

Predicting the future with magnons: Forecasting chaotic time series with reservoir computing

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Forecasting complex, chaotic signals is a central challenge across science and technology, with implications ranging from secure communications to climate modeling. Here we demonstrate that magnons, the collective spin excitations in magnetically ordered materials, can serve as an efficient physical reservoir for predicting such dynamics. Using a magnetic vortex-state microdisk as a magnon-scattering reservoir, we show that intrinsic nonlinear interactions transform a simple microwave input into a high-dimensional spectral output suitable for time-series predictions. Trained on the Mackey-Glass benchmark, which generates a cyclic yet aperiodic time series, the system achieves accurate and reliable predictions that rival other state-of-the-art physical reservoirs. We further identify key design principles: spectral resolution governs the tradeoff between dimensionality and accuracy, while combining multiple device geometries systematically improves performance. These results establish magnonics as a promising platform for unconventional computing, offering a path toward scalable and CMOS-compatible hardware for real-time prediction tasks.

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I. INTRODUCTION

The ability to predict chaotic time series is a long-standing challenge at the crossroads of nonlinear dynamics, machine learning, and physical computing. Chaotic systems, while governed by deterministic rules, exhibit extreme sensitivity to initial conditions, rendering long-term trajectories unpredictable. This combination of determinism and apparent randomness makes them ideal benchmarks for testing new computational architectures aimed at real-time forecasting in complex, high-dimensional systems. Reservoir computing has emerged as a particularly promising approach, offering efficient training and natural suitability for temporal tasks [1–3]. In this framework, a fixed dynamical system projects inputs into a high-dimensional state space, from which a simple

linear readout extracts the relevant information. Crucially, this separation of nonlinear dynamics and trainable output enables hardware realizations, where intrinsic material properties can be harnessed directly. Physical implementations have already been demonstrated in diverse platforms, from optical fibers [4–7] and memristive circuits [8–11] to spintronic devices [12–17], nanomagnetic arrays [18–20], skyrmions [21–25], and magnonic systems [26–32]. Each of these leverages unique mechanisms of nonlinearity and memory.

Here, we demonstrate chaotic time-series prediction using a magnon-scattering reservoir (MSR) operating with modal multiplexing [33,34]. As shown in Fig. 1, the platform consists of a $\text{Ni}_{81}\text{Fe}_{19}$ microdisk in the magnetic vortex state [35,36], where magnetic moments curl in-plane around an out-of-plane vortex core. Different from previous quasi-binary input sequences [33,34], a continuous time-series input, encoded in a microwave current via frequency modulation, is injected into a microwave antenna for exciting the magnetization inside the vortex-state disk. Strong intrinsic nonlinear scattering between various magnon modes project this one-dimensional, serial input signal into a higher-dimensional spectral output which is used to train a simple linear readout. Our results show

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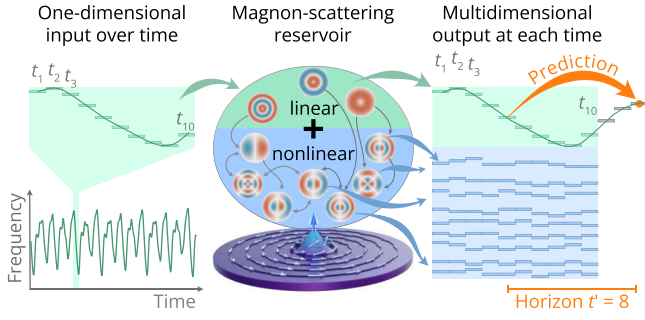


FIG. 1. Principle of chaotic time-series prediction based on a magnon-scattering reservoir (MSR): a one-dimensional temporal input is encoded in a microwave current and applied to an MSR in the form of a $\text{Ni}_{81}\text{Fe}_{19}$ microdisk in the vortex state. Nonlinear interactions between various magnon modes transform the one-dimensional input into a multidimensional spectral output trained to forecast the future trajectory of the chaotic signal.

that the MSR reliably forecasts the dynamics described by the Mackey-Glass equation, even when only relying on a single unseen spectrum, and establish magnon-based reservoirs as a physical computing platform for real-time prediction of complex dynamics.

II. METHODS

A. Time-resolved Brillouin light scattering microscopy

To probe the MSR response, we use time-resolved microfocused Brillouin light scattering (μBLS) spectroscopy [37]. Therefore, a continuous-wave laser (532 nm) is focused onto the sample surface using a $100\times$ objective lens ($\text{NA} = 0.75$), yielding a spatial resolution of approximately 300 nm. The backscattered light is analyzed in a tandem Fabry-Pérot interferometer [38], which resolves the frequency shift due to inelastic photon-magnon scattering with a spectral bin size of 37.5 MHz.

Photon counts, interferometer control signals, and a synchronized clock reference from the arbitrary waveform generator, which is used to excite magnons, are recorded by a time-to-digital converter (Timetagger 20, Swabian Instruments) with 200 ps resolution. From these data, the temporal evolution of the magnon spectra with respect to the stroboscopic microwave excitation is reconstructed.

Sample drift is actively compensated using image recognition of *in-situ* camera images of the structure, with corrections applied via high-precision stages (Newport XMS series). To access modes with different spatial profiles, μBLS spectra are averaged over 25 positions covering one quarter of the disk (five azimuthal angles at five radial positions). All measurements are performed at room temperature.

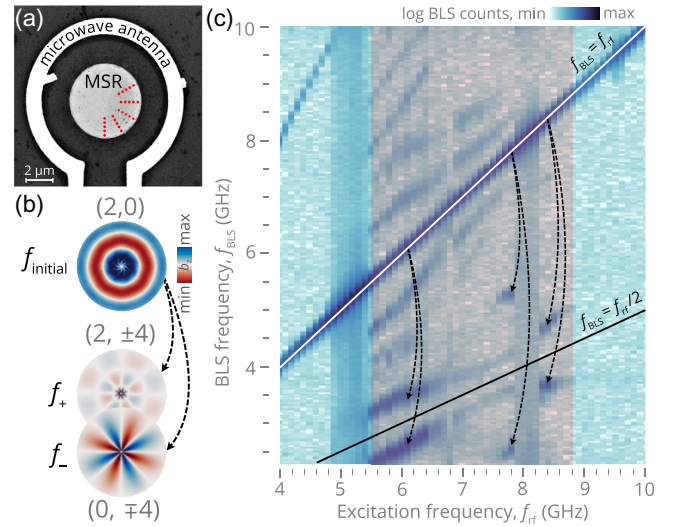


FIG. 2. (a) Scanning electron microscopy image of the MSR in the form of a 5- μm -wide and 50-nm-thick disk embedded in the Ω -shaped microwave antenna. Red dots indicate the measurement positions used for spatial averaging of the Brillouin light scattering (BLS) signal. (b) Schematic of a three-magnon splitting process: a directly excited mode $(2,0)$ at frequency f_{initial} decays into two secondary modes $(2, \pm 4)$ and $(0, \mp 4)$ with frequencies f_+ and f_- , conserving both energy and momentum. (c) BLS spectra measured on the device in (a) at an excitation power of 23 dBm, above the threshold for nonlinear three-magnon splitting. Each column corresponds to a spectrum recorded at a fixed excitation frequency f_{rf} , with intensity color coded on a logarithmic scale. The strongest nonlinear response is observed for excitation frequencies between 5.5 and 8.8 GHz (shaded in red).

B. Sample preparation and characterization

The standard MSR consists of a 5- μm -diameter magnetic disk patterned on a SiO_2 substrate, as shown in the scanning electron microscopy image in Fig. 2(a). Fabrication employed a polymethyl methacrylate (950PMMA A4) resist mask, electron beam lithography, sputter deposition, and liftoff. The $\text{Ni}_{81}\text{Fe}_{19}$ (50 nm)/Ta (4 nm) bilayer was sputtered in a 1 mT rotating magnetic field to suppress anisotropy [39].

To excite magnetization dynamics, an Ω -shaped microwave antenna was patterned around the disk using a double-layer resist stack (ethyl lactate EL11 and PMMA 950 A4), followed by electron beam lithography, deposition of Cr (5 nm)/Au (150 nm), and liftoff. The inner and outer diameters of the antenna are 8.7 and 11 μm , respectively. Microwave currents in the gigahertz range excite well-defined magnon eigenmodes of the vortex-state disk, which are characterized by their radial and azimuthal mode indices (n, m) counting the number of nodes along the disk radius and perimeter, respectively [40,41].

Additional MSR geometries, including 3- μm -diameter disks, rings (5 μm outer diameter, hole widths of 525 nm

and 800 nm) and squares (5 μm edge length), were fabricated simultaneously on the same substrate and each embedded in an individual Ω -shaped antenna [see Appendix A, Figs. 8(a)–8(c)].

First, we focus on the 5- μm -diameter disk. If radial modes therein are excited at microwave powers above threshold, nonlinear three-magnon splitting occurs [42, 43]. Figure 2(b) shows the mode amplitude profiles for an exemplary splitting process: the magnon mode (2, 0) initially excited at frequency f_{initial} splits into two secondary magnons (2, ± 4) and (0, ∓ 4), under conservation of energy ($f_{\text{initial}} = f_+ + f_-$) and angular momentum ($m_{\text{initial}} = m_+ + m_-$).

The BLS spectra in Fig. 2(c) are measured for increasing excitation frequency and demonstrate that several of these three-magnon splitting channels exist. Excitation frequencies between 5.5 and 8.8 GHz yield the strongest nonlinear response for the 5- μm -diameter disk. As shown previously [33, 34], the coexistence of multiple splitting channels leads to nonreciprocal mutual stimulation, such that different secondary modes are populated depending on the temporal order of various frequency components in a multitone excitation signal. This mechanism underpins the nonlinear expansion and temporal memory essential for the reservoir's predictive capability.

C. Time-series generation and MSR response

To evaluate our reservoir's prediction capabilities, we use the Mackey-Glass (MG) time series. This prototypical nonlinear model is capable of generating chaotic signals, which are widely employed to evaluate reservoir computing systems [18, 44, 45]. The MG sequence is based on the biological process modeling the concentration $P(t)$ of mature red blood cells in living organisms mimicking the time-delayed production of new cells in the bone marrow. It is generated from its delay-differential equation

$$\frac{dP(t)}{dt} = \frac{\beta P(t - \tau)}{1 + P(t - \tau)^\alpha} - \gamma P(t), \quad (1)$$

where τ is the delay time, β the production rate, γ the decay rate, and α the nonlinearity parameter.

Depending on the choice of parameters, the equation yields a periodic oscillation of the output value or a chaotic trajectory when the parameters are chosen for strong nonlinear dynamics. In Fig. 3(a), we generated the MG sequence using the parameter set $\beta = 0.2$, $\gamma = 0.1$, $\alpha = 10$, and $\tau = 17$, which yields a chaotic trajectory. The equation was solved using the Python package BrainPy [46]. From the resulting trajectory, we extracted 2000 discrete points $P(t_i)$, which served as the input sequence for the magnon reservoir.

The nonlinear response of the MSR is strongest for excitation frequencies ranging from 5.5 to 8.8 GHz [see the red shaded area in Fig. 2(c)]. To fully utilize this dynamic

response of the MSR, we modulate a microwave current via continuous-phase frequency-shift keying. For each time step t_i , the value $P(t_i)$ obtained from the MG equation is mapped onto a microwave signal $f(t_i) = kP(t_i) + c$. The mapping constants k and c are chosen such that the full dynamic range of the MG sequence matches the frequency interval of the strongest nonlinear response, as shown by the two y axes in Fig. 3(a).

Each discrete frequency value was represented by a sinusoidal burst of duration $\delta t = 0.6$ ns [Fig. 3(b)], synthesized by an arbitrary waveform generator (AWG7000 Tektronix) at a sampling rate of 25 GS/s and V_{pp} of 500 mV. To ensure a continuous waveform, the relative phase between consecutive bursts was adjusted during synthesis. This signal is transmitted through a series consisting of an amplifier (+23 dBm), attenuator (−5 dBm), and amplifier (+16 dBm). Additionally, a signal generator (Keysight N5173B) provides a continuous-wave 8.8 GHz microwave signal at 25 dBm, above the nonlinear threshold, to increase the number of active magnon modes. Both signals are merged using a frequency combiner and applied to the Ω -shaped antenna surrounding the MSR via a ground-signal-ground microwave probe. The effect of choosing different time windows is discussed in Appendix B.

Figure 3(c) shows the spectral intensity measured with time-resolved BLS during the MG sequence. Within the direct excitation band, the response follows the input frequencies. More importantly, strong signals also appear in the frequency range from 2 to 5.5 GHz due to nonlinear three-magnon splitting. This intrinsic nonlinear mode coupling is essential for the MSR's performance. The nonlinearity not only depends on the system's history and provides a unique fingerprint of the dynamic state in which the system is evolving, but also projects the one-dimensional input into a much higher-dimensional spectral output.

In addition, the enlarged view of the spectrum in Fig. 3(d) highlights that the magnon responses to the microwave excitation signal persist well beyond the 0.6 ns input window, contributing to the fading memory. These two features—nonlinear expansion and memory—are the fundamental ingredients for reservoir computing.

To define the reservoir states, the BLS intensity is integrated within each 0.6 ns input window across the entire frequency range from 2 to 8.8 GHz, covering the directly excited modes as well as the nonlinear response, as displayed in Fig. 3(e). The resulting intensities are assembled into a spectral vector $\vec{X}(t_i)$ for each time step [Fig. 3(f)]. The number of entries $j = 182$ of these intensity vectors is determined by the frequency bin size in the BLS measurement, which is set to 37.5 MHz. Concatenation of all vectors yields the reservoir state matrix $\mathbf{X}$, which represents the nonlinear transformation of the MG input by our MSR.

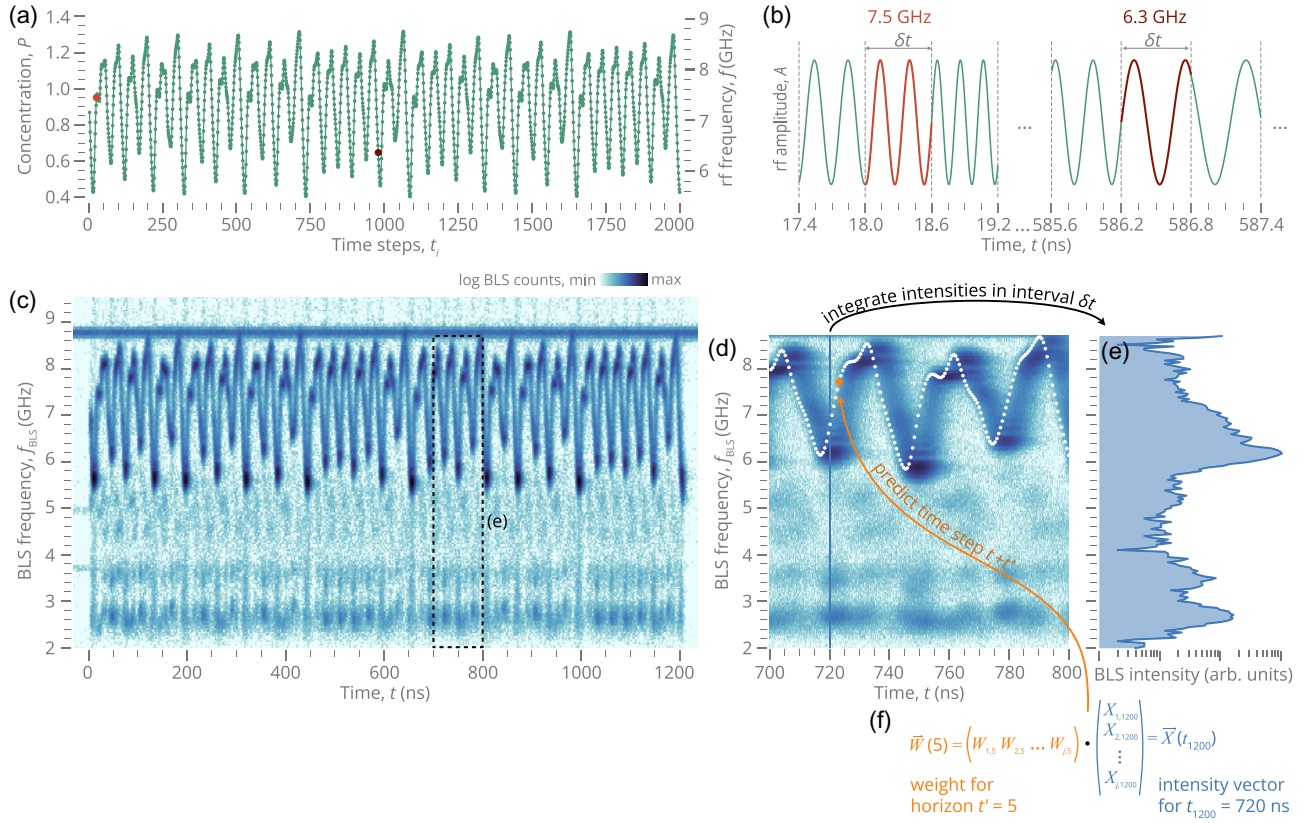


FIG. 3. (a) The Mackey-Glass time series is mapped onto a microwave current using continuous-phase frequency-shift keying. (b) Each microwave frequency is held for a certain time window of $\delta t = 0.6$ ns and injected into the Ω -shaped antenna surrounding the MSR. (c) The time-resolved BLS spectrum reveals both direct responses and nonlinear magnon-magnon scattering, expanding the input into a richer spectral space. (d) Enlarged view of a section of the data from (c). White dots indicate the input frequencies from the arbitrary waveform generator. The measured magnon intensities persist well beyond the direct input window, providing fading memory. (e) The integrated spectral intensities form state vectors that serve as inputs for a linear readout used to generate predictions for a given horizon t' . (f) Definition of intensity vector and weight vector.

D. Training procedure and error metrics

The prediction task was formulated as learning a linear mapping between reservoir states and MG values at a future time step t' ,

$$\vec{y}_{\text{training}}(t') = \vec{W}_{t'} \cdot \mathbf{X} + \text{const.}, \quad (2)$$

with $\vec{y}_{\text{training}}(t') = (P(51 + t'), P(52 + t'), \dots, P(1400 + t'))$ and $\vec{W}_{t'}$ the weight vector trained for each prediction horizon t' . Training and testing sets were created by splitting the MG sequence into nonoverlapping subsets of 1350 ($51 \leq t_i \leq 1400$) and 600 ($1401 \leq t_i \leq 2000$) time steps, discarding the first 50 steps to allow the system to reach steady operation.

The weight vector and constant were found using the LinearRegression model from SCIKIT-LEARN [47], where the model only uses an analytical method to find the suitable parameters without any iterative optimization. This also means that the training time is very short.

To put the MSR's performance into perspective, we follow the same training routine directly on the MG data $P(t_i + t') = w_{t'} P(t_i) + \text{const.}$ with weights $w_{t'}$, assuming a scenario without the MSR projecting the time-series input to the higher-dimensional spectral output space. For this reference task, we use the same learning algorithms as described above.

The prediction performance is quantified by calculating the root mean squared error (RMSE) between the predicted $\hat{y}_i(t')$ and target $y_i(t')$ values:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i(t') - \hat{y}_i(t'))^2}. \quad (3)$$

To allow comparison across different signal amplitudes, the RMSE is normalized to the dynamic range of the MG sequence, yielding the normalized root mean squared error

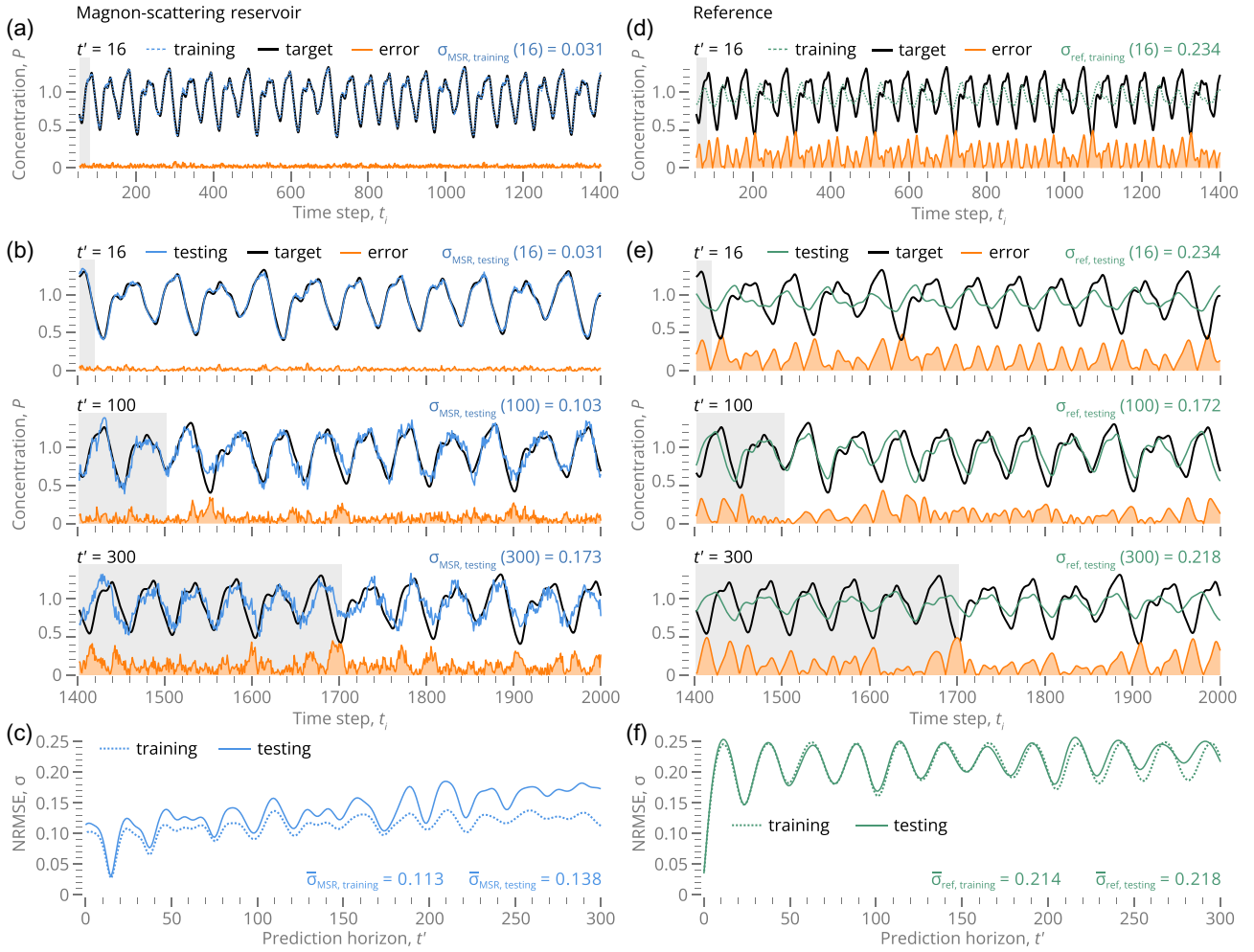


FIG. 4. (a) Training data for the MSR when predicting $t' = 16$ steps into the future, as indicated by the shaded area. (b) Testing results for the MSR for increasing prediction horizon $t' = 16, 100$, and 300 steps, as indicated by shaded areas. (c) Normalized root mean squared error (NRMSE) as a function of prediction horizon t' , comparing training (dotted) and testing (solid). Viable forecasts are achieved even up to 300 steps, demonstrating long-range prediction performance. (d) Training data of the reference prediction task without MSR when predicting $t' = 16$ steps into the future. (e) Testing results without the MSR for increasing prediction horizon $t' = 16, 100$, and 300 steps. (f) NRMSE as a function of prediction horizon t' , comparing training (dotted) and testing (solid) for the reference task. Note that in (a), (b), (d), and (e) the displayed errors correspond to the deviation of the training and testing outputs from the target Mackey-Glass (MG) data and are therefore larger than the NRMSE shown in the lower panels.

(NRMSE):

$$\text{NRMSE} = \sigma(t') = \frac{\text{RMSE}}{y_{\max} - y_{\min}}. \quad (4)$$

A smaller NRMSE indicates higher predictive accuracy. For each prediction horizon t' , the error is computed separately for the training and testing sets to monitor potential overfitting. In addition, the mean prediction error $\bar{\sigma}$ is defined as the average NRMSE over all tested horizons from $t' = 1$ to 300 steps,

$$\bar{\sigma} = \frac{1}{300} \sum_{t'=1}^{300} \sigma(t'), \quad (5)$$

providing a single figure of merit for overall forecasting performance.

III. RESULTS

For reliable forecasting, monitoring the training convergence is essential, as exemplarily shown in Fig. 4(a) for a horizon $t' = 16$.

Figure 4(b) shows successful forecasts for $t' = 16, 100$, and 300 steps, with errors increasing gradually with horizon length. Determining an average NRMSE for each prediction horizon t' , as plotted in Fig. 4(c), shows that the error remains low, even when the MSR predicts 300 steps into the future. The results for the reference task are summarized in Figs. 4(d)–4(f). Overall, the errors remain well

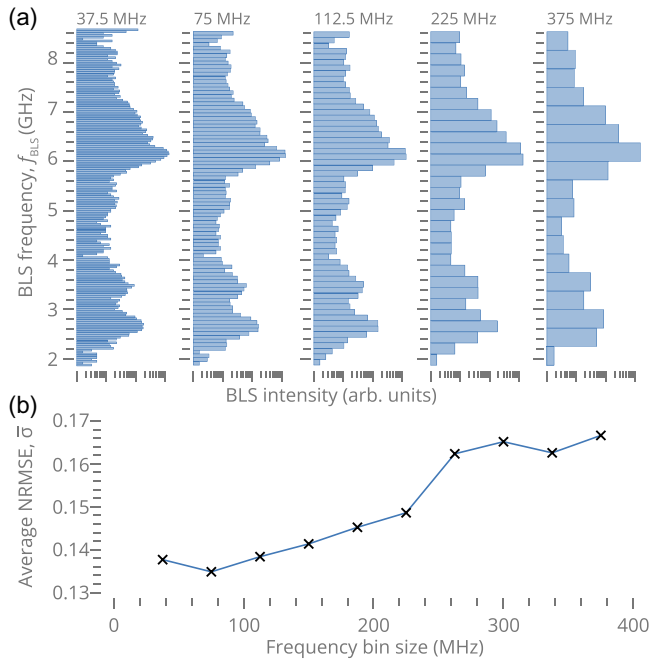


FIG. 5. (a) BLS spectra extracted with different frequency bin sizes. (b) Average NRMSE as a function of bin size, showing an optimal performance at twice the natural BLS spectral resolution. Excessive binning reduces spectral richness and degrades forecasting accuracy.

above those achieved with the MSR across all prediction horizons.

As mentioned before, the dimensionality of the reservoir state is determined by the frequency bin size of the BLS output. Allowing the systematic evaluation of the trade-off between feature richness and regression complexity, we applied additional binning to the spectra and, thereby, to the intensity state vectors, effectively reducing the number of features per time step as shown in Fig. 5(a). Within each frequency bin, the detected BLS intensity is averaged. Smaller state dimensions simplify the regression task by lowering the number of trainable parameters, which can improve stability during training and mitigate overfitting for limited datasets. This can be seen in Fig. 5(b) when doubling the bin size from the BLS inherent 37.5 MHz bins to 75 MHz.

However, excessive binning discards spectral detail, thereby reducing the richness of the nonlinear mapping and degrading prediction performance. We find that moderate binning yields a favorable compromise between computational efficiency and accuracy, whereas large bin sizes significantly diminish the forecasting horizon. This highlights the importance of tuning the reservoir dimensionality to balance training efficiency and predictive power.

Thus far, our predictions were obtained from a single 50-nm-thick and 5- μm -wide vortex-state MSR. To explore how reservoir richness influences performance, we extend

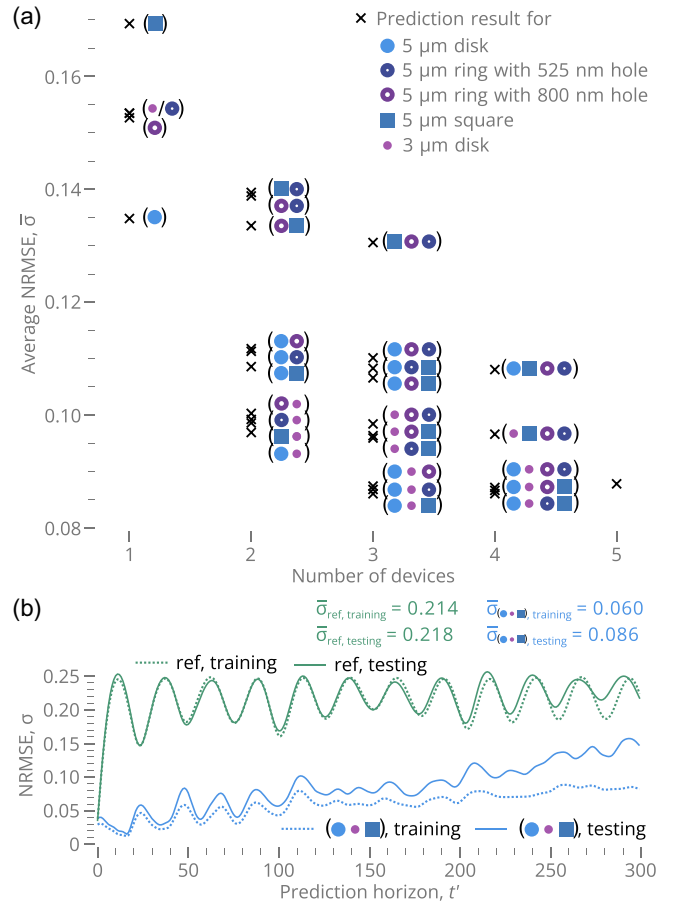


FIG. 6. (a) Average NRMSE for different MSR geometries and their combinations. Appending outputs from multiple devices systematically reduces error, showing that greater reservoir depth enhances forecasting performance. (b) NRMSE as a function of prediction horizon t' , comparing training (dotted) and testing (solid) for the optimum combination of devices and the reference task.

the approach including four other distinct device geometries, all excited via Ω -shaped antennas: a 3- μm -diameter disk, two rings of 5 μm outer diameter with hole widths of 525 nm and 800 nm, and a 5 μm square. On the one hand, additional geometries were chosen similar to the previously studied 5 μm disk to yield adequate nonlinear response when excited with microwave currents in the same frequency range. On the other hand, adding smaller disks and other shapes increased diversity. However, we want to point out that the choice of additional geometries was not optimized yet but already demonstrates the feasibility of increasing the reservoir complexity.

The input waveform was identical across devices, designed based on the spectral properties of the 5 μm disk, and the outputs were measured using the same BLS setup (see Appendix A, Fig. 8 for the temporal responses of the other devices).

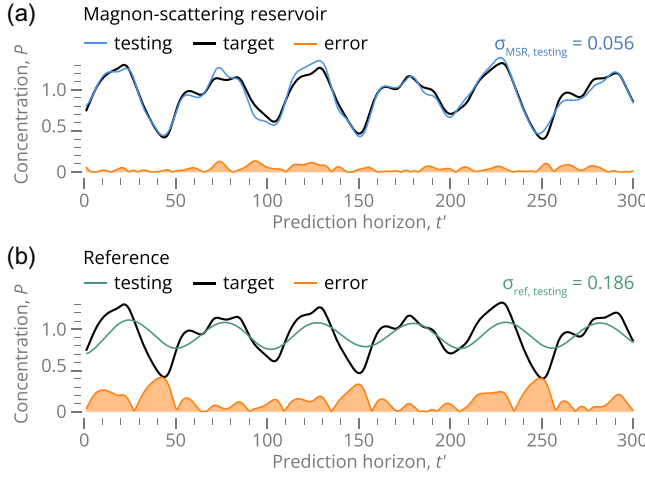


FIG. 7. (a) Predicting 300 steps of the MG series directly from one unseen spectrum of the MSR by concatenating 300 individually trained prediction models into a single weight matrix. This approach yields consistently low errors across all horizons. (b) In stark contrast, models trained only on MG data show much lower accuracy.

To construct an enlarged reservoir state, the frequency-intensity vectors (with 75 MHz binning) from different geometries were combined, forming larger state vectors $\vec{X}(t_i)$. The same training and testing protocol was applied, enabling direct comparison of predictive performance across different reservoir depths. As summarized in Fig. 6(a), prediction performance improves with the number of devices included. In particular, the combination of the 3 μm and 5 μm disks with the 5 μm square yields the lowest NRMSE across the entire prediction horizon, as highlighted in Fig. 6(b). The average NRMSE for this device combination is 0.07, which corresponds to a mean square error of 0.004. This is well below values reported for artificial spin ice systems (NRMSE 0.1758 in Ref. [48] and MSE 0.0155 in Ref. [49]).

Ultimately, we concatenate the 300 individually trained prediction models $\vec{W}_t$ for the optimal device combination (3 μm and 5 μm disks with the 5 μm square) into a single weight matrix $\mathbf{W}$. This allows forecasting up to 300 future steps directly from one unseen spectrum $\vec{X}(t_i = 1401)$,

$$\vec{y}_{\text{testing}} = \mathbf{W} \cdot \vec{X}(1401) + \text{const.}, \quad (6)$$

with $\vec{y}_{\text{testing}} = (P(1402), P(1403), \dots, P(1701))$. As shown in Fig. 7(a), this approach yields consistently low errors, much lower compared to the reference prediction model without the magnon reservoir plotted in Fig. 7(b).

Beyond enhancing accuracy, this approach also changes the prediction paradigm. Instead of relying on long sequences of MG input data, the concatenated models extrapolate far into the future from a single reservoir state. This ability to forecast hundreds of steps from a single

reservoir state underscores the richness of the magnonic representation and illustrates a fundamentally new prediction paradigm, where the future trajectory can be reconstructed from a single snapshot rather than a continuous input stream.

IV. DISCUSSION AND OUTLOOK

Our results demonstrate that a magnon-scattering reservoir can reliably forecast the Mackey-Glass time series over hundreds of time steps, establishing magnons as a viable substrate for physical reservoir computing. A prediction horizon of $t' = 300$ corresponds to approximately six full oscillation cycles of the Mackey-Glass sequence, indicating that the magnon reservoir can reliably capture long-term variations, substantially exceeding previously demonstrated magnetic reservoirs based on artificial spin-ice arrays [18,49,50], which achieved short-term prediction over one to two characteristic cycles with comparable errors. This improvement arises from the continuous, gigahertz-frequency dynamics of magnons, which provide both stronger nonlinearity and intrinsic fading memory on nanosecond timescales [34].

Beyond benchmarking on the Mackey-Glass system, the intrinsic properties of magnons suggest several directions for future exploration. First, strong nonlinear interactions and long-lived excitations provide a natural resource for tackling tasks that require both high-dimensional feature spaces and fading memory, such as speech recognition or real-time sensor data processing. Second, the frequency-tunable nature of magnons opens pathways toward multiplexing and parallelism, potentially enabling multichannel prediction on the same chip. Third, compatibility with CMOS processes points toward scalable integration, where arrays of magnetic microdisks could be cofabricated with conventional electronics.

An additional design principle emerges from our analysis of spectral binning. While reducing dimensionality can simplify training and lower computational cost, excessive compression comes at the expense of predictive accuracy. This tradeoff underscores the importance of tailoring the effective state dimension of the reservoir to the specific task at hand. In scalable architectures, such control could be realized by dynamically adjusting spectral resolution or by combining multiple reservoirs with complementary dimensionalities. More broadly, this highlights that both the physical substrate and the way its output is encoded play a crucial role in optimizing performance.

From a broader perspective, our work connects nonlinear magnetism with machine learning and neuromorphic computing, demonstrating how fundamental spin-wave physics can be leveraged for tasks traditionally reserved for artificial neural networks. The demonstrated ability to map a simple one-dimensional input into a rich spectral output illustrates how magnonic devices can function as

compact, intrinsically energy-efficient reservoirs, where nonlinear transformation and memory emerge naturally from low-loss spin dynamics instead of being emulated through large numbers of active electronic elements. Looking ahead, combining magnon reservoirs with other spintronic or photonic elements may yield hybrid architectures that exploit the strengths of multiple substrates. Such advances could bring physical reservoir computing closer to deployment in edge devices, where real-time prediction and low power consumption are critical.

In summary, the use of magnons for chaotic time-series prediction highlights the potential of magnonics as a platform for unconventional computing. By uniting the fields of nonlinear dynamics, magnetism, and machine learning, this approach opens new avenues for scalable, real-time information processing in both scientific and technological contexts.

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H.S. and K.S. conceptualized the work presented. M.K., J.F., H.S., and K.S. acquired funding. F.K. and K.S. fabricated the sample. Z.X., C.H., and T.D. conducted the experiments. Z.X. and C.H. analyzed the data. Z.X., H.S., and K.S. visualized the results. Z.X. and K.S. wrote the original draft of the paper. All authors reviewed and edited the paper.

The authors have no conflicts of interest to disclose.

DATA AVAILABILITY

The data that support the findings of this article are openly available [51]. Embargo periods may apply.

APPENDIX A: TIME-RESOLVED BLS SPECTRA FOR DIFFERENT GEOMETRIES

To increase the reservoir dimensionality, we input the same frequency-modulated MG data into five different devices: two disks of 5 μm and 3 μm diameter, two rings of 5 μm outer diameter with hole widths of 525 nm and 800 nm, and a 5 μm square. Scanning electron microscopy images of all devices are shown in Figs. 8(a)–8(e).

On each individual device we recorded time-resolved BLS spectra, integrated over multiple scan positions. The spectra are plotted in Figs. 8(f)–8(j). Since the frequency range for the MG input was designed to yield the maximum nonlinear response for the 5 μm disk, the spectra for other devices show less nonlinearity, the more their geometry diverges from the 5 μm disk. This also explains why the 5 μm disk gives the best accuracy among all individual predictions [Fig. 6(a)].

APPENDIX B: INFLUENCE OF INPUT DURATION

The MSR's response to the MG sequence clearly depends on the timescale with which the frequency-modulated microwave current is applied. Therefore, we test different signal durations δt between 0.2 ns and 1 ns to find the timescale optimal for future prediction. The resulting time-resolved BLS spectra are summarized in Fig. 9. By comparing NRMSE values for different time windows, best results are obtained for 0.6 ns. This relates to the balance between reaction time, given by the onset of nonlinearity, and memory capacity in our system, mostly determined by the intrinsic magnon lifetime.

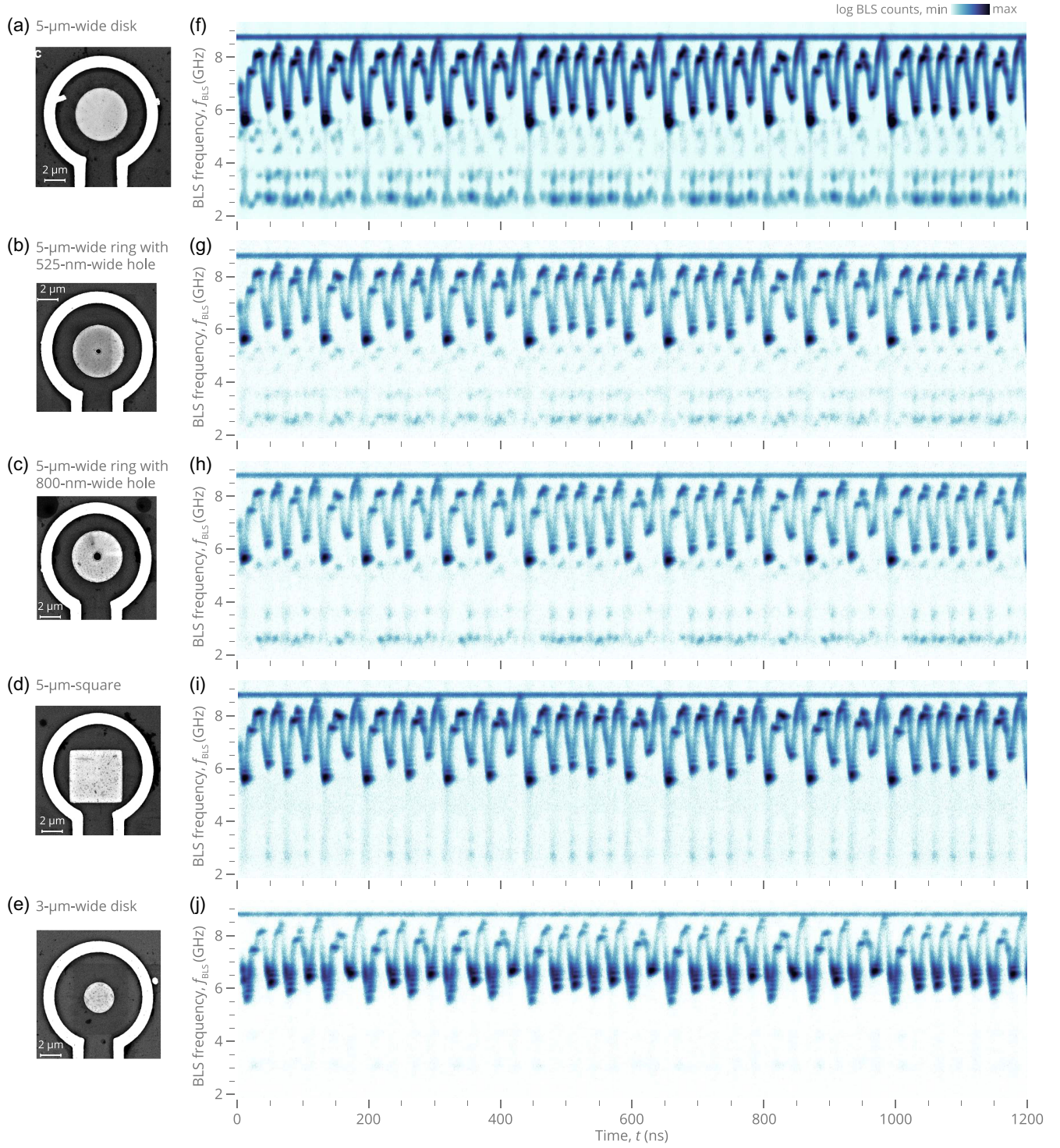


FIG. 8. (a)–(e) Scanning electron microscopy images of magnon reservoirs with different geometries. (f)–(j) Time-resolved BLS spectra measuring the different reservoirs’ response to the complex MG time-series sequence. The nonlinear response recorded for BLS frequencies between 2 and 5.5 GHz gets weaker the more the geometry diverts from the 5- μm -diameter disk. This is to be expected since the frequency range for the microwave current inputting the MG sequence was optimized to address the fundamental modes in the 5- μm -diameter disk.

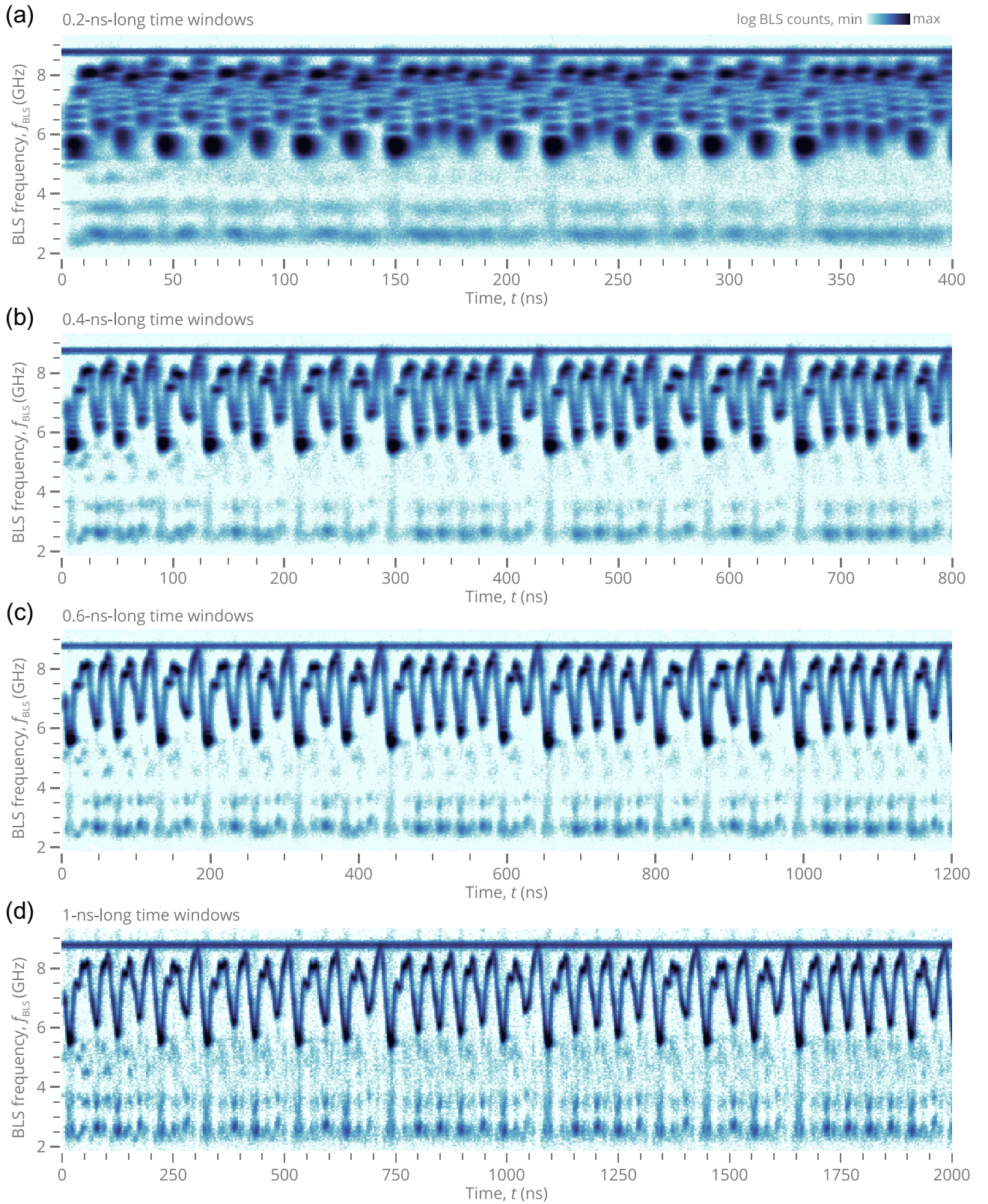


FIG. 9. Time-resolved BLS spectra measured for the MG sequence encoded using different time windows δt of (a) 0.2 ns, (b) 0.4 ns, (c) 0.6 ns, and (d) 1 ns. The 0.2-ns-long input is too fast to allow the magnon system to evolve a clear dynamic response. With increasing δt , more nonlinear scattering sets in. However, if signals are too long, they have less overlap with past data due to the limited lifetime of magnons. Thus, a balance between system response and enough data overlap has to be found. By comparing their average NRMSE values without binning, we determined $\delta t = 0.6$ ns to be the best duration for inputting the microwave current via continuous-phase frequency-shift keying.

- [1] W. Maass, T. Natschläger, and H. Markram, Real-time computing without stable states: A new framework for neural computation based on perturbations, *Neural Comput.* **14**, 2531 (2002).
- [2] L. Appeltant, M. C. Soriano, G. Van der Sande, J. Danckaert, S. Massar, J. Dambre, B. Schrauwen, C. R. Mirasso, and I. Fischer, Information processing using a single dynamical node as complex system, *Nat. Commun.* **2**, 468 (2011).
- [3] D. V. Christensen *et al.*, 2022 roadmap on neuromorphic computing and engineering, *Neuromorph. Comput. Eng.* **2**, 022501 (2022).
- [4] F. Duport, B. Schneider, A. Smerieri, M. Haelterman, and S. Massar, All-optical reservoir computing, *Opt. Express* **20**, 22783 (2012).
- [5] G. Van Der Sande, D. Brunner, and M. C. Soriano, Advances in photonic reservoir computing, *Nanophotonics* **6**, 561 (2017).
- [6] Y. K. Chembo, Machine learning based on reservoir computing with time-delayed optoelectronic and photonic systems, *Chaos: Interdisc. J. Nonlinear Sci.* **30**, 013111 (2020).
- [7] M. Yan, C. Huang, P. Bienstman, P. Tino, W. Lin, and J. Sun, Emerging opportunities and challenges for the future of reservoir computing, *Nat. Commun.* **15**, 2056 (2024).
- [8] C. Du, F. Cai, M. A. Zidan, W. Ma, S. H. Lee, and W. D. Lu, Reservoir computing using dynamic memristors for temporal information processing, *Nat. Commun.* **8**, 2204 (2017).
- [9] J. Moon, W. Ma, J. H. Shin, F. Cai, C. Du, S. H. Lee, and W. D. Lu, Temporal data classification and forecasting using a memristor-based reservoir computing system, *Nat. Electron.* **2**, 480 (2019).
- [10] Y. Zhong, J. Tang, X. Li, B. Gao, H. Qian, and H. Wu, Dynamic memristor-based reservoir computing for high-efficiency temporal signal processing, *Nat. Commun.* **12**, 408 (2021).
- [11] Y. Zhong, J. Tang, X. Li, X. Liang, Z. Liu, Y. Li, Y. Xi, P. Yao, Z. Hao, B. Gao, H. Qian, and H. Wu, A memristor-based analogue reservoir computing system for real-time and power-efficient signal processing, *Nat. Electron.* **5**, 672 (2022).
- [12] T. Kanao, H. Suto, K. Mizushima, H. Goto, T. Tanamoto, and T. Nagasawa, Reservoir computing on spin-torque oscillator array, *Phys. Rev. Appl.* **12**, 024052 (2019).
- [13] S. Tsunegi, T. Taniguchi, K. Nakajima, S. Miwa, K. Yakushiji, A. Fukushima, S. Yuasa, and H. Kubota, Physical reservoir computing based on spin torque oscillator with forced synchronization, *Appl. Phys. Lett.* **114**, 164101 (2019).
- [14] D. Marković, N. Leroux, M. Riou, F. Abreu Araujo, J. Torreon, D. Querlioz, A. Fukushima, S. Yuasa, J. Trastoy, P. Bortolotti, and J. Grollier, Reservoir computing with the frequency, phase, and amplitude of spin-torque nano-oscillators, *Appl. Phys. Lett.* **114**, 012409 (2019).
- [15] T. Yamaguchi, N. Akashi, K. Nakajima, H. Kubota, S. Tsunegi, and T. Taniguchi, Step-like dependence of memory function on pulse width in spintronics reservoir computing, *Sci. Rep.* **10**, 19536 (2020).
- [16] T. Taniguchi, A. Ogihara, Y. Utsumi, and S. Tsunegi, Spintronic reservoir computing without driving current or magnetic field, *Sci. Rep.* **12**, 10627 (2022).
- [17] N. Akashi, Y. Kuniyoshi, S. Tsunegi, T. Taniguchi, M. Nishida, R. Sakurai, Y. Wakao, K. Kawashima, and K. Nakajima, A coupled spintronics neuromorphic approach for high-performance reservoir computing, *Adv. Intell. Syst.* **4**, 2200123 (2022).
- [18] J. C. Gartside, K. D. Stenning, A. Vanstone, H. H. Holder, D. M. Arroo, T. Dion, F. Caravelli, H. Kurebayashi, and W. R. Branford, Reconfigurable training and reservoir computing in an artificial spin-vortex ice via spin-wave fingerprinting, *Nat. Nanotechnol.* **17**, 460 (2022).
- [19] D. A. Allwood, M. O. A. Ellis, D. Griffin, T. J. Hayward, L. Manneschi, M. F. K. Musameh, S. O'Keefe, S. Stepney, C. Swindells, M. A. Trefzer, E. Vasilaki, G. Venkat, I. Vidamour, and C. Wringe, A perspective on physical reservoir computing with nanomagnetic devices, *Appl. Phys. Lett.* **122**, 040501 (2023).
- [20] J. H. Jensen, A. Strømberg, I. Breivik, A. Penty, M. A. Niño, M. W. Khaliq, M. Foerster, G. Tufte, and E. Folven, Clocked dynamics in artificial spin ice, *Nat. Commun.* **15**, 964 (2024).
- [21] J. Zázvorka, F. Jakobs, D. Heinze, N. Keil, S. Kromin, S. Jaiswal, K. Litzius, G. Jakob, P. Virnau, D. Pinna, K. Everschor-Sitte, L. Rózsa, A. Donges, U. Nowak, and M. Kläui, Thermal skyrmion diffusion used in a reshuffler device, *Nat. Nanotechnol.* **14**, 658 (2019).
- [22] D. Pinna, G. Bourianoff, and K. Everschor-Sitte, Reservoir Computing with Random Skyrmion Textures, *Phys. Rev. Appl.* **14**, 054020 (2020).
- [23] Y. Sun *et al.*, Experimental demonstration of a skyrmion-enhanced strain-mediated physical reservoir computing system, *Nat. Commun.* **14**, 3434 (2023).
- [24] O. Lee, R. Msiska, M. A. Brems, M. Kläui, H. Kurebayashi, and K. Everschor-Sitte, Perspective on unconventional computing using magnetic skyrmions, *Appl. Phys. Lett.* **122**, 260501 (2023).
- [25] G. Beneke, T. B. Winkler, K. Raab, M. A. Brems, F. Kammerbauer, P. Gerhards, K. Knobloch, S. Krishnia, J. H. Mentink, and M. Kläui, Gesture recognition with Brownian reservoir computing using geometrically confined skyrmion dynamics, *Nat. Commun.* **15**, 1 (2024).
- [26] R. Nakane, G. Tanaka, and A. Hirose, Reservoir computing with spin waves excited in a garnet film, *IEEE Access* **6**, 4462 (2018).
- [27] A. Papp, G. Csaba, and W. Porod, Characterization of nonlinear spin-wave interference by reservoir-computing metrics, *Appl. Phys. Lett.* **119**, 112403 (2021).
- [28] M.-K. Lee and M. Mochizuki, Reservoir computing with spin waves in a skyrmion crystal, *Phys. Rev. Appl.* **18**, 014074 (2022).
- [29] R. Nakane, A. Hirose, and G. Tanaka, Performance enhancement of a spin-wave-based reservoir computing system utilizing different physical conditions, *Phys. Rev. Appl.* **19**, 034047 (2023).
- [30] W. Namiki, D. Nishioka, Y. Yamaguchi, T. Tsuchiya, T. Higuchi, and K. Terabe, Experimental demonstration of

- high-performance physical reservoir computing with non-linear interfered spin wave multidetection, *Adv. Intell. Syst.* **5**, 2300228 (2023).
- [31] S. Nagase, S. Nezu, and K. Sekiguchi, Spin-wave reservoir chips with short-term memory for high-speed estimation of external magnetic fields, *Phys. Rev. Appl.* **22**, 024072 (2024).
- [32] W. Namiki, D. Nishioka, T. Tsuchiya, and K. Terabe, Fast physical reservoir computing, achieved with nonlinear interfered spin waves, *Neuromorph. Comput. Eng.* **4**, 024015 (2024).
- [33] L. Körber, C. Heins, T. Hula, J.-V. Kim, S. Thlang, H. Schultheiss, J. Fassbender, and K. Schultheiss, Pattern recognition in reciprocal space with a magnon-scattering reservoir, *Nat. Commun.* **14**, 3954 (2023).
- [34] C. Heins, J.-V. Kim, L. Körber, J. Fassbender, H. Schultheiss, and K. Schultheiss, Benchmarking a magnon-scattering reservoir with modal and temporal multiplexing, *Phys. Rev. Appl.* **23**, 054087 (2025).
- [35] R. P. Cowburn, D. K. Koltsov, A. O. Adeyeye, M. E. Welland, and D. M. Tricker, Single-domain circular nanomagnets, *Phys. Rev. Lett.* **83**, 1042 (1999).
- [36] W. Scholz, K. Y. Guslienko, V. Novosad, D. Suess, T. Schrefl, R. W. Chantrell, and J. Fidler, Transition from single-domain to vortex state in soft magnetic cylindrical nanodots, *J. Magn. Magn. Mater.* **266**, 155 (2003).
- [37] T. Sebastian, K. Schultheiss, B. Obry, B. Hillebrands, and H. Schultheiss, Micro-focused Brillouin light scattering: imaging spin waves at the nanoscale, *Front. Phys.* **3**, 35 (2015).
- [38] R. Mock, B. Hillebrands, and R. Sandercock, Construction and performance of a Brillouin scattering set-up using a triple-pass tandem Fabry-Perot interferometer, *J. Phys. E: Sci. Instr.* **20**, 656 (1987).
- [39] O. Lozhkina, F. Kammerbauer, M.-A. Syskaki, A. Puthirath Balan, P. Krautscheid, M. V. Khanjani, J. Kubik, S. O'Brien, R. M. Reeve, G. Jakob, R. Frömter, and M. Kläui, Tailoring magnetic properties and suppressing anisotropy in permalloy films by deposition in a rotating magnetic field, *Phys. Rev. Appl.* **20**, 014021 (2023).
- [40] M. Buess, T. P. J. Knowles, R. Höllinger, T. Haug, U. Krey, D. Weiss, D. Pescia, M. R. Scheinfein, and C. H. Back, Excitations with negative dispersion in a spin vortex, *Phys. Rev. B* **71**, 104415 (2005).
- [41] K. Vogt, O. Sukhostavets, H. Schultheiss, B. Obry, P. Pirro, A. A. Serga, T. Sebastian, J. Gonzalez, K. Y. Guslienko, and B. Hillebrands, Optical detection of vortex spin-wave eigenmodes in microstructured ferromagnetic disks, *Phys. Rev. B* **84**, 174401 (2011).
- [42] K. Schultheiss, R. Verba, F. Wehrmann, K. Wagner, L. Körber, T. Hula, T. Hache, A. Kákay, A. A. Awad, V. Tiberkevich, A. N. Slavin, J. Fassbender, and H. Schultheiss, Excitation of whispering gallery magnons in a magnetic vortex, *Phys. Rev. Lett.* **122**, 097202 (2019).
- [43] R. Verba, L. Körber, K. Schultheiss, H. Schultheiss, V. Tiberkevich, and A. Slavin, Theory of three-magnon interaction in a vortex-state magnetic nanodot, *Phys. Rev. B* **103**, 014413 (2021).
- [44] M. C. Mackey and L. Glass, Oscillation and chaos in physiological control systems, *Science* **197**, 287 (1977).
- [45] C. Wringe, M. Trefzer, and S. Stepney, Reservoir computing benchmarks: a tutorial review and critique, *Int. J. Parallel Emergent Distrib. Syst.* **40**, 313 (2025).
- [46] H.-P. H. Chaoming Wang and Sichao He, Brainpy, 2022, https://github.com/brainpy/examples/blob/main/classical_dynamical_systems/mackey_glass_eq.ipynb
- [47] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, Scikit-learn: Machine learning in Python, *J. Mach. Learn. Res.* **12**, 2825 (2011).
- [48] W. Hu, Z. Zhang, Y. Liao, Q. Li, Y. Shi, H. Zhang, X. Zhang, C. Niu, Y. Wu, W. Yu, X. Zhou, H. Guo, W. Wang, J. Xiao, L. Yin, Q. Liu, and J. Shen, Distinguishing artificial spin ice states using magnetoresistance effect for neuromorphic computing, *Nat. Commun.* **14**, 2562 (2023).
- [49] K. D. Stenning, J. C. Gartside, L. Manneschi, C. T. S. Cheung, T. Chen, A. Vanstone, J. Love, H. Holder, F. Caravelli, H. Kurebayashi, K. Everschor-Sitte, E. Vasilaki, and W. R. Branford, Neuromorphic overparameterisation and few-shot learning in multilayer physical neural networks, *Nat. Commun.* **15**, 7377 (2024).
- [50] O. Lee, T. Wei, K. D. Stenning, J. C. Gartside, D. Prestwood, S. Seki, A. Aqeel, K. Karube, N. Kanazawa, Y. Taguchi, C. Back, Y. Tokura, W. R. Branford, and H. Kurebayashi, Task-adaptive physical reservoir computing, *Nat. Mater.* **23**, 79 (2024).
- [51] Z. Xiong, C. Heins, T. Devolder, F. Kammerbauer, M. Kläui, J. Fassbender, H. Schultheiss, and K. Schultheiss, Data publication: Predicting the future with magnons (2025).