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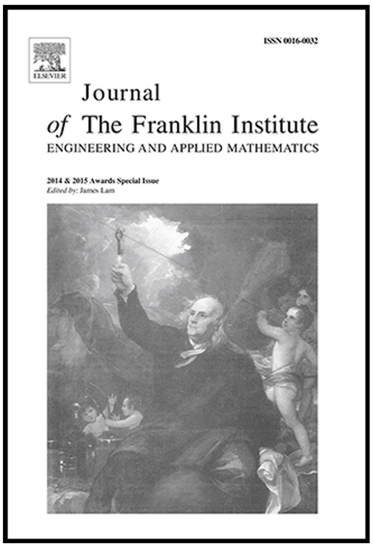

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Mauro Di Marco, Mauro Forti, Luca Pancioni

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Stability of Memristor Neural Networks with Delays Operating in the Flux-Charge Domain

Mauro Di Marco, Mauro Forti, Luca Pancioni

Department of Information Engineering and Mathematics, University of Siena, 53100 Siena, Italy (e-mail: {dimarco, forti, pancioni}@dii.unisi.it)

Abstract

The paper considers a class of neural networks where flux-controlled dynamic memristors are used in the neurons and finite concentrated delays are accounted for in the interconnections. Goal of the paper is to thoroughly analyze the nonlinear dynamics both in the flux-charge domain and in the current-voltage domain. In particular, a condition that is expressed in the form of a linear matrix inequality, and involves the interconnection matrix, the delayed interconnection matrix, and the memristor nonlinearity, is given ensuring that in the flux-charge domain the networks possess a unique globally exponentially stable equilibrium point. The same condition is shown to ensure exponential convergence of each trajectory toward an equilibrium point in the voltage-current domain. Moreover, when a steady state is reached, all voltages, currents and power in the networks vanish, while the memristors act as nonvolatile memories keeping the result of computation, i.e., the asymptotic values of fluxes. Differences with existing results on stability of other classes of delayed memristor neural networks, and potential advantages over traditional neural networks operating in the typical voltage-current domain, are discussed.

1. Introduction

In 2008, the fundamental discovery at Hewlett-Packard laboratories of nanodevices displaying a memristive behavior [1], has boosted an unprecedented interest in the modeling, analysis and applications to signal processing tasks of memristors [2, 3, 4, 5, 6, 7, 8]. The memristor, a shorthand for memory-resistor, was theoretically predicted by Professor Leon Chua, on the basis of symmetry arguments, as the fourth basic passive circuit element in addition to the resistor, capacitor, and inductor, in a seminal paper published in 1971 [9]. However, up until 2008 it remained basically at the level of a theoretic device, mainly due to the difficulty of implementation. Actually, a memristor acts a resistor, with the key difference that the instantaneous value of the resistance is not fixed, but it depends on the past history of memristor voltage or current. When the current (or voltage) in a memristor turns off, the memristor is able to memorize in a nonvolatile way the last value assumed by its resistance (also called memristance) [10]. As such it can be used as a linear programmable resistor in analog processing circuits [11] or to implement programmable neural network interconnections [12]. It can also be used as a dynamic nonlinear time-dependent resistor for the implementation of oscillatory circuits or neuromorphic architectures for real-time signal processing [13, 14, 15].

One main bottleneck of the classical Von Neumann architecture is that processing and storing of information occur on *physically distinct locations*, such as in the CPU and in the random-access-memory. This limits the rate at which information can be transferred and processed. A possible and promising way to overcome this issue is to use a parallel computational approach, as that offered by a neuromorphic architecture, together with unconventional electric devices as the memristors, that are able to *process and store information on the same physical device* [16]. Along this line of reasoning, recent papers [17, 18, 19] have proposed a neural network architecture where the nonlinear resistors in the neurons are replaced by nonlinear memristors. Such memristors play a double role, i.e., they participate in the nonlinear dynamics that is used for processing signals and, at the same time, they are able to store in a nonvolatile way, in the final values of memristances, the result of processing. An intriguing feature of such neural architectures is that, due to the presence of memristors, the processing takes place in the flux-charge domain, rather than in the typical voltage-current domain. As a consequence, when the neural network reaches a steady state, all voltages, current and power in the network turn off, while the memristors act as nonvolatile memories handling the result of computation, i.e., the asymptotic values of fluxes. This is another potential advantage with respect to traditional neural networks