

Experimental Neuromorphic Computing Based on Quantum Memristor

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Machine learning has recently developed novel approaches, mimicking the synapses of the human brain to achieve similarly efficient learning strategies. Such a method retains the universality of standard ones, while attempting to circumvent their excessive requirements, which hinder their scalability. In this landscape, quantum (or quantum inspired) algorithms may bring enhancement. However, high-performing neural networks invariably display nonlinear behaviors, which poses a challenge to quantum platforms, given the intrinsically linear evolution of closed systems. We propose a strategy to enhance the nonlinearity achievable in this context, without resorting to entangling gates and report the first neuromorphic architecture based on a photonic quantum memristor. In detail, we show how the memristive feedback loop enhances the nonlinearity and hence the performance of the tested algorithms. We test our model on several tasks, widely recognized to benchmark the performance of (quantum) neuromorphic models. We highlight the essential role of the quantum memristive element and demonstrate the possibility of using it as a building block in more sophisticated networks.

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I. INTRODUCTION

In the last decades, machine learning has fundamentally changed the approach to solving a wide variety of problems, from everyday life to scientific scopes [1–7]. In this context, artificial neural networks (ANN) have proven to be a pivotal tool, especially for tackling tasks where information needs to

be extracted from high-dimensional data [8]. Nevertheless, a growing number of parameters must be trained as the tasks get more complex, with correspondingly larger training data, resulting in the so-called memory bottleneck [9]. This sparked the development of more dedicated hardware, i.e. neuromorphic architectures, which mimic the human brain [10]. The main advantage of these models is their minimal learning requirements, which circumvents the aforementioned difficulty. Acting as the poster-child of neuromorphic components is the memristor, a passive circuitual component that was postulated in 1971 [11] and demonstrated in 2008 [12]. Its main characteristic is that it retains memory of its past states, in the form of a hysteresis, similarly to neural synapses [10,13–16].

Quantum computing introduced a related but somewhat orthogonal paradigm shift in computer science. The

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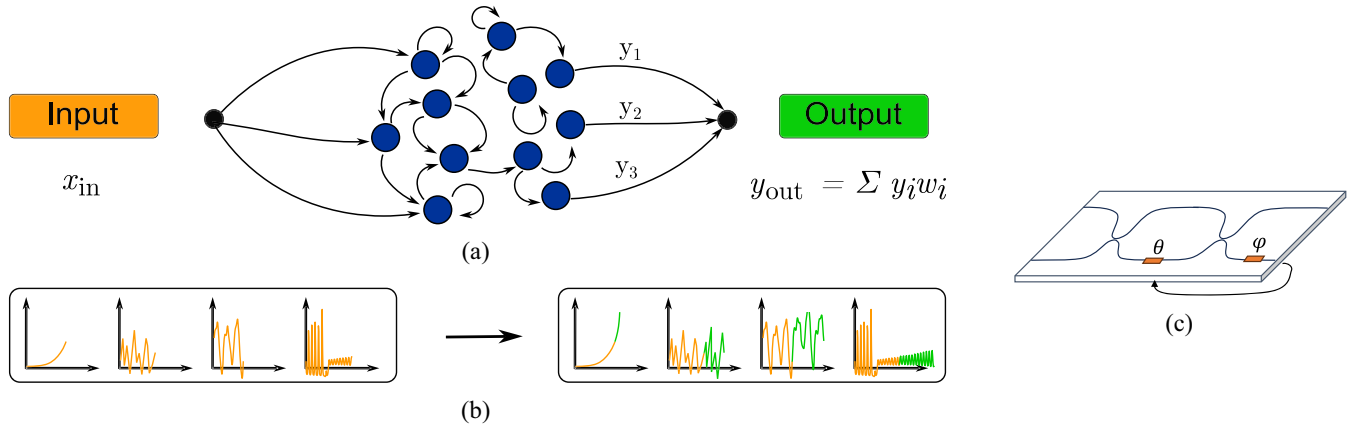


FIG. 1. Neuromorphic computing based on quantum memristor. (a) The investigated hybrid quantum/classical models are implemented in three parts: input encoding (quantum), nonlinear reservoir (quantum) and linear regression at the output, i.e. $y_{\text{out}} = \sum y_i w_i$ (classical). In this work, encoding of classical variables in a one-qubit state exploits the amplitude of the component parallel to $|0\rangle$, i.e. $x \rightarrow \sqrt{x}|0\rangle + \sqrt{1-x}|1\rangle$ and $x|0\rangle + \sqrt{1-x^2}|1\rangle$. The reservoir is implemented as a unitary operation composed of successive rotations, which induce a nonlinear transformation of the input through its nonlinear encoding in the quantum-state density matrix. The feedback loop enhances the nonlinearity while providing short-term memory. The reservoir output is then processed by a linear regression model that computes a weighted sum. (b) The four addressed tasks are the prediction of a smooth nonlinear function and three random time series: NARMA, Mackey-Glass, and Santa Fe. We also numerically simulated the application to vowel recognition. (c) The photonic quantum memristor is realized by a tunable Mach-Zehnder interferometer acting as a beam splitter with variable splitting ratio, whose internal phase θ is updated via feedback based on measurements at one output mode.

interest in this field stems, first, from the possibility of tackling non-classical processing tasks directly related to the investigation of quantum effects and, second, from the promise of outperforming standard algorithms for specific problems [17–22]. For instance, there is practical evidence that quantum computers can simulate quantum dynamics beyond the reach of state-of-the-art classical approximation methods [23]. However, strictly speaking, the only mathematically proven advantages were demonstrated for highly specialized sampling tasks, which lack known practical applications or are far from general-purpose computation [24–26]. Hence, a rapidly evolving research direction arises from the combination of machine learning and quantum computation, that is, quantum machine learning [27,28]. This is fueled by the hope that a computational advantage can be found on practically relevant tasks even when using relatively small-scale quantum information processing. In this context, photonic apparatuses constitute a very promising platform, as they exhibit a vastly lower energy consumption compared to standard electrical ones [29,30], opening the possibility of far more efficient and fast computational platforms. This is further supported by the very recent application of boson sampling experiments to quantum machine learning tasks, showing experimental evidence of enhancements with respect to their classical equivalent [31–33]. However, when considering quantum processes, the natural way of implementing nonlinear evolutions (crucial for machine learning algorithms) consists in the (controlled) interaction among multiple systems, i.e. entangling gates. This kind of evolution is still governed by linear transformations, but it

can be seen as nonlinear from a computational point of view and is particularly challenging on photonic platforms, since photonic nonlinear interactions are weak and hardly controllable. This implies, for example, that very high optical powers need to be used, which, besides the engineering challenges, can also negate the potential energy advantage coming from using optics instead of electronics [29]. This is the reason why, until now, this problem has been circumvented, either through a suitable encoding of the data, as in [31,34], or by exploiting the nonlinearity coming from the measurement, as in [35,36]. These approaches are all proven to be effective, but they present drawbacks. Indeed, the first cannot be used with quantum data and the second cannot implement any memory nor be used as a subroutine.

In this work, we propose a possible approach to solve this apparent conundrum and we implement the first instances of a neuromorphic computing protocol, i.e. reservoir computing (RC), using single photons, manipulated through an integrated circuit [37]. The model (see Fig. 1) may be seen as a building block for more complex networks and is composed of a nonlinear fixed reservoir (equipped with classical memory), followed by a readout unit, implementing a linear regression model, $y_{\text{out}} = \sum y_i w_i$, which is the only part that requires a training phase. Our aim is to implement a quantum/classical hybrid algorithm, where the nonlinearity is generated by a quantum system, while the linear regression model is classical. To achieve this goal we leverage a particular choice for the input encoding and the exploitation of a novel device: the photonic quantum memristor [38]. This

element has the twofold effect of enhancing the non-linearity of the model, while implementing a classical memory.

The notion of quantum memristors was introduced in pioneering works across several platforms, including optical, superconducting, trapped-ion and bosonic systems, with extensions to digital quantum simulations and related quantum memory elements such as memcapacitors and meminductors [39–43]. These contributions span a broad range of platforms and theoretical frameworks for memristive behavior in the quantum regime [44–47]. Our implementation is based on a Mach-Zehnder interferometer (MZI) equipped with a feedback loop, and its behavior is proven to be *memristive*. Moreover, the impact of the feedback on the coherence of the output state was studied, both in a configuration featuring a single device and in a network of two independent quantum memristors, injected with correlated photon pairs [48]. However, its potential use for machine learning tasks was only theorized and its role was not deeply investigated, as the task proposed in the original manuscript, i.e. the recognition of MNIST hand-written digits [49], can be tackled effectively through linear regression and other simple estimators. Before scaling up to larger systems, we investigate the potentialities of one device, to understand what the minimal requirements are to tackle real-world machine learning tasks. To give a better estimation, we also carry out a comparison between our model and simple non-task-specific classical models, to quantify the resources they require to achieve a similar, or slightly better, performance. With our results, we go beyond the previous study and apply this hardware to several machine learning tasks where nonlinearity is a crucial factor and cannot be omitted without compromising performance, highlighting the pivotal role of the quantum reservoir. In all of the considered tasks, we show that the dynamics of the photonic quantum memristor enhances the performance, with respect to the case where no feedback loop is implemented. In summary, the present work shows how a (photonic) quantum system can tackle tasks that were addressed with similar classical architectures [14], but with substantially fewer resources, paving the way to efficient machine learning models and to the possibility of exploring neuromorphic architectures applied to quantum tasks.

II. QUANTUM MEMRISTOR-BASED NEUROMORPHIC MODELS

The photonic quantum memristor can be modeled as a tunable MZI, as depicted in Fig. 2. Then, its internal phase is updated according to a feedback rule that depends on the measurement outcome at one output mode, affecting the temporal dynamics of the device. One of its main features consists in the fact that, when tracing out the mode used for the feedback loop, the reduced state is still partially

coherent, as detailed in the Supplemental Material note I [50]. Consequently, further quantum information processing is possible on the output.

We want to exploit this feedback mechanism to implement nonlinear operations on the input state and utilize a short-term memory, to achieve a proof-of-principle quantum reservoir computing (QRC). The underlying principle is that, due to the feedback, the linear operator $\mathcal{O}$ applied to an input ρ_i has a dependence on the previous output and, therefore, on the input ρ_{i-1} . Consequently $\langle \mathcal{O} \rangle_{i+1} = \text{Tr}(\mathcal{O}(\rho_i)\rho_{i+1})$ and successive observables are correlated with the previous ones, indicating a stateful system. If, on top of this, there is a correlation between consecutive inputs (like in a time series), then $\rho_{i+1} = f(\rho_i)$, and this can imply a nonlinearity, where $\langle \mathcal{O} \rangle_{i+1} = \text{Tr}(\mathcal{O}(\rho_i)\rho_{i+1}) \sim \text{Tr}(\rho_i^2)$. In our algorithm, as a first step, we encode our classical inputs in quantum states that are then injected into a quantum reservoir. This usually consists of randomly connected nodes, whose internal time-based state make up its intrinsic memory and the historical nonlinearity that is necessary for the learning process (see the Supplemental Material note II for further details [50]). In this framework, feedback-driven and (weak-) measurement-based architectures have been recently theoretically investigated [56–58]. Our implementation features one physical node, realized through a MZI, which in concert with a feedback loop acts like a quantum memristor. Then, the randomness is given by unitary operations before and after the memristor itself. Hence, the quantum part of our model consists in the encoding of the classical data and in the reservoir. We exploit one-qubit states, encoded in the path degree of freedom of a single photon state, with a dual-rail scheme [see Fig. 2(b)]. The reservoir is then composed of a sequence of three unitaries over three spatial modes, i.e. $\mathbf{U}_1$, $\mathbf{U}_{\text{mem}}$ and $\mathbf{U}_2$. At the end, a readout unit, i.e. a classical linear regression model, follows.

We experimentally test our model for four tasks, that rely on the two key features of our photonic platform, i.e. nonlinearity and short-term memory. These are a nonlinear function prediction/reproduction, where we exploit mostly the nonlinearity of the model, and three different time series predictions *nonlinear Auto Regressive Moving Average*, i.e. *NARMA*, [59,60] *Mackey-Glass dynamic prediction* [61,62] and *SantaFe laser intensity prediction* [63,64], where short-term memory plays a pivotal role. We also numerically simulate the application of our model to vowel recognition, showing that it can be used for real-world problems.

For the first task, the functions we aim at reproducing and then extrapolating are monomials:

$$f(x) = x^n, \quad n \in \mathbb{Z}. \quad (1)$$

This choice is motivated by the interest in testing the maximal achievable nonlinear behavior of our model and the role of the feedback loop toward its enhancement.

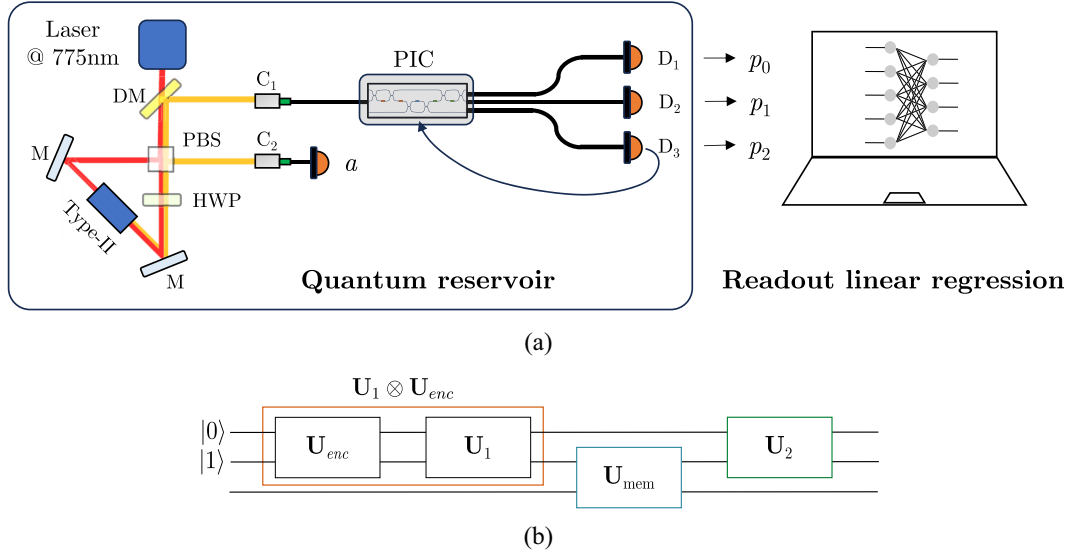


FIG. 2. Physical quantum reservoir with readout linear regression. (a) The setup uses a source of photon pairs pumped at 775 nm, generating degenerate photons at 1550 nm. The laser is transmitted through a dichroic mirror (DM) and polarizing beam splitter (PBS), then focused into a Sagnac interferometer containing a Type-II nonlinear medium and two mirrors (M). The generated photon pairs are reflected at the PBS and DM and collected into fibers (C₁ and C₂). One photon is injected into a three-input/output photonic integrated circuit (PIC), while the other serves as an ancillary photon. The circuit follows an optical Reck decomposition [65] with five phase shifters that suffice here since the inputs are not superpositions of Fock states and measurements are exclusively projective. Consequently, the system is insensitive to global phase shifts before the first MZI and immediately prior to detection (D₁, D₂, D₃). After full chip calibration, phases are set and dynamically modulated via voltages applied to resistive elements acting as thermal phase shifters. The implemented unitary is updated based on statistics from previous runs, and the resulting output distribution is processed by a linear regression model, which is the only trained component. Although our experiments use single-photon inputs, identical output statistics can be obtained with coherent light. (b) The input is encoded into a single qubit via the unitary U_{enc} . The unitaries U_1 and U_2 are model hyperparameters for the monomial functions; in practice, the product of U_1 and U_{enc} is implemented by the first MZI. The unitary U_{mem} represents the memristor action and is adaptively updated based on previous outcomes. The coefficients of the corresponding feedback rule are also hyperparameters [see Eq. (2)]. For time-series prediction tasks, we set $U_1 = U_2 = \mathbb{I}$, leaving the memory decay m_d as the sole hyperparameter [see Eq. (4)].

We encode the inputs as follows: $x \rightarrow \sqrt{x}|0\rangle + \sqrt{1-x}|1\rangle$. Note that this encoding is linear when performing a projective measurement in the eigenbasis of the Pauli operator σ_Z [66], as $\text{Tr}(\sigma_Z \rho_x) = \sum_{i=0,1} (-1)^i p_i = 2x - 1$, where p_i is the probability of getting the outcome i . In contrast, measurements in the σ_X basis give an expectation value that is nonlinear in x , $\text{Tr}(\sigma_X \rho_x) = \sqrt{x}\sqrt{1-x}$. Let us note that the choice of the input encodings was aimed at looking for a tradeoff between inducing the least amount of nonlinearity and achieving a good performance of the model. In this way, it is possible to systematically quantify the nonlinearity given by the encoding and by the reservoir itself. This nonlinearity can be enhanced by a proper choice of the rotations U_1 and U_2 . Then, we pick a linear feedback rule which modifies U_{mem} . The feedback loop additionally enhances the nonlinearity, by inducing a dependence of the measurement operator on the previous output state. This results in a nonlinear form of the output, i.e. (x_{t-1}, x_t) , already after one step (for the full analytical derivation, see Supplemental Material note II [50]), and also in a memory of the previous states. From an operational point of view, the internal variable of the memristor

R_t , which can be seen as the reflectivity of a beam splitter, is updated via,

$$R_t = \frac{1}{m} \sum_{T=t-m}^t R_T = \frac{1}{m} \sum_{T=t-m}^t (a \cdot p_{T,2} + b) \quad (2)$$

where $p_{T,2}$ is the probability of detecting a photon in the update mode and the internal phase of the MZI that implements U_{mem} is given by $2 \times \arccos(\sqrt{R})$. The rotations U_1 and U_2 , along with a and b , are optimizable hyperparameters (see Supplemental Material note IIA for further details [50]). In this case, m can be seen as the *memory extent*, which amounts to the number of previous steps which are used when performing the average reported in Eq. (2), to retrieve the reflectivity at each time step t .

The goal of the second task is to predict the output of a nonlinear dynamical system, introduced in [59,60], called *NARMA* (Nonlinear AutoRegressive Moving Average), which consists of predicting the next value of a discrete-time sequence where the output depends

nonlinearly on a fixed number of previous inputs and outputs. This was already widely used as a benchmark for classical [67,68] and quantum [62,69] RC models. The recurrence relation of the system is described by the following equation:

$$y_{t+1} = 0.4y_t + 0.4y_t y_{t-1} + 0.6x_t^3 + 0.1, \quad (3)$$

where x_t and y_t are the input and the output, respectively, at time t . From Eq. (3), it is visible that the output y_{t+1} depends on past two outputs y_t and y_{t-1} .

The time series $\mathbf{x} = \{x_t\}_{t=1}^N$ is generated by sampling each x_t independently and uniformly in the interval $U(0, \frac{1}{2})$, and then the outputs $\mathbf{y} = \{y_t\}_{t=1}^N$ come sequentially from Eq. (3). For this task, we are using the amplitude encoding $x_t \mapsto x_t|0\rangle + \sqrt{1-x_t^2}|1\rangle$ and the feedback rule

$$R_t = R_{t-1} + \frac{p_{t-1,2} - R_{t-1}}{m_d}, \quad (4)$$

where p_{ti} at time t is the probability of detecting one photon in the i -th mode ($i = 0, 1, 2$), while m_d is the fixed *memory decay* of the memristor. The memory decay, analogously to the memory extent mentioned before, is also a hyperparameter, but it is related to how fast the memory of past outcomes will fade. Indeed, this feedback rule does not involve any average and, as detailed in the Supplemental Material note IIB [50], it modulates the dependence of R_t on each previous output.

The other two tasks are *one-step-ahead* predictions of a real data series. This implies that, given y_t , the model needs to predict y_{t+1} . The first of them is the solution to the *Mackey-Glass* differential equation [61,62], and the last is the so-called *Santa Fe* time series, which is a dataset recorded from a far-infrared laser in a chaotic state [63,64]. For both tasks, we use amplitude encoding $x_i \mapsto \sqrt{1-x_i}|0\rangle + \sqrt{x_i}|1\rangle$ and the feedback rule in Eq. (4) with $m_d = 2$ for Mackey-Glass task and $m_d = 6$ for Santa Fe. Both data sets have been scaled down to fall within the range of 0 to 1. For more details see the Supplemental Material note IIB [50].

For all the tasks, after the quantum processing, a classical linear regression is used to find the best prediction. We note that during this process no non-linearity or memory is added. As a benchmark, we performed the monomial prediction tasks without any feedback loop and with no reservoir. The latter is a fully classical procedure, only injecting the x values into the final linear regression, to highlight the role of our physical platform. For the time series predictions, instead, we performed a comparison with slightly more complex fully classical models, even featuring some nonlinearity and memory of past states.

III. EXPERIMENTAL IMPLEMENTATION

The main part of the experimental setup, fully represented in Fig. 2, is the physical quantum reservoir. It consists of an integrated waveguide circuit with 3 input/output modes and is designed according to a universal architecture [70]. The waveguides are fabricated by direct femtosecond laser writing [38,71,72] in an aluminoborosilicate glass substrate and feature single-mode operation at 1550 nm. Microstructured thermo-optic phase shifters are integrated on-chip, to provide efficient phase tunability [73]. Let us highlight that, for borosilicate glass circuits equipped with thermal heaters, the main source of noise is given by thermal crosstalk, which usually takes place among parallel MZIs [74]. However, due to the limited size, our circuit displays only three consecutive MZIs, see Fig. 2(b), and therefore a negligible crosstalk (for more detailed information about the calibration procedure, see the Supplemental Material note III [50]). Furthermore, due to the low birefringence of the substrate, this circuit is polarization independent. Input and output ports are pigtailed with single-mode fibers.

The encoding of the classical input is set via an initial unitary transformation $\mathbf{U}_{\text{enc}}$, through an on-chip MZI, as shown in Fig. 2(b). For example, to encode the state $\sqrt{x}|0\rangle + \sqrt{1-x}|1\rangle$, apply a phase $\phi = 2 \arccos(x)$ when injecting a photon into the lower mode of the MZI. However, since the optical circuit consists of three MZIs in total, we implement the product $\mathbf{U}_1 \cdot \mathbf{U}_{\text{enc}}$ through the first MZI, as detailed in Fig. 2(b).

The input single photon state is generated by a collinear Type-II spontaneous parametric down conversion source, pumped at 775 nm, which emits pairs of degenerate photons with a wavelength of 1550 nm. The employed nonlinear crystal is a periodically poled titanyl phosphate, placed within a Sagnac interferometer. Since for this application we do not need entangled states, the crystal is pumped only in one spatial direction and generates the separable state $|01\rangle$. One photon is ancillary and heralds the generation of the second photon that is injected into the photonic processor. This implies that we post-select our statistics, considering only the cases where both the heralding and signal photons are detected (with an average rate of 30 kHz). The three output modes of the photonic processor are connected to superconducting nanowire single photon detectors.

At this point, the frequencies of the clicks registered by the three detectors at the output of the chip, in coincidence with the one detecting the heralding photon, give the probabilities p_0 , p_1 and p_2 as $p_i = \frac{N_{i,a}}{\sum_{j=1}^3 N_{j,a}}$. Let us point out that, although in our implementation we use single photon inputs, the same output statistics can be obtained by using a coherent light source.

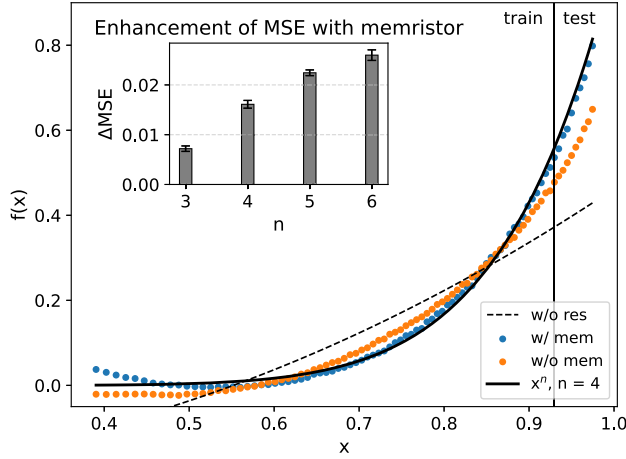


FIG. 3. Monomial function prediction. Blue markers show the prediction of the power function $f_i(x) = x^n$ with $n = 4$ (solid black curve) obtained using the memristor-based feedback loop, whereas orange markers correspond to the same task performed without feedback. The last ten inputs are used for testing and the remainder for training, with hyperparameters optimized independently in the two cases; the dashed black line denotes the reference configuration without a physical reservoir. Performance is quantified by the mean squared error (MSE), whose statistical uncertainty was estimated through Monte Carlo simulations. This is not reported in the plot, since the bar corresponding to 1 standard deviation is smaller than the marker size. For the data shown, the memristor-based implementation yields a mean MSE of $(6.34 \pm 1.03) \times 10^{-4}$, compared to $(1698.28 \pm 0.77) \times 10^{-5}$ in the absence of feedback. The inset shows the difference $\Delta\text{MSE} = \text{MSE}_{w/o\text{ mem}} - \text{MSE}_{w/\text{ mem}}$ for $n = 3, 4, 5, 6$, with error bars indicating the corresponding standard deviation and highlighting the systematic improvement enabled by the feedback loop.

IV. RESULTS

To quantify the quality of the performance of predictive tasks, we use the so-called *mean squared error* [75], defined as follows:

$$\text{MSE}(\mathbf{y}, \tilde{\mathbf{y}}) := \frac{1}{N} \sum_{t=1}^N (y_t - \tilde{y}_t)^2 \quad (5)$$

with y_t target values, $\tilde{y}_t$ predicted values and N data points.

For the monomial prediction tasks three different cases are compared: (i) with quantum memristor, (ii) without memory (with no feedback loop) and (iii) with no reservoir. The prediction of x^n with $n = 4$ is shown in Fig. 3, and the inset plot shows the difference between the MSEs obtained in the case where the loop is implemented and without it, for different n . The results show that even without the feedback loop some nonlinearity can be generated, due to the encoding from x to ρ_x . However, the loop enhances the impact of the nonlinear measurement process and ultimately the performance of the

algorithm. Let us highlight that, when comparing the cases with and without feedback, we are picking the best hyperparameters (namely U_1 and U_2 and the coefficients of the feedback function), separately for the two cases, to have a fair comparison. In contrast, in the case of no reservoir, the output is simply a linear function, since the final linear regression only gives a weighted sum of the inputs. Note that, due to the fact that the considered loss function is only a sum of the absolute difference between predicted and true values, the model has a worse performance on the lower values of x , since they have a lower impact on the loss function. This does not hinder, however, the effectiveness of the model, given that this slightly worse performance affects only the training region.

In Fig. 4, we show the experimental prediction of the network for the previously described time series prediction tasks. For the case with no feedback loop, each output depends only on the last input, since there is no storing the information of previous data points. It is worth noting that cases without feedback loops still achieve fairly good results (although worse than the case where the quantum memristor is employed). For the NARMA task, this is due to its low nonlinearity, while for the Mackey-Glass and Santa Fe, it results from the high density of probing points, which makes the prediction almost linear. To have a more complete overview of the performance of our algorithm, we present the results achieved on the same tasks by simple classical algorithms. First, we consider a model without memory, where the prediction is a polynomial function of the input data. In particular, we consider two models, featuring 2 and 4 free parameters. Next, we examine two models with the simplest possible memory, which records only the previous input. Hence, the final prediction will be given by a polynomial function of the current and previous input. In this case, the two models have, respectively, 3 and 9 free parameters. Our model featuring the quantum memristor has a better performance than those models (see Table I), even when the classical one has access to past inputs. For the comparison of the other tasks and the mathematical description of these models, see Supplemental Material note IIC [50]. In [50], we report also the comparison between the experiment and the ideal (noiseless) case, which highlight that the registered improvements are statistically significant and consistently displayed.

Another study that we carried out concerned the extension of the output space of our quantum reservoir, either by considering multiple parallel units (whose results were then merged and fed to the readout unit) or by multiplexing the data belonging to different time steps in the classical post-processing of the data. With all of these strategies, it is possible to improve the results and it is noteworthy that this happens in particular in the presence of noisy input for the NARMA task. For a more detailed

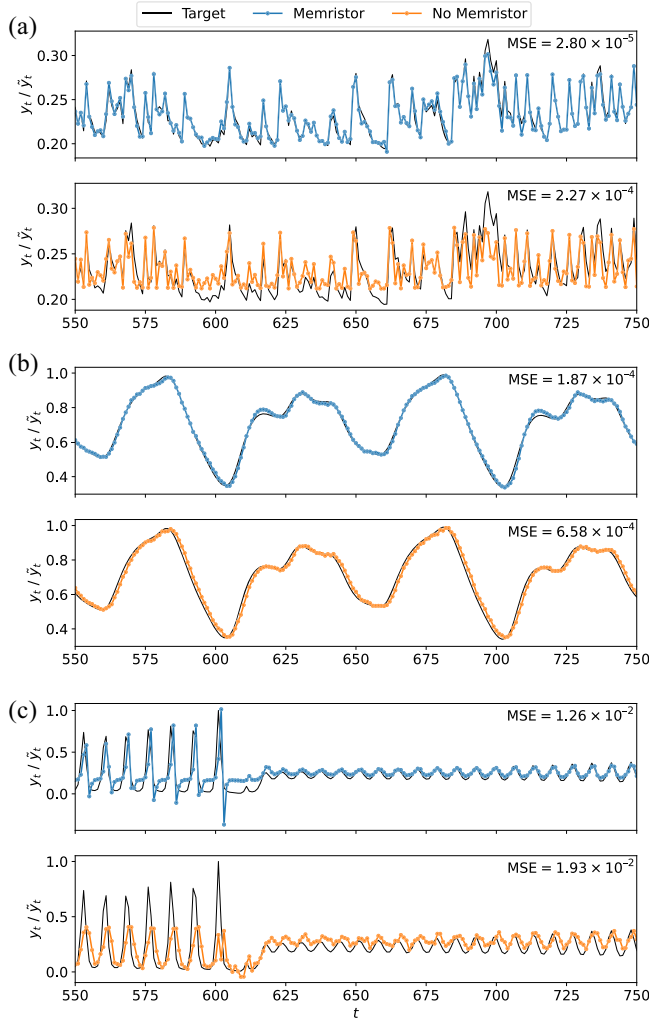


FIG. 4. NARMA, Mackey-Glass, and Santa Fe task results. We show the performance of our model on the following prediction tasks: NARMA (a), Mackey-Glass (b), and Santa Fe (c). The true values of the time series are plotted in black. Predictions with and without the memristor are shown, respectively, in blue and orange. In each subplot, the MSE score is reported in the top right corner. Each of the adopted datasets contains 1000 points. Out of those, the first 20 correspond to the so-called *washout*, i.e. the time required to the model to initialize. Then, the training process is carried out on the following 480 points, while the validation is performed on the rest of the dataset. For the sake of clarity, the plot shows only 200 points of the test.

report on these strategies, see Supplemental Material note IV [50].

We also successfully applied our model to a real-world task, i.e. vowel recognition [76], which is widely recognized as a benchmark of reservoir computing models. For this task, our model achieves an average accuracy of $(82.25 \pm 4.59)\%$, where removing the reservoir, the result would amount to $(72.00 \pm 7.01)\%$. The largest improvement is achieved for the sound *uw*, where our model reaches 86% of accuracy and a linear model only 28%.

TABLE I. Mean squared errors for classical machine learning models for NARMA task. This table shows the average MSE achieved by several classical models, which have access to a similar amount of resources, in terms of memory and free variables, in comparison with the one presented in this work, indicated by QMEM. The numbers in the bracket indicate one standard deviation of 100 runs. $\text{Poly}_d(a_1, \dots, a_n)$ is the polynomial of variables $\{a_1, \dots, a_n\}$ of degree at most d . In detail, L and C stand, respectively, for models that can base their predictions on linear and cubic manipulation of the input. The first features 2 and the second 4 free variables. $L + M$ indicates the same models, but with access to the previous element of the output series. In this case, the first features 3 and the second 9 free variables. For an accurate description of such models, see Supplemental Material note II [50]. The reported values are obtained through numerical simulations. We note that polynomials of higher order improve neither of the results. Our model features only 1 free variable, given by the memory decay m_d [see Eq. (4)]. Within the brackets, we report 1 standard deviation.

Model	Equation	MSE ($\times 10^{-4}$)
L	$y_t \approx \text{Poly}_1(x_t)$	2.76(29)
C	$y_t \approx \text{Poly}_3(x_t)$	2.05(22)
$L + M$	$y_t \approx \text{Poly}_1(x_t, x_{t-1})$	1.83(19)
$C + M$	$y_t \approx \text{Poly}_3(x_t, x_{t-1})$	0.92(11)
QMEM	$\dots$	0.330(80)

Furthermore, we were able to improve the predictions, considering two parallel units (hence doubling the size of the output vector), where we achieved an average accuracy of $(86.50 \pm 2.15)\%$. These results are comparable to those achieved in other recent works, e.g. [32,77], which had access to larger models, with a significantly higher number of parameters. For additional details, see Supplemental Material note V [50].

V. DISCUSSION

In this work, we have implemented the first instance of QRC exploiting single photon states. These machine learning models work by injecting input data into a fixed random quantum reservoir, whose memory and nonlinearity is mainly given by a photonic quantum memristor, equipped with a feedback loop, which is then followed by a classical linear regression model [37]. Moreover, we carry out a systematic analysis to distinguish the nonlinearity coming from the quantum memristor and the one given by the input encoding. For this reason, we compare our results with the performance we would achieve without feedback loop, consistently showing a worse overall nonlinearity.

We tested our algorithm on multiple function prediction tasks: several monomial functions, and then NARMA, Santa Fe and Mackey-Glass time series. Due to its regularity, the first task is only to test the nonlinearity,

while the others test also the memory of our model. We also numerically extended our QRC, either by using parallel independent units or exploiting classical multiplexing in the data post-processing. In all these cases, we demonstrate an improvement over the achieved results, especially in the presence of noisy inputs for the NARMA task.

Furthermore, we addressed a real-world task, i.e. vowel recognition, which is a widely used benchmark task for reservoir computing schemes. Also in this case, we showed an improvement when using two parallel units. In summary, for all the considered scenarios, we consistently obtained higher accuracy results with respect to linear models, undoubtedly proving that our scheme provides a nonlinearity, which can be effectively used for practical purposes. We show that the feedback improves the overall nonlinearity, as it is visible both from the experimental results, as well as from the ideal (noiseless) cases that were numerically simulated. Considering the existing literature, we either outperformed or obtained comparable results, with respect to significantly larger and more complex reported quantum models, exploiting a higher amount of resources [77,78]. For instance, in the context of continuous variables [32,79], the proposed methods require generating and controlling multimode squeezed and entangled states with a complex bulk optical setup, involving precise spectral amplitude and phase control via a spatial light modulator and mode-selective homodyne detection. This grants access to a significantly larger space than our model, but at the cost of being significantly more challenging to stabilize and to scale up. Indeed, in our case, using multiple parallel units, without significant experimental overhead, is already sufficient to tackle real-world tasks. Our results are also remarkable with respect to classical works, if we point out that our reported NARMA task was also tackled in, e.g., [14], which was exploiting a system featuring 88 memristors. These comparisons show that the experimental feasibility of our model does not hinder its applicability, but instead constitutes a remarkable strength for scalable and realistic implementations. To benchmark the statistical significance of the results, we compared all of our experimental results to the ideal (noiseless) case, distinguishing the registered trends from finite statistics fluctuations (see Supplemental Material note IID [50]).

Our scheme can both be used as a standalone, as we showed in this work, as well as a building block for more complex networks, given that the non-measured output of the memristor preserves coherence and can be used as an input for successive layers (see the Supplemental Material note I for further details [50]). This is of particular relevance, considering that extending it to larger systems involving multi-photon inputs would allow to exploit quantum interference effects, which have been proven to lead to enhanced expressivity with respect to classical

light [31,80]. The versatility of choosing the operation mode depending on the context and on the particular task is intrinsically different from state-of-art optical-based reservoir computing schemes, which cannot easily be adapted to operate at the single photon regime. Indeed, when the nonlinear behavior comes either from physical properties of the material, e.g. through micro-ring resonators [81] or Kerr effect [82], or through optical-electronic conversion, operating in the single photon regime would bring a drastic simplification of the model, because optical nonlinearities require significant circulating field intensity to become appreciable, and, in the second case, it would simply be useless and detrimental, because converting optical signal into an electronic one would destroy any coherence. Also when nonlinearity comes from encoding the input data in experimental parameter, it is in general not possible to adapt the model to operate in the single photon regime. For instance, in the proposed experiment [34], the model is based on the evaluation of the scattering matrix of the used material as the ratio between a coherent probe and the system response: a procedure that is inherently incompatible with single-photon inputs.

Another important point is that achieving nonlinearity through a feedback, rather than with the aforementioned strategies allows our model a remarkable tunability, given that the memory and nonlinearity can be chosen through the integration time and tailoring the feedback rule. On the contrary, when the model relies on physical properties of the material, the memory and nonlinearity are determined by properties of the material itself and on the particular fabrication of the device, which cannot be modified. Furthermore, with respect to models that use nonlinearity coming from the encoding, our model can be applied to quantum native tasks, where this aspect cannot be used.

A potential way of enhancing the expressivity of the proposed model is to use multiple memristors in a consecutive way, as shown for instance in [83], and updating both their internal variables, as well as the input state, so that new inputs would interfere with states encoding previous outcomes. Analogously, the implementation of a fast feedback would allow to make coherent adjustments to the quantum state, enabling quantum memory effects. Recent works, such as Ref. [58], have studied how a quantum back-action retains a higher memory capacity, with respect to a classical feedback, analogous to the one explored in this work. Therefore, a natural step forward would consist in the implementation of an online learning scheme, where the memory throughout consecutive inputs is implemented through quantum interference and nonlinearity is displayed through partial measurements. This would result in a larger memory storage and open up the possibility of tackling a wider range of tasks. Moreover, feeding parts of the outputs as new inputs, for instance through a loop architecture [84], could unlock the possibility of tackling forecasting tasks [85]. Another interesting feature is that a quantum reservoir

could be used to directly process quantum systems, tackling tasks with no classical equivalent. For instance, to investigate foundational aspects or quantum state properties [35,86,87].

Besides exploring the possibilities unlocked by the quantum features of the memristor, this study paves the way for further investigations related to the nonlinearities achievable on photonic platforms, for optical computing. This is particularly relevant, considering that hybrid optical-electronic ANNs have been proven to require a lower energy consumption than standard ones [29,30]. In this framework, the memristor could be employed to constitute the activation function layer of quantum neural networks and, after further investigations on the relation between the memristor's dynamics with neurons one, it could unlock the possibility of implementing spiking optical neural networks [88–90].

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Mir. S. and I. A. designed and conducted the experiment, Mich. S. developed the theory and algorithm for the time series predictions and analyzed the corresponding data, I. A. developed the algorithm for power predictions, and I. A. and Mir. S. analyzed the corresponding data. R. A., A. C. and F. C. conducted the design, fabrication and calibration of the integrated photonic processor. Mir. S., I. A. and Mich. S. wrote the first draft of the manuscript.

I. A., Mag. S., R. O., B. D. and P. W. supervised the whole project. All authors discussed the results and reviewed the manuscript.

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DATA AVAILABILITY

The data that support the findings of this article are openly available, embargo periods may apply.

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