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Modeling of Nano-Contact Vortex Oscillator Using Recurrent Neural Network

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Abstract—NanoContact Vortex Oscillator (NCVO) is a highly nonlinear electronic device that can depict chaotic or nonchaotic behaviors according to the applied DC bias current or the magnetic field. The potential use of such device in computing systems requires the build of a realistic model capable of describing its dynamics. In this paper, we demonstrate an efficient approach for the modeling of the NCVO device based on a recurrent neural network. The proposed model compared to micromagnetic simulations at different current values, shows promising results.

Index Terms—computing systems, NCVO, modeling, chaos, recurrent neural network

I. INTRODUCTION

NanoContact Vortex Oscillator (NCVO) is a highly nonlinear spintronic device. Depending on the DC bias current and the applied magnetic field, the NCVO can engage to a chaotic state or stay in a non-chaotic state. Chaos involves highly nonlinear dynamics that leads to apparent random largely unpredictable signals that are in fact deterministic but sensitive to initial conditions [1]. For that, NCVO can be exploited in complex computing applications such as random numbers generation, data encryption, and reservoir computing. In fact, it has been shown recently [2] that, for a well-defined geometry, it is possible to move continuously from a commensurable or stable state to an incommensurable or chaotic state. This easy switching between different regimes is very promising to obtain optimal computational performances [3].

Modeling NCVO device is not a trivial task. This is mainly because the magnetization dynamics that govern the NCVO operation involves too many degrees of freedom. In fact, physics stands helpless so far to find explicit equations that describe the accurate change in the state of NCVO. Thus, the use of SPICE, VerilogA, or any similar modeling tool becomes impossible due to the lack of an obvious mathematical model. In this paper, we resort to neural networks that seem very appropriate to deal with the NCVO's nonlinear magnetization oscillations, as they are data-driven and self-adaptive that can learn several time series and regenerate them. Furthermore, these networks involve large number of nonlinearly-connected neurons, which makes them well worthy for such purpose.

The rest of this paper is organized as follows: Section II introduces the NCVO, its structure and the physics behind. It also reveals the influence on the current behavior. In Section III, we expose our own work in modeling NCVO based on recurrent neural network. The obtained results are shown in Section IV. Finally, Section V gives some concluding remarks.

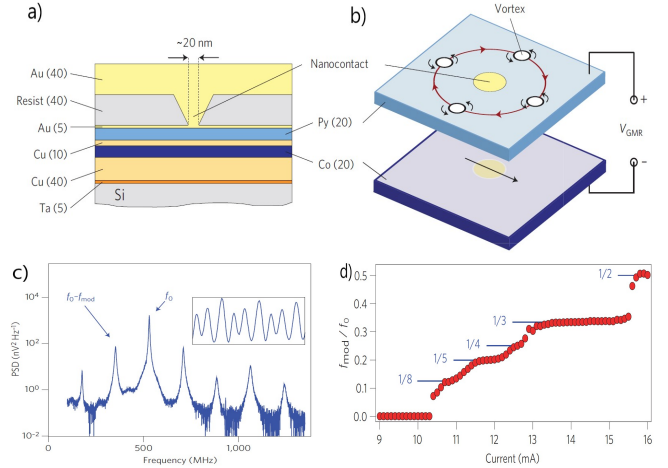


Fig. 1: (a) Composition of a spin valve. (b) Vortex's gyrotropic motion in permalloy layer, with uniform magnetization in cobalt layer. (c) Power spectra and time traces (in set) of the magnetization in chaotic case. (d) Variation of f_{mod}/f_0 versus current [2].

II. NCVO AND PHYSICS BEHIND

NCVO consists in an extended spin valves structure made of multiple stacked thin layers including two ferromagnetic layers (Fig. 1a). The electrical current passes through a metallic NanoContact (NC) lithography on top. Most of the flowing currents are perpendicular to the surface, producing a large Oersted Ampère field with a circulating configuration. This allows the formation of a magnetic vortex only in the upper ferromagnetic layer below the NC. The remaining currents spread in the plane to farther regions, generating a spin transfer torque that move the vortex core away from the center. At a given distance from the NC, this torque is compensated by a magnetic damping, leading to a self-sustained gyration of the vortex core around the NC (Fig. 1b). In contrast, the magnetization of the lower magnetic cobalt layer remains uniform. This layer serves as a reference for measuring the magnetoresistance (MR) signal of the spin valve. The resistance of the device is then proportional to the azimuthal angle of the vortex core. With an applied DC current and due to the MR effect, an oscillating voltage V_{GMR} at the vortex gyration frequency appears across the device, [2].

To study this phenomenon, an NCVO has been tested experimentally for different current values I . At some values above 10.3 mA , the power spectrum shows a modulation effect (Fig. 1c) where two sideband frequencies $\pm f_{mod}$ are associated to the gyration frequency f_0 . Figure 1d shows the variation of the fraction f_{mod}/f_0 as function of I . The plateaux are a sign

of phase-locking phenomenon. At these points the state of the NCVO is said to be commensurate, otherwise the device operates in a chaotic manner.

III. RECURRENT NEURAL NETWORK

The behavior of an NCVO varies with respect to the value of the current flowing through the device. Thus, there is a need for Neural Long-Term memory [4] capable of saving and regenerating large amount of time series patterns. We suggest the use of Conceptors-Reservoir Computing [5] that passes serially through two phases: 'Loading phase' where patterns are installed to the network, and 'Recall phase' at which the patterns are regained according to the conceptor's value.

To model this system, an RNN with N neurons is built by randomly creating a $N \times N$ internal connection matrix W^* , an $N \times M$ input weights matrix W^{in} , and a N random bias vector b . The scalar pattern $p(n)$ drives the network by the state-update equation below, then the final output is computed linearly from the network through the readout matrix W^{out} :

$$x(n+1) = \tanh(W^*x(n) + W^{in}p(n) + b) \quad (1a)$$

$$y(n) = W^{out}x(n) \approx p(n) \quad (1b)$$

Before start, the network undergoes a sequence of steps:

- *Training readout matrix:* an M -dimensional white noise $\nu(n)$ is introduced to the network to collect the states. Accordingly, W^{out} is computed via the optimization problem below. Note that the readout neuron is trained on a random signal, and thus it should perform well for any temporal signal.

$$x^\nu(n+1) = \tanh(W^*x^\nu(n) + W^{in}\nu(n) + b) \quad (2a)$$

$$\min_{W^{out}} \sum_n (W^{out}x^\nu(n) - \nu(n))^2 \quad (2b)$$

- *Training recurrent reservoir matrix:* The input internalization weights matrix W is induced from W^* . This transformation enables the new reservoir to mimic the impact of the drivers p^j in the absence of them. For that, the K patterns are fed into the reservoir by separate runs to compute the states x^j where $1 \leq j \leq K$. Then W is calculated by minimizing the quadratic loss below after the washout period n_0 ends:

$$x^j(n+1) = \tanh(W^*x^j(n) + W^{in}p^j(n) + b) \quad (3a)$$

$$\sum_{j=1, \dots, K} \sum_{n=n_0, \dots, L} \|W^*x^j(n) + W^{in}p^j(n) - Wx^j(n)\|^2 \quad (3b)$$

- *Computation of Conceptors:* Conceptors are $N \times N$ matrices that guide the system to which temporal pattern it should engage at the exploitation time (see Eq (4a)). The quadratic loss function for the computation of the matrices C^j is derived in [5] and its explicit solution is as shown in Equation (4b):

$$x(n+1) = C^j \tanh(Wx(n) + b) \quad (4a)$$

$$C^j = R^j(R^j + (\alpha^j)^{-2}I)^{-1} \quad (4b)$$

$R^j = E[x^j(n)x^j(n)^T]$ is the $N \times N$ correlation matrix of state $x^j(n)$, and α is the aperture parameter that can be understood as a virtual scaling factor of the reservoir states.

IV. RESULTS

In this section, we present the dynamics generated by the recurrent neural network, built in Section III, in its try to depict the real dynamics of the NCVO magnetizations. The 1000-unit reservoir was loaded with the 81 training samples $p^j(n)$, is that from $12mA$ to $20mA$ with a step of $0.1mA$. Then the conceptors C^j are computed after tuning their apertures α^j . Due to the limited space, we will only show examples of the x -magnetization component corresponding to some chaotic and commensurate regimes. Note that this technique works well regardless of the applied current and for the y -component as well. The reservoir is able to mimic the real behavior of the magnetization oscillations even in its chaotic region, where at the current values taken below the NCVO is locked to a commensurate state only at $I = 12mA$.

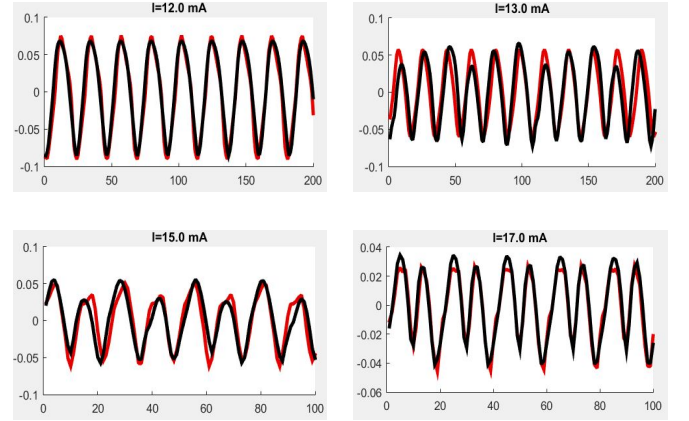


Fig. 2: Variation of M_x magnetization component of NCVO at $I = 12mA, 13mA, 15mA$, and $17mA$ with Original signal (black plot) and generated signal (red plot).

V. CONCLUSION

We have demonstrated the way of building a recurrent neural network responsible for describing the magnetization oscillations of a NCVO device. Regardless of the value of current flowing in the NCVO, the LTM network performs well. This work could be considered as the first footprint in the field of circuit design based on NCVO components.

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