

Reservoir Computing as an Effective Tool for Predicting the Behavior of Stochastic Systems

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Abstract—Predicting the behavior of stochastic systems, where noise is not a mere perturbation but a defining factor, remains a significant challenge in data-driven science. This work presents a reservoir computing (RC) framework specifically designed to forecast the dynamics of such noise-influenced systems. We demonstrate that our approach operates in two distinct regimes: a strong prediction mode for the high-accuracy reconstruction of system trajectories under fixed noise conditions, and a weak prediction mode for the statistical characterization of system behavior when precise forecasting is unstable. The transition between these regimes is shown to follow an on-off intermittency pattern, analogous to noise-induced synchronization in nonlinear systems. Our results indicate that a carefully tuned reservoir computer can effectively capture complex, noise-dependent dynamics like stochastic and coherent resonance, opening new avenues for applications in biomedical engineering, adaptive control, and brain-computer interfaces.

Index Terms—Reservoir computing, Stochastic system, Prediction

I. INTRODUCTION

The rise of machine learning has fundamentally altered our ability to analyze and forecast the behavior of complex systems. This is particularly true for systems governed by stochastic dynamics, where intrinsic or external noise plays a crucial and often constructive role [1]. In this landscape, reservoir computing (RC) has emerged as a particularly powerful technique due to its computational efficiency and proven capability to model complex dynamical systems, including those exhibiting chaos and spatial complexity [2]–[11]. A central problem in this field is the development of models that can not only withstand noise but also predict systems whose very dynamics are shaped by it [12].

Canonical examples of such noise-mediated phenomena include stochastic resonance and coherence resonance, where noise enhances a system's response to weak signals or induces order in nonlinear oscillators [13]–[17]. These effects are ubiquitous across scientific disciplines, from the operation of neural networks and sensory systems to the dynamics of

lasers and climate models. They are often vital for biological functions, such as the amplification of subtle signals and the synchronization of neural activity. In this work, we introduce an RC-based framework to address the challenge of predicting such stochastic systems. We delineate two complementary prediction paradigms and show how a well-designed reservoir computer can learn the interplay between a system's deterministic structure and its stochastic forcing, providing a versatile tool for understanding and harnessing noise-influenced dynamics.

II. RESULTS

We implemented and evaluated our reservoir computing framework on nonlinear systems known to exhibit noise-driven dynamics, such as stochastic resonance. The key finding is that the RC model can operate effectively in two distinct prediction modes, contingent on the stability of the forecasting task.

Strong Prediction Regime: When the underlying stochastic conditions are fixed, the reservoir computer demonstrates a remarkable ability to perform strong prediction. In this mode, the model achieves high-fidelity, short-term reconstruction of the system's trajectories. It accurately predicts the temporal evolution of the state variables by effectively learning the system's dynamics as conditioned on the specific noise realization.

Weak Prediction Regime: In scenarios where precise trajectory forecasting becomes inherently unstable, for instance, when the system is highly sensitive to initial conditions or noise perturbations, the RC model transitions to a weak prediction mode. Here, while it may not predict the exact future state, it successfully captures the long-term statistical properties of the system's behavior, such as power spectra and probability distributions.

Furthermore, we identified that the transition between the strong and weak prediction regimes is not gradual but follows a distinct pattern of on-off intermittency. This dynamical transition, characterized by periods of synchronized (strong) prediction interrupted by desynchronized (weak) bursts, closely mirrors the phenomenon of noise-induced synchronization

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observed in coupled nonlinear stochastic systems. This result underscores that the reservoir computer does not merely filter out noise but dynamically interacts with it in a way that mimics the behavior of the target system itself.

III. CONCLUSIONS

In this study, we have established reservoir computing as an effective and versatile tool for predicting the behavior of stochastic systems where noise is integral to the dynamics. By demonstrating a dual-mode operation—comprising strong trajectory prediction and weak statistical prediction—our framework provides a comprehensive solution for forecasting in noisy environments. The discovery that the regime transition follows an on-off intermittency pattern provides a deeper dynamical systems perspective on how RC models interact with and learn from noise.

The ability of a carefully tuned reservoir to capture nuanced, noise-dependent phenomena like stochastic resonance opens up significant new possibilities for practical applications. This approach is particularly promising for fields that deal with inherently stochastic and complex signals, such as biomedical engineering (e.g., predicting neural activity or processing biosignals), the design of adaptive control systems for fluctuating environments, and the development of robust brain-computer interfaces. Our work thus positions reservoir computing as a key methodology for leveraging the power of noise, rather than simply combating it, in the prediction of complex systems.

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