Guest Editorial Special Issue on New Frontiers in Extremely Efficient Reservoir Computing

WITH the penetration of artificial intelligence (AI) technology into industrial applications, not only computational effectiveness but also computational efficiency in machine learning (ML) methods has been increasingly demanded. Reservoir computing (RC) is an ML framework leveraging a dynamic *reservoir* for a nonlinear transformation of sequential inputs and a *readout* for mapping the reservoir state to a desired output. Since only the readout is trained with a simple learning algorithm, RC has attracted much attention as a promising approach to enhance compatibility between high computational performance and low learning cost. In addition, recent studies on physical reservoirs implemented with various physical substrates have boosted the potential of RC in the development of effective and efficient AI hardware. Therefore, it is time to further explore the new frontiers in extremely efficient RC.

The aim of this Special Issue is to focus on new challenges for fully exploiting the potential of RC in machine learning applications and realizing extremely efficient AI hardware. This Special Issue was organized in part as an activity of the IEEE task force on reservoir computing (TFRC) for promoting and stimulating the development of RC research under both theoretical and application perspectives (https://sites.google.com/view/reservoir-computing-tf/). Around 30 articles were initially submitted for this SI and, after a peer-review process, 13 research articles were accepted for publication. These articles deal with cutting-edge approaches based on RC, which pose new directions in RC research. We give a brief introduction to these articles, which are separated into three groups, as follows.

The first group is associated with theoretical aspects of RC for efficient model design and reliable RC applications, including the following articles:

In [A1], Paaßen *et al.* introduce a novel reservoir neural network architecture, namely, the reservoir memory machines (RMMs) which is equipped with an external memory but can still be trained using convex optimization. The authors prove in their work that RMMs are strictly more powerful than finite state machines and conducted a series of experiments, demonstrating that RMMs can solve many benchmark tasks for differentiable neural computers (extensions of artificial neural networks with an explicit memory without interference but noticeably difficult to train) that are beyond the abilities of standard recurrent models.

In [A2], Jüngling *et al.* use the concept of consistency capacity to analyze the functional dependence of reservoir states from the driving input signals. In the article, several experiments are presented targeting diverse reservoir organizations and input settings. Interestingly, for the case of multidimensional driving input, the presented analysis reveals a hierarchy of capacities that characterizes the interference of the input signals in the different input dimensions. For the case of a 1-D driving input, the results show a nonlinear fading memory profile of the reservoir system.

In [A3], Manjunath studies in detail the curve fitting abilities of echo state networks (ESNs) in relation with the so-called echo state property and the existence of what he calls a universal semiconjugacy. The results in this article are one more step in the design of rational guidelines in the choice of reservoir architectures capable of enhancing learning performances. As an important corollary of these results, the existence of universal semiconjugacies helps us understand the failure of the ESNs to approximate some chaotic dynamical systems.

The second group explores new model designs and new applications of RC for better computational performance and efficiency in pattern recognition tasks, including the following articles:

In [A4], Schwedersky *et al.* apply an RC approach to adaptive practical nonlinear model predictive control (NMPC) formulation, which is a relevant methodology in industrial applications. To obtain an online nonlinear system identification method, the proposed RC approach combines an online recursive least-squares training algorithm with an adaptive forgetting factor. Finally, in the adaptive NMPC algorithm, the full nonlinear ESN model is used to obtain the nonlinear system free response, and a linearized version is calculated at each time step to get a local approximation of the system step response. The proposed model shows reliable results, compared with the baseline and state-of-the-art methods in the field, with a significant gain for the computational time.

In [A5], Jordanou *et al.* introduce an efficient data-driven strategy for control of nonlinear dynamic plants devoid of known models, toward an ESN–practical nonlinear model predictive controller (PNMPC) hybrid model. A specific aspect of the proposal is the substitution of the finite difference method of PNMPC for a fast analytical computation of the derivative in terms of the ESN, while also proposing a procedure to

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recursively calculate the Jacobians of the state equations, with other expedients concerning the error correction filter for the controller. The results are successfully compared with models including linear MPC, approximate predictive control, and PNMPC with a LSTM model, using the four-tank system benchmark and an oil production platform application.

In [A6], Jalalvand *et al.* apply an RC model with adaptation mechanisms to a plasma state prediction from experimentally monitored plasma profile data. They demonstrate that the adaptive RC methods can achieve comparable prediction performance to the CNN-LSTM (convolutional neural networks combined with long short-term memory), with a significantly easier and faster training procedure. The results suggest that the RC approach is extremely efficient when a predictor needs to be retrained frequently under changing operational conditions and device settings.

In [A7], Pasa *et al.* propose a multiresolution reservoir graph neural network (MRGNN) for structured data. The proposed method extracts multiresolution features from graph data by using an unrolled reservoir convolutional layer, which are subsequently integrated to train a feedforward neural network in the readout. The experimental results for graph classification benchmarks demonstrate that the proposed method enables extremely fast learning and can achieve comparable or higher classification accuracy compared to other state-of-the-art methods.

In [A8], Pedrelli and Hinaut propose a kind of deep RC model constructed with multiple reservoirs which are aimed at processing different levels of language information, such as phoneme, word, part-of-speech, and semantic role, inspired by hierarchical organizations and learning mechanisms in the brain. The proposed method enables to progressively enhance abstraction levels of language information in the transformation from input continuous speech signals to the output semantic role labels. The experimental results for online semantic role labelling tasks show that the proposed method can outperform other state-of-the-art RC-based and deep learning methods, with efficient computational efforts.

In [A9], Nokkala *et al.* design reservoir systems using the quantum or classical fluctuations of a network of interacting harmonic oscillators. They show that this strategy can lead to performances comparable to that of a standard echo state network in several nonlinear benchmark tasks. Furthermore, they find that the performance of the network of harmonic oscillators in nonlinear tasks is robust to errors both in input and reservoir observables caused by external noise. These results pave the way toward the use of RC in harnessing fluctuations in disordered linear systems.

The third group makes efforts for studying new architectures and mechanisms in physical RC and its hardware implementation, including the following articles.

In [A10], Gupta *et al.* propose a design of a split-reservoir-based RC model for low-power pattern recognition and demonstrate its hardware implementation with field-programmable gate array (FPGA). In speech and human action recognition tasks, the authors show that the proposed hardware architecture combined with on-the-fly binary weight generation can significantly reduce computational and memory resources compared to existing FPGA models, which can be further developed toward edge-computing ML devices.

In [A11], Nakajima *et al.* show a new family of neural networks based on the Schrödinger equation, which the authors named SE-NET. There the trainable weights of the neural networks correspond to the physical quantities of the Schrödinger equation. A trained network is transferable to actual optical systems. A numerical demonstration of end-to-end ML is performed with an optical frontend toward a compact spectrometer. The results extend the application field of ML to hybrid physical-digital optimizations.

In [A12], Kleyko *et al.* study the reservoir operations under the formalism of collective-state computing, addressing the memory-computation trade-off. The authors explore the potentialities of cellular automata implementing rule 90 (CA90) in generating the weight values needed for the reservoir update equation, alleviating the random matrix memorization bottleneck and enabling the computation to scale to high reservoir dimensionality.

In [A13], Vettelschoss *et al.* experimentally evaluate the information processing capacity (IPC) measure of a reservoir computer based on a single-analog nonlinear node coupled with delay. The authors link the extracted IPC measures to the dynamical regime of the reservoir. They also find a nonhomogeneous distribution of the linear and nonlinear contributions as a function of the system operating conditions. Furthermore, they show a part of the role of noise in the IPC of the analog implementation.

These articles totally cover a wide variety of RC-related topics, such as theory, algorithm, model architecture, applications, and implementation of RC. We hope that this Special Issue offers an overview of extremely efficient RC-based methods and promotes further development in this research field.

Finally, the Guest Editors would like to cordially thank all the contributions of the authors and the great dedication of the reviewers to this Special Issue. Without their efforts, this Special Issue would not have been completed. The Guest Editors would also wish to thank the former Editor-in-Chief, Prof. Haibo He, and the current Editor-in-Chief, Prof. Yongduan Song, for their administrative support.

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APPENDIX: RELATED ARTICLES

[A1] B. Paaßen, A. Schulz, T. C. Stewart, and B. Hammer, "Reservoir memory machines as neural computers," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2575–2585, Jun. 2022.
[A2] T. Jungling, T. Lymburn, and M. Small, "Consistency hierarchy of reservoir computers," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2586–2595, Jun. 2022.
[A3] G. Manjunath, "An echo state network imparts a curve fitting," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2596–2604, Jun. 2022.
[A4] B. B. Schwedersky, R. C. C. Flesch, and S. B. Rovea, "Adaptive practical nonlinear model predictive control for echo state network models," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2605–2614, Jun. 2022.
[A5] J. P. Jordanou, E. A. Antonelo, and E. Camponogara, "Echo state networks for practical nonlinear model predictive control of unknown dynamic systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2615–2629, Jun. 2022.
[A6] A. Jalalvand, J. Abbate, R. Conlin, G. Verdoolaege, and E. Kolemen, "Real-time and adaptive reservoir computing with application to profile prediction in fusion plasma," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2630–2641, Jun. 2022.
[A7] L. Pasa, N. Navarin, and A. Sperduti, "Multiresolution reservoir graph neural network," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2642–2653, Jun. 2022.
[A8] L. Pedrelli and X. Hinaut, "Hierarchical-task reservoir for online semantic analysis from continuous speech," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2654–2653, Jun. 2022.
[A9] J. Nokkala, R. Martinez-Pena, R. Zambrini, and M. C. Soriano, "High-performance reservoir computing with fluctuations in linear networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2664–2675, Jun. 2022.
[A10] S. Gupta, S. Chakraborty, and C. S. Thakur, "Neuromorphic time-multiplexed reservoir computing with on-the-fly weight generation for edge devices," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2676–2685, Jun. 2022.
[A11] M. Nakajima, K. Tanaka, and T. Hashimoto, "Neural Schrödinger equation: Physical law as deep neural network," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2686–2700, Jun. 2022.
[A12] D. Kleyko, E. P. Frady, and F. T. Sommer, "Cellular automata can reduce memory requirements of collective-state computing," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2701–2713, Jun. 2022.
[A13] B. Vettelschoss, A. Rohm, and M. C. Soriano, "Information processing capacity of a single-node reservoir computer: An experimental evaluation," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 6, pp. 2714–2725, Jun. 2022.

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