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Nota di contenuto	List of Contributors xv -- Preface xxi -- Part I Spectrum Intelligence and Adaptive Resource Management 1 -- 1 Machine Learning for Spectrum Access and Sharing 3 /Kobi Cohen -- 1.1 Introduction 3 -- 1.2 Online Learning Algorithms for Opportunistic Spectrum Access 4 -- 1.2.1 The Network Model 4 -- 1.2.2 Performance Measures of the Online Learning Algorithms 5 -- 1.2.3 The Objective 6 -- 1.2.4 Random and Deterministic Approaches 6 -- 1.2.5 The Adaptive Sequencing Rules Approach 7 -- 1.2.5.1 Structure of Transmission Epochs 7 -- 1.2.5.2 Selection Rule under the ASR Algorithm 8 -- 1.2.5.3 High-Level Pseudocode and Implementation Discussion 9 -- 1.3 Learning Algorithms for Channel Allocation 9 -- 1.3.1 The Network Model 10 -- 1.3.2 Distributed Learning, Game-Theoretic, and Matching Approaches 11 -- 1.3.3 Deep Reinforcement Learning for DSA 13 -- 1.3.3.1 Background on Q-learning and Deep Reinforcement Learning (DRL): 13 -- 1.3.4 Existing DRL-Based Methods for DSA 14 -- 1.3.5 Deep Q-Learning for Spectrum Access (DQSA) Algorithm 15 -- 1.3.5.1 Architecture of the DQN Used in the DQSA Algorithm 15 -- 1.3.5.2 Training the DQN and Online Spectrum Access 16 -- 1.3.5.3 Simulation Results 17 -- 1.4 Conclusions 19 -- Acknowledgments 20 -- Bibliography 20 -- 2 Reinforcement Learning for Resource Allocation in Cognitive Radio Networks 27 /Andres Kwasinski, Wenbo Wang, and

Fatemeh Shah Mohammadi -- 2.1 Use of Q-Learning for Cross-layer Resource Allocation 29 -- 2.2 Deep Q-Learning and Resource Allocation 33 -- 2.3 Cooperative Learning and Resource Allocation 36 -- 2.4 Conclusions 42 -- Bibliography 43 -- 3 Machine Learning for Spectrum Sharing in Millimeter-Wave Cellular Networks 45 /Hadi Ghauch, Hossein Shokri-Ghadikolaei, Gabor Fodor, Carlo Fischione, and Mikael Skoglund -- 3.1 Background and Motivation 45 -- 3.1.1 Review of Cellular Network Evolution 45 -- 3.1.2 Millimeter-Wave and Large-Scale Antenna Systems 46 -- 3.1.3 Review of Spectrum Sharing 47 -- 3.1.4 Model-Based vs. Data-Driven Approaches 48. 3.2 System Model and Problem Formulation 49 -- 3.2.1 Models 49 -- 3.2.1.1 Network Model 49 -- 3.2.1.2 Association Model 49 -- 3.2.1.3 Antenna and Channel Model 49 -- 3.2.1.4 Beamforming and Coordination Models 50 -- 3.2.1.5 Coordination Model 50 -- 3.2.2 Problem Formulation 51 -- 3.2.2.1 Rate Models 52 -- 3.2.3 Model-based Approach 52 -- 3.2.4 Data-driven Approach 53 -- 3.3 Hybrid Solution Approach 54 -- 3.3.1 Data-Driven Component 55 -- 3.3.2 Model-Based Component 56 -- 3.3.2.1 Illustrative Numerical Results 58 -- 3.3.3 Practical Considerations 58 -- 3.3.3.1 Implementing Training Frames 58 -- 3.3.3.2 Initializations 59 -- 3.3.3.3 Choice of the Penalty Matrix 59 -- 3.4 Conclusions and Discussions 59 -- Appendix A Appendix for Chapter 3 61 -- A.1 Overview of Reinforcement Learning 61 -- Bibliography 61 -- 4 Deep Learning-Based Coverage and Capacity Optimization 63 /Andrei Marinescu, Zhiyuan Jiang, Sheng Zhou, Luiz A. DaSilva, and Zhisheng Niu -- 4.1 Introduction 63 -- 4.2 Related Machine Learning Techniques for Autonomous Network Management 64 -- 4.2.1 Reinforcement Learning and Neural Networks 64 -- 4.2.2 Application to Mobile Networks 66 -- 4.3 Data-Driven Base-Station Sleeping Operations by Deep Reinforcement Learning 67 -- 4.3.1 Deep Reinforcement Learning Architecture 67 -- 4.3.2 Deep Q-Learning Preliminary 68 -- 4.3.3 Applications to BS Sleeping Control 68 -- 4.3.3.1 Action-Wise Experience Replay 69 -- 4.3.3.2 Adaptive Reward Scaling 70 -- 4.3.3.3 Environment Models and Dyna Integration 70 -- 4.3.3.4 DeepNap Algorithm Description 71 -- 4.3.4 Experiments 71 -- 4.3.4.1 Algorithm Comparisons 71 -- 4.3.5 Summary 72 -- 4.4 Dynamic Frequency Reuse through a Multi-Agent Neural Network Approach 72 -- 4.4.1 Multi-Agent System Architecture 73 -- 4.4.1.1 Cell Agent Architecture 75 -- 4.4.2 Application to Fractional Frequency Reuse 75 -- 4.4.3 Scenario Implementation 76 -- 4.4.3.1 Cell Agent Neural Network 76 -- 4.4.4 Evaluation 78 -- 4.4.4.1 Neural Network Performance 78. 4.4.4.2 Multi-Agent System Performance 79 -- 4.4.5 Summary 81 -- 4.5 Conclusions 81 -- Bibliography 82 -- 5 Machine Learning for Optimal Resource Allocation 85 /Marius Pesavento and Florian Bahlke -- 5.1 Introduction and Motivation 85 -- 5.1.1 Network Capacity and Densification 86 -- 5.1.2 Decentralized Resource Minimization 87 -- 5.1.3 Overview 88 -- 5.2 System Model 88 -- 5.2.1 Heterogeneous Wireless Networks 88 -- 5.2.2 Load Balancing 89 -- 5.3 Resource Minimization Approaches 90 -- 5.3.1 Optimized Allocation 91 -- 5.3.2 Feature Selection and Training 91 -- 5.3.3 Range Expansion Optimization 93 -- 5.3.4 Range Expansion Classifier Training 94 -- 5.3.5 Multi-Class Classification 94 -- 5.4 Numerical Results 96 -- 5.5 Concluding Remarks 99 -- Bibliography 100 -- 6 Machine Learning in Energy Efficiency Optimization 105 /Muhammad Ali Imran, Ana Flavia dos Reis, Glauber Brante, Paulo Valente Klaine, and Richard Demo Souza -- 6.1 Self-Organizing Wireless Networks 106 -- 6.2 Traffic Prediction and Machine Learning 110 -- 6.3 Cognitive Radio and Machine Learning 111 -- 6.4 Future Trends and Challenges 112 --

6.4.1 Deep Learning 112 -- 6.4.2 Positioning of Unmanned Aerial Vehicles 113 -- 6.4.3 Learn-to-Optimize Approaches 113 -- 6.4.4 Some Challenges 114 -- 6.5 Conclusions 114 -- Bibliography 114 -- 7 Deep Learning Based Traffic and Mobility Prediction 119 /Honggang Zhang, Yuxiu Hua, Chujie Wang, Rongpeng Li, and Zhifeng Zhao -- 7.1 Introduction 119 -- 7.2 Related Work 120 -- 7.2.1 Traffic Prediction 120 -- 7.2.2 Mobility Prediction 121 -- 7.3 Mathematical Background 122 -- 7.4 ANN-Based Models for Traffic and Mobility Prediction 124 -- 7.4.1 ANN for Traffic Prediction 124 -- 7.4.1.1 Long Short-Term Memory Network Solution 124 -- 7.4.1.2 Random Connectivity Long Short-Term Memory Network Solution 125 -- 7.4.2 ANN for Mobility Prediction 128 -- 7.4.2.1 Basic LSTM Network for Mobility Prediction 128 -- 7.4.2.2 Spatial-Information-Assisted LSTM-Based Framework of Individual Mobility Prediction 130. 7.4.2.3 Spatial-Information-Assisted LSTM-Based Framework of Group Mobility Prediction 131 -- 7.5 Conclusion 133 -- Bibliography 134 -- 8 Machine Learning for Resource-Efficient Data Transfer in Mobile Crowdsensing 137 /Benjamin Sliwa, Robert Falkenberg, and Christian Wietfeld -- 8.1 Mobile Crowdsensing 137 -- 8.1.1 Applications and Requirements 138 -- 8.1.2 Anticipatory Data Transmission 139 -- 8.2 ML-Based Context-Aware Data Transmission 140 -- 8.2.1 Groundwork: Channel-aware Transmission 140 -- 8.2.2 Groundwork: Predictive CAT 142 -- 8.2.3 ML-based CAT 144 -- 8.2.4 ML-based pCAT 146 -- 8.3 Methodology for Real-World Performance Evaluation 148 -- 8.3.1 Evaluation Scenario 148 -- 8.3.2 Power Consumption Analysis 148 -- 8.4 Results of the Real-World Performance Evaluation 149 -- 8.4.1 Statistical Properties of the Network Quality Indicators 149 -- 8.4.2 Comparison of the Transmission Schemes 149 -- 8.4.3 Summary 151 -- 8.5 Conclusion 152 -- Acknowledgments 154 -- Bibliography 154 -- Part II Transmission Intelligence and Adaptive Baseband Processing 157 -- 9 Machine LearningBased Adaptive Modulation and Coding Design 159 /Lin Zhang and Zhiqiang Wu -- 9.1 Introduction and Motivation 159 -- 9.1.1 Overview of ML-Assisted AMC 160 -- 9.1.2 MCS Schemes Specified by IEEE 802.11n 161 -- 9.2 SL-Assisted AMC 162 -- 9.2.1 k-NN-Assisted AMC 162 -- 9.2.1.1 Algorithm for k-NN-Assisted AMC 163 -- 9.2.2 Performance Analysis of k-NN-Assisted AMC System 164 -- 9.2.3 SVM-Assisted AMC 166 -- 9.2.3.1 SVM Algorithm 166 -- 9.2.3.2 Simulation and Results 170 -- 9.3 RL-Assisted AMC 172 -- 9.3.1 Markov Decision Process 172 -- 9.3.2 Solution for the Markov Decision 173 -- 9.3.3 Actions, States, and Rewards 174 -- 9.3.4 Performance Analysis and Simulations 175 -- 9.4 Further Discussion and Conclusions 178 -- Bibliography 178 -- 10 Machine LearningBased Nonlinear MIMO Detector 181 /Song-Nam Hong and Seonho Kim -- 10.1 Introduction 181 -- 10.2 A Multihop MIMO Channel Model 182 -- 10.3 Supervised-Learning-based MIMO Detector 184. 10.3.1 Non-Parametric Learning 184 -- 10.3.2 Parametric Learning 185 -- 10.4 Low-Complexity SL (LCSL) Detector 188 -- 10.5 Numerical Results 191 -- 10.6 Conclusions 193 -- Bibliography 193 -- 11 Adaptive Learning for Symbol Detection: A Reproducing Kernel Hilbert Space Approach 197 /Daniyal Amir Awan, Renato Luis Garrido Cavalcante, Masahario Yukawa, and Slawomir Stanczak -- 11.1 Introduction 197 -- 11.2 Preliminaries 198 -- 11.2.1 Reproducing Kernel Hilbert Spaces 198 -- 11.2.2 Sum Spaces of Reproducing Kernel Hilbert Spaces 199 -- 11.3 System Model 200 -- 11.3.1 Symbol Detection in Multiuser Environments 201 -- 11.3.2 Detection of Complex-Valued Symbols in Real Hilbert Spaces 202 -- 11.4 The Proposed Learning Algorithm 203 -- 11.4.1 The Canonical Iteration

203 -- 11.4.2 Practical Issues 204 -- 11.4.3 Online Dictionary Learning  
205 -- 11.4.3.1 Dictionary for the Linear Component 206 -- 11.4.3.2  
Dictionary for the Gaussian Component 206 -- 11.4.4 The Online  
Learning Algorithm 206 -- 11.5 Simulation 207 -- 11.6 Conclusion  
208 -- Appendix A Derivation of the Sparsification Metric and the  
Projections onto the Subspace Spanned by the Nonlinear Dictionary 210  
-- Bibliography 211 -- 12 Machine Learning for Joint Channel  
Equalization and Signal Detection 213 /Lin Zhang and Lie-Liang Yang  
-- 12.1 Introduction 213 -- 12.2 Overview of Neural Network-Based  
Channel Equalization 214 -- 12.2.1 Multilayer Perceptron-Based  
Equalizers 215 -- 12.2.2 Functional Link Artificial Neural Network-  
Based Equalizers 215 -- 12.2.3 Radial Basis Function-Based Equalizers  
216 -- 12.2.4 Recurrent Neural Networks-Based Equalizers 216 --  
12.2.5 Self-Constructing Recurrent Fuzzy Neural Network-Based  
Equalizers 217 -- 12.2.6 Deep-Learning-Based Equalizers 217 --  
12.2.7 Extreme Learning Machine-Based Equalizers 218 -- 12.2.8  
SVM- and GPR-Based Equalizers 218 -- 12.3 Principles of Equalization  
and Detection 219 -- 12.4 NN-Based Equalization and Detection 223  
-- 12.4.1 Multilayer Perceptron Model 223.  
12.4.1.1 Generalized Multilayer Perceptron Structure 224 -- 12.4.1.2  
Gradient Descent Algorithm 225 -- 12.4.1.3 Forward and Backward  
Propagation 226 -- 12.4.2 Deep-Learning Neural Network-Based  
Equalizers 227 -- 12.4.2.1 System Model and Network Structure 227  
-- 12.4.2.2 Network Training 228 -- 12.4.3 Convolutional Neural  
Network-Based Equalizers 229 -- 12.4.4 Recurrent Neural Network-  
Based Equalizers 231 -- 12.5 Performance of OFDM Systems With  
Neural Network-Based Equalization 232 -- 12.5.1 System Model and  
Network Structure 232 -- 12.5.2 DNN and CNN Network Structure 233  
-- 12.5.3 Offline Training and Online Deployment 234 -- 12.5.4  
Simulation Results and Analyses 235 -- 12.6 Conclusions and  
Discussion 236 -- Bibliography 237 -- 13 Neural Networks for Signal  
Intelligence: Theory and Practice 243 /Jithin Jagannath, Nicholas  
Polosky, Anu Jagannath, Francesco Restuccia, and Tommaso Melodia --  
13.1 Introduction 243 -- 13.2 Overview of Artificial Neural Networks  
244 -- 13.2.1 Feedforward Neural Networks 244 -- 13.2.2  
Convolutional Neural Networks 247 -- 13.3 Neural Networks for Signal  
Intelligence 248 -- 13.3.1 Modulation Classification 249 -- 13.3.2  
Wireless Interference Classification 252 -- 13.4 Neural Networks for  
Spectrum Sensing 255 -- 13.4.1 Existing Work 256 -- 13.4.2  
Background on System-on-Chip Computer Architecture 256 -- 13.4.3  
A Design Framework for Real-Time RF Deep Learning 257 -- 13.4.3.1  
High-Level Synthesis 257 -- 13.4.3.2 Design Steps 258 -- 13.5 Open  
Problems 259 -- 13.5.1 Lack of Large-Scale Wireless Signal Datasets  
259 -- 13.5.2 Choice of I/Q Data Representation Format 259 -- 13.5.3  
Choice of Learning Model and Architecture 260 -- 13.6 Conclusion 260  
-- Bibliography 260 -- 14 Channel Coding with Deep Learning: An  
Overview 265 /Shugong Xu -- 14.1 Overview of Channel Coding and  
Deep Learning 265 -- 14.1.1 Channel Coding 265 -- 14.1.2 Deep  
Learning 266 -- 14.2 DNNs for Channel Coding 268 -- 14.2.1 Using  
DNNs to Decode Directly 269 -- 14.2.2 Scaling DL Method 271.  
14.2.3 DNNs for Joint Equalization and Channel Decoding 272 --  
14.2.4 A Unified Method to Decode Multiple Codes 274 -- 14.2.5  
Summary 276 -- 14.3 CNNs for Decoding 277 -- 14.3.1 Decoding by  
Eliminating Correlated Channel Noise 277 -- 14.3.1.1 BP-CNN Reduces  
Decoding BER 279 -- 14.3.1.2 Multiple Iterations Between CNN and BP  
Further Improve Performance 279 -- 14.3.2 Summary 279 -- 14.4  
RNNs for Decoding 279 -- 14.4.1 Using RNNs to Decode Sequential  
Codes 279 -- 14.4.2 Improving the Standard BP Algorithm with RNNs

281 -- 14.4.3 Summary 283 -- 14.5 Conclusions 283 -- Bibliography  
 283 -- 15 Deep Learning Techniques for Decoding Polar Codes 287  
 /Warren J. Gross, Nghia Doan, Elie Ngomseu Mambou, and Seyyed Ali  
 Hashemi -- 15.1 Motivation and Background 287 -- 15.2 Decoding of  
 Polar Codes: An Overview 289 -- 15.2.1 Problem Formulation of Polar  
 Codes 289 -- 15.2.2 Successive-Cancellation Decoding 290 -- 15.2.3  
 Successive-Cancellation List Decoding 291 -- 15.2.4 Belief Propagation  
 Decoding 291 -- 15.3 DL-Based Decoding for Polar Codes 292 --  
 15.3.1 Off-the-Shelf DL Decoders for Polar Codes 292 -- 15.3.2 DL-  
 Aided Decoders for Polar Codes 293 -- 15.3.2.1 Neural Belief  
 Propagation Decoders 293 -- 15.3.2.2 Joint Decoder and Noise  
 Estimator 295 -- 15.3.3 Evaluation 296 -- 15.4 Conclusions 299 --  
 Bibliography 299 -- 16 Neural Network-Based Wireless Channel  
 Prediction 303 /Wei Jiang, Hans Dieter Schotten, and Ji-ying Xiang --  
 16.1 Introduction 303 -- 16.2 Adaptive Transmission Systems 305 --  
 16.2.1 Transmit Antenna Selection 305 -- 16.2.2 Opportunistic  
 Relaying 306 -- 16.3 The Impact of Outdated CSI 307 -- 16.3.1  
 Modeling Outdated CSI 307 -- 16.3.2 Performance Impact 308 -- 16.4  
 Classical Channel Prediction 309 -- 16.4.1 Autoregressive Models 310  
 -- 16.4.2 Parametric Models 311 -- 16.5 NN-Based Prediction Schemes  
 313 -- 16.5.1 The RNN Architecture 313 -- 16.5.2 Flat-Fading SISO  
 Prediction 314 -- 16.5.2.1 Channel Gain Prediction with a Complex-  
 Valued RNN 314 -- 16.5.2.2 Channel Gain Prediction with a Real-  
 Valued RNN 315.  
 16.5.2.3 Channel Envelope Prediction 315 -- 16.5.2.4 Multi-Step  
 Prediction 316 -- 16.5.3 Flat-Fading MIMO Prediction 316 -- 16.5.3.1  
 Channel Gain Prediction 317 -- 16.5.3.2 Channel Envelope Prediction  
 317 -- 16.5.4 Frequency-Selective MIMO Prediction 317 -- 16.5.5  
 Prediction-Assisted MIMO-OFDM 319 -- 16.5.6 Performance and  
 Complexity 320 -- 16.5.6.1 Computational Complexity 320 --  
 16.5.6.2 Performance 321 -- 16.6 Summary 323 -- Bibliography 323  
 -- Part III Network Intelligence and Adaptive System Optimization 327  
 -- 17 Machine Learning for Digital Front-End: a Comprehensive  
 Overview 329 /Pere L. Gilabert, David Lopez-Bueno, Thi Quynh Anh  
 Pham, and Gabriel Montoro -- 17.1 Motivation and Background 329 --  
 17.2 Overview of CFR and DPD 331 -- 17.2.1 Crest Factor Reduction  
 Techniques 331 -- 17.2.2 Power Amplifier Behavioral Modeling 334 --  
 17.2.3 Closed-Loop Digital Predistortion Linearization 335 -- 17.2.4  
 Regularization 337 -- 17.2.4.1 Ridge Regression or Tikhonov ]]  
 >o<U+0081><![CDATA[2 Regularization 338 -- 17.2.4.2 LASSO or ]]  
 >o<U+0081><![CDATA[1 Regularization 339 -- 17.2.4.3 Elastic Net  
 340 -- 17.3 Dimensionality Reduction and ML 341 -- 17.3.1  
 Introduction 341 -- 17.3.2 Dimensionality Reduction Applied to DPD  
 Linearization 343 -- 17.3.3 Greedy Feature-Selection Algorithm: OMP  
 345 -- 17.3.4 Principal Component Analysis 345 -- 17.3.5 Partial Least  
 Squares 348 -- 17.4 Nonlinear Neural Network Approaches 350 --  
 17.4.1 Introduction to ANN Topologies 350 -- 17.4.2 Design  
 Considerations for Digital Linearization and RF Impairment Correction  
 353 -- 17.4.2.1 ANN Architectures for Single-Antenna DPD 354 --  
 17.4.2.2 ANN Architectures for MIMO DPD, I/Q Imbalances, and DC  
 Offset Correction 355 -- 17.4.2.3 ANN Training and Parameter  
 Extraction Procedure 357 -- 17.4.2.4 Validation Methodologies and  
 Key Performance Index 361 -- 17.4.3 ANN for CFR: Design and Key  
 Performance Index 364 -- 17.4.3.1 SLM and PTS 364 -- 17.4.3.2 Tone  
 Injection 365 -- 17.4.3.3 ACE 366 -- 17.4.3.4 Clipping and Filtering  
 368.  
 17.5 Support Vector Regression Approaches 368 -- 17.6 Further  
 Discussion and Conclusions 373 -- Bibliography 374 -- 18 Neural

Networks for Full-Duplex Radios: Self-Interference Cancellation 383  
 /Alexios Balatsoukas-Stimming -- 18.1 Nonlinear Self-Interference Models 384 -- 18.1.1 Nonlinear Self-Interference Model 385 -- 18.2 Digital Self-Interference Cancellation 386 -- 18.2.1 Linear Cancellation 386 -- 18.2.2 Polynomial Nonlinear Cancellation 387 -- 18.2.3 Neural Network Nonlinear Cancellation 387 -- 18.2.4 Computational Complexity 389 -- 18.2.4.1 Linear Cancellation 389 -- 18.2.4.2 Polynomial Nonlinear Cancellation 390 -- 18.2.4.3 Neural Network Nonlinear Cancellation 390 -- 18.3 Experimental Results 391 -- 18.3.1 Experimental Setup 391 -- 18.3.2 Self-Interference Cancellation Results 391 -- 18.3.3 Computational Complexity 392 -- 18.4 Conclusions 393 -- 18.4.1 Open Problems 394 -- Bibliography 395 -- 19 Machine Learning for Context-Aware Cross-Layer Optimization 397 /Yang Yang, Zening Liu, Shuang Zhao, Ziyu Shao, and Kunlun Wang -- 19.1 Introduction 397 -- 19.2 System Model 399 -- 19.3 Problem Formulation and Analytical Framework 402 -- 19.3.1 Fog-Enabled Multi-Tier Operations Scheduling (FEMOS) Algorithm 403 -- 19.3.2 Theoretical and Numerical Analysis 405 -- 19.3.2.1 Theoretical Analysis 405 -- 19.3.2.2 Numerical Analysis 406 -- 19.4 Predictive Multi-tier Operations Scheduling (PMOS) Algorithm 409 -- 19.4.1 System Model 409 -- 19.4.2 Theoretical Analysis 411 -- 19.4.3 Numerical Analysis 413 -- 19.5 A Multi-tier Cost Model for User Scheduling in Fog Computing Networks 413 -- 19.5.1 System Model and Problem Formulation 413 -- 19.5.2 COUS Algorithm 416 -- 19.5.3 Performance Evaluation 418 -- 19.6 Conclusion 420 -- Bibliography 421 -- 20 Physical-Layer Location Verification by Machine Learning 425 /Stefano Tomasin, Alessandro Brighente, Francesco Formaggio, and Gabriele Ruvoletto -- 20.1 IRLV by Wireless Channel Features 427 -- 20.1.1 Optimal Test 428 -- 20.2 ML Classification for IRLV 428. 20.2.1 Neural Networks 429 -- 20.2.2 Support Vector Machines 430 -- 20.2.3 ML Classification Optimality 431 -- 20.3 Learning Phase Convergence 431 -- 20.3.1 Fundamental Learning Theorem 431 -- 20.3.2 Simulation Results 432 -- 20.4 Experimental Results 433 -- 20.5 Conclusions 437 -- Bibliography 437 -- 21 Deep Multi-Agent Reinforcement Learning for Cooperative Edge Caching 439 /M. Cenk Gursoy, Chen Zhong, and Senem Velipasalar -- 21.1 Introduction 439 -- 21.2 System Model 441 -- 21.2.1 Multi-Cell Network Model 441 -- 21.2.2 Single-Cell Network Model with D2D Communication 442 -- 21.2.3 Action Space 443 -- 21.3 Problem Formulation 443 -- 21.3.1 Cache Hit Rate 443 -- 21.3.2 Transmission Delay 444 -- 21.4 Deep Actor-Critic Framework for Content Caching 446 -- 21.5 Application to the Multi-Cell Network 448 -- 21.5.1 Experimental Settings 448 -- 21.5.2 Simulation Setup 448 -- 21.5.3 Simulation Results 449 -- 21.5.3.1 Cache Hit Rate 449 -- 21.5.3.2 Transmission Delay 450 -- 21.5.3.3 Time-Varying Scenario 451 -- 21.6 Application to the Single-Cell Network with D2D Communications 452 -- 21.6.1 Experimental Settings 452 -- 21.6.2 Simulation Setup 452 -- 21.6.3 Simulation Results 453 -- 21.6.3.1 Cache Hit Rate 453 -- 21.6.3.2 Transmission Delay 454 -- 21.7 Conclusion 454 -- Bibliography 455 -- Index 459.

Sommario/riassunto

"Due to its powerful nonlinear mapping and distribution processing capability, deep neural networks based machine learning technology is being considered as a very promising tool to attack the big challenge in wireless communications and networks imposed by the explosively increasing demands in terms of capacity, coverage, latency, efficiency (power, frequency spectrum and other resources), flexibility, compatibility, quality of experience and silicon convergence. Mainly categorized into the supervised learning, the unsupervised learning and the reinforcement learning, various machine learning algorithms can be

used to provide a better channel modelling and estimation in millimeter and terahertz bands, to select a more adaptive modulation (waveform, coding rate, bandwidth, and filtering structure) in massive multiple-input and multiple-output (MIMO) technology, to design a more efficient front-end and radio-frequency processing (pre-distortion for power amplifier compensation, beamforming configuration and crest-factor reduction), to deliver a better compromise in self-interference cancellation for full-duplex transmissions and device-to-device communications, and to offer a more practical solution for intelligent network optimization, mobile edge computing, networking slicing and radio resource management related to wireless big data, mission critical communications, massive machine-type communications and tactile internet"--

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