Digital Twin of Stochastic FitzHugh-Nagumo System: Coherence Resonance under Lévy Noise Driving

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***Abstract*—A digital twin of a stochastic system has to reproduce the statistics of its original rather than any single trajectory of it. We examine this requirement for a FitzHugh-Nagumo neuron driven by symmetric alpha-stable Levy noise with stability index 1.6. The twin is a reservoir computing network trained at a single noise scale and then run semi-autonomously, the true realization of the noise being supplied to it while both state variables are replaced by its own output. Across eighteen test intensities spanning a fifty-fold range, the twin reproduces the coherence resonance curve of the neuron: the coherence mismatch stays below the weak prediction threshold at all but the strongest forcing, whereas trajectory tracking succeeds only within a band around the training intensity. Outside that band the prediction fails intermittently, and laminar phase durations follow a power law of exponent -1.46, consistent with the on-off scenario and close to the value known for Gaussian driving.**

***Index Terms*—reservoir computing, digital twin, coherence resonance, Levy noise, FitzHugh-Nagumo neuron, on-off intermittency, stochastic prediction**

I. Introduction

A digital twin is a model that runs alongside its original, evolves on its own and reproduces the behavior of that original closely enough to be used for monitoring, forecasting and virtual intervention. For nonlinear dynamical systems, two routes to building such a model are usually distinguished, sparse optimization of the governing equations and machine learning of the flow directly from data [1]. Recent surveys place the concept at the meeting point of complexity theory and machine learning and review the mathematical machinery available for building such twins, from physics-informed neural networks and reduced-order models to graph neural networks and reservoir computing [2]. Reservoir computing (RC) is well matched to the second route: the trained network advances its own state without requiring further state input, which is precisely the requirement a digital twin has to meet, and RC twins have been shown to extrapolate to parameter regimes never encountered during training, to keep working under changing external driving and to infer variables that were never measured [3]. A twin left to run on its own nevertheless drifts away from a chaotic original over long horizons, and the cost of holding it on track has been quantified for the Lorenz system, where injecting real-time measurements on a sparse schedule keeps the error low at a few updates per hundred steps [4]. The same idea has entered neuroscience, both as personalized generative whole-brain models built from individual data [5] and as RC-based in silico replicas of measured brain activity [6]. Next-generation reservoir computing recovers corrupted EEG channels from the remaining ones more accurately than spherical spline interpolation, and its margin widens as the recordings become noisier [7]; choosing the delay vectors of such a network from the temporal structure of the signal itself further allows hidden states to be recovered and chaotic dynamics to be forecast with little tuning [8].

Building a digital twin of a neuron differs from the deterministic case in one essential respect: the original is stochastic, no single trajectory can be tracked indefinitely, and the twin must therefore be faithful to the statistics of the original rather than to any one of its realizations. For an excitable neuron the statistical signature of interest is coherence resonance, the non-monotonic dependence of spiking regularity on the

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intensity of the driving noise, quantified by the coefficient of variation of the interspike intervals [9]. When the driving is not Gaussian but α-stable, this signature is reshaped rather than destroyed: the stability index and the skewness of the Lévy noise decide whether noise-induced coherence is enhanced or suppressed, as established numerically and confirmed on an electronic circuit [10], and resonance-like ordering under α-stable forcing has also been reported with respect to the size of coupled FitzHugh-Nagumo (FHN) ensembles [11]. Heavy-tailed forcing is more than a mathematical generalization [12]: rare large-amplitude events are a defining feature of real neurophysiological recordings, to the point that extreme value theory has been adopted as the working principle of seizure detection [13]. A digital twin of an excitable neuron thus has to stay trustworthy under a forcing whose increments are occasionally very large.

What is currently known about RC twins of stochastic FHN neurons has been obtained for Gaussian driving. A reservoir trained at a single noise intensity was shown to recover the whole coherence resonance curve of the neuron [14]. This ability was subsequently separated into two distinct notions, strong prediction, in which the twin follows the trajectory of the original, and weak prediction, in which it only reproduces its statistics, the latter surviving over a considerably wider range of intensities than the former [15]. The same distinction was then carried over to systems observed only in part, where exact cloning of a stochastic system proved attainable only when a deterministic functional relation exists between the external noise and the response of the system [16]. Near the boundary between the two regimes the twin does not degrade smoothly: intervals of accurate tracking alternate with intervals of complete failure, and the statistics of this alternation were shown to correspond to on-off intermittency [17], a scenario long established in nonlinear dynamics [18], [19]. Such a failure mode is natural once RC forecasting is viewed as generalized synchronization between the reservoir and the system it replicates, a viewpoint that also supplies design criteria for the reservoir itself [20], and given that noise-induced synchronization and generalized synchronization have been argued to be one and the same type of synchronous behavior [21]. How far such a twin can be pushed also depends on the reservoir itself: the number of nodes has been shown to control how faithfully both the dynamics and the coherence resonance of a noise-driven FHN neuron are reproduced [22], and a topology built from cliques of varying size improves, among other tasks, the prediction of stochastic neuron dynamics and the reconstruction of EEG signals [23].

Whether these properties survive when the driving noise is heavy-tailed has not been examined. In this work we construct an RC digital twin of an FHN neuron driven by symmetric α-stable Lévy noise with a fixed stability index $\alpha = 1.6$. The twin is trained at a single noise scale and is then tested semi-autonomously, the true realization of the noise being supplied to it while the state variables are replaced by its own output, over 18 values of the noise scale spanning 0.01 to 0.5. We show, first, that the twin reproduces the coherence resonance curve of the original across this whole range, weak prediction holding almost everywhere while strong prediction remains confined to a band around the training intensity, and, second, that outside this band the prediction becomes intermittent, with a laminar phase exponent of -1.46 that is consistent with the on-off scenario and close to the value reported for Gaussian driving.

II. Methods

A. Stochastic FitzHugh-Nagumo Neuron under Lévy Noise

The original system whose twin we build is the FitzHugh-Nagumo (FHN) neuron in its stochastic form,

$$\begin{aligned} \dot{v} &= v - v^3/3 - w + 0.3, \\ \dot{w} &= 0.08\,(v - 0.8w + 0.7) + \xi^{\alpha\sigma}(t), \end{aligned} \tag{1}$$

with v the fast membrane potential variable and w the slow recovery variable. In the absence of the driving term the system is excitable: it possesses a single stable fixed point, and only a perturbation exceeding a finite amplitude produces a spike, so that all spiking considered below is noise induced.

The forcing $\xi^{\alpha\sigma}(t)$ is symmetric α-stable Lévy noise with skewness $\beta = 0$ and location $\mu = 0$, entering the slow equation additively. Its stability index α fixes the weight of the tails and its scale parameter σ the overall intensity. Throughout this work $\alpha = 1.6$ is held fixed and only σ is varied, so that the driving law always has infinite variance and produces rare large-amplitude increments.

The system was integrated with the Euler-Heun scheme at a step $\Delta t = 10^{-2}$.

B. Reservoir Computing Model

The digital twin is a reservoir of $N = 1002$ nodes whose state evolves as

$$\mathbf{s}_t = \tanh\big(\mathbf{V}\mathbf{z}_t + \mathbf{Q}\mathbf{s}_{t-1}\big), \tag{2}$$

driven by the three-component input $\mathbf{z}_t = [v_t,\, w_t,\, \xi_t^{\alpha\sigma}]^\top$. The input matrix $\mathbf{V} \in \mathbb{R}^{N\times 3}$ is partitioned, each input component feeding exactly $N/3$ nodes and each node receiving exactly one component, with non-zero entries drawn uniformly from $[-1, 1]$. The recurrent matrix $\mathbf{Q}$ is a sparse Erdős-Rényi graph of mean node degree $\langle k\rangle$, rescaled so that its spectral radius equals λ. These two hyperparameters are the ones optimized in Sec. III-A.

Only the linear readout is trained. It acts on the augmented state $\hat{\mathbf{s}}_t$, obtained from $\mathbf{s}_t$ by squaring its odd components,

$$\tilde{\mathbf{z}}_t = \mathbf{W}\hat{\mathbf{s}}_t, \quad \mathbf{W} = \mathbf{Y}\hat{\mathbf{S}}^\top\big(\hat{\mathbf{S}}\hat{\mathbf{S}}^\top + \eta\mathbf{I}\big)^{-1}, \tag{3}$$

where $\hat{\mathbf{S}}$ collects the augmented states over the training window, $\mathbf{Y}$ the corresponding targets, and $\eta = 10^{-4}$ is the ridge parameter. The targets are $[v_t,\, w_t]^\top$ only, so the readout is two-dimensional while the input is three-dimensional: the twin never predicts the forcing, which is supplied to it externally at every step.

Training used 6×10^5 consecutive steps, of which the first 10^5 were discarded as warmup and the remaining 5×10^5

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entered the ridge regression. Testing began with its own warmup of 10^5 steps, during which all three true variables were fed in. The twin then ran semi-autonomously: the true realization of $\xi_t^{\alpha\sigma}$ continued to be supplied, while v_t and w_t in the input vector were replaced by the twin's own outputs from the previous step. This is response prediction under a known stochastic forcing rather than autonomous forecasting of a stochastic system. The seeds generating $\mathbf{V}$ and $\mathbf{Q}$ were fixed across all runs, and the training and testing noise realizations were drawn from different seeds, so that the twin is always evaluated on forcing it has not seen.

C. Prediction Quality Metrics

Interspike intervals (ISIs) are the differences between consecutive spike times, and their coefficient of variation

$$\mathrm{CV} = \mathrm{std}(\mathrm{ISI})/\mathrm{mean}(\mathrm{ISI}) \tag{4}$$

measures spike coherence. It is the quantity whose non-monotonic dependence on σ constitutes coherence resonance, and it is therefore what the twin has to reproduce.

Two quantities assess the twin at each tested noise scale. Trajectory fidelity is measured by the error on the membrane potential normalized by the peak-to-peak range of the target,

$$\mathrm{NRMSE} = \frac{\sqrt{\frac{1}{M}\sum_{t=1}^{M}\left(v_t - \hat{v}_t\right)^2}}{\max_t v_t - \min_t v_t}, \tag{5}$$

and statistical fidelity by the mismatch of the coherence measure, $|\Delta\mathrm{CV}| = |\mathrm{CV}_{\mathrm{pred}} - \mathrm{CV}_{\mathrm{target}}|$. Following [15], the prediction is called strong when NRMSE ≤ 0.05 and weak when $|\Delta\mathrm{CV}| < 0.05$.

D. Intermittency Analysis

To characterize how the twin fails once it leaves the strong prediction regime, every time step was labelled laminar when $|v_t - \hat{v}_t| \leq \varepsilon_0$ and turbulent otherwise, with $\varepsilon_0 = 0.04$. Laminar phases are the maximal runs of consecutive laminar steps. The distribution $\mathrm{PDF}(L)$ of laminar phase durations was estimated by logarithmic binning between the shortest and the longest observed phase, using 185 bins with counts normalized to a density, and the exponent was taken as the least-squares slope of $\ln \mathrm{PDF}$ against $\ln L$.

III. Results

A. Hyperparameter Optimization

The two reservoir hyperparameters were selected on a grid of $19 \times 10 = 190$ combinations, the mean node degree running over $\langle k \rangle \in \{2, 3, \ldots, 20\}$ and the spectral radius over $\lambda \in \{0.1, 0.2, \ldots, 1.0\}$. Every reservoir on this grid was trained at the single scale $\sigma_{\mathrm{train}} = 0.04$ and then evaluated at three test intensities, $\sigma_{\mathrm{test}} \in \{0.01, 0.04, 0.5\}$, spanning the low, intermediate and high noise regimes, over a prediction horizon of 2×10^5 steps. The selection criterion was the NRMSE of Eq. (5) averaged over the three test intensities, and the optimum was taken as the minimum of that averaged surface.

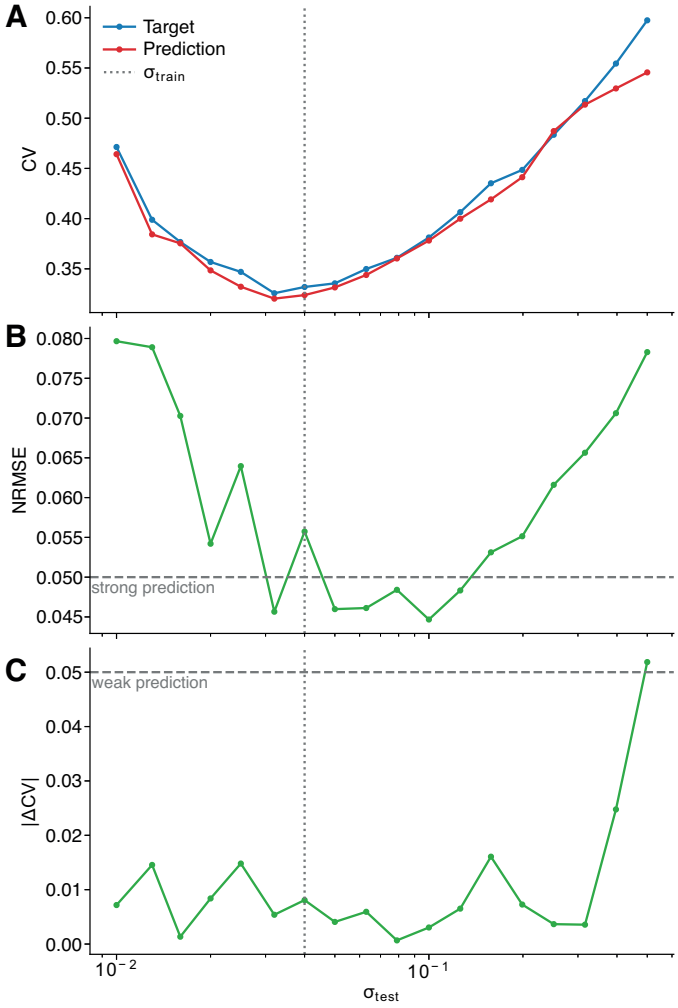


Fig. 1. Reproduction of coherence resonance by the digital twin. All panels share a logarithmic axis of the test noise scale σ_{test}, sampled at 18 points between 0.01 and 0.5; the dotted vertical line marks the training scale $\sigma_{\mathrm{train}} = 0.04$. (A) Coefficient of variation of the interspike intervals for the target neuron and for the twin. (B) NRMSE of the membrane potential, with the dashed line at the strong-prediction threshold 0.05. (C) Coherence mismatch $|\Delta\mathrm{CV}|$, with the dashed line at the weak-prediction threshold 0.05. Reservoir parameters $\langle k \rangle = 16$, $\lambda = 0.3$; stability index $\alpha = 1.6$; prediction horizon 5×10^6 steps.

The grid minimum is $\langle k \rangle^* = 16$ and $\lambda^* = 0.3$, with a mean NRMSE of 0.0710, made up of 0.0512 at $\sigma_{\mathrm{test}} = 0.01$, 0.0265 at $\sigma_{\mathrm{test}} = 0.04$ and 0.1352 at $\sigma_{\mathrm{test}} = 0.5$. The error is by far the smallest at the intensity the twin was trained on and grows towards both edges of the range, most steeply towards the strong-forcing edge. That the selected spectral radius is well below unity is consistent with what heavy-tailed forcing demands of the reservoir: the rare large increments of an α-stable process drive the network far from its operating point, and a strongly contracting reservoir returns to it quickly, whereas a radius near unity would let each such excursion persist.

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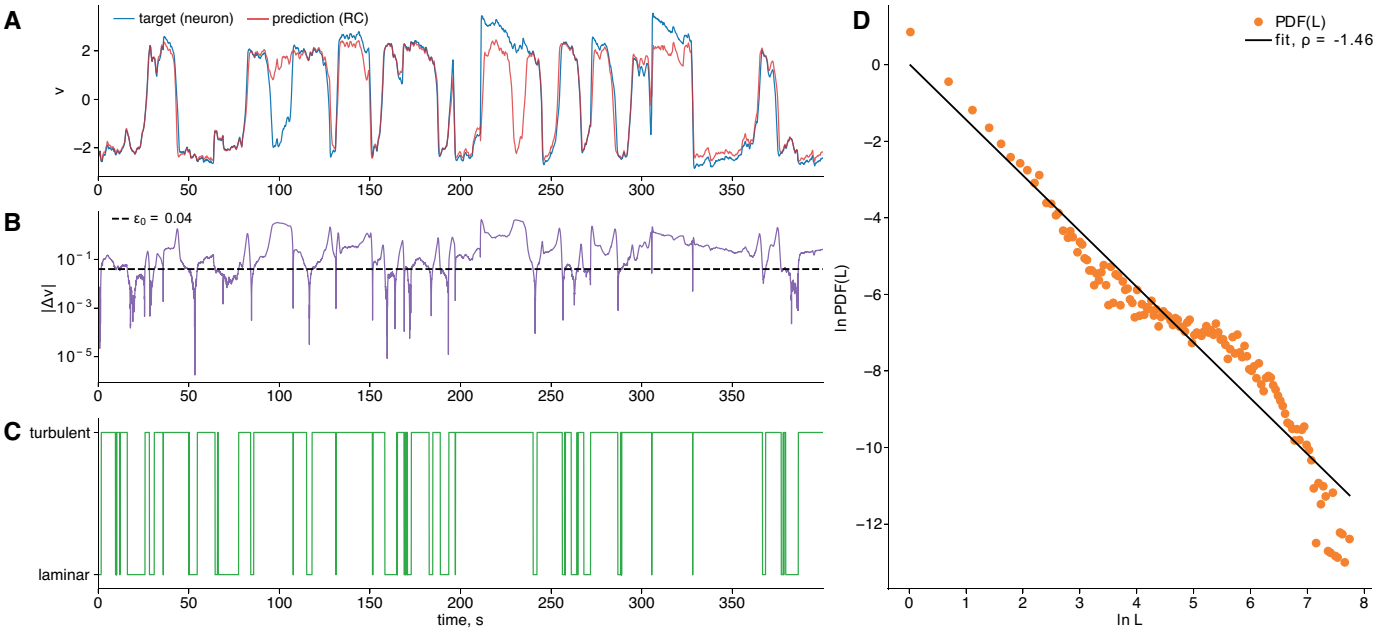


Fig. 2. Intermittency of the prediction at $\sigma_{\text{test}} = 0.5$. Panels (A)–(C) share a common time axis spanning 4×10^4 steps: (A) membrane potential of the target neuron and of the twin; (B) absolute deviation $|\Delta v|$ on a logarithmic scale, with the dashed line at $\varepsilon_0 = 0.04$; (C) the resulting laminar and turbulent labelling. (D) Distribution of laminar phase durations over the full 5×10^6-step record, $\ln \text{PDF}(L)$ against $\ln L$, with a least-squares fit of slope $\rho = -1.46$. Stability index $\alpha = 1.6$, $\sigma_{\text{train}} = 0.04$, $\langle k \rangle = 16$, $\lambda = 0.3$.

B. Reproduction of Coherence Resonance

The optimal twin was then run over a prediction horizon of 5×10^6 steps at 18 test intensities spaced geometrically between $\sigma_{\text{test}} = 0.01$ and $\sigma_{\text{test}} = 0.5$, the long horizon being needed for the ISI statistics to converge. Figure 1 collects the outcome.

The coherence resonance curve itself is reproduced (Fig. 1A). The target CV falls from ≈ 0.47 at the weakest forcing to a minimum of ≈ 0.33 near $\sigma_{\text{test}} \approx 0.03$, immediately adjacent to the training scale, and rises again to ≈ 0.60 at the strongest forcing. The predicted curve follows this shape point by point over the entire range, including both branches that the twin never saw during training; the only systematic departure is a slight underestimate of the CV at the largest intensities, where the twin returns ≈ 0.55 against a target of ≈ 0.60.

The two fidelity measures behave very differently (Fig. 1B and 1C). The NRMSE stays between ≈ 0.045 and ≈ 0.080 and traces a shallow minimum: it is largest at the two edges of the range and drops to its lowest values for intermediate forcing. Its variation from one intensity to the next is not smooth, and the strong-prediction threshold is crossed repeatedly rather than once, the curve running below 0.05 at most intensities between $\sigma_{\text{test}} \approx 0.03$ and ≈ 0.13 but slightly above it at a few of them, the training scale itself included. The boundary of strong prediction is therefore a band rather than a sharp point. The coherence mismatch, in contrast, stays below 0.016 at seventeen of the eighteen intensities, that is at less than a third of the weak-prediction threshold, and exceeds that threshold only at the single largest intensity $\sigma_{\text{test}} = 0.5$, where it reaches 0.052.

The twin is thus statistically faithful over a far wider range of forcing than it is trajectory faithful. Trained at one intensity, it recovers the coherence resonance curve across a fifty-fold range of σ, while following the trajectory itself only within a band around the training scale.

C. Intermittency of Prediction

It remains to ask how the twin behaves outside that band. Figure 2 examines the strongest forcing, $\sigma_{\text{test}} = 0.5$, the one intensity at which even the weak criterion is violated.

The failure is not a uniform loss of accuracy. Over the 4×10^4-step window shown, the predicted and the target membrane potential coincide during some excursions and separate visibly during others, the departures appearing both in the height of the plateaus and in individual spikes (Fig. 2A). The absolute deviation resolves this into two clearly separated states (Fig. 2B): it remains for the most part above $\varepsilon_0 = 0.04$ and drops several orders of magnitude below it in short episodes. At this intensity the twin is turbulent most of the time, and the laminar phases are the brief interruptions.

Over the whole 5×10^6-step record 4976 laminar phases were collected. Their distribution $\text{PDF}(L)$ is close to a power law over durations from a single step up to $\approx 2 \times 10^3$ steps, and the least-squares slope in double logarithmic coordinates is $\rho = -1.46$ (Fig. 2D); the longest phases fall below the fitted line, as expected for a system driven away from the transition. The exponent is close to $-3/2$, the value characteristic of on-off intermittency, and close to the -1.53 reported for the same reservoir architecture predicting a Gaussian-driven neuron [17]. Heavy tails in the forcing therefore do not destroy this failure mode.

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IV. Conclusions

We have built a reservoir computing digital twin of a FitzHugh-Nagumo neuron driven by symmetric α-stable Lévy noise and asked how far the fidelity of that twin extends beyond the conditions it was trained on. Trained at the single scale $\sigma_{\text{train}} = 0.04$ with a fixed stability index $\alpha = 1.6$, the twin reproduces the coherence resonance curve of the original over the whole tested range of intensities: the coherence mismatch stays below a third of the weak-prediction threshold at seventeen of the eighteen tested intensities and exceeds that threshold only at the strongest forcing. Trajectory fidelity is far more fragile and holds only within a band around the training scale. Statistical and trajectory fidelity are therefore not two grades of one quantity but two properties with markedly different ranges of validity, and it is the statistical one that survives extrapolation in σ.

Where trajectory fidelity is lost, it is lost intermittently rather than gradually. At $\sigma_{\text{test}} = 0.5$ the deviation between the twin and its original separates cleanly into laminar and turbulent states, and the durations of the laminar phases follow a power law $\text{PDF}(L) \sim L^{\rho}$ with $\rho = -1.46$, close both to the $-3/2$ of on-off intermittency and to the -1.53 obtained for the same architecture under Gaussian driving [17]. The failure mode known from the Gaussian case thus persists once the forcing acquires heavy tails.

References

[1] Y.-C. Lai, "Digital twins of nonlinear dynamical systems: a perspective," *The European Physical Journal Special Topics*, vol. 233, no. 6, pp. 1391–1399, 2023.

[2] A. V. Andreev, L. S. Daraselya, V. S. Dozhdev, A. V. Shenderyuk-Zhidkov, V. V. Shpak, and A. E. Khramov, "Digital twins: a synthesis of complexity theory and artificial intelligence," *Izvestiya VUZ. Applied Nonlinear Dynamics*, vol. 34, no. 3, pp. 371–419, 2026.

[3] L.-W. Kong, Y. Weng, B. Glaz, M. Haile, and Y.-C. Lai, "Reservoir computing as digital twins for nonlinear dynamical systems," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 33, no. 3, p. 033111, 2023.

[4] S. Tkach and A. Andreev, "State correction via data injection for a reservoir computing-based digital twin of the lorenz system," *The European Physical Journal Special Topics*, pp. 1–10, 2026.

[5] H. E. Wang, P. Triebkorn, M. Breyton, B. Dollomaja, J.-D. Lemarechal, S. Petkoski, P. Sorrentino, D. Depannemaecker, M. Hashemi, and V. K. Jirsa, "Virtual brain twins: from basic neuroscience to clinical use," *National Science Review*, vol. 11, no. 5, p. nwae079, 2024.

[6] G. Di Antonio, T. Gili, A. Gabrielli, and M. Mattia, "Linearizing and forecasting: a reservoir computing route to digital twins of the brain," *Advanced Science*, vol. 13, no. 28, p. e17234, 2026.

[7] A. Badarin, F. Ratnikov, and A. Andreev, "Reconstruction of eeg signals using next-generation reservoir computing," *The European Physical Journal Special Topics*, pp. 1–10, 2026.

[8] A. Badarin, A. Andreev, and A. Hramov, "Hidden data recovery and forecasting via next-generation reservoir computing with multiscale delay selection," *IEEE Transactions on Neural Networks and Learning Systems*, 2026.

[9] A. S. Pikovsky and J. Kurths, "Coherence resonance in a noise-driven excitable system," *Physical Review Letters*, vol. 78, no. 5, pp. 775–778, 1997.

[10] I. Korneev, A. Zakharova, and V. V. Semenov, "Lévy noise-induced coherence resonance: Numerical study versus experiment," *Chaos, Solitons & Fractals*, vol. 184, p. 115037, 2024.

[11] Z. Wang, Y. Gao, A. Zaikin, H. Li, and Y. Xu, "System-size coherence resonance in coupled fhn neurons with α-stable lévy noise," *Chaos, Solitons & Fractals*, vol. 200, p. 116985, 2025.

[12] D. Applebaum, *Lévy Processes and Stochastic Calculus*, 2nd ed., ser. Cambridge Studies in Advanced Mathematics. Cambridge: Cambridge University Press, 2009.

[13] O. E. Karpov, V. V. Grubov, V. A. Maksimenko, S. A. Kurkin, N. M. Smirnov, N. P. Utyashev, D. A. Andrikov, N. N. Shusharina, and A. E. Hramov, "Extreme value theory inspires explainable machine learning approach for seizure detection," *Scientific Reports*, vol. 12, no. 1, p. 11474, 2022.

[14] A. E. Hramov, N. Kulagin, A. V. Andreev, and A. N. Pisarchik, "Forecasting coherence resonance in a stochastic fitzhugh–nagumo neuron model using reservoir computing," *Chaos, Solitons & Fractals*, vol. 178, p. 114354, 2024.

[15] A. E. Hramov, N. Kulagin, A. N. Pisarchik, and A. V. Andreev, "Strong and weak prediction of stochastic dynamics using reservoir computing," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 35, no. 3, p. 033140, 2025.

[16] A. V. Andreev, A. N. Pisarchik, N. Kulagin, R. Jaimes-Reátegui, G. Huerta-Cuellar, A. A. Badarin, and A. E. Hramov, "Stochastic cloning of dynamical systems with hidden variables," *Physical Review E*, vol. 112, no. 1, p. 015303, 2025.

[17] N. Kulagin, A. Andreev, A. A. Koronovskii, O. I. Moskalenko, A. P. Sergeev, A. Badarin, and A. E. Hramov, "Intermittency in predicting the behavior of stochastic systems using reservoir computing," *Physical Review E*, vol. 111, no. 2, p. 024209, 2025.

[18] N. Platt, E. Spiegel, and C. Tresser, "On-off intermittency: A mechanism for bursting," *Physical Review Letters*, vol. 70, no. 3, p. 279, 1993.

[19] J. Heagy, N. Platt, and S. Hammel, "Characterization of on-off intermittency," *Physical Review E*, vol. 49, no. 2, p. 1140, 1994.

[20] J. A. Platt, A. Wong, R. Clark, S. G. Penny, and H. D. Abarbanel, "Robust forecasting using predictive generalized synchronization in reservoir computing," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 31, no. 12, 2021.

[21] A. E. Hramov, A. A. Koronovskii, and O. I. Moskalenko, "Are generalized synchronization and noise-induced synchronization identical types of synchronous behavior of chaotic oscillators?" *Physics Letters A*, vol. 354, no. 5-6, pp. 423–427, 2006.

[22] N. Kulagin, A. Andreev, and A. Hramov, "Analysis of the effect of a recurrent neural network size on modeling and prediction accuracy of a stochastic fitzhugh–nagumo neuron," *Bulletin of the Russian Academy of Sciences: Physics*, vol. 89, no. 3, pp. 471–475, 2025.

[23] A. Hramov, A. Andreev, N. Kulagin, A. Badarin, S. Kurkin, H. Gao, L. Minati, and S. Boccaletti, "Clique-based topology enhances reservoir computing performance," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 36, no. 7, 2026.

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