# Simulation of reservoir computing utilizing artificial spin ice

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Reservoir computing (RC) framework (Fig. 1a) is a simplified neural network minimizing the computation cost, which is widely used for temporal data processing [1]. Physically, the reservoir can be established by any non-linear dynamical systems such as photonic devices [2] and spintronic devices [3]. Artificial spin ices (ASI) are arrays of interacting nanomagnets causing geometrical frustration, which provides a large number of degenerate states for computation use [4]. It is found that ASI exhibits good capability to separate temporal pattern [5]. In this study, we evaluate the memory and nonlinear computational abilities of ASI for RC. The simulation is performed by employing the macrospon model based on the Landau-Lifshitz-Gilbert equation at temperature of 0 K. The artificial spin ice is formed by 72 nanomagnets arranged in a honeycomb lattice (Fig. 1b). The central nanomagnets act as the input layer of the RC. After input is sent to the central nanomagnets (Fig. 1c), external magnetic fields in various direction are successively applied to the ASI to update its reservoir state (Fig. 1d). The optimized short-term capacity of 3.5 and nonlinear computational capacity of 2.9 are achieved when the strength of the magnetic field is just below the switching field of the nanomagnets. In addition, the capacities can be adjusted by engineering the aspect ratios of the nanomagnets.
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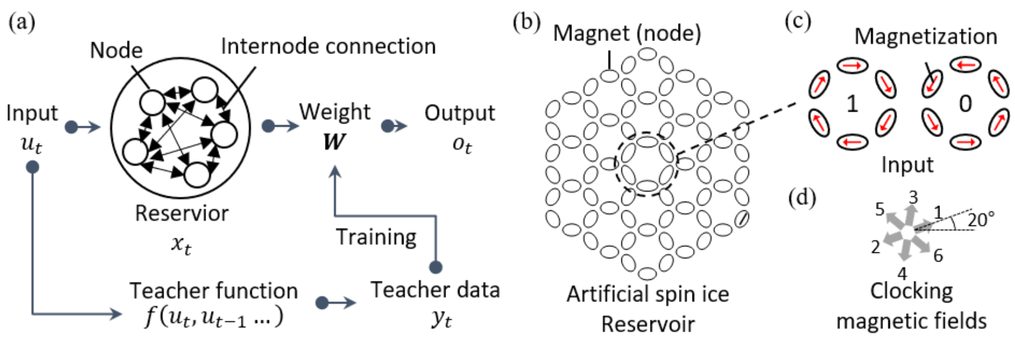


Fig. 1 (a) Schematic of reservoir computing in this study. (b) Schematic of artificial spin ice reservoir. (c) Input configurations of the central nanomagnets (d) External magnetic fields to update the reservoir. The number represents the application order.

References

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