

UNIVERSITY OF TECHNOLOGY SYDNEY

Faculty of Engineering and Information Technology

School of Electrical and Data Engineering

AI-empowered Communications

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A THESIS SUBMITTED
IN FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE

Doctor of Philosophy

under the supervision of

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Sydney, Australia

September 2021

CERTIFICATE OF ORIGINAL AUTHORSHIP

I, HUYNH NGUYEN VAN declare that this thesis, is submitted in fulfilment of the requirements for the award of DOCTOR OF PHILOSOPHY, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Date: December 13, 2021

ABSTRACT

AI-empowered Communications

by

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Artificial Intelligence (AI) has been successfully applied to various areas and received great attention from both industry and academia. The recent advances in deep learning, convolutional neural networks, and reinforcement learning hold significant promise for solving intractable problems in future communication systems. This thesis aims to develop novel AI-based solutions to address different problems in communications, including resource allocation, security, and secure and effective computing.

Firstly, we propose an optimal and fast real-time resource slicing framework that maximizes the long-term profit of the network provider while considering the uncertainty of resource demand from tenants. To obtain the optimal resource allocation policy under the dynamics of slicing requests, e.g., uncertain service time and resource demands, we develop a deep reinforcement learning-based solution with an advanced deep learning architecture, called deep dueling. Extensive simulations show that the proposed solution yields up to 40% higher long-term average profit while being few thousand times faster, compared with state-of-the-art network slicing approaches.

Secondly, we introduce an optimal anti-jamming framework that allows wireless transceivers to effectively defeat jamming attacks. Specifically, while being attacked, wireless devices can either harvest energy from the jamming signals or backscatter the jamming signals to transmit data by using the ambient backscatter communication technique. Then, the deep dueling algorithm is adopted to learn about the jammer and obtain the optimal countermeasures thousand times faster than tradi-

tional reinforcement learning algorithms. Extensive simulations demonstrate that our solution can successfully defeat jamming attacks even with very high attack power levels/budgets. Interestingly, we show that by leveraging the jamming signals, the more frequently the jammer attacks the channel, the greater performance the system can achieve.

Finally, we propose a joint optimal coding and scheduling framework for secure and effective distributed learning (DL) over wireless edge networks. In particular, we use the coded computing technique to encode learning tasks by adding data/computing redundancy. As such, a learning task can be completed without waiting for straggling nodes. To account for the dynamics and uncertainty of wireless connections and edge nodes, several reinforcement learning algorithms are proposed to jointly obtain the optimal coding scheme and the best set of edge nodes for different learning tasks. Simulations show that the proposed framework reduces the average learning delay in wireless edge computing up to 66% compared with other DL approaches.

Acknowledgements

First and foremost, I would like to take this opportunity to express my deepest gratitude to my supervisors, Dr. Diep N. Nguyen, Dr. Hoang Dinh, and Prof. Eryk Dutkiewicz, for all the support, guidance, and encouragement. Without them, this dissertation would have been impossible. During my study, they not only guided me to pursue great and impactful research but also encouraged me to go beyond my boundary to do things that seem impossible. I am truly privileged and lucky to be supervised by them.

I would like to thank all my colleagues and friends at the University of Technology Sydney for their support, discussion, and friendship. They made my PhD life more colorful. My thanks also go to the SEDE admin team for handling all the paperwork and forms during my PhD study. I would like to thank the university and the Faculty of Engineering and Information Technology (FEIT) for giving me the International Research Scholarship and FEIT Scholarship. I also would like to thank Google for supporting my research through the Google PhD Fellowship program.

I would especially like to thank my dearest family for encouraging and supporting me. Their endless love gives me strength and power to overcome difficulties in my life. My final words of love and gratitude are dedicated to my beloved wife, Hong Ngoc, for her infinite love, sacrifice, and patience.

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- B-1. D. T. Hoang, D. Niyato, D. I. Kim, **N. V. Huynh**, and S. Gong, *Ambient Backscatter Communication Networks*, Cambridge University Press, (Authored book) 2019. (*Partly corresponding to Chapter 4*)
- B-2. D. T. Hoang, **N. V. Huynh**, D. N. Nguyen, E. Hossain, and D. Niyato, *Deep Reinforcement Learning for Wireless Communications and Networking: Theory, Applications and Implementation*, Wiley, expected third quarter of 2022. (*Corresponding to Chapter 2*)

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- J-2. **N. V. Huynh**, D. N. Nguyen, D. T. Hoang, and E. Dutkiewicz, “Jam Me If You Can: Defeating Jammer with Deep Dueling Neural Network Architecture and Ambient Backscattering Augmented Communications,” *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 11, pp. 2603-2620, Nov. 2019. (*Corresponding to Chapter 4*)

- J-3. **N. V. Huynh**, D. T. Hoang, D. N. Nguyen, and E. Dutkiewicz, “DeepFake: Deep Dueling-based Deception Strategy to Defeat Reactive Jammers,” *IEEE Transactions on Wireless Communications*, Early Access, May 2021 (*Partly corresponding to Chapter 4*)
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Abbreviation

AI	Artificial Intelligence
DL	Distributed learning
M2M	Machine-to-machine
QoS	Quality of service
SINR	Signal-to-interference-plus-noise ratio
SDN	Software-defined networking
NFV	Network functions virtualization
SMDP	Semi-Markov decision processes
FHSS	Frequency-hopping spread spectrum
DSSS	Direct sequence spread spectrum
RA	Rate adaptation
RF	Radio frequency
MDP	Markov decision process
MDS	Maximum distance separable
ARC	Aligned repetition coding
AMC	Aligned minimum distance separable coding
MEC	Mobile edge server
RMO	Resource management and orchestration
URLLC	Ultra-reliable and low-latency communications
SiS	Self-interference suppression
BER	Bit error rate
PDR	Packet delivery ratio
ARP	Action-replay process