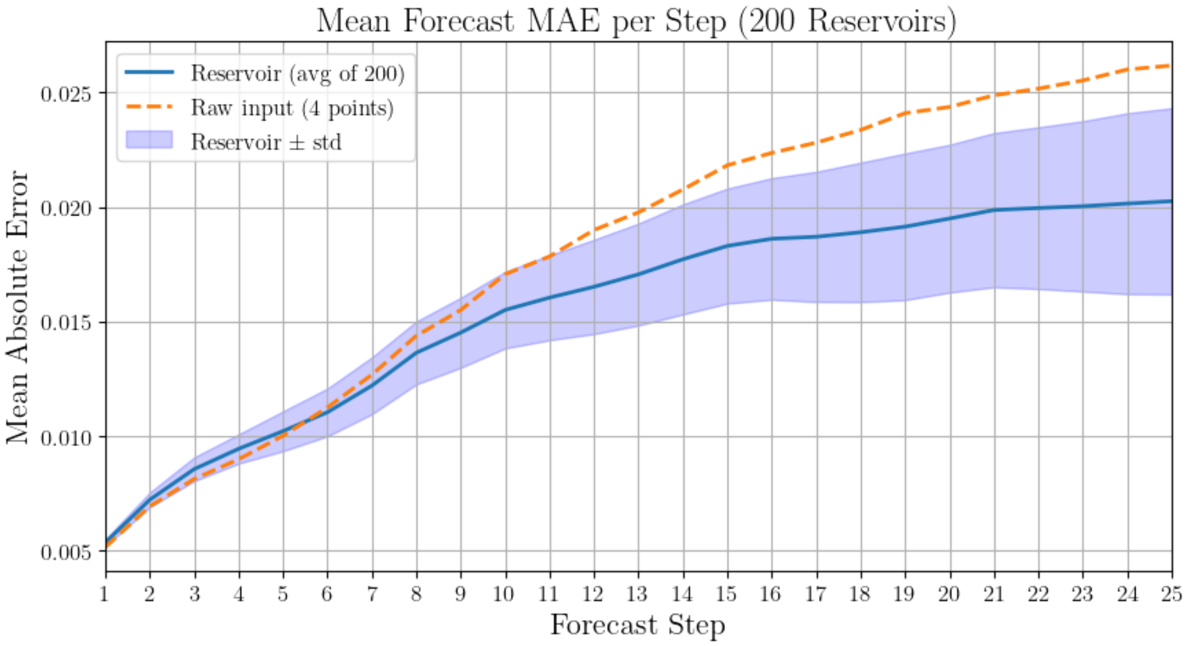

Figure 1: Average mean absolute error (MAE) over 200 randomly initialized quantum reservoirs compared to a baseline linear readout model.

4. Conclusions and Future Work

We presented a quantum reservoir computing (QRC) model based on a fully-connected transverse-field Ising Hamiltonian for univariate time series forecasting. Our implementation introduced a simplified and coherent reservoir design, with fixed inter-qubit couplings and product-state initialization in $|+\rangle^{\otimes N}$, which led to improved predictive accuracy and stability across runs. Experiments on financial time series data show that QRC-enhanced models consistently outperform a baseline linear predictor trained directly on raw inputs. As shown in Fig. 1, the quantum reservoir significantly reduces the mean absolute error (MAE) for longer forecast steps, while maintaining comparable performance to the baseline in the short term. The results also demonstrate robustness across 200 randomly initialized reservoirs, as reflected by the confidence region.

Looking ahead, we aim to extend this framework to multivariable time series, which better reflect the complexity of real-world forecasting tasks. Possible architectural adaptations include multi-qubit input encoding, where each input channel is mapped to a separate qubit, and more compact encodings that embed multiple classical features into a single qubit, for example, via independent parameterized rotations. In addition, we will investigate how varying the reservoir size, particularly the number of qubits, influences predictive accuracy and dynamical richness.

We also plan to explore alternative physical realizations of the quantum reservoir, such as quantum systems based on neutral atoms [6], which may offer improved scalability, coherence, and compatibility with near-term quantum hardware. Beyond architectural development, we will evaluate our models on a broader set of synthetic and real-world multivariate datasets to better understand generalization behavior.

Finally, a promising future direction is to refine the prediction objective itself. Inspired by reward discounting in reinforcement learning, one could investigate loss functions that assign greater weight to near-term predictions within the forecasting horizon. This could potentially bias the model toward more stable or actionable outputs, depending on application needs.

Acknowledgments

This work has been supported by grant PID2023-146520OB-C{1, 2}, funded by MICIU/AEI/10.13039/501100011033; by the Ministry for Digital Transformation and Civil Service of the Spanish Government through the QUANTUM ENIA project call – Quantum Spain project, and by the European Union through the Recovery, Transformation and Resilience Plan – NextGenerationEU within the framework of the Digital Spain 2026 Agenda; and by ARQUIMEA Research Center and Horizon Europe, Teaming for Excellence, under grant agreement No 101059999, project QCircle. The work of Jesús Bonilla was partially supported by the Spanish Ministry of Science, Innovation and Universities through the Torres Quevedo grant PTQ2023-013228. The work of Jorge Ballesteros is financially supported by Instituto Tecnológico y de Energías Renovables (ITER) and Cabildo de Tenerife.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] G. Tanaka, T. Yamane, J. B. Héroux, R. Nakane, N. Kanazawa, S. Takeda, H. Numata, D. Nakano, A. Hirose, Recent advances in physical reservoir computing: A review, Neural Networks 115 (2019) 100–123. URL: https://www.sciencedirect.com/science/article/pii/S0893608019300784. doi:https://doi.org/10.1016/j.neunet.2019.03.005.

[2] K. Fujii, K. Nakajima, Harnessing disordered-ensemble quantum dynamics for machine learning, Phys. Rev. Appl. 8 (2017) 024030. URL: https://link.aps.org/doi/10.1103/PhysRevApplied.8.024030. doi:10.1103/PhysRevApplied.8.024030.

[3] A. Kutvonen, K. Fujii, T. Sagawa, Optimizing a quantum reservoir computer for time series prediction, Scientific Reports 10 (2020) 14687. URL: https://doi.org/10.1038/s41598-020-71673-9. doi:10.1038/s41598-020-71673-9.

[4] N. Lambert, E. Giguère, P. Menczel, B. Li, P. Hopf, G. Suárez, M. Gali, J. Lishman, R. Gadhvi, R. Agarwal, A. Galicia, N. Shammah, P. Nation, J. R. Johansson, S. Ahmed, S. Cross, A. Pitchford, F. Nori, Qutip 5: The quantum toolbox in python, 2024. URL: https://arxiv.org/abs/2412.04705. arXiv:2412.04705.

[5] S&P 500 stock data, https://www.kaggle.com/datasets/camnugent/sandp500, 2020. Accessed from a publicly available financial dataset.

[6] M. Kornjača, et al., Large-scale quantum reservoir learning with an analog quantum computer (2024). arXiv:2407.02553.