Task 16: Reinforcement Learning Control for Cyber Physical Systems

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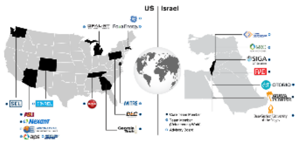
Arizona State University

1/24/2022

Task Overview



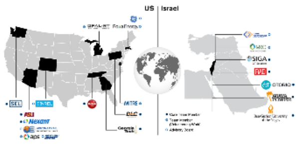
- **Main Objective**: to develop a machine-learning framework for devising the “best” control policies to significantly suppress or even eliminate cascading failures in distributed electrical power networks.

- **Idea**: The digital twin developed in Task 11 will enable a systematic test of various control scenarios. The same principle used in building up an attack-scenario library using the digital twin will be exploited to build up a control-scenario library.

- **Anticipated Outcome**: a library of control scenarios that can be implemented in the real world to prevent cascading failures in distributed power networks.

- **Reinforcement Learning**: to find the optimal control path for any given attack scenario.

Technical Content



- When an attack or an intrusion has been detected and deemed to be harmful in the sense that the likelihood of cascading failures cannot be neglected, control becomes necessary.

- Working Principle: For a given type of intrusion or attack that can result in cascading failures, a large number of control scenarios will be tested by simulating the **digital twin**.

- Such control scenarios include disabling of a small number of links (e.g., transmission lines) in the network so as to enhance the capacity of the vast majority of nodes and links in the network against cascading failures.

- The top-ranked control scenarios in terms of cost and speed of implementation will be chosen. That is, by taking advantage of the digital twin, for any given attack scenario in the library, one can find a small number of optimal control scenarios.

- **Reinforcement learning** will be exploited for finding the optimal control paths.

Controlling nonlinear dynamical systems into arbitrary states using machine learning

Alexander Haluszczynski & Christoph Räth

Scientific Reports **11**, Article number: 12991 (2021) | Cite this article

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Research

Check for updates

Cite this article: Bucci MA, Semeraro O, Allauzen A, Wisniewski G, Cordier L, Mathelin L. 2019 Control of chaotic systems by deep reinforcement learning. *Proc. R. Soc. A* **475**: 20190351.

Control of chaotic systems by deep reinforcement learning

M. A. Bucci[1], O. Semeraro[1], A. Allauzen[1], G. Wisniewski[1], L. Cordier[2] and L. Mathelin[1]

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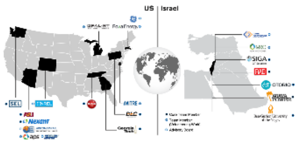
Deep reinforcement learning (DRL) is applied to

Team Members and How They Interact



Team for Task 16

- Amin Moradi (main), new PhD student in ASU Electrical Engineering with experience in reinforcement learning (one refereed-journal paper)
- Ling-Wei Kong (secondary), PhD candidate in ASU Electrical Engineering with experience in reservoir computing, nonlinear dynamics, and complex systems (In ASU EE for three years; eight refereed-journal papers)
- Ying-Cheng Lai (Task lead), ASU Electrical Engineering
- Yang Weng (Consortium lead-PI), ASU Electrical Engineering
- John Dirkman, VP of Product Management and Resource Innovations of Nexant

Main student researcher:

Mohammad Amin Moradi

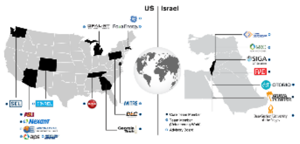
PhD Student at University of Florida
Verified email at ufl.edu
Reinforcement Learning   Machine Learning   Q-Learning   Control Systems

TITLE	CITED
Adaptive optimal control of unknown discrete-time linear systems with guaranteed prescribed degree of stability using reinforcement learning SE Razavi, MA Moradi, S Shamaghdari, MB Menhaj International Journal of Dynamics and Control, 1-9	

Team interaction/collaboration

- Lai will work with the two PhD students on basic principles of reinforcement learning control of cyber physical systems, in collaboration with Weng.
- The Task 16 team will work with Dirkman to develop the software based on reinforcement learning control for distributed electrical power systems.

Relevant Previous Work



TITLE	CITED BY	YEAR
Cascade-based attacks on complex networks AE Motter, YC Lai Physical Review E 66 (6), 065102	1930	2002
The control of chaos: theory and applications S Boccaletti, C Grebogi, YC Lai, H Mancini, D Maza Physics reports 329 (3), 103-197	1063	2000
Optimal weighting scheme for suppressing cascades and traffic congestion in complex networks R Yang, WX Wang, YC Lai, G Chen Physical Review E 79 (2), 026112	184	2009

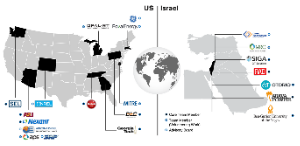
ASU

Mohammad Amin Moradi

Adaptive optimal control of unknown discrete-time linear systems with guaranteed prescribed degree of stability using reinforcement learning

Authors	Seyed Ehsan Razavi, Mohammad Amin Moradi, Saeed Shamaghdari, Mohammad Bagher Menhaj
Publication date	2021/8/24
Journal	International Journal of Dynamics and Control

Commercialization Plan



Past encounter with commercialization (Lai):

- In August 2020, the Air Force/MIT Artificial Intelligence Accelerator launched a public challenge to help create the artificial intelligence needed to solve the magnetic navigation problem.
- The specific call is for the signal enhancement for magnetic navigation (MagNav) challenge problem with the goal to use magnetometer readings recorded from within a cockpit and remove the aircraft magnetic noise to yield a clean magnetic signal.
- The ASU team led by Lai responded and tested three types of machine learning methods: multilayer perceptrons (MLPs), reservoir computing, and long short-term memory (LSTM) neural networks.
- In December 2020, the Air Force/MIT Artificial Intelligence Accelerator placed the ASU team as the winning team.
- The involved Air Force officers suggested to Lai commercializing the machine-learning technique.

The ASU Task 16 team will work with Nexant to implement the principle and methodologies of reinforcement learning control of cyber physical systems into the existing industrial Operational Technology and Industrial Control Systems management software tools.