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DOCTORAL THESIS

Deep Reinforcement Learning for Cognitive Radio and
Software-Defined Networks

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BSc (Telecommunication and Networking)

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in the

Interdisciplinary Machine Learning Research Group

School of Information and Physical Sciences

College of Engineering, Science and Environment

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In memory of my father
To my mother
with love and eternal appreciation

Statement of Originality

I hereby certify that the work embodied in the thesis, titled 'Deep Reinforcement Learning for Cognitive Radio and Software-Defined Networks', is my own work, conducted under normal supervision. The thesis contains no material which has been accepted, or is being examined, for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made. I give consent to the final version of my thesis being made available worldwide when deposited in the University's Digital Repository, subject to the provisions of the Copyright Act 1968 and any approved embargo.

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Acknowledgement of Authorship

I, Syed Jalil, hereby certify that the work embodied in this thesis contains published and submitted papers of which I am a joint author. I declare that I have contributed to the following papers,

- **S.Q. Jalil**, M.H.Rehmani, S. Chalup, “DQR: Deep Q-Routing in Software Defined Networks”, in International Joint Conference on Neural Networks (IJCNN), Virtual on July 19-24, 2020. Publisher: IEEE, DOI: [IJCNN48605.2020.9206767](https://doi.org/10.1109/IJCNN48605.2020.9206767).
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- **S.Q. Jalil**, M.H.Rehmani, S. Chalup, “Spectrum Sensing in Cognitive Radio Networks using Offline Deep Reinforcement Learning” (Under review).

by,

- contributing to each study’s conception and design,
- developing analysis plans,
- developing research material and collecting data,
- performing both quantitative and qualitative analyses,

- writing code and execution of programs,
- interpreting data,
- and leading the writing of the manuscripts.

Supervisor endorsement:

By signing below I, Dr Stephan Chalup, confirm that my PhD student Syed Qaisar JALIL contributed to the above listed papers as stated,

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Date: 27-02-2021

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* میں ڈاکٹر مبشر حسین رحمانی کا بے حد مشکور ہوں جنہوں نے نہ صرف مجھے ڈاکٹریٹ کی ڈگری حاصل کرنے کی ترغیب دی بلکہ اپنے قیمتی ان پیٹ اور حوصلہ افزائی سے پی ایچ ڈی کے دوران میری رہنمائی بھی کی۔ آپ کی رہنمائی کی وجہ سے پی ایچ ڈی کے سفر کی مشکلات کا سامنا کرنے میں مجھے مدد ملی۔

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List of Abbreviations

ACER Actor Critic with Experience Replay. [135](#)

ANN Artificial Neural Network. [52](#)

BS Base Station. [24](#)

CM Covariance Matrix. [52](#)

CNN Convolutional Neural Network. [57](#)

CQL Conservative Q-Learning. [31](#)

CR Cognitive Radio. [22](#)

CRN Cognitive Radio Network. [23](#)

CSS Cooperative Spectrum Sensing. [28](#)

CTMC Continuous-Time Markov Chain. [102](#)

D3QN-PER Dueling Double Deep Q-Networks with Prioritised Experience Replay. [31](#)

DCQL Discrete Conservative Q-Learning. [43](#)

DCS Deep Cooperative Sensing. [97](#)

DCS-HD Deep Cooperative Sensing Hard. [97](#)

DCS-SD Deep Cooperative Sensing Soft. [97](#)

-
- DDPG** Deep Deterministic Policy Gradient. [162](#)
- DL** Deep Learning. [20](#)
- DNN** Deep Neural Network. [39](#)
- DQN** Deep Q-Network. [39](#)
- DQR** Deep Q-Routing. [32](#)
- DRL** Deep Reinforcement Learning. [20](#)
- DSA** Dynamic Spectrum Access. [22](#)
- DTMC** Discrete-Time Markov Chain. [101](#)
- ED** Energy Detection. [51](#)
- FC** Fusion Center. [28](#)
- GOOSE** Generic Object-Oriented Substation Even. [168](#)
- GPD** Generalised Pareto Distribution. [102](#)
- HMM** Hidden Markov Model. [56](#)
- IQL** Independent Q-learning. [41](#)
- LARAC** Lagrangian relaxation-based aggregated cost. [168](#)
- LSS** Local Spectrum Sensing. [27](#)
- LSTM** Long Short-Term Memory. [107](#)
- MDP** Markov Decision Processes. [34](#)
- ML** Machine Learning. [19](#)
- NBIs** Northbound Interfaces. [145](#)

NOMA Non-Orthogonal Multiple Access. [50](#)

OOD Out-of-distribution. [42](#)

PDF Probability Density Function. [102](#)

PER Prioritised Experience Replay. [41](#)

PPO Proximal Policy Optimisation. [82](#)

PUs Primary Users. [23](#)

QoS Quality-of-service. [21](#)

RL Reinforcement Learning. [19](#)

SBIs Southbound Interfaces. [145](#)

SDN Software-defined Network. [25](#)

SNR Signal-to-noise. [57](#)

SOP Spectrum Occupancy Prediction. [28](#)

SP Shortest Path. [153](#)

SUs Secondary Users. [23](#)

SV Sampled Values. [168](#)

TM Traffic Matrix. [162](#)

Abstract

Reinforcement learning is a branch of machine learning that enables machines to learn by trial and error. It is an experience-driven sequential learning process to achieve a particular goal. Recent advances in reinforcement learning have combined deep learning, which has led to the emergence of a new field called deep reinforcement learning (DRL). DRL algorithms have shown great success on various complex decision-making tasks that were earlier thought to be extremely difficult for a computer. Communication networks play a fundamental role in today's information age, where connectivity has become a basic commodity of life. They will play an even more critical role in the future, when *everything* from people, animals, wearable devices and cars to buildings and industries, will be connected. Providing connectivity on such a massive scale calls for an advanced set of solutions that can deal with complex, large-scale, and dynamic wireless and wired networks. DRL has the potential to meet these challenges due to its ability to learn from experience and adapt to the changing complex decision-making environment. Thus, we use DRL as a primary tool in this thesis and investigate one wireless and one wired technology.

Spectrum scarcity is one of the major issues for wireless communications, due to the limited availability of spectrum bands. A cognitive radio network (CRN) is one of the potential technologies that can overcome spectrum scarcity by efficiently utilising idle spectrum. In a CRN, cognitive users dynamically utilise idle spectrum with the requirement of no harmful interference to the licensed spectrum users. The first part of this thesis investigates CRN from the viewpoint of enhancing the process of dynamic spectrum access, and identifies three research objectives. First, a non-cooperative distributed CRN is considered where the goal is to achieve fairness of spectrum resources while avoiding collision. This is a highly challenging research problem due to the non-cooperating network users and non-stationary environment. A multi-agent DRL solution is proposed that significantly improves the network performance in terms of fairness of spectrum resources

and collision avoidance among all users of the network. Second, the task of local and cooperative spectrum sensing in a centralised CRN is investigated. For licensed users, time-inhomogeneous discrete and continuous activity models are considered. An offline DRL solution is proposed that significantly improves the detection of licensed spectrum users and idle spectrum utilisation. Third, prediction-based spectrum sensing in a centralised CRN is investigated. A k -step prediction framework with an offline DRL solution is proposed for both local and cooperative spectrum sensing. The proposed solution significantly improves the energy efficiency and transmission time of cognitive users.

For wired communications, a software-defined network (SDN) is a logically centralised network that provides various benefits over traditional distributed networks, such as on-demand resource allocation and easy reconfiguration. In an SDN, quality of service (QoS) routing is basic functionality that determines the path between a source and destination which fulfils the QoS requirements. It plays a vital role in various crucial network services, such as substation communication in a smart grid. The second part of this thesis investigates QoS routing in an SDN. Existing DRL solutions formulate routing as a continuous control problem using k -shortest paths, whereas we propose a discrete control QoS routing framework called deep Q-routing that does not use predefined k -shortest paths. Instead, the proposed framework learns the network topology and optimises QoS parameters while avoiding network loops and invalid actions. The effectiveness of the proposed framework is shown for both soft and hard QoS routing.