

# **Novel Architectures and Networking Solutions for Intelligent Mobile Edge Computing Networks**

**by Yuris Mulya Saputra**

Thesis submitted in fulfilment of the requirements for  
the degree of

**Doctor of Philosophy**

under the supervision of Dr. Diep N. Nguyen, Dr. Dinh Thai  
Hoang, and Prof. Eryk Dutkiewicz

University of Technology Sydney  
Faculty of Engineering and Information Technology

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# CERTIFICATE OF ORIGINAL AUTHORSHIP

I, YURIS MULYA SAPUTRA 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.

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# ABSTRACT

## **Novel Architectures and Networking Solutions for Intelligent Mobile Edge Computing Networks**

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Mobile edge computing (MEC) has emerged as a highly-effective solution to address the proliferation of smart devices and growing demands for computationally-intensive applications. The key idea of MEC networks is to distribute computing resources closer to mobile users (MUs) by deploying servers at the “edge” of the networks, i.e., mobile edge nodes (MENs). Nonetheless, the development of MEC networks has been facing various challenges including the decentralized nature, small coverage, unreliable computing/communication resources, and limited storage capacity of the MENs. This thesis aims to address the above challenges through developing novel collaborative architectures and intelligent networking strategies for MEC networks.

Firstly, we introduce a novel MEC network architecture that leverages an optimal joint caching-delivering with horizontal cooperation among MENs. Particularly, we first formulate the content-access delay minimization problem by jointly optimizing content caching and delivering decisions under various network constraints, aiming at minimizing the total average delay for the MEC network. Then, we design centralized and distributed solutions to find the decisions of joint caching and delivering policy for the transformed problem.

As the second contribution, we propose a novel economic-efficiency framework for the MEC network to maximize the profits for MENs. Specifically, we first introduce a demand prediction method for MENs leveraging federated learning (FL) approaches. Based on the predicted demands, each MEN can reserve demands from the MEC

service provider (MSP) in advance to optimize its profit. Nonetheless, due to the competition among the MENs as well as unknown information from the MSP, we develop a multi-principal one-agent (MPOA) contract-based utility optimization under the MSP's constraints as well as other MENs' contracts. We then develop an iterative algorithm to find the optimal contracts for the MENs.

Finally, we propose a novel dynamic FL-based framework leveraging dynamic selection of MENs for the FL process in the MEC network. Particularly, the MSP first implements an MU selection method to determine a set of the best MUs for the FL process according to the location and information significance at each learning round. Then, each selected MU can collect information and offer a payment contract to the MSP based on its collected QoI. For that, we develop an MPOA contract-based policy to maximize the profits of the MSP and learning MUs under the MSP's limited payment budget and asymmetric information between the MSP and MUs.

# Dedication

To my beloved wife, son, parents, parents-in-law, university, and country, Indonesia.

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# List of Publications

## Book Chapters

- B-1. **Y. M. Saputra**, D. T. Hoang, D. N. Nguyen, E. Dutkiewicz, and D. Niyato, “Wireless Edge Caching for Mobile Social Networks,” in *Wireless Edge Caching: Modelling, Analysis, and Optimization*, Cambridge University Press, Mar. 2021. <https://www.cambridge.org/au/academic/subjects/engineering/wireless-communications/wireless-edge-caching-modeling-analysis-and-optimization?format=HB>. (Partly corresponding to Chapter 1)

## Journal Papers

- J-1. **Y. M. Saputra**, D. T. Hoang, D. N. Nguyen, and E. Dutkiewicz, “A Novel Mobile Edge Network Architecture with Joint Caching-Delivering and Horizontal Cooperation,” *IEEE Transactions on Mobile Computing*, vol. 20, no. 1, pp. 19-31, Jan. 2021. <https://ieeexplore.ieee.org/document/8821308>. (Corresponding to Chapter 2)
- J-2. **Y. M. Saputra**, D. N. Nguyen, D. T. Hoang, T. X. Vu, E. Dutkiewicz, and S. Chatzinotas, “Federated Learning Meets Contract Theory: Economic-Efficiency Framework for Electric Vehicle Networks,” Early Access, *IEEE Transactions on Mobile Computing*, Dec. 2020. <https://ieeexplore.ieee.org/document/9300192>. (Corresponding to Chapter 3)
- J-3. **Y. M. Saputra**, D. T. Hoang, D. N. Nguyen, L. N. Tran, S. Gong, and E. Dutkiewicz, “Dynamic Federated Learning-Based Economic Framework for Internet-of-Vehicles,” Early Access, *IEEE Transactions on Mobile Computing*, Oct. 2021. <https://ieeexplore.ieee.org/document/9585537>. (Corresponding to Chapter 4)

- J-4. **Y. M. Saputra**, D. T. Hoang, D. N. Nguyen, E. Dutkiewicz, D. Niyato, and D. I. Kim, “Distributed Deep Learning at the Edge: A Novel Proactive and Cooperative Caching Framework for Mobile Edge Networks,” *IEEE Wireless Communications Letters*, vol. 8, no. 4, Aug. 2019. <https://ieeexplore.ieee.org/document/8693954>.
- J-5. **Y. M. Saputra**, D. N. Nguyen, D. T. Hoang, Q. V. Pham, E. Dutkiewicz, and W. J. Hwang, “Federated Learning Framework with Straggling Mitigation and Privacy-Awareness for AI-based Mobile Application Services,” submitted to *IEEE Transactions on Mobile Computing*, under review. <https://arxiv.org/abs/2106.09261>.

### Conference Papers

- C-1. **Y. M. Saputra**, D. T. Hoang, D. N. Nguyen, and E. Dutkiewicz, “JOCAR: A Jointly Optimal Caching and Routing Framework for Cooperative Edge Caching Networks,” in *IEEE GLOBECOM*, Hawaii, USA, Dec. 2019, pp. 1-6. <https://ieeexplore.ieee.org/document/9013745>. (Corresponding to Chapter 2)
- C-2. **Y. M. Saputra**, D. T. Hoang, D. N. Nguyen, E. Dutkiewicz, M. D. Mueck, and S. Srikanteswara, “Energy Demand Prediction with Federated Learning for Electric Vehicle Networks,” in *IEEE GLOBECOM*, Hawaii, USA, Dec. 2019, pp. 1-6. <https://ieeexplore.ieee.org/document/9013587>. (Corresponding to Chapter 3)
- C-3. **Y. M. Saputra**, D. N. Nguyen, D. T. Hoang, E. Dutkiewicz and M. D. Mueck, “Common Agency-Based Economic Model for Energy Contract in Electric Vehicle Networks,” in *IEEE GLOBECOM*, Taipei, Taiwan, Dec. 2020, pp. 1-6. <https://ieeexplore.ieee.org/document/9322376>. (Corresponding to Chapter 3)
- C-4. **Y. M. Saputra**, D. N. Nguyen, D. T. Hoang, and E. Dutkiewicz, “Selective Federated Learning for On-Road Services in Internet-of-Vehicles,” presented in *IEEE GLOBECOM*, Madrid, Spain, Dec. 2021. (Corresponding to Chapter

4)

- C-5. **Y. M. Saputra**, D. N. Nguyen, D. T. Hoang, and E. Dutkiewicz, “Incentive Mechanism for AI-Based Mobile Applications with Coded Federated Learning,” presented in *IEEE GLOBECOM*, Madrid, Spain, Dec. 2021.
- C-6. **Y. M. Saputra**, D. N. Nguyen, D. T. Hoang, and E. Dutkiewicz, “In-Network Caching and Learning Optimization for Federated Learning in Mobile Edge Networks,” submitted to *IEEE ICC 2022*, under review.

### Other Papers

- O-1. T. V. Khoa, **Y. M. Saputra**, D. T. Hoang, N. L. Trung, D. N. Nguyen, N. V. Ha, and E. Dutkiewicz, “Collaborative Learning Model for Cyberattack Detection Systems in IoT Industry 4.0,” in *IEEE WCNC*, Seoul, South Korea, May 2020, pp. 1-6. <https://ieeexplore.ieee.org/document/9120761>.
- O-2. C. T. Nguyen, **Y. M. Saputra**, N. V. Huynh, N. T. Nguyen, T. V. Khoa, B. M. Tuan, D. N. Nguyen, D. T. Hoang, T. X. Vu, E. Dutkiewicz, S. Chatzino-tas, and B. Ottersten, “A Comprehensive Survey of Enabling and Emerging Technologies for Social Distancing - Part I: Fundamentals and Enabling Technologies,” *IEEE Access*, vol. 8, pp. pp. 153479-153507, Aug. 2020. <https://ieeexplore.ieee.org/document/9172058>.
- O-3. C. T. Nguyen, **Y. M. Saputra**, N. V. Huynh, N. T. Nguyen, T. V. Khoa, B. M. Tuan, D. N. Nguyen, D. T. Hoang, T. X. Vu, E. Dutkiewicz, S. Chatzino-tas, and B. Ottersten, “A Comprehensive Survey of Enabling and Emerging Technologies for Social Distancing - Part II: Emerging Technologies and Open Issues,” *IEEE Access*, vol. 8, pp. 154209-154236, Aug. 2020. <https://ieeexplore.ieee.org/document/9172065>.
- O-4. C. T. Nguyen, N. V. Huynh, N. H. Chu, **Y. M. Saputra**, D. T. Hoang, D. N. Nguyen, Q. V. Pham, D. Niyato, E. Dutkiewicz, and W. J. Hwang, “Transfer Learning for Future Wireless Networks: A Comprehensive Survey,” submitted to *Proceedings of the IEEE*, under review. <https://arxiv.org/abs/2102.07572>.

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## Abbreviation

<b>5G</b>	The fifth generation technology standard for cellular networks
<b>AADF</b>	Average Annual Daily Flow
<b>AUD</b>	Australian Dollar
<b>BS</b>	Base Station
<b>CLS</b>	Cloud Server
<b>CN</b>	Core Network
<b>CS</b>	Charging Station
<b>CSP</b>	Charging Station Provider
<b>D2D</b>	Device-to-Device
<b>DFEL</b>	Decentralized Federated Energy Learning
<b>DNN</b>	Deep Neural Network
<b>ETSI</b>	The European Telecommunications Standards Institute
<b>EV</b>	Electric Vehicle
<b>FL</b>	Federated Learning
<b>FNN</b>	Feedforward Neural Network
<b>FoA</b>	Frequency-of-Access
<b>GAMS</b>	General Algebraic Modeling Language
<b>GB</b>	Giga Bytes
<b>GPS</b>	Global Positioning System
<b>HetNets</b>	Heterogeneous Networks
<b>iBBA</b>	Improved Branch-and-Bound Algorithm
<b>IC</b>	Incentive Compatibility
<b>IEEE</b>	Institute of Electrical and Electronics Engineers
<b>i.i.d</b>	independent and identically distributed
<b>IL</b>	Inner Level

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<b>IPM</b>	Interior-Point Method
<b>IoT</b>	Internet-of-Things
<b>IoV</b>	Internet-of-Vehicles
<b>IR</b>	Individual Rationality
<b>JOCAD</b>	Joint Cooperative Caching and Delivering
<b>kNN</b>	k-Nearest Neighbor
<b>kWh</b>	kilo Watt hours
<b>MB</b>	Mega Bytes
<b>MEC</b>	Mobile Edge Computing
<b>MEN</b>	Mobile Edge Node
<b>MINLP</b>	Mixed Integer Non Linear Programming
<b>ML</b>	Machine Learning
<b>MPOA</b>	Multi-Principal One-Agent
<b>MSP</b>	MEC Service Provider
<b>MU</b>	Mobile User
<b>MWh</b>	Mega Watt hours
<b>NP</b>	Non-deterministic Polynomial-time
<b>OL</b>	Outer Level
<b>QoI</b>	Quality-of-Information
<b>RAM</b>	Random Access Memory
<b>RMSE</b>	Root Mean Square Error
<b>RP</b>	Root Problem
<b>SGP</b>	Smart Grid Provider
<b>SNN</b>	Shallow Neural Network
<b>SP</b>	Subproblem
<b>SV</b>	Smart Vehicle
<b>UK</b>	United Kingdom
<b>UPF</b>	User Plane Function
<b>VSP</b>	Vehicle Service Provider
<b>Wi-Fi</b>	Wireless Fidelity