

Reservoir Computing with Nanostructured Magnetic Arrays

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1. Introduction

- Artificial Spin Vortex Ice presents itself as a strong candidate for reservoir computing

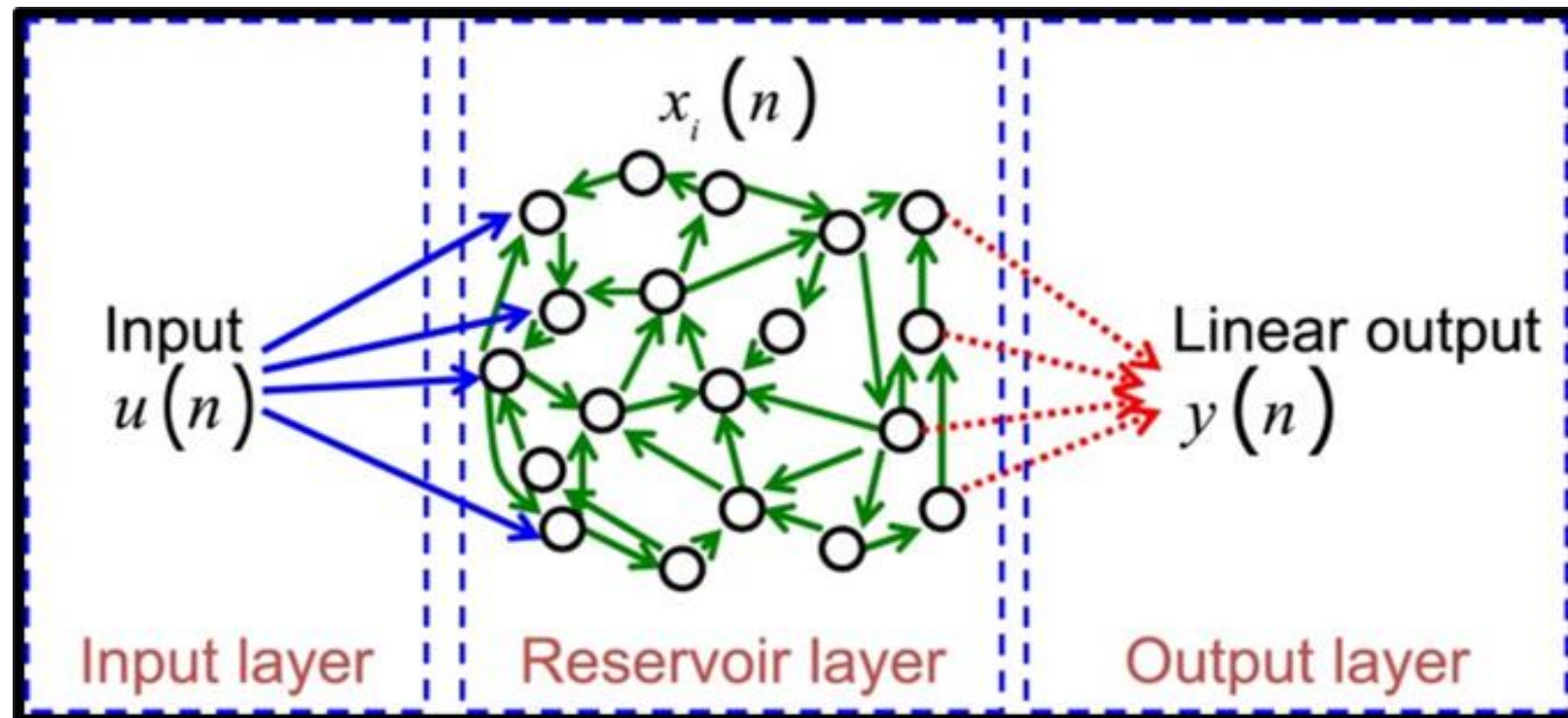


Fig. 1. Diagram illustrating reservoir computing [1].

2. Objective

- Simulating the reservoir response to provide rapid insight into the system
- Evaluate properties of ASVI that make it suitable for reservoir computing

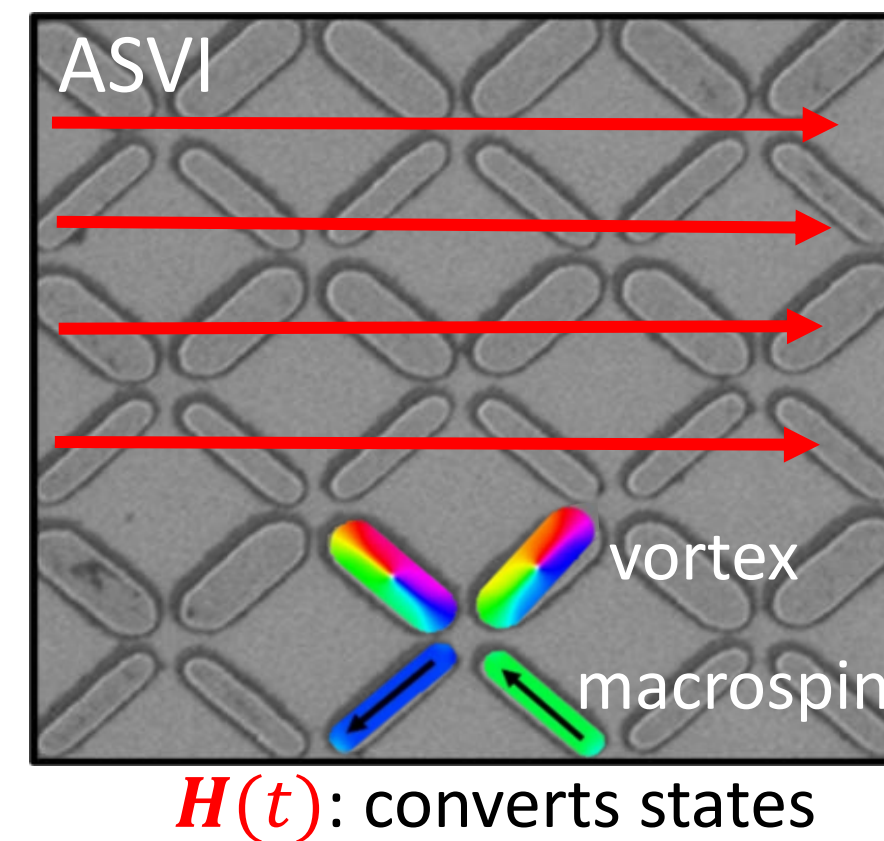
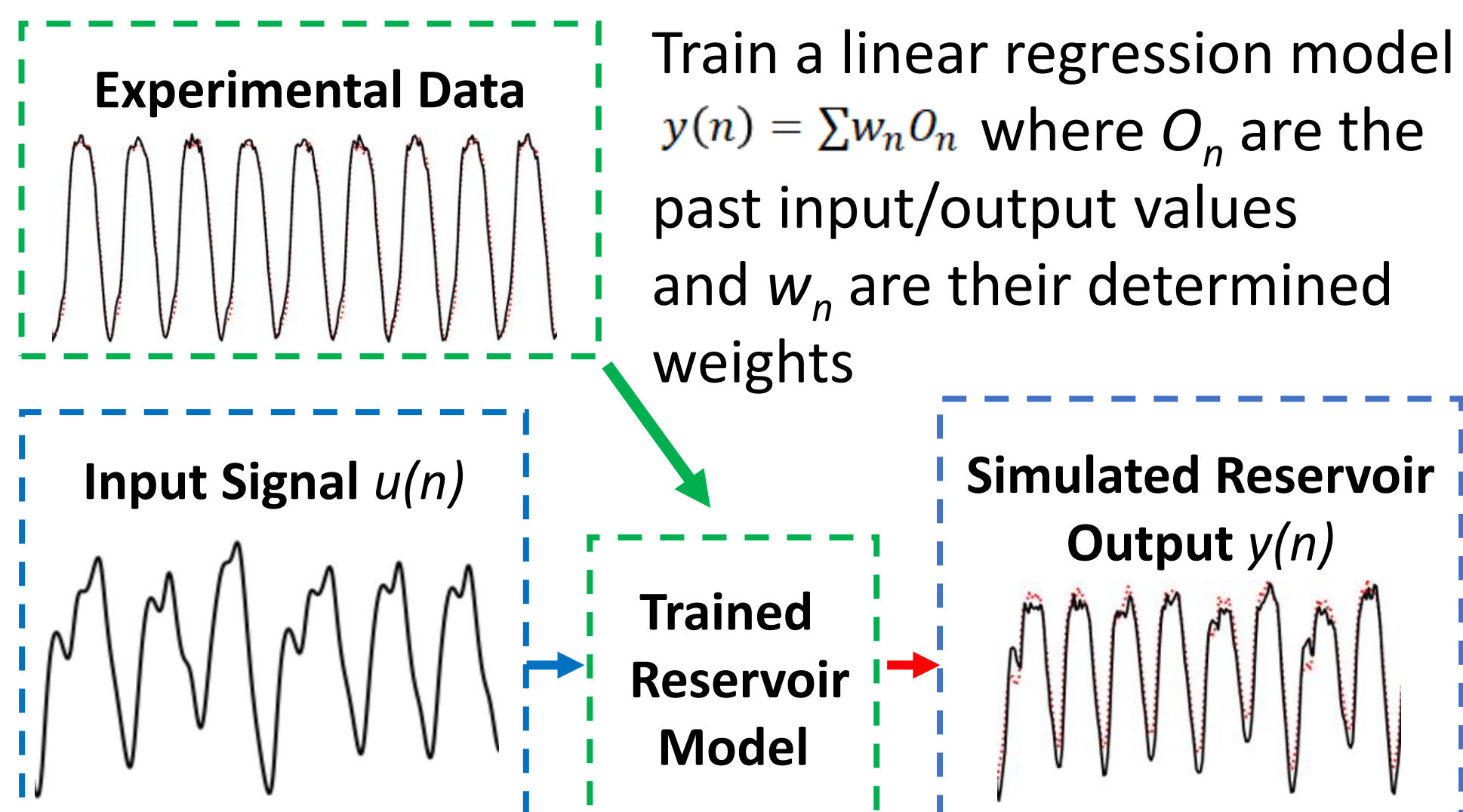
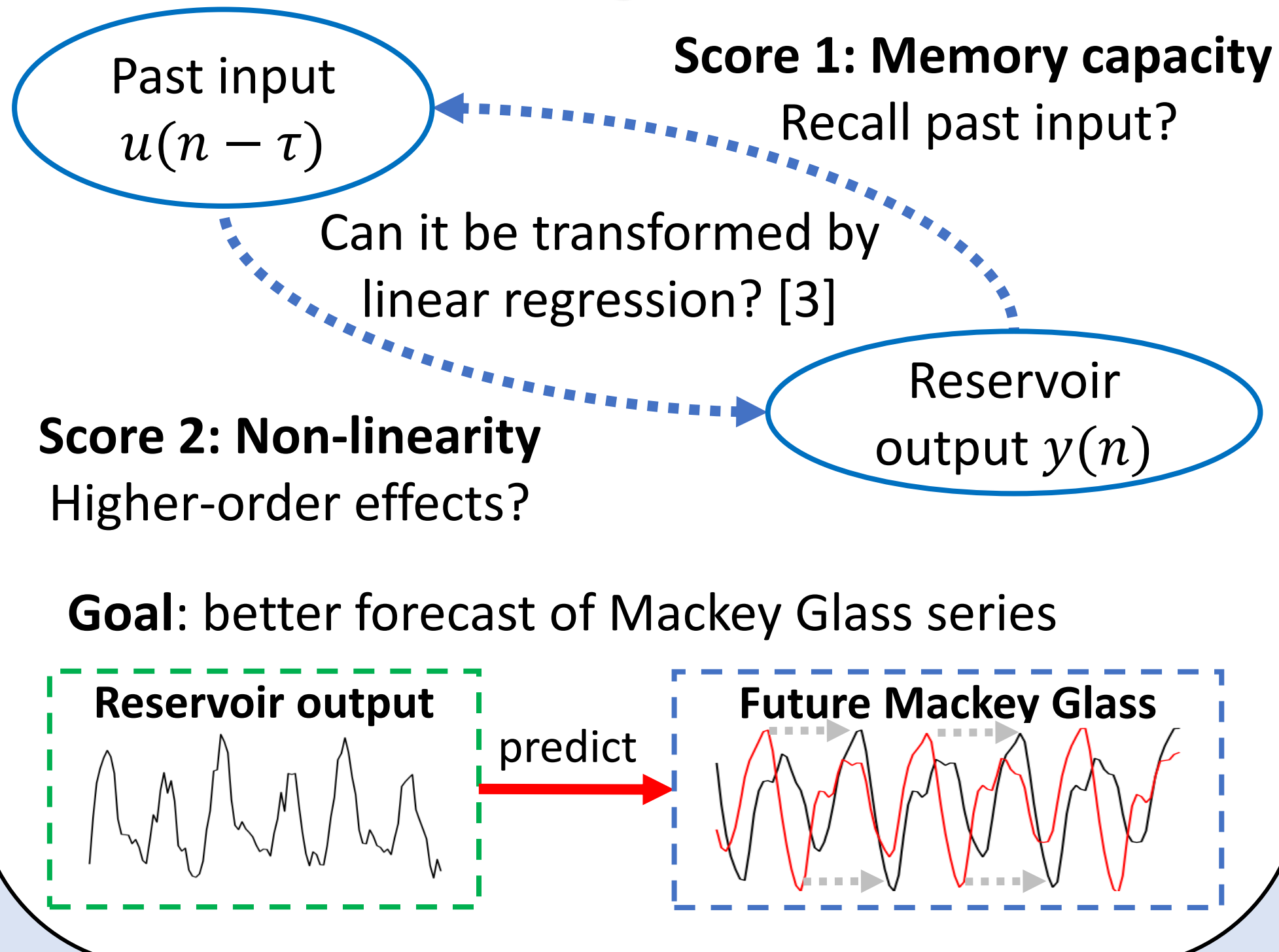


Fig. 2. Evolution in population of states (vortex/macrospin) can be used for reservoir computing [2].

3a. Simulating the Reservoir



3b. Evaluating the Reservoir



4. Results

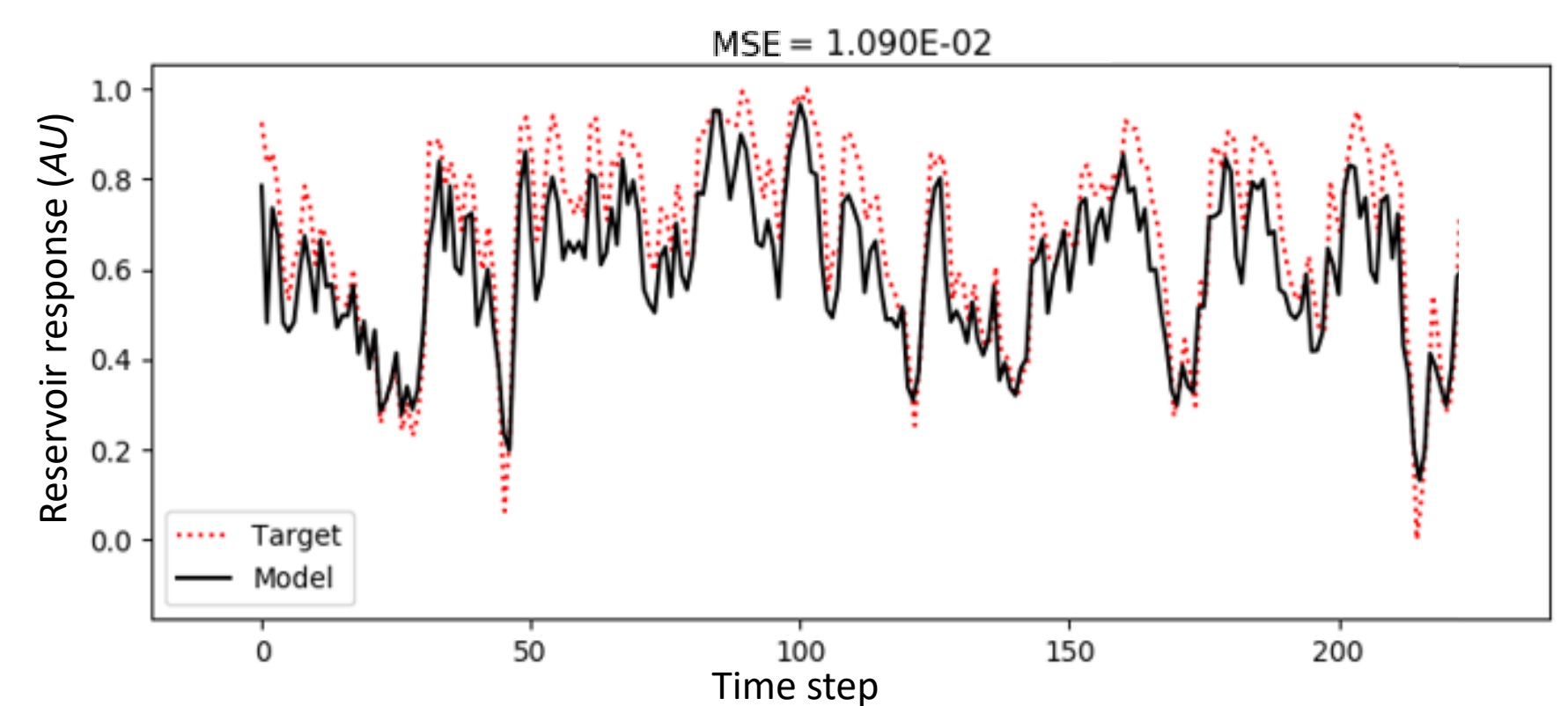


Fig. 3. Simulated reservoir response to a random input function, trained using experimental data from a sin, inverse saw and Mackey Glass input.

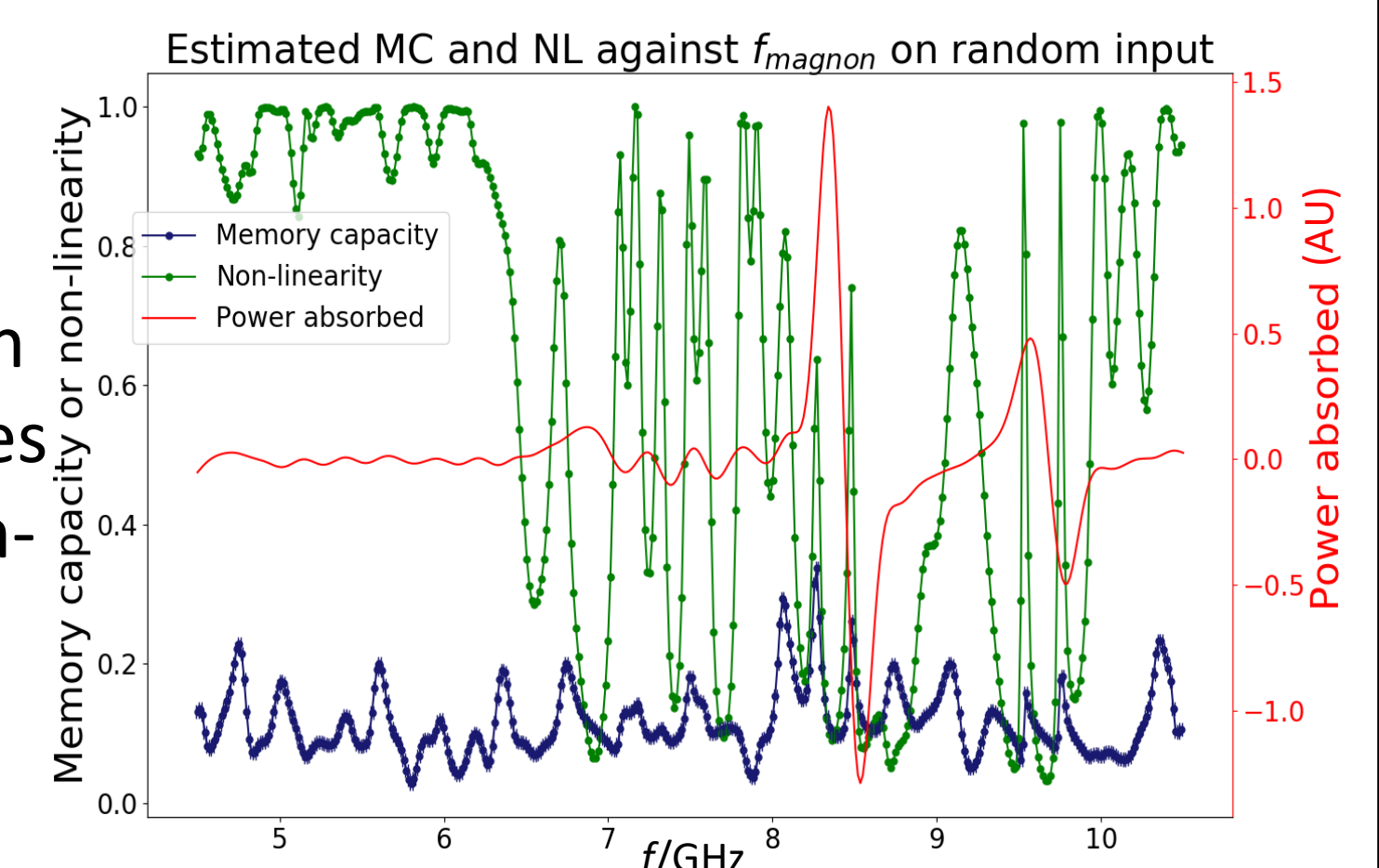


Fig. 4. Absorption spectrum encodes memory and non-linear effects.

Variation of error in MG prediction after 9 steps against MC÷NL

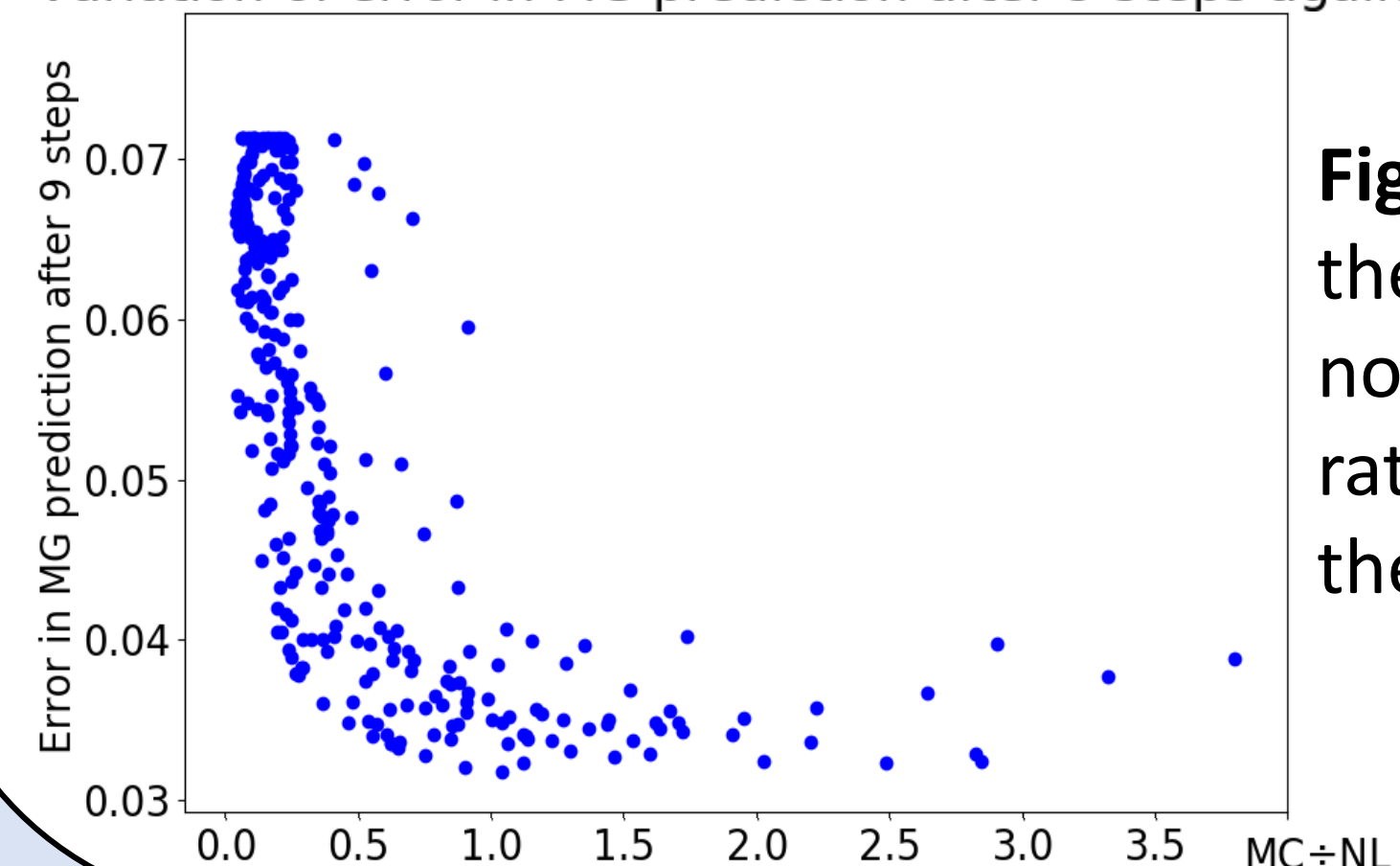


Fig. 5. The higher the memory to non-linearity ratio, the better the prediction!

5. Conclusions and Outlook

- Generated reservoir responses have mean squared error $\mathcal{O}(10^{-2})$ when tested against experimental data.
- The best frequencies in the spectrum to use for forecasting are the ones dominated by memory effects.
- Simulated output can be used to sample the reservoirs' ability to perform tasks like digit/vowel recognition and ECG classification.

[1] Duport, F., et al. (2016). Fully analogue photonic reservoir computer. *Scientific Reports*, 6(1). <https://doi.org/10.1038/srep22381>

[2] Gartside, J., et al. (2022). Reconfigurable Training and Reservoir Computing in an Artificial Spin-Vortex Ice via Spin-Wave Fingerprinting. *arXiv*. <http://arxiv.org/abs/2107.08941>

[3] Love, J., et al. (2021). Task Agnostic Metrics for Reservoir Computing. *arXiv*:2108.01512.