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ABSTRACT

Adaptive dynamical networks (ADNs) describe systems in which the states of the network nodes and the network structure itself co-evolve over time. This interplay of two coupled dynamical processes underlies a wide range of natural and technological phenomena, such as neural plasticity, learning, and opinion formation. The inherently co-evolutionary nature of ADNs poses significant challenges to mathematical theory and modeling, driving strong interest and rapid advances in recent years. This Focus Issue presents 25 research articles highlighting recent developments in the field, including new analytical and computational techniques, the discovery of novel dynamical phenomena in ADNs, and diverse applications of ADNs in neuroscience, Earth science, biology, social sciences, machine learning and control.

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Complex systems in nature, society, and technology often exhibit a dynamic interplay between the states of their components and the network of interactions connecting them. In many cases, the network topology is not fixed resulting in adaptive dynamical networks (ADNs). Such co-evolving systems display an extraordinary range of behaviors, from multistability and clustering to pattern formation, synchronization transitions, and changes in the level of resilience. Over the past two decades, the study of ADNs has grown into a highly active interdisciplinary field, drawing on methods from nonlinear dynamics, statistical physics, and network science, and finding applications in areas as diverse as neuroscience, physiology, climate science, epidemiology, opinion dynamics, and machine learning. The 25 contributions in this Focus Issue on *Advances in Adaptive Dynamical Networks* reflect the breadth and rapid progress of the field, presenting new theoretical frameworks, computational tools, and empirical insights across multiple domains. Together, they reveal how adaptivity can fundamentally reshape the dynamics of complex networks—and, in turn, our ability to understand, predict, and control them.

I. INTRODUCTION

This special issue focuses on the rapidly developing field of Adaptive Dynamical Networks (ADNs), which play an important role in modeling of many challenging real-world problems. While the term *adaptation* can be interpreted very broadly,[1] the concept of *adaptive dynamical networks* is more clearly specified. ADNs are systems that possess the following properties:[2]

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1. ADN is a dynamical system that describes the temporal evolution of some dynamical variables $x_i(t)$, $i = 1, \ldots, N$.
2. The interactions between the variables x_i can be described by a network (graph) $\mathcal{N}$, which may be directed, undirected, a hypergraph, weighted, etc. The variables x_i play the role of the nodes in the network.
3. The evolution of the variables $x_i(t)$ depends on the network structure $\mathcal{N}$.
4. The network $\mathcal{N}$ itself evolves over time, i.e., $\mathcal{N}(t)$. This can involve the evolution of the graph structure or its weights.
5. The temporal evolution of the graph $\mathcal{N}(t)$ depends on the states of the node variables x_i. This may be the case when the weights change over time and their dynamics depend on x_i. Another example is when the network connectivity depends on the current or past states of the nodes.

Systems that only fulfill properties 1, 2, and 3 are *non-adaptive* dynamical networks. Systems that satisfy properties 1–4, but not 5, are dynamical networks with a prescribed temporally evolving network structure. Strictly speaking, such systems do not belong to the ADN category.

Obviously, properties 1–5 still contain a great deal of ambiguity and cannot be considered a rigorous definition of a class of dynamical systems. However, we believe that this qualitative description adequately captures an exciting and important research field. The most recent review of this research field, from 2023, is by Berner *et al.*,[2] while earlier reviews are available, including those by Gross and Blasius,[3] from 2008, and by Maslennikov and Nekorkin,[4] from 2017.

This focus issue, *Advances in Adaptive Dynamical Networks*, includes 25 research articles, which present recent contributions to the theory and application of ADNs. In the following, we provide a brief overview of these studies grouped by subtopics.

Articles in this special issue contribute to the development and analysis of an adaptive Kuramoto model in a continuum limit,[5] adaptive higher-order network models,[6,7] theta-neurons with plasticity,[8,9] a system with adaptive time delay,[10] an adaptive climate tipping model,[11] a system of vascular networks,[12] opinion dynamics models,[13,14] and adaptive multiplex networks.[15] A new phenomenon of recurrent adaptive chaotic clustering[16] has been reported. New techniques have been developed to identify and analyze communities in time-varying graph structures,[17] derive effective deterministic equations for populations of randomly coupled phase oscillators,[18] and create a novel machine learning framework using multi-scale graph learning.[19] Furthermore, it is demonstrated that ADNs are useful in machine learning beyond training, enabling them to adjust to changing environments.[20] The effect of adaptation is investigated on inverse stochastic resonance[21] and traveling waves.[22] It has been demonstrated that ADNs can be utilized to determine the frequencies of audio signals,[23] in city planning,[24] to achieve faster synchronization,[25] and other control problems.[26–29]

II. PARADIGMATIC ADN SYSTEMS AND GENERAL THEORY

Cestnik and Martens[5] studied the adaptive Kuramoto model with slow adaptation in the continuum limit, revealing dense multistability arising from oscillators that can lock at different phases or switch between locking and drifting, depending on initial conditions. Predictions based on a reduced model via row-averaging of the coupling matrix and developing a self-consistency equation to compute a stability diagram were confirmed via numerical simulations.

Rolim Sales *et al.*[16] reported the phenomenon of recurrent adaptive chaotic clustering, in which chaos is observed on a slow timescale, whereas regular dynamics are exhibited on a fast timescale. This slow chaos is characterized by long regimes of frequency clusters or frequency-synchronized dynamics (relative to the fast time scale), which are interrupted by fast jumps between these regimes.

Trower *et al.*[17] developed techniques to identify and analyze communities within time-varying graph structures. They defined the spatiotemporal graph Laplacian and investigated its spectral properties.

Emelianova and Nekorkin[7] considered resynchronization mechanisms in a network of heterogeneous phase oscillators with triadic and adaptive couplings.

Pikovsky and Smirnov[18] studied large populations of phase oscillators interacting via random coupling functions of the Kuramoto–Daido or Winfree type. They derived reduced, averaged equations with effective nonrandom coupling terms.

Sharma *et al.*[6] studied the Kuramoto oscillator model with a phase lag and adaptation in higher-order interactions. They found that the type of transition to synchronization changes from the first-order to second-order type depending on the adaptation parameters.

III. ADN IN NEUROSCIENCE AND OTHER BIOLOGICAL SYSTEMS

Augustsson and Martens[8] investigated two adaptively coupled theta-neurons using bifurcation analysis and simulations to study how adaptivity shapes dynamics. In the non-adaptive limit, they identified stability regions of quiescence and mode-locked spiking. Increasing adaptivity widens Arnold tongues, enabling multistability and period-doubling cascades to chaos.

Fennelly *et al.*[9] considered theta-neuron networks with plasticity. They employed phase-difference-dependent plasticity rules and two distinct implementations of this plasticity: pairwise updates to individual coupling strengths and global updates applied to the mean coupling strength.

Klinshov and Nekorkin[10] showed that adaptive myelination leads to slow oscillations in recurrent neural loops. Activity-dependent myelination is a form of brain plasticity that changes the speed at which action potentials propagate along axons. Consequently, axonal delays become adaptive and state-dependent.

Bukh *et al.*[23] investigated the spike activity of a network of excitable FitzHugh–Nagumo neurons under the influence of two-frequency auditory signals. They demonstrated how the network could be configured to recognize a specific frequency ratio.

Yamakou *et al.*[21] conducted a numerical investigation of the impact of adaptivity (via spike-time dependent plasticity or homeostatic structural plasticity) on inverse stochastic resonance in a small

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world network of noisy FitzHugh–Nagumo neurons, demonstrating possible improvement of inverse stochastic resonance due to adaptivity and prompting a way to optimize information transfer.

Korneev *et al.*[22] studied traveling waves in an ensemble of excitable FitzHugh–Nagumo neurons with memristive coupling.

Klemm and Martens[12] studied the self-organization of vascular networks for the transport of fluids from sources to sinks, adapting to pressure changes. They discovered a new nonlocal transition between cyclic and tree-like self-organized topologies of transport networks.

IV. ADN IN EARTH SCIENCES

A conceptual model describing the dynamics of interacting tipping elements was studied in the paper by Bdolach *et al.*[11] This paper extends the model presented in Ref. 30 by incorporating the Global Mean Temperature (GMT) feedback induced by crossing a tipping point. The authors demonstrated that large tipping cascades are less probable due to the negative GMT feedback of ocean circulation systems. In the adaptive model, some tipping elements change their roles in cascades. In particular, the Amazon rainforest could become a trigger in a tipping cascade. Overall, the adaptation mechanism stabilizes the network to a slight extent.

V. ADN IN SOCIAL SCIENCES

Nugent *et al.*[13] proposed a novel control approach for opinion dynamics on evolving networks. Rather than influencing opinions directly, the controls modify the strength of connections in the network, with the overall goal of steering the population toward a target opinion.

Xiong *et al.*[15] studied a spatial coevolutionary model on multiplex networks consisting of two layers: a relationship layer and an interaction layer.

Djurdjevac Conrad *et al.*[14] modeled the co-evolving opinion and social dynamics using stochastic agent-based models. The mobility of agents within a social space is determined by the degree of their social connections and opinions. The dynamics of opinion formation are driven by the opinions of agents in their social vicinity.

Bader *et al.*[24] proposed a nonlinear dynamical algorithm for city planning, aiming to predict relevant parameters, such as health, artistic freedom, and financial developments of different social and political stakeholders.

VI. ADN IN MACHINE LEARNING

Pourcel *et al.*[20] demonstrated how keeping parts of the recurrent neural network adaptive even after training improves its functionality and robustness. Their results highlight the potential of adaptive networks in machine learning beyond training, showing that they can learn complex patterns and dynamically adjust to changing environments.

Zou *et al.*[19] employed multiscale graph learning to introduce a novel machine learning framework with the aim of improving forecast performance.

VII. ADAPTIVE CONTROL

Venegas-Pineda *et al.*[29] studied the problem of controlling a networked system to stabilize a desired oscillatory pattern. The controllers were implemented as adaptive rules within an extended controller network.

Sinha[25] explored adaptive link change strategies that can lead a system to network configurations with ordered dynamical states.

Adaptive impulsive/blinking control techniques were introduced by Irankhah *et al.*[26] and by Diao and He.[27]

Yang *et al.*[28] studied the robustness of interdependent networks, in which the states of the nodes follow a certain failure probability.

VIII. OUTLOOK

The present focus issue clearly shows the enormous breadth of the field of ADNs. Nevertheless, it still just provides a snapshot of a rapidly (and adaptively!) evolving field. It is expected that within current and completely novel application areas, ADNs are going to play a prominent role since most complex systems are expected to have some form of coupling adjustment based upon their desired functionality. Indeed, just looking back at the last decade, we have seen social distancing mechanisms in the COVID-19 pandemic, fragmentation transitions in political opinion formation, deep neural networks adapting through new data availability, and changing couplings within socio-ecological-climate systems. Therefore, it is very natural to conjecture that many future areas can use the framework of ADNs effectively. This demand necessitates the development of further theoretical tools. On the one hand, we expect ADNs being able to display interesting dynamical phenomena, but categorizing their behavior is evidently much more challenging than for classical low-dimensional dynamical systems. A key reason is not only the large number of variables, which is a challenge also classical network dynamics encounters. The problem is that adaptivity generally allows for much wider classes of heterogeneous network topologies than many classical interacting particle systems on networks. This makes the application of established mathematical tools, such as mean-field, continuum limit, moment expansions, invariant manifolds, symmetry reduction, and many other techniques far from obvious. It is likely that studying a sufficiently large number of concrete examples of ADNs can provide us with a better understanding to build a much more coherent theoretical framework that is sufficiently generic to be applicable to future challenges. The focus contributes toward this process and hopes to stimulate further progress.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Author Contributions

Serhiy Yanchuk: Conceptualization (lead); Formal analysis (equal); Funding acquisition (equal); Investigation (equal); Project administration (equal); Writing – original draft (lead); Writing – review & editing (equal). **Erik Andreas Martens:** Formal analysis (equal); Funding acquisition (equal); Investigation (equal); Project administration (equal); Writing – review & editing (equal). **Christian Kuehn:** Formal analysis (equal); Funding acquisition (equal); Investigation (equal); Project administration (equal); Writing – review & editing (equal). **Jürgen Kurths:** Formal analysis (equal); Funding acquisition (equal); Investigation (equal); Project administration (equal); Writing – review & editing (equal).

DATA AVAILABILITY

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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