

Temporal information processing on a 4,500-qubit quantum annealer

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Introduction- Over the past century, quantum computation has transformed our understanding of computer science [1]. From a theoretical perspective, several well-established quantum algorithms offer computational-complexity speedups over their best-known classical counterparts [2–5]. At the same time, rapid advances in quantum hardware are demonstrating the experimental success of quantum error correction, marking important steps toward large-scale fault-tolerant quantum computation [6, 7].

Despite these exciting milestones, identifying practical applications of currently available quantum computers that cannot be achieved by classical devices remains a major challenge. Among the different quantum-computing platforms, quantum annealers have recently shown promise in this direction, particularly in the context of quantum simulation [8].

Beyond that, one of the most anticipated applications of quantum computers is machine learning, arguably one of the most successful technologies of this century [9]. In particular, quantum devices may be able to identify statistical patterns that remain inaccessible to classical models [10]. However, before a quantum advantage in machine learning can be realized, it is crucial to identify architectures that are scalable in practice. Overcoming this potential limitation, we experimentally demonstrate, for the first time, a quantum machine-learning model implemented on a D-Wave quantum annealer that is able to process temporal data at utility scale using 4,500 physical qubits, realizing the largest quantum machine-learning experiment to date. Our approach follows the paradigm of quantum reservoir computing [11, 12], in which the intrinsic quantum dynamics of the platform are used to process temporal input data, avoiding the inefficient optimization procedures that often limit other quantum machine-learning approaches [13].

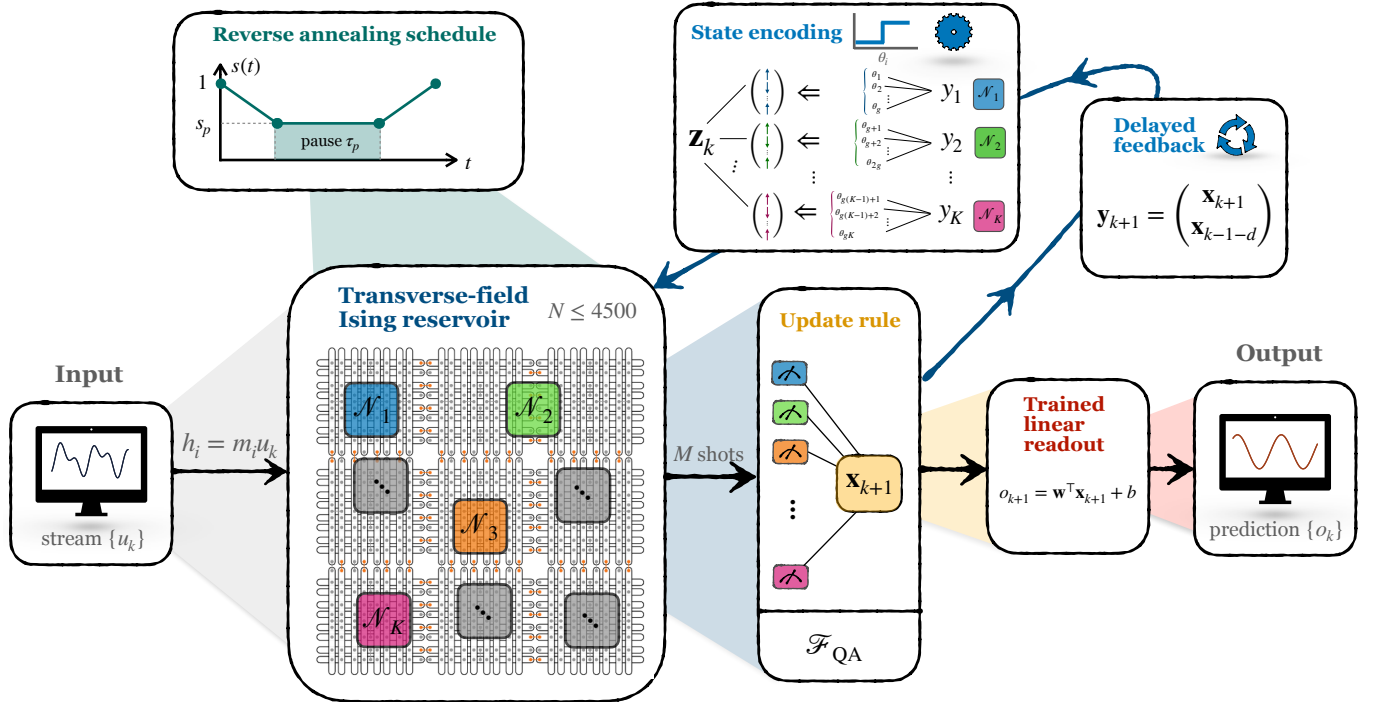


FIG. 1. Illustration of the quantum reservoir architecture.

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Reservoir computing protocol- The proposed quantum reservoir computing protocol consists of a vector of real numbers iteratively updated by the native many-body dynamics of the D-Wave quantum annealer, following the scheme of quantum reservoir computers based on incoherent memory [14, 15]. Given N physical qubits, the device realizes a transverse-field Ising Hamiltonian [16]

$$H(s) = A(s) \sum_{i=1}^N \sigma_i^x + B(s) \left(\sum_{i=1}^N h_i \sigma_i^z + \sum_{i>j} J_{ij} \sigma_i^z \sigma_j^z \right), \quad (1)$$

where $\sigma_i^{x,z}$ are Pauli matrices acting on the i -th qubit, $s \in [0, 1]$ is the annealing parameter, $A(s)$ and $B(s)$ are hardware-specific functions such that $A(0) \gg B(0)$ and $A(1) \ll B(1)$, h_i are local fields used for encoding the inputs, and J_{ij} are fixed random couplings defining the reservoir connectivity.

The reservoir state at step k is represented by a vector

$$\mathbf{x}_k = (x_{k,1}, \dots, x_{k,K}), \quad (2)$$

where $K = N/g$ and g is the number of physical qubits, $\mathcal{N}_k$, associated with each reservoir node. The protocol proceeds according to the following steps.

Step 1: State encoding and delayed feedback. The reservoir state, augmented with delayed components from a previous reservoir state, is mapped onto the initial configuration of a reverse annealing protocol. Specifically, we start by defining a vector $\mathbf{y}_k$ by combining the current reservoir state with a delayed one: the first half contains the components of the current reservoir state, while the second half is filled with the reservoir state from d time steps earlier:

$$\mathbf{y}_k = (x_{k,1}, \dots, x_{k,K/2}, x_{k-d,K/2+1}, \dots, x_{k-d,K}). \quad (3)$$

This delayed feedback mechanism provides an explicit memory channel in addition to the memory generated by the quantum dynamics, overcoming the memory limitations related to Markovian maps as recently identified [17].

The vector $\mathbf{y}_k$ is then converted into a binary spin configuration, since the standard D-Wave annealer can only be initialized in a computational-basis state and therefore requires a discrete spin assignment. The conversion is performed through the threshold rule

$$z_i(k) = \Theta(y_{k,\ell(i)} - \theta_i), \quad (4)$$

where $\ell(i) = \lfloor i/g \rfloor$ identifies the reservoir node associated with qubit i , Θ is the Heaviside function, and θ_i is a random threshold. The resulting binary configuration $\mathbf{z}_k \in \mathbb{F}_2^N$ is used as the initial state of the annealer.

Step 2: Input encoding and annealer evolution. Starting from the state just defined, a reverse-annealing protocol is executed. The system is annealed backward from $s = 1$ to an intermediate point s_p , held for a pause time τ_p , and then annealed forward again to $s = 1$. For any input value u_k , the local fields are programmed as

$$h_i(k) = m_i u_k, \quad (5)$$

where m_i is a fixed random mask. This maps the scalar input into a high-dimensional term of the quantum Hamiltonian.

The resulting many-body dynamics generate a nonlinear transformation of the pair $(\mathbf{x}_k, u_k)$.

Step 3: Reservoir state update. The final state is sampled M times and the reservoir response is obtained from coarse-grained magnetizations,

$$x_{k+1,\ell} = \frac{1}{gM} \sum_{i \in G_\ell} \sum_{j=1}^M \mathcal{R}(\sigma_i^{z,j}(k)), \quad (6)$$

where G_ℓ denotes the set of qubits associated with reservoir node ℓ with $|G_\ell| = g$, and $\mathcal{R}$ the reverse annealing dynamics.

The overall recurrent update can therefore be expressed as

$$\mathbf{x}_{k+1} = \mathcal{F}_{QA}(\mathbf{x}_k, u_k; \mathbf{x}_{k-d}), \quad (7)$$

where $\mathcal{F}_{QA}$ denotes the nonlinear map generated by the reverse-annealing dynamics together with the explicit delayed feedback.

Step 4: Classical readout. For a given learning task, the sequence of reservoir states is used as the feature representation of the input series, and only the output layer is trained. The corresponding outputs will be

$$o_{k+1} = \mathbf{w}^\top \mathbf{x}_{k+1} + b, \quad (8)$$

where $\mathbf{w} \in \mathbb{R}^K$ is the vector of trained readout weights and $b \in \mathbb{R}$ is a bias term. The parameters $\mathbf{w}$ and b are optimized using the training data, while all reservoir parameters remain fixed.

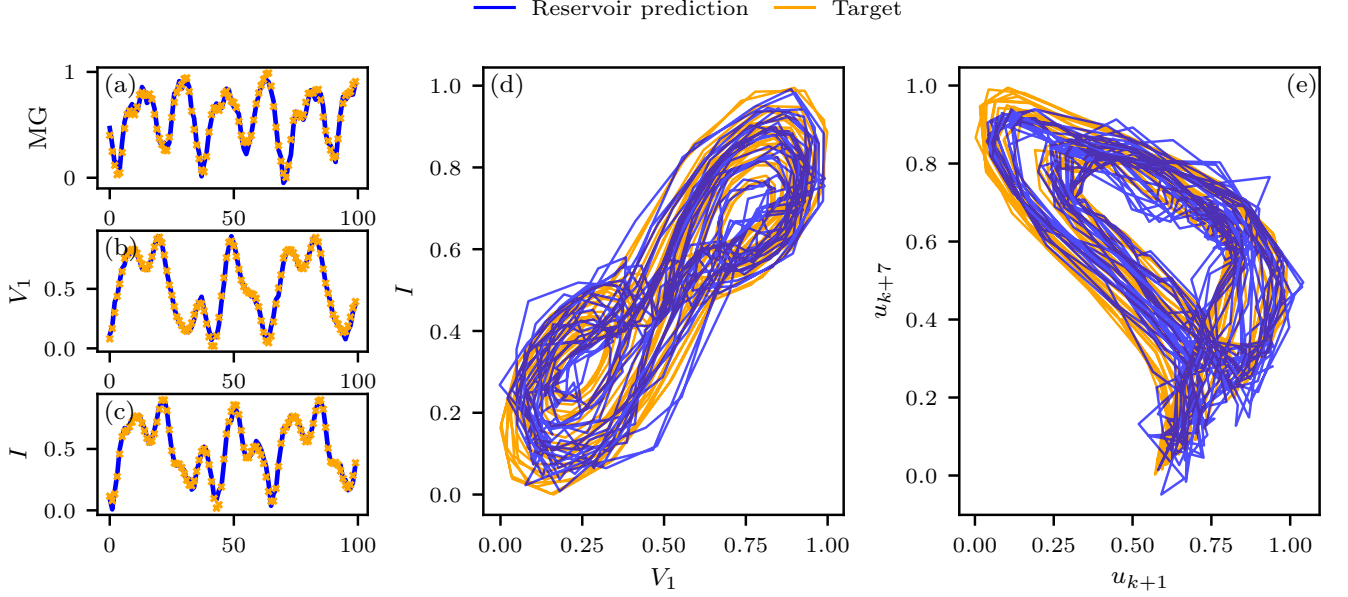


FIG. 2. Reservoir predictions compared with target values for the Mackey–Glass forecasting task: time signals in panel (a) and the corresponding chaotic attractor in panel (e). For the Double-Scroll task, predictions of the voltage V_1 and current I are shown in panels (b) and (c), while the attractor formed by the two time series is plotted in panel (e).

In Fig. 1, an illustration of the reservoir architecture is shown.

Results- We demonstrate the ability of the proposed reservoir to perform chaotic time-series forecasting using the Mackey–Glass system [18] and the Double-Scroll attractor [19]. As shown in Fig. 2, the reservoir successfully predicts the temporal evolution of both systems, capturing their chaotic dynamics. To the best of our knowledge, this is the first demonstration of a chaotic attractor reproduced on a quantum computer. For each realization, the Ising couplings $J_{i,j}$ in Eq. (1) were randomly initialized and kept fixed throughout the computation. Coupling strengths were independently sampled from a uniform distribution over $[-0.1, 0.1]$ for all active couplers among the selected qubits. Likewise, the input masks m_i and discretization thresholds θ_i were independently sampled from $[-1, 1]$ and fixed within each realization. The reverse annealing was implemented using the following schedule, with consecutive points connected by linear interpolation: $(0 \mu\text{s}, 1) \rightarrow (0.5 \mu\text{s}, 0.5) \rightarrow (1.5 \mu\text{s}, 0.5) \rightarrow (2 \mu\text{s}, 1)$.

Moreover, we analytically showed that when the couplings are turned off, $J_{i,j} = 0$, the reservoir is not able to operate because of the failure of the echo state property [20], showing that the interactions generated by the D-Wave machine are crucial. In Fig. 3, we experimentally showed this behaviour by computing the performance for the linear memory capacity [21]. Specifically, for a given delay τ , the target output at time step k is defined as: $\hat{u}_k = u_{k-\tau}$, where τ determines how far into the past the reservoir must recall the input. The quality of the reconstruction is quantified by the capacity (C) [22], which coincides with the squared Pearson correlation coefficient between predicted output and target. Importantly, we observe that non-Markovian revivals emerge only when the number of qubits, N , is sufficiently large:

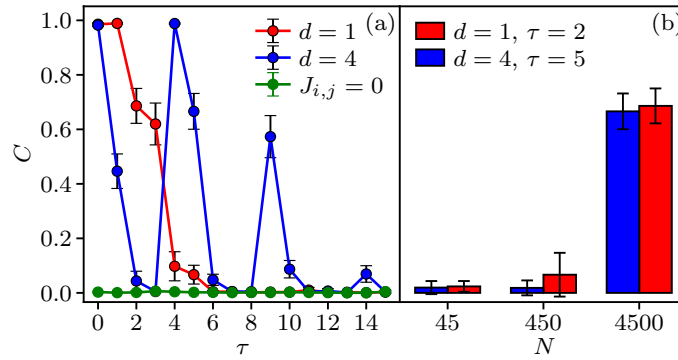


FIG. 3. (a) Linear memory capacity as a function of the delay (b) Linear memory capacity as a function of the number of physical qubits.

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