



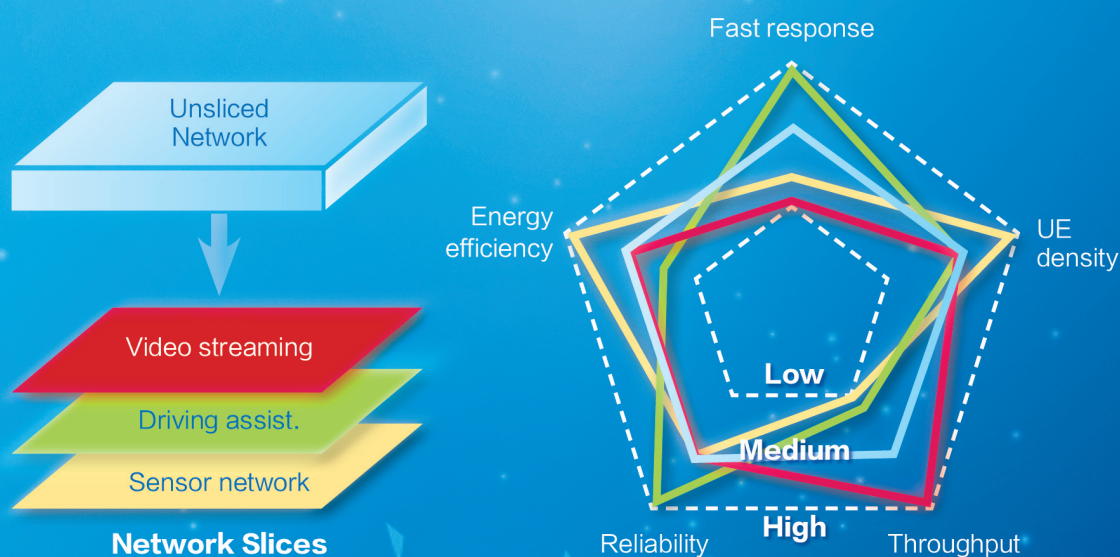
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Computational Radio Intelligence: One Key for 6G Wireless



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CONTENTS

ZTE COMMUNICATIONS December 2019 Vol. 17 No. 4 (Issue 68)

Special Topic

Computational Radio Intelligence: One Key for 6G Wireless

Editorial 01

JIANG Wei and LUO Fa-Long

To Learn or Not to Learn: Deep Learning 03

Assisted Wireless Modem Design

There is an ongoing debate as to what additional values artificial intelligence (or machine learning) could bring to us, particularly on the physical layer design; and what penalties there may have? These questions motivate a fundamental rethinking of the wireless modem design in the artificial intelligence era. Through several physical-layer case studies, the authors argue for a significant role that machine learning could play and discuss the fundamental bottlenecks of machine learning as well as their potential solutions in this paper.

XUE Songyan, LI Ang, WANG Jinfei, YI Na, MA Yi, Rahim TAFAZOLLI, and Terence DODGSON

A Machine Learning Method for Prediction of 12 Multipath Channels

In this paper, a machine learning method for predicting the evolution of a mobile communication channel based on a specific type of convolutional neural network is developed and evaluated in a simulated multipath transmission scenario. The simulation and channel estimation are designed to replicate real-world scenarios and common measurements supported by reference signals in modern cellular networks. The capability of the predictor meets the requirements that a deployment of the developed method in a radio resource scheduler of a base station poses.

Julian AHRENS, Lia AHRENS, and Hans D. SCHOTTEN

19 A Case Study on Intelligent Operation System for Wireless Networks

In this paper, the authors focus on the intelligent operation of wireless network through ML algorithms. A comprehensive and flexible framework is proposed to achieve an intelligent operation system. Two use cases are also studied to use ML algorithms to automate the anomaly detection and fault diagnosis of key performance indicators (KPIs) in wireless networks. The effectiveness of the proposed ML algorithms is demonstrated by the real data experiments, thus encouraging the further research for intelligent wireless network operation.

LIU Jianwei, YUAN Yifei, and HAN Jing

27 Machine Learning for Network Slicing Resource Management: A Comprehensive Survey

The emerging technology of multi-tenancy network slicing is considered as an essential feature of 5G cellular networks. It provides network slices as a new type of public cloud services and therewith increases the service flexibility and enhances the network resource efficiency. Meanwhile, it raises new challenges of network resource management. A number of various methods have been proposed over the recent past years, in which machine learning and artificial intelligence techniques are widely deployed. In this article, the authors provide a survey to existing approaches of network slicing resource management, with a highlight on the roles played by machine learning in them.

HAN Bin and Hans D. SCHOTTEN

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CONTENTS

ZTE COMMUNICATIONS December 2019 Vol. 17 No. 4 (Issue 68)

Machine Learning Based Unmanned Aerial Vehicle Enabled Fog-Radio Access Network and Edge Computing 33

Mobile edge computing (MEC) and fog radio access network (F-RAN) together with machine learning algorithms are an emerging approach to solving complex network problems. In this paper, the authors suggest a new orientation with UAV enabled F-RAN architecture. Additionally, the authors summarized the works on machine learning approaches for UAV networks and MEC networks, which are related to the suggested architecture and discussed some technical challenges in the smart UAV-IoT, F-RAN 5G and Beyond 5G (6G).

Mohammed SEID, Stephen ANOKYE, and SUN Guolin

A Survey on Machine Learning Based Proactive Caching 46

In this paper, a survey of mobile edge caching using machine learning is explored. This survey shows that edge caching can reduce delay and subsequently the backhaul traffic of the network; most caching is conducted at the small base stations (SBSs) and caching at unmanned aerial vehicles (UAVs) is recently used to accommodate mobile users who dissociate from the SBSs.

Stephen ANOKYE, Mohammed SEID, and SUN Guolin

Review

A Survey on Network Operation and Maintenance Quality Evaluation Models 56

In this paper, the authors analyze the general process of quality evaluation models for network operation and maintenance. The authors further describe the working principle of each step, especially the methods for indicator selection and weight determination. Finally, the authors review the recently proposed evaluation models and the international standards of network operation and maintenance quality evaluation.

LIU Lixia, WU Muyang, JI Feng, and LIU Zheng

Research Paper

62 An Improved Non-Geometrical Stochastic Model for Non-WSSUS Vehicle-to-Vehicle Channels

In this paper, the authors propose a novel non-geometrical stochastic model (NGSM) for non-wide sense stationary uncorrelated scattering (non-WSSUS) vehicle-to-vehicle (V2V) channels. The proposed model is based on a conventional NGSM and employs a more accurate method to reproduce the realistic characteristics of V2V channels. Moreover, the statistical properties of the proposed model in different scenarios are simulated and compared with those of the existing NGSM. Furthermore, the simulation results demonstrate not only the utility of the proposed model, but also the correctness of our theoretical derivations.

HUANG Ziwei, CHENG Xiang, and ZHANG Nan

72 Fiber-Wireless Integrated Reliable Access Network for Mobile Fronthaul Using Synclastic Uniform Circular Array with Dual- Mode OAM Multiplexing

The authors propose an access network that integrates fiber and wireless for mobile fronthaul (MFH) with simple protection capabilities, using dual-mode orbital angular momentum (OAM) multiplexing. The authors experimentally demonstrate a 3.35 Gbit/s DMT-32QAM pre-equalized system with 10 km and 15 km fiber links in the 5.9 GHz band; then there is a link of two channels with a 0.5 m wireless link.

XU Yusi, WU Xingbang, YANG Guomin, and CHI Nan

Roundup

I Table of Contents for Volume 17, 2019

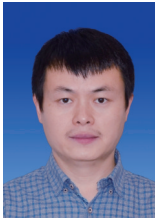
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Editorial: Special Topic on Computational Radio Intelligence: One Key for 6G Wireless



Guest Editor

JIANG Wei is an IEEE Senior Member and a Senior Researcher at German Research Center for Artificial Intelligence (DFKI), which is the birthplace of the concept “Industry 4.0”. Additionally, he serves as a Senior Lecturer in part time at University of Kaiserslautern, Germany, teaching “Wireless Communications”. He received his Ph. D. degree in computer science from Beijing University of Posts and Telecommunications in 2008 and was a Post-Doctoral Fellow with Institute of Digital Signal Processing, University of Duisburg-Essen, Germany, from 2012 to 2015. He has also extensive experience in wireless standardization research and development as a 3GPP standardization engineer. He is the author of three book chapters and more than 50 conference and journal papers. He holds around 30 granted patents in wireless communications, and participated in a number of research projects, such as EU FP7 ABSOLUTE, H2020 5G COHERENT and 5G SELFNET, and German BMBF TACNET4.0. He now serves as an associate editor for *IEEE Access*.



Guest Editor

LUO Fa-Long is an IEEE Fellow and an Affiliate Full Professor of Electrical & Computer Engineering Department at the University of Washington in Seattle, USA. Having gained international high recognition, Dr. LUO has 36 years of research and industry experience in wireless communications, neural networks, signal processing, machine learning, and broadcasting with real-time implementation, applications and standardization. Including his well-received books: “Applied Neural Networks for Signal Processing” (1999, Cambridge) and “Signal Processing for 5G” (2016, Wiley-IEEE), Dr. LUO has published six books and more than 100 technical papers in the related fields. Dr. LUO has also contributed 61 patents/inventions which have successfully resulted in a number of new or improved commercial products in mass production. He has served as the Chairman of IEEE Industry DSP Standing Committee and the Technical Board Member of Signal Processing Society. Dr. LUO was awarded the Fellowship by the Alexander von Humboldt Foundation of Germany.

The year of 2019 is the first deployment year of the fifth generation (5G) mobile communications. As we are writing the editorial for this special issue, a list of countries such as South Korea, the United States, China, Switzerland, the United Kingdom, and Spain have launched commercial 5G services for the general public, while this list is growing quickly and is envisioned to become much longer in the near future. For the past months, 5G has been continuously a hot buzzword in the news, attracting a huge focus from the whole society. It even goes beyond the technical and commercial scopes, becoming the frontline of geopolitical contention and conflict. As a revolutionary technology, 5G will penetrate into all aspects of society—not only human daily life but also manufacturing, education, health care, and scientific activities—generating tremendous economic and societal benefits. From the perspective of technology research, however, it is already the time to start considering what future beyond-5G or the sixth generation (6G) mobile networks should be, in order to satisfy the demand on communications and networking in 2030. Although a discussion is ongoing within the wireless community about whether counting should be stop at 5, adopting the Microsoft Windows’ approach where Windows 10 is the ultimate version, several pioneering works on the next-generation wireless networks have been initiated. The International Telecommunication Union Telecommunication Standardization Sector (ITU-T) Focus Group Technologies for Network

2030 (FG NET-2030) was established in July 2018. The Focus Group intends to study the capabilities of networks for the year 2030 and beyond, when it is expected to support novel forward-looking scenarios, such as holographic type communications, extremely fast response in critical situations, and high-precision communication demands of emerging market verticals. The European Commission initiated to sponsor beyond-5G research activities, such as its recent Horizon 2020 call—5G Long Term Evolution—where a number of pioneer projects will be kicked off at the early beginning of 2020. In Finland, the University of Oulu has begun ground-breaking 6G research as part of Academy of Finland’s flagship program, 6G-Enabled Wireless Smart Society and Ecosystem (6Genesis), which focuses on several challenging research areas including reliable near-instant unlimited wireless connectivity, distributed computing and intelligence, as well as materials and antennas to be utilized in future for circuits and devices.

Among the short list of 6G enabling technologies that can be envisioned currently, such as Terahertz communications, visible light communications, photonics-defined radio, holographic radio, super massive multiple-input and multiple-output (MIMO), quantum communications, and dense satellite constellation, artificial intelligence (AI) is the most recognized candidate, which can provide computational radio and network intelligence from the fundamental physical layer to the upper network management layer. 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 in-

creasing 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 MIMO, to design a more efficient front-end and RF processing (pre-distortion for power amplifier compensation, beam-forming and crest-factor reduction), to deliver a better compromise in self-interference cancellation for full-duplex transmission and device-to-device communications, and to offer a more practical solution for intelligent network optimization, orchestration and management, mobile edge and fog computing, networking slicing and radio resource management related to wireless big data, mission critical communications, massive machine-type communications and tactile internet.

From practical application and research development perspective, this special issue aims to be the first single form to provide a comprehensive and highly coherent treatment on all the technology aspects related to machine learning for wireless communications and networks by covering multipath fading channel, channel coding, physical-layer design, network slicing, resource management, mobile edge architecture, fog computing, and autonomous network management. The call-for-papers of this special issue have brought excellent submissions in both quality and quantity. After rigorous reviews, six excellent articles have been selected for publication in this special issue which is organized into the following three category groups.

Consisting of two articles, the first group of this special issue focuses on the exploration of replacing conventional model-based statistical methods with data-driven learning approaches in spatial-temporal-spectral radio signal processing, in order to simplify the physical layer implementation or boost the transmission performance. As its title “To Learn or Not to Learn: Deep Learning Assisted Wireless Modem Design” exactly means, the first article by XUE Songyan et al. provides a fundamental rethink of the wireless modem design to answer a frequently-asked question: what additional values artificial intelligence could bring to the physical layer. Three case studies, i. e., deep learning assisted parallel decoding of convolutional codes for a substantial reduction of decoding latency, deep learning aided multi-user frequency synchronization, and deep learning based coherent multi-user multi-antenna signal detection, are presented in this article. By adapting transmission parameters such as the constellation size, coding rate, and transmit power to instantaneous fading channel conditions, adaptive wireless communications can potentially achieve great performance. To realize this potential, accurate channel state information (CSI) is required at the transmitter. However, unless the mobile speed is very low, the obtained CSI quickly becomes outdated due to the

rapid channel variation caused by multi-path fading. The second article, “A Machine Learning Method for Prediction of Multipath Channels” by Julian AHRENS et al., investigates the feasibility of predicting fading channels by means of a convolutional neural network. The numerical results verify the effectiveness of machine learning based channel prediction in the presence of outdated CSI. It is envisioned that the channel prediction is applicable to a wide variety of adaptive transmission techniques, such as pre-coding and multi-user scheduling in MIMO systems, massive MIMO, beam-forming, interference alignment, closed-loop transmit diversity, transmit antenna selection, opportunistic relaying, orthogonal frequency-division multiplexing (OFDM), coordinated multi-point transmission (CoMP), mobility management, and physical layer security.

Mobile networks’ troubleshooting (systems failures, cyber-attacks, performance optimization, etc.) still cannot avoid manual operations. A mobile operator has to keep an operational group with a large number of network administrators with high expertise, leading to a costly Operational Expenditure (OPEX) that is currently three times that of Capital Expenditure (CAPEX) and keeps rising. The 5G and next-generation networks are more complicated and heterogeneous than previous systems. It inevitably imposes a great challenge on manual and semi-automatic network management that is already costly, vulnerable and time-consuming. Therefore, the second group of this special issue is about the application of machine learning approaches to realize an intelligent and autonomous network management that can keep OPEX under an affordable level, improve system Quality-of-Service (QoS) and end users’ Quality-of-Experience (QoE), and shorten time-to-market of new services. In the third article entitled “A Case Study on Intelligent Operation System for Wireless Networks”, LIU Jianwei et al. propose a comprehensive and flexible framework to achieve an intelligent operation system. Two use cases are studied to illustrate machine learning algorithms to automate the anomaly detection and fault diagnosis of key performance indicators in wireless networks. The effectiveness of the proposed machine learning algorithms is demonstrated by the real data experiments. Next, HAN Bin et al. provide a comprehensive overview on the metrics of machine learning for network slicing resource management in their article “Machine Learning for Network Slicing Resource Management: A Comprehensive Survey”. Two problems of resource management in network slicing, namely the slice admission control and the cross-slice resource management, are discussed, illustrating the benefits of machine learning techniques in the improvement of service flexibility and network resource efficiency.

The new demanding features for advanced networks, e. g., mobile edge computing and fog computing, foster novel services and applications that never emerged in previous networks, such as Unmanned Aerial Vehicle (UAV), the Internet of Things, connected and automated cars, and tactile internet.

➔ To Page 18



To Learn or Not to Learn: Deep Learning Assisted Wireless Modem Design

XUE Songyan¹, LI Ang¹, WANG Jinfei¹, YI Na¹, MA Yi¹, Rahim TAFAZOLLI¹, and Terence DODGSON²

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Abstract: Deep learning is driving a radical paradigm shift in wireless communications, all the way from the application layer down to the physical layer. Despite this, there is an ongoing debate as to what additional values artificial intelligence (or machine learning) could bring to us, particularly on the physical layer design; and what penalties there may have? These questions motivate a fundamental rethinking of the wireless modem design in the artificial intelligence era. Through several physical-layer case studies, we argue for a significant role that machine learning could play, for instance in parallel error-control coding and decoding, channel equalization, interference cancellation, as well as multiuser and multiantenna detection. In addition, we discuss the fundamental bottlenecks of machine learning as well as their potential solutions in this paper.

Keywords: deep learning; neural networks; machine learning; modulation and coding

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1 Introduction

With the launch of commercial 5G mobile networks in 2019, the research of wireless communications is now well on the way towards Vision 2030 and beyond. Today, the picture of future wireless communications is becoming much clearer than ever. According to ITU Network 2030 Working Group [1], future networks should be architected to support holographic communications and smart connectivity, providing seemingly zero latency, guaranteed ultra-reliability (e. g. 99.9999%), massive Internet of Things (IoT) connectivity, and Tbit/s wireless speed. Communication networks are no longer only a medium for information flow, but also act as distributed computers to form over-the-top (OTT)-like platforms to provide services (such as computing-as-

a-service and design-as-a-service) for vertical users. To achieve this goal, wireless technologies should be fundamentally re-designed to be able to fully explore the spectrum; as such, this is driving the development of extreme physical-layer (PHY) technologies, which are able to handle wireless systems with many nonlinearities, due to the use of very-high order modulations, unexploited mmWave or THz bands, and/or low-cost electronic components (such as low-noise amplifiers (LNAs), mixers, oscillators and low-resolution analog-to-digital converters (ADCs)). Moreover, PHY solutions should be made scalable to the number of connected devices; and they should be parallel computing ready, as future high-performance computing technologies (including future quantum computing technology) rely highly on the parallel computing power.

With such a big picture in mind, machine learning or more specifically, deep learning can play a significant role in the PHY design, at least from the following five aspects:

1) Conventional PHY algorithms, particularly for wireless receivers, are mostly not parallel computing ready. For instance,

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most of the linear or nonlinear coherent receivers (such as linear zero-forcing, minimum mean-square error, lattice reduction, and sphere decoding) require either channel matrix inversions or channel matrix decompositions, which are difficult to execute in an efficient and parallel manner. This can cause a bottleneck for the implementation of advanced channel equalizers or multiuser detectors at the receiver side. An exception could be the matched-filter algorithm, which is of low-complexity and parallel computing architecture. On the other hand, matched filtering is often too suboptimum for most wireless applications. One might also argue for parallel computing abilities of brute-force search, likelihood ascent search, or Tabu search. However, those algorithms trade off complexity for parallel computing, and thus they are not cost-effective solutions. In this paper, we will study the merits of deep-learning assisted solutions, with specific to their inborn parallel computing ability.

2) Conventional hand-engineered PHY algorithms face the fundamental trade-off between performance and complexity. Optimum algorithms are often too complex to implement and low-complexity algorithms are often too suboptimum. Deep-learning assisted PHY algorithms have the potential to achieve (near-)optimum performances with low computation complexities. We argue for the merits of performance-complexity trade-off when using deep learning.

3) Current PHY technologies are designed for linear communication channels and they are not optimized for future wireless systems often operating in nonlinear conditions. Nonlinear systems are often much harder for mathematical analysis, and in general, we even do not know their channel capacities. Hand-engineered approaches for PHY design and optimization are currently very challenging; and this is where deep learning can be of much assistance.

4) Sensing and communication is an emerging concept in the scope of network automation. Basically, wireless networks are able to capture environmental changes through local and remote sensors or even live video records, based on which networks can adapt their operating states for optimum uses of their local radio resources. On the PHY layer, environmental information can be translated into channel-side information through machine learning [2], and this can be useful for advanced modem functions such as adaptive modulation, coding and beamforming. In addition, machine learning can play a central role in building and reconfiguring state machines for local networks through extensive online background learning.

5) Since Shannon's ground-breaking work on communication theory reported in 1948, most telecommunications research effort has been targeting the Level A problem, i. e., how accurately can the information-bearing symbols be conveyed from one point to another? In the academic domain, this research problem has been almost saturated. In the industrial domain, it is very challenging to apply the outcome of Level A research so as to satisfy the growing demand of future

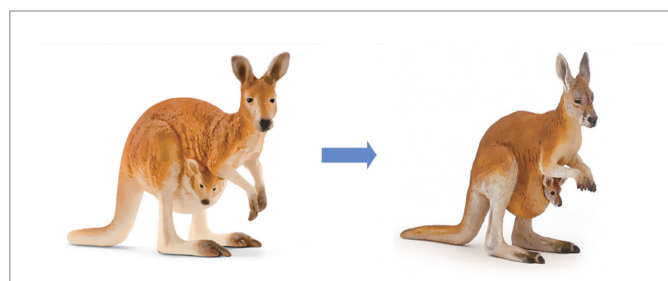
wireless networks in terms of smart connectivity, providing seemingly zero latency and perceived infinite capacity. Therefore, it is perhaps the right time to revisit or invest more research effort on the Level B problem, i. e., how precisely do the symbols of communication convey the desired meaning? This problem goes well beyond traditional source encoding practices; as for now, source encoders are expected to understand the meaning of objects instead of just the probability distribution. A simple example of the Level B problem is illustrated in **Fig. 1**, where the picture on the left-hand side is the original picture for transmission. Instead of compressing the picture using current codec processing methods, source encoders that have been trained to understand the meaning of the picture could send a textual description, such as "a white background picture, with a mother kangaroo carrying her baby in her pouch." The receiver then rebuilds the picture based on the meaning of the received symbols; this can be termed semantic communications, which involves heavy use of artificial intelligence/machine learning in semantic source encoding and decoding.

Certainly, we shall be able to find more merits and interesting topics when applying artificial intelligence/machine learning in wireless communications; some are already under fast development and some are just emerging. In the following sections, our discussion will be mainly focused on points 1), 2), and 3), as they are suitable for both current and future communication networks. We will also discuss fundamental bottlenecks when applying deep learning to wireless modem design.

The rest of this paper is organized as follows. Section 2 outlines the principles of deep learning assisted modem design in the wireless communication physical layer. Section 3 provides the design details of three practical physical layer applications. Section 4 provides further discussions and open research problems. Section 5 draws the conclusion.

2 Principles of Deep Learning Assisted Modem Design

By deep learning, we often mean machine learning through deep artificial neural networks (ANNs). An ANN is called deep when it has two or more hidden layers. Mathematically,



▲ **Figure 1.** A simple example of Level B communication problem (semantic communication).

the main function of each hidden layer is to perform classification of input vectors which might be referred to as perception in the artificial intelligence domain. If each output neuron yields a binary-type output, a hidden layer, consisting of L neurons, is able to classify at least L clusters. When a hidden layer is trained according to the nearest-neighbor rule, the machine is able to learn optimum classifications [3]. One might also employ the k-nearest neighbor rule to train the hidden layer, and in this case, the machine can form at most 2^L clusters. This is a possible way to scale up ANN when input vectors have to be partitioned into clusters that are growing exponentially. However, we will have to trade off the classification accuracy.

Prior to studying deep learning assisted wireless modem design, let us have a brief review of the PHY procedure of point-to-point communications (Fig. 2). Basically, signal waveforms are drawn from a finite-alphabet set, say A , with the size J . After going through the fading channel, received waveforms in their discrete-time equivalent form are vectors forming an infinite set. The role of receivers is to map the received vectors back onto the finite-alphabet set A . This procedure mimics the ANN-based classification procedure, as described above. Indeed, it is rather straightforward to replace the receiver box in Fig. 2 with an ANN black-box. The input vectors are formed by received waveforms combined with the channel state information, as they together form a bijection to the original waveform set A . Alternatively, the input vectors can be channel-equalized signals which also form bijection with the original waveform set A . The bijection allows the ANN black-box to be trained through supervised learning. In fact, this example is not the only way to apply deep learning for modem designs. It is also possible to replace both the transmitter and receiver with their corresponding ANN black-boxes, so as to form an autoencoder which can be trained end-to-end for joint transmitter and receiver design [4], [5]. Theoretically, a shallow-ANN (i. e. an ANN with a single hidden layer) would be sufficient to perform signal classification at the receiver side, as a receiver is normally a single-task classifier. Joint transmitter and receiver designs (autoencoders) are different, as they need at least one hidden layer at the transmitter side to construct the waveform set and another hidden layer at the receiver side to carry out corre-

sponding signal classification. Here, the implication is that deep-ANN is more meaningful when a PHY module or procedure can have a breakdown of two or more different tasks; or otherwise, a shallow-ANN would be more than enough. This issue will be further elaborated in Section 3.

In addition to the ANN architecture, ANN training algorithms or methods are crucial when improving machine learning efficiency. Analogous to ANN-assisted machine learning practices in the general artificial intelligence domain, it is always important to pay particular attention to the following three aspects:

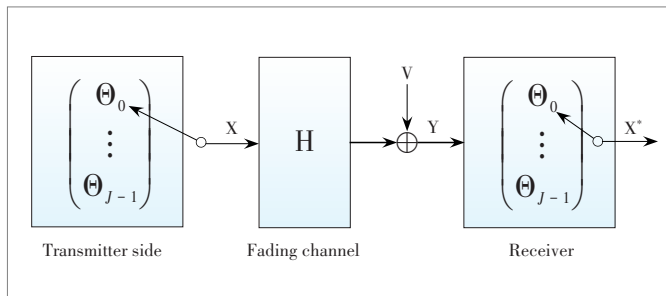
1) Weighting vectors (including biases) in each hidden layer should be carefully initialized. They are often randomly generated according to a certain independent probability distribution within a certain range, which can vary from case to case in practical applications. Specific to modem design, we should bear in mind that those weighting vectors during training become reference vectors for the eventual signal classification. Therefore, they should be initialized in a way that facilitates the capture of the characteristics of communication signals by machines.

2) Activation functions must be carefully selected to improve the optimality or efficiency of ANN-assisted machine learning. For instance, Softmax(.) is suitable for small-scale ANNs to adopt the nearest-neighbor rule in machine learning. This enables Euclidean-distance optimality when training a hidden layer. Moreover, Softmax(.) allows machines to produce soft outputs that are often useful for soft-demodulation and decoding practices. Alternatively, we can employ Sigmoid(.) to scale up ANNs when they are expected to handle massive-region classifications. Certainly, we will have to pay for the classification optimality. For more information, a relatively comprehensive list of activation functions as well as their descriptions can be found in [6].

3) Backpropagation (BP) is essential at the ANN training stage to recursively update neuron weighting vectors, with the aim of minimizing the loss function such as the mean-square error, mean absolute error or categorical cross-entropy between the ANN output and labeled training target, depending on the applications. A commonly used BP method is called mini-batch gradient descent, which randomly picks up a certain number of training samples from the entire training data set on each training iteration. Compared to another commonly used BP algorithm called batch gradient descent, mini-batch gradient descent can significantly reduce computational complexities, particularly when the path to the desired minima is quite noisy.

3 Deep Learning Assisted Modem Designs and Their Merits

In this section, we will offer three case studies on deep-learning assisted wireless modem design and argue for their ad-



▲ Figure 2. Block diagram of the physical-layer (PHY) procedure of point-to-point communication.

vantages in computing latency reduction, remarkable complexity-performance trade-off, as well as robustness to nonlinear physical distortions.

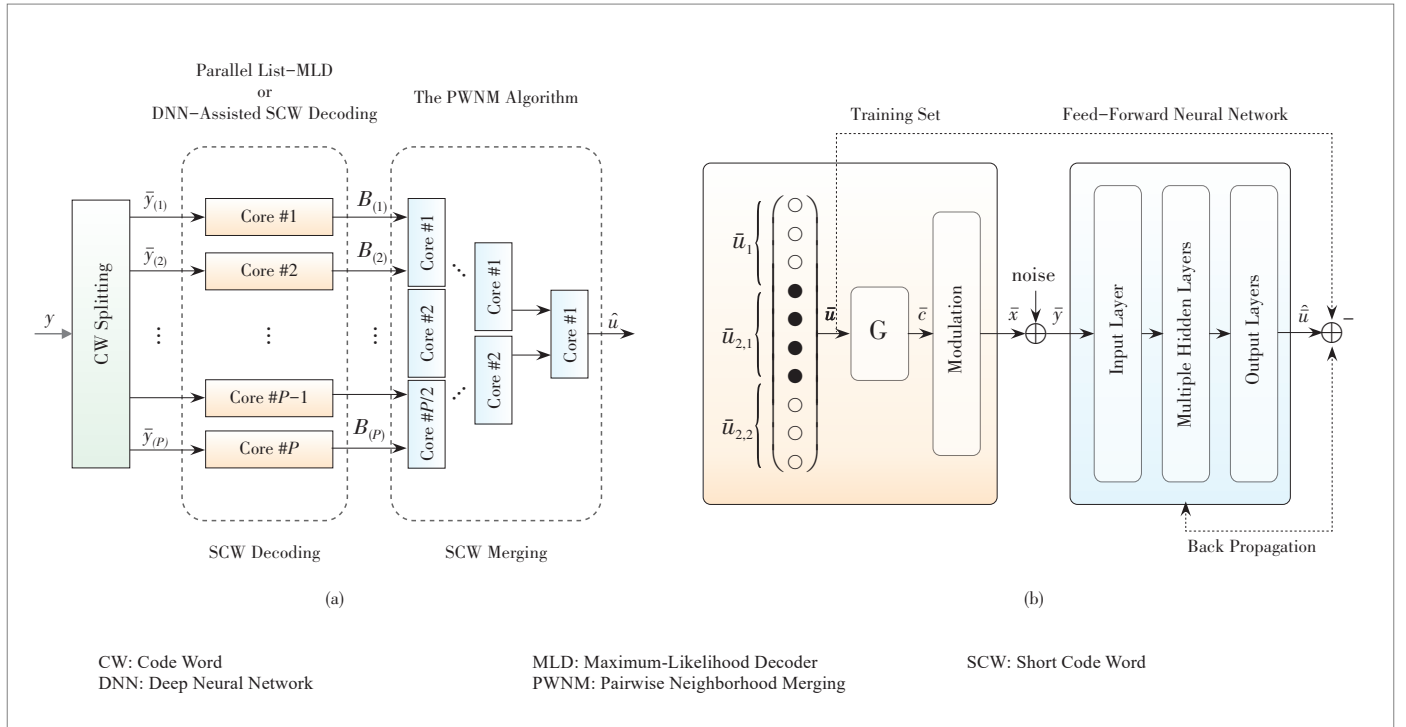
3.1 Case Study 1: Deep Learning Assisted Parallel Decoding of Convolutional Codes

Error-control codes often have a serial computing architecture in nature due to correlations amongst codeword bits. This fact is challenging the design of parallel-computing ready decoding algorithms. Recent advances towards ANN-assisted decoders are mainly based on recurrent neural networks [7], [8] and there is a clear show of advantages in performance-complexity trade-off. Here, we review a more recent contribution in this domain, which proposes to the employment of feed-forward neural networks for low-complexity parallel decoding of convolutional codes [9].

The basic idea is to partition a long convolutional codeword into a number of pieces, forming so-called sub-codewords. When the length of sub-codewords is sufficiently long, there exists a bijection between sub-codewords and their corresponding original information bits, subject to an initial state uncertainty. As depicted in **Fig. 3a**, sub-codewords are first decoded in parallel using a list maximum-likelihood decoder (List-MLD), and then initial state uncertainties are removed through the sub-codeword merging process, referred to as a two-stage decoding process that can be implemented in parallel. In this case study, the role of the ANN is to replace the List-MLD al-

gorithm at the sub-codeword decoding stage, as the latter is of very high computation complexity. **Fig. 3b** illustrates the ANN training procedure, where the sub-codeword decoder is modelled as a deep-ANN black-box. The input vector is the noisy version of all possible sub-codewords, and the output vector is the corresponding estimate of the original information bits. It is worthwhile highlighting that the training set of input vectors should be carefully defined so as to incorporate the effect of initial state uncertainty (as detailed in [9]), as this is crucial for the sub-codeword merging stage. Moreover, it is suggested to partition a long convolutional codeword evenly, as in this case we only need to train one ANN block-box and can reuse it for all sub-codewords, thus resulting in an efficient way to reduce the training complexity.

Fig. 4 illustrates the bit reliability of convolutional decoders in additive white Gaussian noise (AWGN), considering a half-rate non-recursive convolutional code with a codeword length of 64. The illustrated simulation results are only for $E_b/N_0=4$ dB and similar conclusions can be drawn for other E_b/N_0 values [9]. The ANN black-box was trained at $E_b/N_0=2$ dB. When comparing the parallel decoder with the conventional MLD, it can be seen from **Fig. 4** that they have no difference in bit reliability; and thus, the parallel decoder is optimum. Moreover, due to the parallel computing nature, the parallel decoder has the potential to reduce computing latency, subject to the number of sub-codewords. When the sub-codeword decoder is realized through the ANN black-box described in **Fig. 3b**, we can



▲ **Figure 3. An artificial neural network (ANN)-assisted parallel decoder: (a) two-stage parallel decoding and (b) ANN-assisted sub-codeword decoder. There are three hidden layers, with each employing Rectified Linear Unit (ReLU) activation function; the output layer is equipped with sigmoid activation function, which outputs the estimated original information bits.**

see a little bit of a performance loss in bit reliability (around 0.03%); this is mainly due to using an insufficient number of epochs during the ANN training stage. Nevertheless, the computation time for sub-codeword decoding is reduced by around 95%. It is clear that ANN helps to achieve a very good complexity-performance trade-off. In addition, the ANN decoder can be executed fully in parallel and this is an additional advantage for latency reduction.

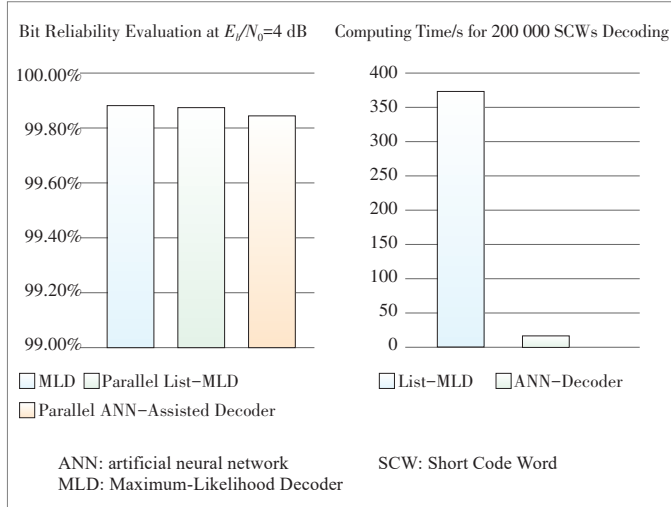
3.2 Case Study 2: Deep Learning Assisted Multiuser OFDMA Frequency Synchronization

Consider a multiuser frequency-synchronization problem in the context of orthogonal frequency-division multiple-access (OFDMA) uplink communications, where transmitters experience independently generated carrier-frequency-offsets (CFOs), due to oscillator instability or Doppler-induced ran-

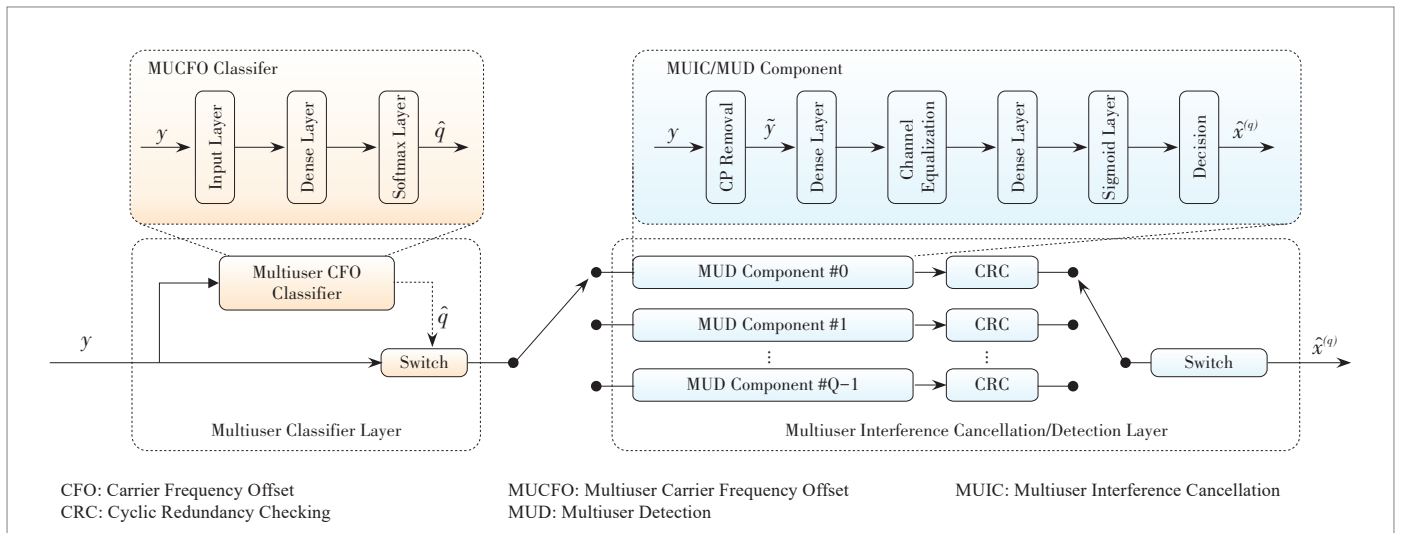
dom frequency modulations. This problem involves two sub-problems. One is the multiuser-CFO estimation and the other is multiuser detection (MUD) or multiuser interference (MUI) cancellation given the CFO estimates. Multiuser-CFO estimation can be implemented by employing either pilot-assisted approaches or blind approaches that exploit statistical behaviors inherent in signal waveforms. When CFO estimates are assumed available at the transmitter side, each transmitter can carry out CFO pre-compensation, individually. However, link-level latency will be a considerable issue due to the CFO feedback delay. Alternatively, multiuser frequency synchronization can also be carried out at each individual user domain (e.g., sub-band) using the filterbank approach, which can be combined with iterative parallel interference cancellation (PIC). However, such a method is vulnerable to the CFO estimation accuracy and it could introduce extra baseband processing latency into the system.

Fig. 5 illustrates a deep-learning assisted multiuser frequency synchronization approach, named classification-and-then-MUD (CAT-MUD) in [10]. The deep-ANN has two functional layers: one is responsible for multiuser-CFO classification and the other is for the MUI cancellation. The CFO classifier is employed to tell the CFO sub-range where transmitters' CFOs fall in. This is very different from the conventional CFO estimation in the sense that the classifier only estimates the CFO range instead of CFOs. With the estimated CFO sub-range index, received signals are then fed into the MUD layer for the MUI cancellation; please find a detailed introduction of CAT-MUD in [10].

Fig. 6 illustrates the overall system performance (in block-error rate, BLER) for OFDMA systems, where 4 transmitters evenly share 32 subcarriers. Original information bits are first modulated into 16-QAM symbols and then transmitted through an 8-tap frequency-selective Rayleigh fading channel (3GPP Channel Model A). To be more robust to CFO classification er-



▲ **Figure 4.** Bit reliability and latency evaluation for decoding of half-rate non-recursive convolutional codes with a codeword length of 64.



▲ **Figure 5.** Block diagram of the deep artificial neural network (deep-ANN) assisted classification-and-then-multiuser-detection (CAT-MUD).

rors, the switch depicted in Figure 5 can simultaneously turn on multiple adjacent MUD branches. Figure 6 shows that the 3-branch model achieves the best performance-complexity trade-off. It outperforms the conventional PIC approach by around 3 dB in E_b/N_0 and offers comparable performances with the CFO-free case at low and moderate SNRs (such as $E_b/N_0 < 15$ dB).

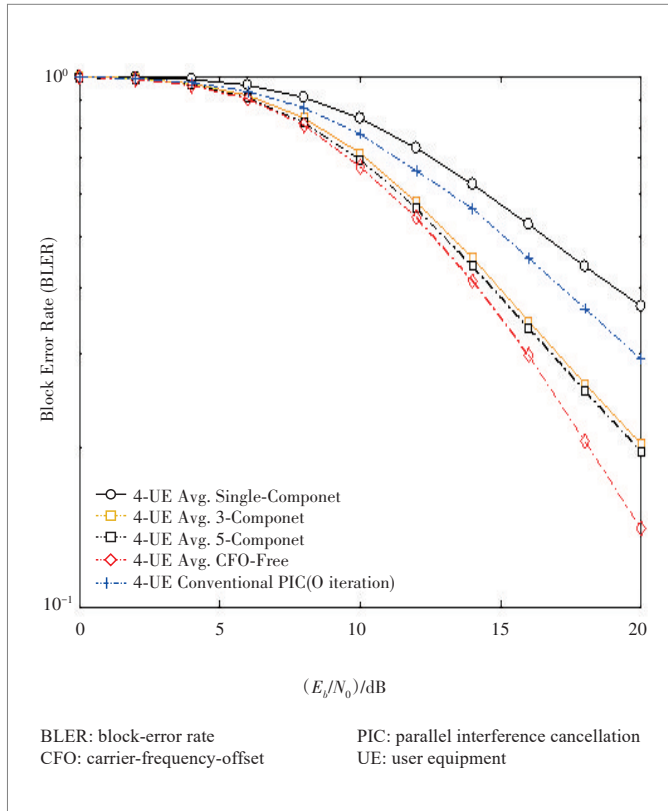
3.3 Case Study 3: Deep Learning Assisted Coherent MU-MIMO Detection

Multuser multiple-input multiple-out (MU-MIMO) signal detection over noisy fading channel is mathematically an integer least-squares (ILS) problem, which aims to minimize the pairwise Euclidean distance between the transmitted signal multiplied by channel matrix and the received signal [11]. Concerning the optimal MLD solution to be computationally expensive, the usual practice is to employ linear channel equalization algorithms, such as the matched filter (MF), zero forcing (ZF) and linear minimum mean-square error (LMMSE), to trade off the optimality for lower computational complexity. However, linear algorithms are often too sub-optimum due to their use of symbol-by-symbol detection. Therefore, enormous research efforts have been paid in the last two decades to achieve the best performance-complexity trade-off through the use of non-linear algorithms (e. g., Vertical-Bell

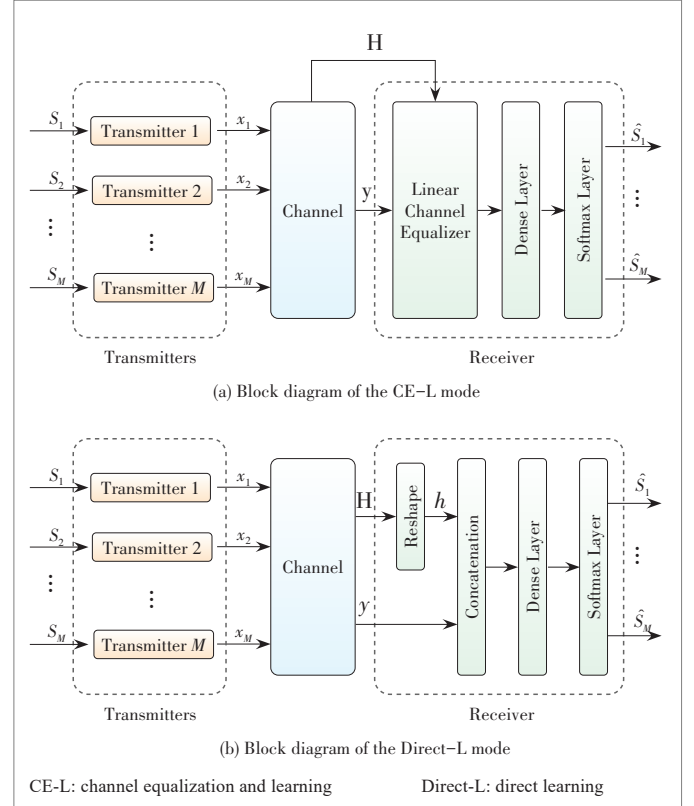
Laboratories Layered Space-Time (V-BLAST) [12], Linear Minimum Mean-Square Error-Successive Interference Cancellation (LMMSE-SIC [13], and so on). The problem is that most of the non-linear algorithms are too complex for current DSP technology and do not lend themselves well to parallel computing. This goes against the trend of computing technology development.

Deep learning assisted solutions have demonstrated their potential for offering computational complexity close to linear receivers, without compromising the detection performance. Moreover, most of the deep learning algorithms are parallel computing ready. According to the ways of utilizing channel state information at the receiver side (CSIR), deep-learning solutions can be divided into two categories: channel equalization and learning (CE-L) mode (Fig. 7a) and direct learning (Direct-L) mode (Fig. 7b). The difference is that the CE-L mode employs ANN black-box after channel equalization, and the Direct-L mode takes both CSIR and received signal as the input vector for signal classification.

A major advantage of the CE-L mode lies in the use of channel equalization for multiuser signal orthogonalization. Hence, the input vector to the ANN black-box is effectively a noisy version of the transmitted signal vector. By such means, the CE-L mode can turn the ANN classification problem from the vector level to the symbol level. However, the performance of



▲ Figure 6. BLER of classification-and-then-multiuser-detection (CAT-MUD) as a function of E_b/N_0 (dB) over Rayleigh fading channels.



▲ Figure 7. Block diagram of deep-learning assisted multiuser multiple-input multiple-out (MU-MIMO) detection algorithms.

the CE-L mode is limited by the symbol-by-symbol MLD bound. Theoretically, the Direct-L mode is able to achieve the optimum MLD performance for the vector-level classification. In addition, the Direct-L mode does not need channel equalization. This is a remarkable advantage as channel equalizers often require channel matrix inversions which do not support parallel computing. On the other hand, the Direct-L model is not a scalable approach with the size of MIMO, due to ANN's reduced classification ability with the growth of multiuser interferences.

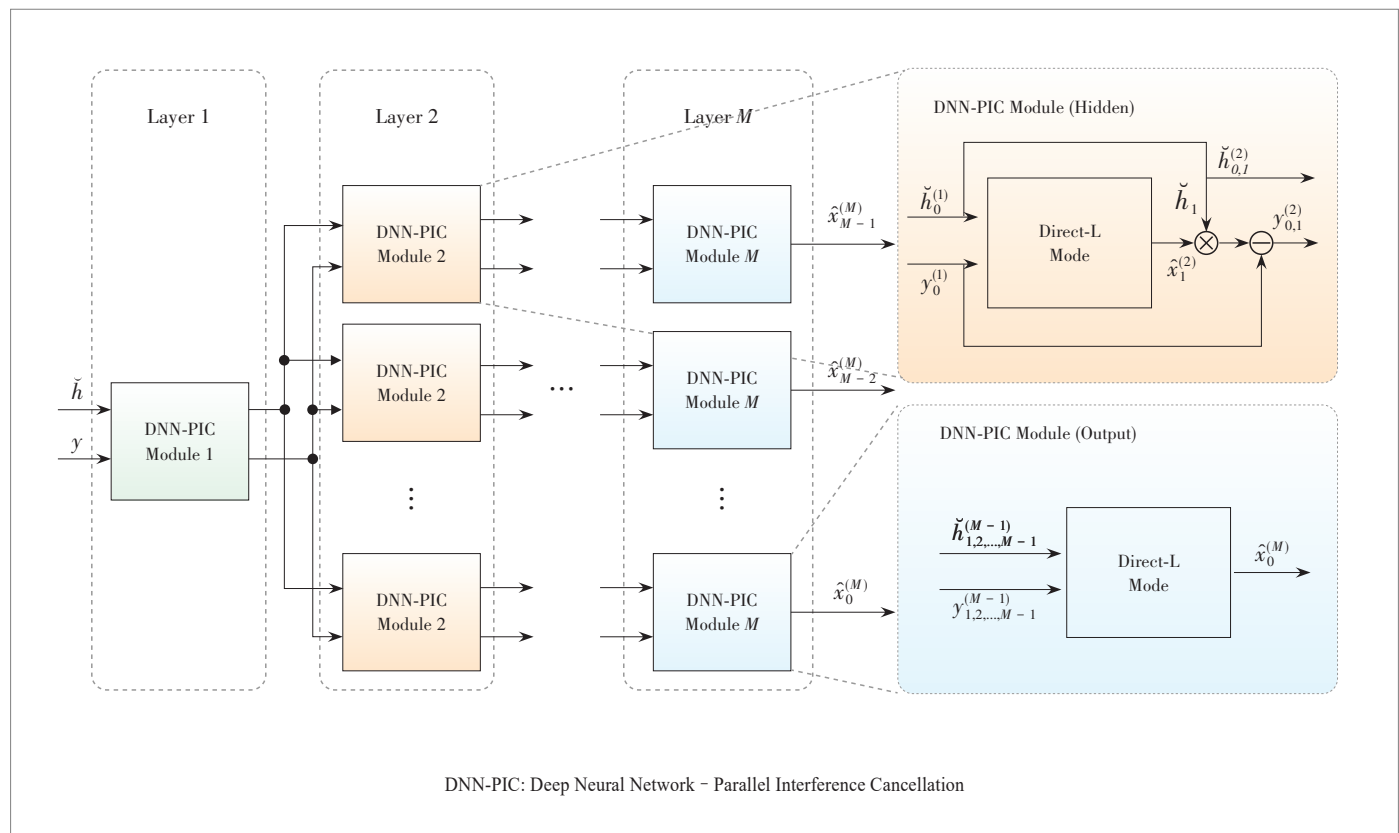
Fig. 8 illustrates a novel deep-ANN approach, where a multi-layer modularized ANN is combined with PIC to scale up the Direct-L mode. This approach is called DNN-PIC in [14]. Basically, the entire ANN consists of a number of cascaded PIC layers, with each layer employing a group of identical pre-trained DNN-PIC modules for signal classification and interference cancellation. Therefore, multiuser interference decreases linearly with the feed-forward procedure, and the last layer is able to provide a better classification of MU-MIMO signals.

Fig. 9 compares the average bit-error-rate (BER) performance between conventional MU-MIMO receivers and the DNN-assisted solutions. For the CE-L and Direct-L mode, the ANN was trained at $E_b/N_0=5$ dB. For the DNN-PIC approach, the ANN was trained at three different E_b/N_0 points (i. e. $E_b/N_0=0$ dB,

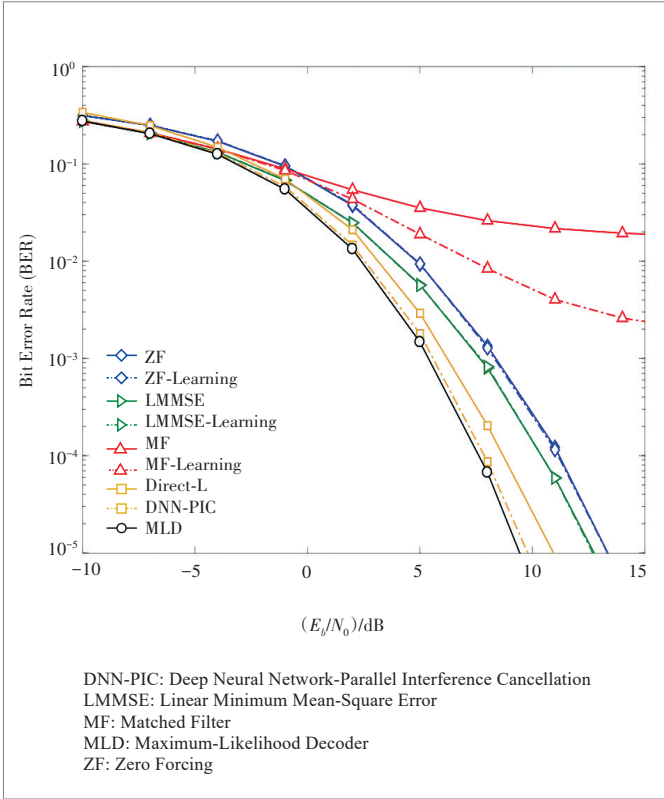
5 dB and 10 dB), and were optimally selected in the communication procedure in order to obtain the best achievable performance. Simulation results show that deep learning modules largely improve the detection performance of the MF-based receiver (around 8 dB at BER of 10^{-3}) due to better use of the sequence-detection gain. For both the ZF and LMMSE receiver, the sequence-detection gain vanishes since channel equalization orthogonalizes multiuser signals. Meanwhile, the Direct-L mode significantly outperforms all CE-L modes and this result confirms the accuracy of the theoretical analysis. Finally, the proposed DNN-PIC approach further improves the BER performance of the Direct-L approach by around 1.5 dB. The performance gap between the DNN-PIC and the MLD receiver is only about 0.2 dB. Again, it should be emphasized that the DNN-PIC approach is parallel computing ready.

4 Discussion and Research Challenges

Although deep learning has achieved widespread empirical success in many areas, the applications of deep learning for wireless communication physical layer design are still at the early stage of research and engineering implementation. In this section, we list several fundamental bottlenecks together with the potential future research directions.



▲ Figure 8. Block diagram of the DNN-PIC approach.



▲ Figure 9. Average BER as a function of E_b/N_0 for uncoded 4-by-8 multiuser multiple-input multiple-out (MU-SIMO) system with BPSK modulation.

1) Training set overfitting.

Overfitting is a modeling problem which occurs when a function too closely fits a limited data set [15]. In PHY, it could refer to the case that an ANN-assisted receiver trained for a specific wireless environment (or channel model) is not suitable for another environment (or channel model). It is a severe problem since a deep learning solution with limited generalization capability is less useful in real practice. However, this issue can be viewed more positively if deep learning algorithm can be used to optimize wireless receivers integrated into access points based on their local environments.

2) Scalability of DL-based solutions.

In machine learning theory, scalability refers to the effect of an increasing training data set on the computational complexity of a learning algorithm. For instance, the ANN solution in Fig. 7b has its learning capacity rapidly degraded with the growth of transmit antennas [14]. The current approach to mitigate this problem is by means of training the ANN with channel equalized signals (Fig. 7a). However, in this case, ANN-assisted receivers are not able to exploit maximally the spatial diversity-gain due to the multiuser orthogonalization enabled by channel equalizers, and the performance goes far from optimum. To tackle this issue, novel deep learning algorithms with good scalability are required (and expected) in the future.

3) Training strategies and performance evaluation.

Deep learning for wireless communication is a new research area and people lack experience in training strategies. For example, the optimal training SNR points for different PHY scenarios remain unknown [15]. In [9], it can be observed that the training of an ANN at relatively high SNRs gives an excellent generalization performance at low SNR regime in AWGN channel. However, when wireless channel becomes fading [14], the learned PHY feature at high SNR regime can no longer indicate the feature of low SNRs. A potential solution is to train ANNs at different SNR regimes separately and then merge the results together, but this solution introduces additional training complexities and requires SNR estimation. A related question is whether there is a more appropriate way to measure the training process in PHY solutions. It is well known that ANN training aims to minimize a given loss function, and we consider that an ANN is well trained if the loss is converged to an ideal state. On the other hand, PHY performance is normally measured by BER or SER. In most of the ANN-assisted PHY solutions, we make a hard decision on ANN outputs to obtain the bit-level (or symbol-level) estimates. However, the loss function might not be able to accurately indicate the training progress when complicated PHY scenarios are considered (e. g., high-order modulation and fast fading channel). In [14], the authors introduce a method which measures the training progress by computing the average BER/SER over the last few training epochs, and the estimated BER performance is shown to be very close to the validation performance. In general, the training strategies, especially for PHY applications, are worthy of investigation in future research.

4) Hardware implementation.

Currently, most of the ANN-assisted PHY solutions are still in their software simulation stages, but hardware implementation normally requires more practical considerations [16] – [18]. Apart from the channel model and data set that we have discussed in the previous sections, power consumption also needs to be considered since the ANN training process often involves very high computation cost. The aim of reducing ANN learning expenses has recently motivated a new research area on the non von Neumann computing architecture.

5 Conclusions

This paper presents several promising ANN-assisted PHY applications. The idea lies in the use of ANNs to replace parts of the conventional signal processing blocks in the communication chain. It is shown that ANN-assisted approaches achieve competitive performance in terms of both reliability and latency in various applications. More importantly, deep learning offers us a fundamentally new way to design and optimize the conventional communication systems. A wide range of open challenges need to be solved and theoretical analysis is also expected in future research.

References

- [1] FG-NET-2030. Network 2030: Blueprint of Technology A, Applications and Market Drivers Towards the Year 2030 and Beyond [EB/OL]. (2019-05-20). https://www.itu.int/en/ITU-T/focusgroups/net2030/Documents/White_paper.pdf
- [2] O'SHEA T J, ERPEK T, CLANCY T. Deep Learning Based MIMO Communications [EB/OL]. (2017-07-25). <https://arxiv.org/abs/1707.07980>
- [3] NAOUM R S, AL-SULTANI Z N. Learning Vector Quantization (LVQ) and K-nearest Neighbor for Intrusion Classification [J]. *World of Computer Science and Information Technology Journal*, 2012, 2(3):105-109
- [4] O'SHEA T J, HOYDIS J. An Introduction to Deep Learning for the Physical Layer [J]. *IEEE Transactions on Cognitive Communications and Networking*, 2017, 3(4): 563-575. DOI: 10.1109/TCCN.2017.2758370
- [5] XUE S Y, MA Y, YI N, et al. Unsupervised Deep Learning for MU-SIMO Joint Transmitter and Noncoherent Receiver Design [J]. *IEEE Wireless Communication Letter*, 2019, 8(1): 177-180. DOI: 10.1109/LWC.2018.2865563
- [6] BIRCANOGLU C, ARICA N. A Comparison of Activation Functions in Artificial Neural Networks [C]/Signal Processing and Communications Applications Conference (SIU), Izmir, Turkey, 2018: 1-4. DOI: 10.1109/SIU.2018.8404724
- [7] HAMALAINEN A, HENRIKSSON J. Convolutional Decoding Using Recurrent Neural Networks [C]/International Joint Conference on Neural Networks. Washington, DC, USA, 1999: 3323-3327. DOI: 10.1109/IJCNN.1999.836193
- [8] PAYANI A, FEKRI F. Decoding LDPC Codes on Binary Erasure Channels using Deep Recurrent Neural-Logic Layers [C]/IEEE International Symposium on Turbo Codes & Iterative Information Processing (ISTC), Hongkong, China, 2018: 1-5. DOI: 10.1109/ISTC.2018.8625326
- [9] WANG J, MA Y, XUE S Y, et al. Parallel Decoding for Non-Recursive Convolutional Codes and its Enhancement Through Artificial Neural Networks [C]/IEEE International Workshop on Signal Processing Advances in Wireless Communications. Cannes, France, 2019: 1-1
- [10] LI A, MA Y, XUE S Y, et al. Unsupervised Deep Learning for Blind Multiuser Frequency Synchronization in OFDMA Uplink [C]/IEEE International Conference on Communications. Shanghai, China, 2019: 1-1. DOI: 10.1109/ICC.2019.8761937
- [11] DE LUNA DUCOING J C, MA Y, YI N, et al. A Real-Complex Hybrid Modulation Approach for Scaling up Multiuser MIMO Detection [J]. *IEEE Transactions on Communications*, 2018, 66(9): 3916-3929. DOI: 10.1109/TCOMM.2018.2833101
- [12] WOLNIANSKY P W, FOSCHINI G J, GOLDEN G D, et al. V-BLAST: An Architecture for Realizing Very High Data Rates over The Rich-scattering Wireless Channel [C]/URSI International Symposium on Signals, Systems, and Electronics. Conference Proceedings. Pisa, Italy, 1998: 295-300. DOI: 10.1109/ISSSE.1998.738086
- [13] LIU T, LIU Y Y. Modified Fast Recursive Algorithm for Efficient MMSE-SIC Detection of the V-BLAST System [J]. *IEEE Transactions on Wireless Communications*, 2008, 7(10): 3713-3717. DOI: 10.1109/T-WC.2008.070487
- [14] XUE S Y, MA Y, LI A, et al. On Unsupervised Deep Learning Solutions for Coherent MU-SIMO Detection in Fading Channels [C]/IEEE International Conference on Communications. Shanghai, China, 2019: 1-6. DOI: 10.1109/ICC.2019.8761999
- [15] KENTON W. Overfitting [EB/OL]. [2019-07-02]. <https://www.investopedia.com/terms/o/overfitting.asp>
- [16] GEORGE D, HUERTA E A. Deep Neural Networks to Enable Real-time Multimessenger Astrophysics [J]. *Physical Review D*, 2018, 97(4): 044039. DOI: 10.1103/PhysRevD.97.044039
- [17] DORNER S, CAMMERER S, HOYDIS J, et al. Deep Learning Based Communication Over the Air [J]. *IEEE Journal of Selected Topics in Signal Processing*, 2018, 12(1): 132-143. DOI: 10.1109/JSTSP.2017.2784180
- [18] SAHOO D, PHAM Q, LU J, et al. Online Deep Learning: Learning Deep Neural Networks on the Fly [C]/International Joint Conferences on Artificial Intelligence Organization. Stockholm, Sweden, 2018: 2660-2666. DOI: 10.24963/IJCAI.2018/369

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A Machine Learning Method for Prediction of Multipath Channels

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Abstract: A machine learning method for predicting the evolution of a mobile communication channel based on a specific type of convolutional neural network is developed and evaluated in a simulated multipath transmission scenario. The simulation and channel estimation are designed to replicate real-world scenarios and common measurements supported by reference signals in modern cellular networks. The capability of the predictor meets the requirements that a deployment of the developed method in a radio resource scheduler of a base station poses. Possible applications of the method are discussed.

Keywords: channel estimation; channel prediction; convolutional neural network; machine learning; multipath transmission

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1 Introduction

Today's mobile communication networks are driven by the demand of a steadily increasing number of subscribers for ever higher data rates. This demand has led to the introduction of support for technologies such as millimeter wave transmissions and massive multiple-input multiple-output (MIMO) into the current 5G standards. Apart from the introduction of these new technologies, the available spectrum has to be utilised in the most efficient manner possible. This has already led to the move to orthogonal frequency-division multiple access (OFDMA) and orthogonal frequency-division multiplexing (OFDM) in the fourth-generation mobile broadband standards, which allow for fine grained control over the utilisation of the available radio resources across both the time and frequency domains. While OFDM combats frequency-selective fading by using long symbol times, OFDMA provides further benefits by allowing multiple users to schedule transmission on the subcarriers which are best for them at the time [1]. OFDM also allows for different encodings to be used across the available spectrum, thereby giving the scheduler fine

grained control over the trade-off transmission data rate vs. signal robustness.

The dynamic allocation of radio resources and its scheduling are key to achieving efficient utilisation of the available spectrum. Since base stations manage a large number of transmissions, each across a different channel depending on the position and environment of the individual user equipment (UE), they are natural candidates for hosting an optimisation through dynamic scheduling of the radio resources. To achieve efficient radio resource management, scheduling algorithms need to have information about the current and future states of the transmission channels. In particular, two things are required: On the one hand, a mechanism for the estimation of the transmission channels needs to be in place, i. e., there has to be a measurement of the channel transfer function; on the other hand, the development of the transmission channels over time has to be predicted to allow for estimates of future channel quality.

In Long Term Evolution (LTE) systems, channel estimation can be implemented by observing the Cell-Specific Reference

Signals (CRS). LTE release 10 (LTE Advanced) supplemented the CRS by the introduction of Channel State Information Reference Signals (CSI-RS). 5G New Radio (NR) does not provide CRS, instead relying exclusively on the flexibly configurable CSI-RS. In this paper, we use a simulation of a multipath propagation transmission channel based on the empirical evidence and the models devised in [2]. The channel is estimated by transmitting and measuring a test signal containing a similar amount of information as the LTE CRS. In particular, very similar estimates can be derived from the observation of LTE CRS.

The present work focusses on the aspect of predicting the time-variant transmission channels. A convolutional neural network (CNN) operating on the time-frequency domain and using multiple time resolutions is designed in order to achieve the necessary prediction performance. The proposed CNN is a two-dimensional variant of the WaveNet network architecture proposed in [3] and uses dilated kernels on the time axis to achieve the incorporation of multiple time resolutions. A further enhancement to the WaveNet architecture presented here consists in enabling simultaneous multi-step predictions, allowing for the instantaneous predictions of the channel development over a period of 5 ms (one half-frame) at a resolution of 500 μ s (one slot) each. This is especially useful, since the allocation of resource blocks can be changed at the half-frame level, necessitating the prediction over at least this time period.

The remainder of this work is structured as follows: Section 2 introduces the simulation from which the transfer functions of a fading channel scenario based on real-world observations are derived. Section 3 describes the employed channel estimation procedure. Section 4 describes the channel predictor that is the essential part of this work. Section 5 summarises the obtained results. In Section 6, we provide a discussion of possible applications and an outlook on future research. Section 7 concludes the paper.

2 Simulation

Setting the position and carrier frequency of the transmitter to $(0, 0) \in \mathbb{R}^2$ and $f_{\text{carrier}} = 900$ MHz, respectively, the multipath transmission is simulated by generating 256 scatterers. Each scatterer starts at a randomly chosen initial position $(x'_0, y'_0) \in \mathbb{R}^2$ such that the power delay profile of the resulting multipath transmission matches the typical urban scenario described in [2], and moves at a random time-invariant velocity $(v'_x, v'_y) \in \mathbb{R}^2$ with $v'_x, v'_y \sim \mathcal{N}(0, \sigma^2)$, $\sigma = 10$ m/s, for $\iota = 0, \dots, 63$, and $v'_x, v'_y = 0$ for $\iota \geq 64$. The receiver is supposed to move from an initial position $(x_0^*, y_0^*) = (400, 0) \in \mathbb{R}^2$ near the transmitter at velocity $v^* = (v_x^*, v_y^*) \in \mathbb{R}^2$ with $|v^*| = 10$ m/s, $\arctan_2(v_y^*, v_x^*) \sim \mathcal{U}(-\pi, \pi)$ where $\exp(i \arctan_2(y, x)) = (x + iy) / \sqrt{x^2 + y^2}$ for $(x, y) \in \mathbb{R}^2$. The transmissions are assumed to be conducted periodically in blocks. The time for transmitting one block is assumed to be $T = 500$ μ s, which leads to a dis-

crete time simulation with step size 500 μ s. The simulation time amounts to $2^{12} = 4096$ time steps in total. The bandwidth of transmission is set to 12.8 MHz. A time interval of length 20 μ s at the beginning of each block is used for the transmission of a test signal generated for the channel estimation. All values are computed and stored using International System of Units (SI) base units.

An example configuration of this simulation is shown in Fig. 1. The large red and black dots represent the transmitter and receiver, respectively. The smaller dots represent the scatterers which are coloured according to the phase offsets observed on the corresponding transmission path (shown as lines) with red representing zero offset and cyan representing a phase offset of π .

At each simulation step t and for each ι , the path length reflected by the ι -th scatterer $l_t^{(\iota)} = |(x'_t, y'_t) - (0, 0)| + |(x_t^*, y_t^*) - (x'_t, y'_t)|$ and its derivative with respect to time $\frac{d}{dt} l_t^{(\iota)}$ are computed. For each scatterer ι , we recorded the corresponding transmission delay time $\sigma_t^{(\iota)}$, the constant phase offset $\theta_t^{(\iota)}$, and the Doppler frequency $f_{D_t}^{(\iota)}$ caused by the ι -th scatterer following the rules $\sigma_t^{(\iota)} = l_t^{(\iota)} / c_0$, $\theta_t^{(\iota)} = \left((-l_t^{(\iota)} f_{\text{carrier}} / c_0) \bmod 1 \right) \cdot 2\pi$, and $f_{D_t}^{(\iota)} = -\frac{d}{dt} l_t^{(\iota)} f_{\text{carrier}} / c_0$, respectively, as well as the received signal amplitude $a_t^{(\iota)}$ computed using the free-space propagation model $a_t^{(\iota)} = c_0 / (4\pi f_{\text{carrier}} l_t^{(\iota)})$ [1]. (Here, c_0 refers to the speed of light in vacuum.)

In a setting without line of sight, using linearisation of the phase offset with respect to the Doppler frequency, the time-variant channel impulse response evaluated at time $t + \tau$ for each simulation step t and small τ resulting from the multipath transmission simulated using the above parameters can be approximated by

$$h(\cdot, t + \tau) = \frac{1}{\sqrt{\sum_{\iota=0}^{255} (a_t^{(\iota)})^2}} \sum_{\iota=0}^{255} a_t^{(\iota)} \exp(i\theta_t^{(\iota)} + i2\pi f_{D_t}^{(\iota)} \tau) \delta_{\sigma_t^{(\iota)}}(\cdot). \quad (1)$$

For any signal $\{S_\tau\}_{0 \leq \tau < T}$ being transmitted in the block beginning at time step t through the simulated channel, this consideration leads to a received signal $\{R_\tau\}_{0 \leq \tau < T}$ in the form of

$$R_\tau = (h(\cdot, t + \tau) * S_\tau)(\tau) = \frac{1}{\sqrt{\sum_{\iota=0}^{255} (a_t^{(\iota)})^2}} \sum_{\iota=0}^{255} a_t^{(\iota)} \exp(i\theta_t^{(\iota)} + i2\pi f_{D_t}^{(\iota)} \tau) (\delta_{\sigma_t^{(\iota)}}(\cdot) * S_\tau)(\tau). \quad (2)$$

This parametrisation is used in [4] and delivers a realistic



▲ Figure 1. Example configuration of the designed simulation.

approximation of real-world scenarios for numbers of summands greater than 100 [5]. In order to allow continuous time delays to be applied to discrete time signals, the impulse functions $\delta_{\sigma_i(\cdot)}$ in (1) and (2) are convolved with a windowed sinc(\cdot) function scaled with a given bandwidth. Overall, the channel transmission including pulse shaping with bandwidth restricted to half the sample rate and additive noise is approximated by replacing the $\delta_{\sigma_i(\cdot)}$ in (1) and (2) by $\sin(\pi(\cdot/2))/(\pi(\cdot/2))\mathbf{1}_{[-8,8]}$ and adding independent and identically distributed Gaussian white noise $\sim \mathcal{N}(0, \sigma^2)$ to the transmitted signal with power σ^2 resulting in a signal-to-noise ratio of 12 dB.

3 Channel Estimation

For both the channel estimation and prediction, we will work in the frequency domain. Apart from the obvious usefulness of frequency domain estimation and prediction for OFDM systems, working in the frequency domain allows for a channel estimation scheme of lower computational complexity compared to equalisers operating in the time domain and requiring matrix inversions. Moreover, the frequency domain mode of operation has some benefits on the predictor further detailed in Section 4. Throughout the remainder of this paper, for a discrete time complex-valued signal $\{X_\tau\}_{\tau=0, \dots, N-1}$, let $\mathcal{F}X = \{\mathcal{F}X_f\}_{f=0, \dots, N-1}$ denote its (discrete) Fourier transform.

The time-variant channel transfer functions $\mathcal{F}h(\cdot, t + \tau)$ for $t = 0, \dots, 4095T$ and $0 \leq \tau < T$ simulated in Section 2 are approximated by a time series of block wise time-invariant transfer functions $\{\mathcal{F}h^t\}_{t=0, \dots, 4095}$ based on which the estimation and prediction of the channel transmission are conducted. For each

transmission block beginning at time step t , in order to estimate the corresponding channel transfer function $\mathcal{F}h^t$, a complex-valued (white noise) test signal $\{\tilde{S}_\tau^t\}_{\tau=0, \dots, N-1}$ whose Fourier transform has constant amplitude and random phases $\sim \mathcal{U}(-\pi, \pi)$ is generated and then transmitted through the multipath transmission channel with additive white noise simulated in Section 2, resulting in a received signal $\{R_\tau^t\}_{\tau=0, \dots, N-1}$. The transfer function $\mathcal{F}h^t$ is in a first step estimated by

$$\mathcal{F}\tilde{h}^t := \frac{\mathcal{F}R^t}{\mathcal{F}\tilde{S}^t}. \quad (3)$$

In order to improve the quality of the preliminary estimator $\mathcal{F}\tilde{h}^t = \{\mathcal{F}\tilde{h}_f^t\}_f$ which is noise corrupted, the corresponding impulse response \tilde{h}^t is windowed by a step function of width $N/2$ and then Fourier transformed, i. e., the estimator $\mathcal{F}\hat{h}^t$ of the channel transfer function is given by

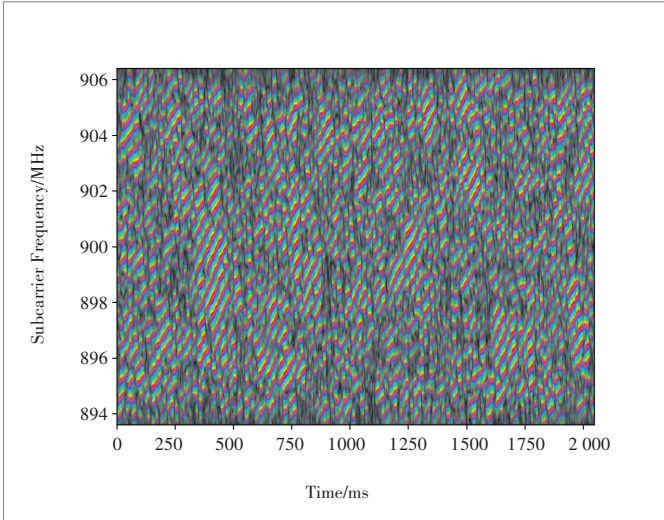
$$\mathcal{F}\hat{h}^t = \mathcal{F}\left(\mathbf{1}_{[0, N/2]} \mathcal{F}^{-1} \mathcal{F}\tilde{h}^t\right), \quad (4)$$

where $\mathcal{F}^{-1}Y = \{\mathcal{F}^{-1}Y_\tau\}_{\tau=0, \dots, N-1}$ refers to the inverse Fourier transform of the considered signal $\{Y_f\}_{f=0, \dots, N-1}$ in the frequency domain. The step of windowing the preliminarily estimated impulse response $\tilde{h}^t = \mathcal{F}^{-1} \mathcal{F}\tilde{h}^t$ is conducted due to the observation of a long noisy tail showing up in the recorded \tilde{h}^t , which, according to the simulation with maximum transmission delay time less than $N/2$, should be eliminated; this, at the same time, yields a discrete approximation to convolving the estimated channel transfer function with the kernel $\sin(\pi(\cdot/2))/(\pi(\cdot/2))$ so that down sampling with step size 2 (instead of the original step size 1) in the frequency domain delivers an error corrected version of the estimated channel transfer function $\{\mathcal{F}\hat{h}_{2f}^t\}_{f=0, \dots, N/2-1}$.

When applied to a multipath transmission channel with additive white noise such as the transmission channel simulated in Section 2, the above method of estimating the channel transfer function yields a reasonably accurate estimate.

The initial resolution level of the frequency spectrum is set to $N = 2^9$ which results in an estimated channel transfer function $\mathcal{F}\hat{h}^t$ of length $N/2 = 256$ for each block beginning at simulation step t . Overall, the simulation is run 16 times independently, which results in 16 independent time series of the form $\{\mathcal{F}\hat{h}^t\}_{t=0, \dots, 4095}$ with $\mathcal{F}\hat{h}^t \in \mathbb{C}^{256}$.

An example realisation of transfer functions estimated during one simulation is shown in Fig. 2. The x -axis represents time, labelled by time steps t , and the y -axis represents frequency, labelled by indices of subcarriers f . Brightness corre-



▲ Figure 2. Example plot of estimated transfer functions.

sponds to amplitude with bright colors representing good signal reception. Colors correspond to phases with red representing phase 0 and cyan representing phase π . One can clearly see the thin dark areas reflecting the effect of frequency selective fading.

In order to ensure that the proposed system could indeed be implemented on current cellular radio equipment, the method of estimation of the simulated channel is chosen in such a manner that the level of channel information obtained is very similar to that commonly available from the reference signals in real-world systems.

4 Channel Prediction

The time series of estimated channel transfer functions from Section 3 are used as labels for training and testing a carefully chosen convolutional neural network (CNN) that delivers one- or multi-step ahead predictions of the time-variant channel transfer functions resulting from the simulation in Section 2. Since additive noise is included in the simulation of the channel, the trained neural network also contributes to the denoising of the channel transfer function along with the channel estimation scheme in Section 3.

In general, CNNs are a specific architecture of feed-forward neural networks, where linear filters (convolution kernels) instead of traditional single weight parameters are used in a shift invariant manner for the transformation between adjacent layers, making use of local temporal and spatial structure of the input signal within a local receptive field. The local receptive field can be enlarged without the need for increasing the number of parameters by means of the dilation parameter. In the one-dimensional case, a CNN with dilation is known as WaveNet that is introduced in [3] for processing audio signals. For more details on CNNs, the readers are referred to [6]. Compared to traditional fully connected neural networks and recur-

rent neural networks such as long short-term memory units (LSTMs) [7], CNNs use fewer parameters and are less receptive to overfitting.

The shift invariant nature of CNNs necessitates that the signals processed by a CNN have some amount of homogeneity, as the layers of the CNN have no way of varying the processing performed by them between different regions of the input signal. In our particular case, this means that the method in which predictions are performed for a certain consecutive group of subcarriers is exactly the same as that used for any other group of consecutive subcarriers. This is a reasonable approach, as the manner in which the influence of the channel on the transmission develops over time is indeed very homogeneous across the entire considered bandwidth. This assumption would not hold, if we were to work directly on the time domain channel impulse response, as most of the power of this impulse response is contained within the first few microseconds, suggesting a different approach for processing this earlier part of the impulse response.

In our setting, a two-dimensional convolutional neural network (CNN) with partial dilation is used for building the prediction model, which is described in the remainder of this section.

CNNs are a special type of feed-forward neural networks made up of one or several convolutional layers. A feed-forward neural network is a function mapping an input vector to an output vector, making use of a set of parameters which are to be adapted through the training. In a multi-layer neural network, this function operates in the form of several such functions in succession, each transforming the corresponding input vector into an output vector. In our setting, for processing the time series of channel transfer functions $\{\mathcal{F}\hat{h}^t\}_{t=0,1,\dots}$ with $\mathcal{F}\hat{h}^t \in \mathbb{C}^{256}$,

we use two-dimensional convolutional layers where each input vector is indexed with three axes related to the real-or-imaginary part of the complex plane, the simulation time steps, and the frequency domain, and the transformation is conducted by convolving the input vector with a convolution kernel made up of free parameters to be adapted and adding a free parameter vector called bias to the result. For our purpose of multi-step prediction, we also consider the evolution of the time series over a long period of time, for which we use the so-called dilation parameter on the time axis defining the spacing between the free parameters in the convolution kernel. The introduction of the dilation parameter enables us to extend the receptive field of the CNN in time without taking extra parameters for fitting.

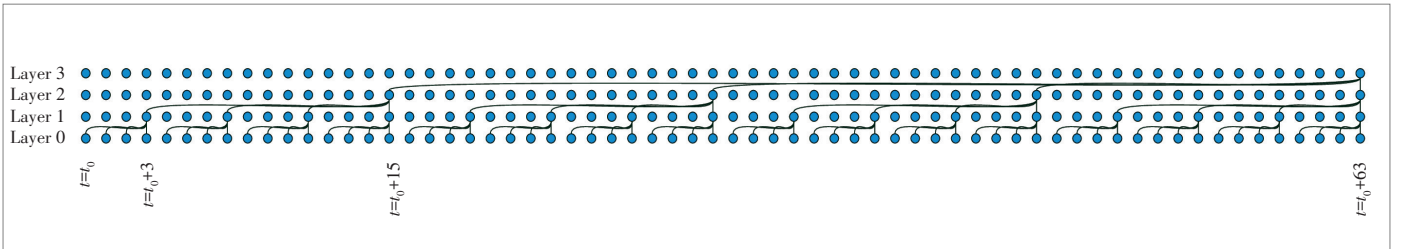
For delivering at most m -step ahead predictions of the future channel transfer function, we use a 5-layer CNN beginning with 4 consecutive partially dilated convolutional layers along the t -axis with channel sizes 2, 6, 12, 12, 6, followed by one convolutional layer with $2m$ output channels. In each partially dilated convolutional layer, the size of the free convolutional kernel is set to (4,5) for the time and frequency axis, respectively, and the dilation parameter is defined by 4 to the power

of the corresponding layer number. The final layer is endowed with 1×1 convolution kernels. Apart from the last layer, the hyperbolic tangent is used as activation function in each layer. In order to improve the back propagation of the gradient [8], a residual convolutional layer [9] with kernel size $(1, 1)$ is added to each partially dilated convolutional layer. The above layout is common in convolutional neural networks and is designed to best adapt to our task and the nature of the input signals. The layout of our CNN is summarised in **Table 1**. For illustration, a diagram of the dilated layers along the t -axis is presented in **Fig. 3**.

During the training, the free parameters in our CNN are adjusted to the labelled training data by minimising the mean squared error (MSE) of prediction along the negative direction of the gradient of the error function with respect to the parameters, for which we use a refined version of stochastic gradient descent (SGD) called ADAM training algorithm [10]. The gradient for each update is computed by means of the so-called backpropagation algorithm [8] based on the chain rule.

▼ **Table 1. Layout of the 2D CNN for m -step ahead prediction**

Layer Number	Layer Type	Channel Sizes	Kernel Size (t, f)	Dilation Parameter	Residual Layer
0	Dilated convolution	$2 \rightarrow 6$	$(4, 5)$	$(1, 1)$	1×1 convolution
1	Dilated convolution	$6 \rightarrow 12$	$(4, 5)$	$(4, 1)$	1×1 convolution
2	Dilated convolution	$12 \rightarrow 12$	$(4, 5)$	$(16, 1)$	1×1 convolution
3	Dilated convolution	$12 \rightarrow 6$	$(4, 5)$	$(64, 1)$	1×1 convolution
4	Convolution	$6 \rightarrow 2m$	$(1, 1)$	$(1, 1)$	None



▲ **Figure 3. Structure of the dilated convolutional layers along the t -axis.**

In our setting, the 16 independent time series of channel transfer functions $\{\mathcal{F}\hat{h}^t\}_{t=0,\dots,4095}$ with $\mathcal{F}\hat{h}^t \in \mathbb{C}^{256}$ are each divided into 8 segments which are to be fed into the CNN as input vectors and grouped as training, validation, and test parts with the proportion 6:1:1. The ADAM optimiser with learning rate $\gamma = 0.01$ is run for 30 training epochs in total.

5 Results

The performance of our approach to delivering multi-step ahead prediction is measured in a setting with $m = 10$ for training the corresponding CNN to output 10-step ahead predic-

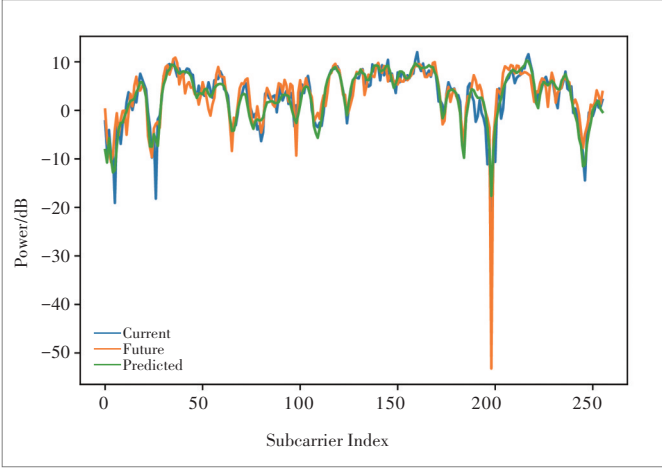
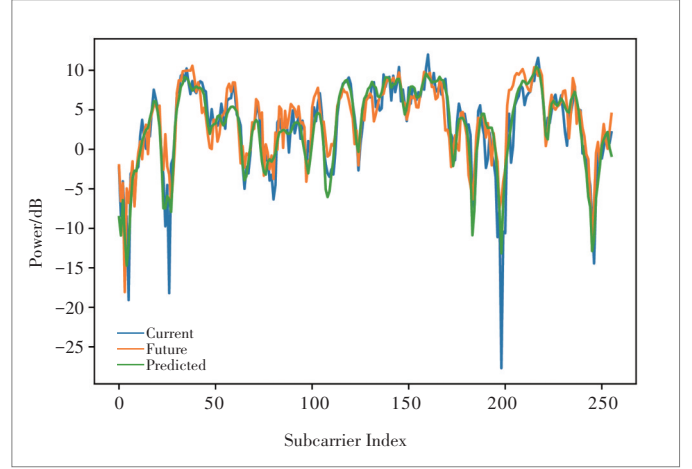
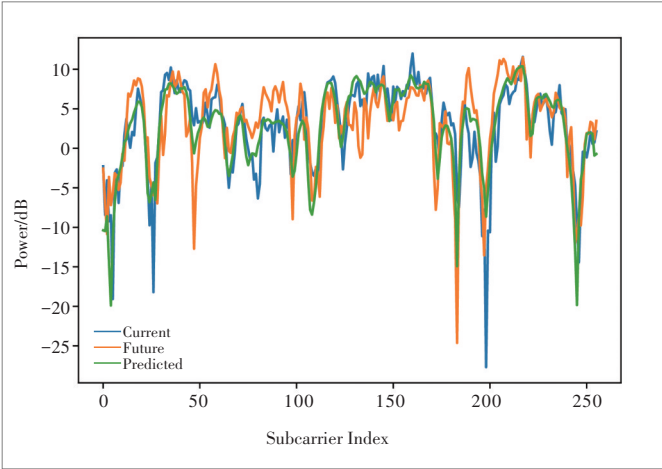
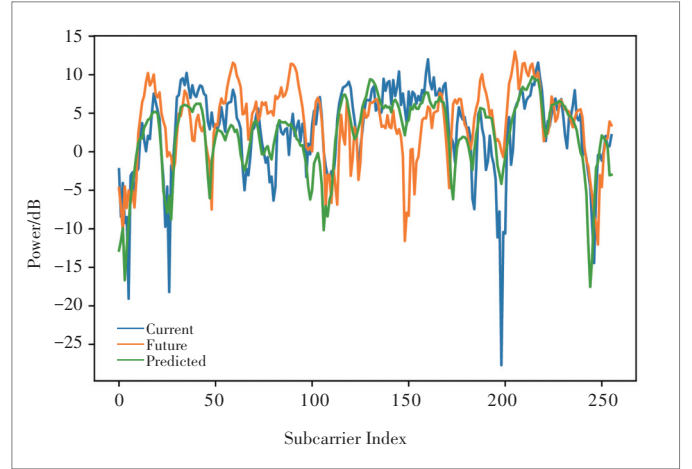
tions at most. The MSEs are evaluated for training, validation, and test data (**Table 2**). The similarity of performance evaluated on all three sub-datasets indicates no significant overfitting.

As a baseline, we consider the trivial prediction where all future values of the time series are set to the latest observed value; the MSE of such a prediction scheme provides a measure for the variation of the underlying time series over time (Table 2). Overall, the instantaneous long-term prediction with our CNN using $m = 10$ facilitated by employing the dilation parameter in time delivers much more accurate results than the trivial prediction scheme.

In **Figs. 4, 5, 6, and 7**, the power density spectra in dB of an example channel transfer function evaluated at time steps t_0 and $t_0 + \Delta t$ and the Δt -step ahead instantaneous prediction for time $t_0 + \Delta t$, $\Delta t = 1, 2, 5, 10$, output by the trained CNN with $m = 10$, are plotted in blue, yellow, and green, respectively. Note in particular that most of the negative peaks of the future power density spectra are correctly detected by the predictor, which suggests the utility of our approach in handling situa-

▼ **Table 2. Mean squared errors (MSEs) for prediction length Δt from 1 to 10**

Δt	Training	Validation	Test	Trivial
1	0.1466	0.1460	0.1424	0.2217
2	0.1579	0.1569	0.1538	0.2532
3	0.1753	0.1735	0.1707	0.3047
4	0.2014	0.1988	0.1962	0.3750
5	0.2357	0.2321	0.2298	0.4621
6	0.2757	0.2723	0.2704	0.5644
7	0.3249	0.3208	0.3183	0.6788
8	0.3821	0.3763	0.3735	0.8040
9	0.4459	0.4393	0.4354	0.9382
10	0.5133	0.5055	0.5005	1.0797

▲ Figure 4. Power density spectrum in dB for $\Delta t = 1$.▲ Figure 5. Power density spectrum in dB for $\Delta t = 2$.▲ Figure 6. Power density spectrum in dB for $\Delta t = 5$.▲ Figure 7. Power density spectrum in dB for $\Delta t = 10$.

tions with frequency selective fading in an OFDM transmission scheme (see Section 6 for more discussion).

6 Discussion

As mentioned in the introduction, the method proposed in the preceding sections can be employed to provide an OFDMA/OFDM radio resource scheduler located in a base station with predictions necessary for an efficient scheduling of radio resources. There are two main aspects of the scheduler, which can benefit from this information:

The predictions can be used to decide to which user a specific radio resource element should be allocated by estimating the relative usefulness of assigning the element to a specific user compared to the utility another user may have of it. For instance, consider the case where two radio resource blocks RRB A and RRB B are assigned to users UE A and UE B, respec-

tively. If the predictor predicts that during the next half-frame the part of the spectrum on which RRB A is transmitted will become faded for UE A, but a strong signal could be received by UE B, it would be advantageous to change the allocation and assign RRB B to UE A and RRB A to UE B.

The other aspect is that the scheduler may control the choice of encoding used on each of the radio resource elements. In particular, if a prediction reveals that a certain part of the spectrum will become faded for a particular user and a reallocation among the users as in the case discussed previously is not applicable, the scheduler may initiate a change of the employed encoding, for instance from 64QAM¹ down to 16QAM, thereby increasing the robustness of the signal and counteracting the decreasing signal-to-noise ratio. In extreme cases of frequency selective fading, transmissions on the corresponding frequencies could even be disabled completely.

In future research, we hope to expand on both of these topics by developing an adaptive coding scheme and a dynamic

¹ Quadrature amplitude modulation

scheduler for the multi-user case based on the research performed in this article.

7 Conclusions

In this paper, we simulated a multipath transmission scenario, implemented a channel estimation scheme, and designed a machine learning model for predicting the resulting channel transfer functions over multiple time steps. Our results show that the machine learning model is capable of capturing characteristics of the channel evolution and provides reasonable predictions. We addressed possible applications of the method in real-world systems, which we plan to implement and evaluate in future research.

References

- [1] BEARD C, STALLINGS W. Wireless Communication Networks and Systems, Global Edition [M]. London, UK: Pearson, 2015
- [2] COST 207 Management Committee. COST 207 Digital land mobile radio communications [R]. Brussels, Belgium; Luxembourg, Luxembourg: Commission of the European Communities, 1990
- [3] VAN DEN OORD A, DIELEMAN S, ZEN H, et al. WaveNet: A Generative Model for Raw Audio [EB/OL]. (2016–09–19). <https://arxiv.org/abs/1609.03499>
- [4] SCHULZE H. Stochastische Modelle und digitale Simulation von Mobilfunkkanälen [C]//Kleinheubacher Berichte. Kleinheubach, Germany, 1988: 473 – 483
- [5] K-DKAMMEYER. Nachrichtenübertragung [M]. Wiesbaden, Germany: Vieweg+Teubner Verlag, 2004. DOI:10.1007/978-3-322-94062-9
- [6] GOODFELLOW I, BENGIO Y, COURVILLE A. Deep Learning [M]. Cambridge, USA: MIT Press, 2016
- [7] HOCHREITER S, SCHMIDHUBER J. Long Short - Term Memory [J]. Neural Computation, 1997, 9(8): 1735 – 1780. DOI: 10.1162/neco.1997.9.8.1735
- [8] RUMELHART D E, HINTON G E, WILLIAMS R J. Learning Representations by Back - Propagating Errors [J]. Nature, 1986, 323: 533 – 536. DOI: 10.1038/323533a0
- [9] HE K, ZHANG X, REN S, et al. Deep Residual Learning for Image Recognition

[C]//29th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016. Las Vegas, USA, 2016. DOI:10.1109/CVPR.2016.90

[10] KINGMA D P, BA J L. Adam: A Method for Stochastic Optimization [C]//3rd International Conference on Learning Representations, ICLR 2015. San Diego, USA, 2015. arXiv:1412.6980 [cs.LG]

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◀ From Page 02

This will in turn impose new technical challenges on the cellular networks but can well be overcome in the 6G networks. Organized into the third group, the fifth and sixth articles of this special issue focus on cross-layer optimization for the novel network architecture and new services by taking advantage of machine learning techniques. More specifically, the fifth article “Machine Learning Based Unmanned Aerial Vehicle Enabled Fog-Radio Access Network and Edge Computing” by Mohammed SEID et al. presents the use of machine learning in the UAV-enabled fog-radio access network of edge computing architecture. Moreover, this article also addresses the future research direction of machine learning roles in UAV connected cellular networks. Last but not the least, the sixth article of this special is-

sue “A Survey on Machine Learning Based Proactive Caching” by Stephen ANOKYE et al. provides an overview on smart and efficient mobile edge caching relying on machine learning approaches. Issues affecting edge caching, such as caching entities, policies, and algorithms, are discussed, followed by a summary on challenges and future research directions.

As we conclude the introduction to this special issue and the content of six articles, we would like to thank all authors for their valuable contributions. We also express our sincere gratitude to all the reviewers for their timely and insightful comments on all submitted articles. It is hoped that this special issue is informative and useful from various aspects related to the application of machine learning approaches for next-generation wireless networks.

A Case Study on Intelligent Operation System for Wireless Networks



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Abstract: The emerging fifth generation (5G) network has the potential to satisfy the rapidly growing traffic demand and promote the transformation of smartphone-centric networks into an Internet of Things (IoT) ecosystem. Due to the introduction of new communication technologies and the increased density of 5G cells, the complexity of operation and operational expenditure (OPEX) will become very challenging in 5G. Self-organizing network (SON) has been researched extensively since 2G, to cope with the similar challenge, however by predefined policies, rather than intelligent analysis. The requirement for better quality of experience and the complexity of 5G network demands call for an approach that is different from SON. In several recent studies, the combination of machine learning (ML) technology with SON has been investigated. In this paper, we focus on the intelligent operation of wireless network through ML algorithms. A comprehensive and flexible framework is proposed to achieve an intelligent operation system. Two use cases are also studied to use ML algorithms to automate the anomaly detection and fault diagnosis of key performance indicators (KPIs) in wireless networks. The effectiveness of the proposed ML algorithms is demonstrated by the real data experiments, thus encouraging the further research for intelligent wireless network operation.

Keywords: 5G; self-organizing network; machine learning; anomaly detection; fault diagnosis

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1 Introduction

The wireless communication technologies have experienced significant advancement over the past three decades, from the first generation (1G) system to fourth generation (4G) networks. The cellular networks successfully transform from pure telephony systems to versatile networks that can transport rich multimedia content and have a profound impact on our daily life. The rapid development of the mobile Internet generates a tremendous amount of traffic and consequently requires more bandwidth

and better quality of experience. The next-generation wireless networks, i.e., the fifth generation (5G) cellular networks, which are assumed to be commercially deployed in 2020, have the potential to satisfy such a rapidly growing demand for data traffic [1].

The 5G networks mainly have three types of scenarios [2]: first, the enhanced mobile broadband (eMBB) aims to provide broadband multimedia to human-centric use cases; second, the ultra-reliable low latency service (URLLC) with strict requirements in terms of latency (ms level) and reliability (five nines and beyond) is used for remote control of robots or tactile Internet applications; third, massive machine type communications (mMTC) is mainly used to connect a very large number of devices and transmit a low load of non-delay-sensitive informa-

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tion. It is believed that 5G will significantly promote the transformation of the smartphone-centric networks into an Internet of Things (IoT) ecosystem [3] that integrates a heterogeneous mix of wireless-enabled devices ranging from smart-phones to connected vehicles, drones, wearables, sensors, and virtual reality devices. The throughput will be 1 000 times more in aggregate from 2015 to 2020 and the number of devices will grow to 500 billion [4]. In order to achieve the capacity growth, 5G cells have to be densely deployed, about 40 to 50 times as many as 4G networks. Moreover, a typical 5G node is expected to have 2 000 parameters to be configured and optimized, significantly more than a typical 2G node (500 parameters), a 3G node (1 000 parameters) and a 4G node (1 500 parameters) [5]. It is foreseen that the network operations of 5G will become an enormous challenge. As estimated in [5], there will be 53 to 67 times increase in operational complexity in 5G compared to 4G.

The operational expenditure (OPEX) is always an important issue for wireless networks. The idea of self-organizing network (SON) was evolved in 2G, 3G and 4G. However, the automation is realized by predefined policies, rather than intelligent analysis and smart decisions. It is time-consuming and expensive for 5G operators to operate and configure the network all manually by humans. In order to reduce the OPEX and facilitate the efficiency of the next generation networks, several studies have investigated the benefits of applying machine learning (ML) and big data technology in SON, showing promising results [5] – [8]. The ML engine has the potential to automate many scenarios of SON, for example, node deployment planning, advanced load balancing, resource allocation strategy, quality-of-experience (QoE)/quality-of-service (QoS) analysis, and network monitoring, paving a way to a proactive, self-aware, self-adaptive and highly efficient networking. In this paper, we focus on the intelligent operation of wireless network through applying ML technology.

This paper is organized as follows. In Section 2, the ML preliminaries are demonstrated, and a framework of intelligent operation system designed by layered scheme is proposed. Then two use cases are illustrated, which use ML algorithms to automate the anomaly detection and fault diagnosis of key performance indicators (KPIs) in wireless networks. Promising results for on-site data analyses are shown in Section 3. Finally, we draw the conclusions in Section 4.

2 Framework of the Intelligent Operation System

2.1 Machine Learning Preliminaries

ML technology has attracted wide attentions for several decades, especially with the third wave of artificial intelligence (AI) facilitated by rapid developments of deep neural networks, big data analysis and cloud computing. ML is being

applied to more and more areas, for example, image processing, face recognition, speech recognition, natural language processing, computational advertising, recommendation system, and automated driving. Depending on the type of data input and output, and the type of task or problem intended to solve, there are three main categories of learning algorithms as follows:

1) Supervised Learning.

A supervised learning algorithm is fed with a set of data that contains both the inputs and the desired outputs. The data is known as the training data that consists of a set of training examples. Through iterative optimization of an objective function, a supervised learning algorithm aims to determine a general rule that can nicely map inputs to outputs. There are a number of popular supervised learning algorithms which have been developed and achieve successful applications, for example, regression model (RM), support vector machine (SVM), hidden Markov model (HMM), random forest (RF), and time series forecasting. In wireless networks, these models have the potential to solve a number of problems. For example, in massive multi-input multi-output (MIMO) systems associated with hundreds of antennas, both detection and channel estimation lead to high-dimensional search-problems, which can be addressed by these models to estimate or predict radio parameters that are associated with specific users [9]. Forecasting the trend of user equipment (UE) mobility or the traffic volume of different services is another possible application.

2) Unsupervised Learning.

Different from the aforementioned supervised learning, the input information for unsupervised learning does not contain priori labels. Therefore, the unsupervised learning algorithm has to rely on its own capability to find the embedded structure or pattern from its input, like grouping or clustering of data points. The typical unsupervised learning algorithms include K-means clustering, principal component analysis (PCA), independent component analysis (ICA), one-class SVM, etc. The K-means clustering was studied in [10] to partition the mesh access points (MAPs) into several groups in a hybrid optical/wireless network scenario, in order to optimize both the gateway partitioning and the virtual-channel allocation. K-means clustering can also be used to detect network anomaly. PCA and ICA are two common algorithms used for signal processing and feature dimension reduction. They can be developed for the physical layer signal dimension reduction of massive MIMO systems to reduce the computational complexity or in the area of anomaly-detection, and fault-detection problems of wireless networks with multi-performance data monitoring.

3) Reinforcement Learning.

Inspired by both control theory and behaviorist psychology, reinforcement learning is an area of machine learning regarded with how software agents ought to take actions in an environment so as to maximize some notion of cumulative reward. Many reinforcement learning algorithms use dynamic program-

ming techniques and do not assume explicit knowledge of whether they have come close to its goal. They are used when exact models are infeasible. Due to its generality, the field is studied in many other disciplines, such as control theory, operations research, information theory, multi-agent systems, and swarm intelligence. There are several typical reinforcement learning algorithms, for example, Markov decision processes (MDP), partially observable Markov decision process (POMDP), Q-learning, and multi-armed bandit (MAB). In conjunction with MDP models, Q-learning has been extensively applied in heterogeneous networks. As in [11], the authors presented a heterogeneous fully distributed multi-objective strategy for the self-configuration/optimization of femto cells. The reinforcement learning methods can also be applied in problems like spectrum sharing for device-to-device networks and energy modeling in energy harvesting.

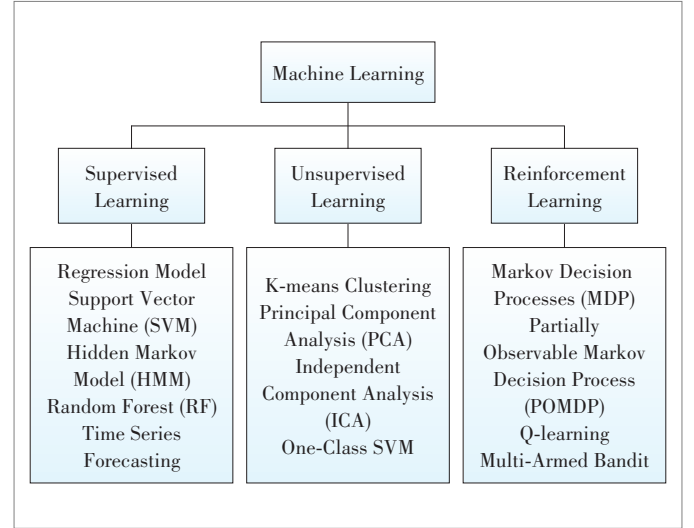
The three categories of machine learning algorithms and the typical methods in each category are summarized in Fig. 1.

2.2 Intelligent Operation System Design

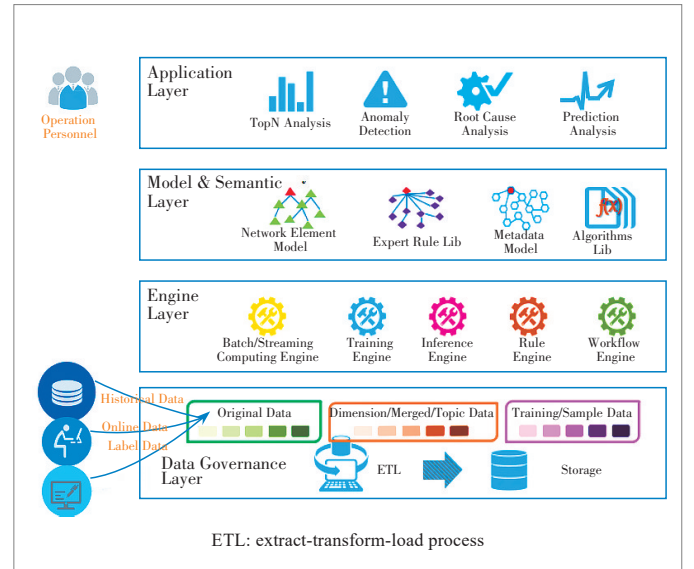
Although ML can be applied in a number of aspects in SON, this paper focuses on the application of ML technology in the intelligent operation and maintenance (O&M) of wireless networks. Fig. 2 demonstrates a possible implementation for the framework of intelligent operation system. The system is designed in such a layered manner as to maximize the flexibility, scalability, and manageability. The system consists of four layers: the data governance layer, engine layer, model & semantic layer, and application layer. Detailed description of each layer is demonstrated as follows.

1) Data Governance Layer.

The original data are collected, screened and transformed in this layer. Data is the fundamental ingredient for successful implementation of ML. In the wireless network system, diverse kinds of and large amount of data are produced from individual modules, which contain valued information for network maintenance. Examples of data include KPI data, key quality indicator (KQI) data, alarm data, configuration data, log data, etc. The data could be collected in three ways. Historical data are collected from a wide range in the history, mainly used for model training. Online data are collected automatically in real-time, which are used for online application of the trained model, such as anomaly detection of KPIs. Label data are collected by labeling tools and used to train supervised machine learning algorithms or improve the algorithm performance. For example, the operation expert can label each data point of a KPI whether anomalous. Then, these label data can be used to train an anomaly detection model. The collected original data are managed with an extract-transform-load (ETL) process, producing the dimensional data, merged data, topic data or training data. Dimensional data are produced from original data according to different perspectives, for example, KPIs could be classified into accessibility indicators, retainability indicators,



▲ Figure 1. Three categories of machine learning algorithms and typical methods in each category.



▲ Figure 2. A general overview of intelligent operation system.

mobility indicators, etc. The original data could be merged spatially or temporally, for example, the cell-level KPIs are merged into sub-network level. Original data could be organized into topic data according to application scenario, for example, traffic flow data are used to network traffic monitoring. Training data are the final processed data that are able to calibrate the ML algorithms.

2) Engine Layer.

The engine layer provides a number of common engine modules for the upper application layer. The batch computing engine processes the off-line and high volumes of data, and the data often spread a wide period of time. A famous technology used for batch computing is the Hadoop Map/Reduce. The streaming computing engine is suitable for processing data in

real-time, usually used for the computing of online ML models after they have been trained off-line. The training engine supplies a framework with training ML models. It defines several standard steps to train a ML model, such as data normalization, feature extraction, feature selection, model training, and post-processing. The rule engine and inference engine can be used to build expert systems, which are essentially composed of two sub-systems: the knowledge base and the inference engine. Both forward chaining and backward chaining reasoning modes are available in such an engine. The workflow engine provides tools for managing the processes of developing a ML application. It facilitates the organization of such modules as the data reading module, data preprocess module, training module, and online testing module. The engine layer can include other engine types, which are not showed here.

3) Model & Semantic Layer.

The model & semantic layer provides several abstract models and basic libraries to fulfill an end ML application. The network element (NE) model defines several explicit mathematical models of individual wireless network modules, for example, the communication model in physical layer, the device parameters of some physical components, the exact relationship between some KPIs, and the network topology of different elements. The metadata model is adopted to define some general concepts when a set of objects share the same attributes, operations, relations, and semantics. For example, a time series metadata model is formulated to represent all those data (KPIs/KQIs) of time series nature. The metadata model should define several common attributes: sampling frequency, time-range, period, sampling value, time-stamps, and etc. The expert rule library collects a number of rules defined by O&M experts. These rules can be used as input to ML algorithms or to improve the performance of the algorithm. For example, the experts can define the correlation of some alarms, for instance, one KPI is the root cause of another KPI. The algorithm library collects plenty of ML algorithm modules used for developing ML applications. As mentioned above, the ML algorithms include SVM, HMM, RF, ICA, PCA, K-means clustering, and so on.

4) Application Layer.

The application layer includes a number ML applications developed for facilitating the intelligent O&M of wireless network. These applications are produced by utilizing the components from the lower layers. They are usually developed case by case, to solve practical O&M problems and should be easily used by operation personnel. TopN analysis application would automatically show the top-n cells whose QoS are poor, such as with a high drop call rate, low connection rate, and low paging success rate. The TopN analysis is one of the most common functions for network maintenance. Its automation can significantly reduce the load of an O&M engineer. The anomaly detection application is used for automating the process of fault detecting in the network. For example, whether abnormal in

each point of a KPI can be detected depends on dynamic threshold technology. Comparing with the static threshold configured by manner, a ML-directed dynamic threshold has the potential to improve detection accuracy and efficiency. Root cause analysis could be used for automatic association or correlation analysis between different events and detect the root cause, like an alarm or a detected KPI anomaly. The root cause analysis is critical for fault diagnosis and fault recovery. Prediction analysis is useful for QoS/QoE or other variable prediction according to historical and current state of the network. It is a critical step toward proactive operation of the system with possible applications like fault prediction, load balance, and capacity plan, consequently reducing the fault rate and increasing the resource utilization. It is worth noting that here only a few examples are enumerated and many other applications would be developed according to different requirements.

3 Use Cases

The aforementioned framework illustrates a unified solution for implementing an O&M operation system. In this section, two use cases will be described in detail, demonstrating the ML algorithms developed for anomaly detection and anomaly diagnosis with KPIs. They are the example functions of the anomaly detection application and root cause analysis application in Fig. 2.

3.1 Anomaly Detection with KPIs

The KPI anomaly detection is quite important for network maintenance. Due to the complexity of a 5G network that contains numerous radio nodes and other components, there are a huge amount of KPI data to be monitored, which may be time consuming, error-prone and even impossible. An ML-based anomaly detection method is proposed in this paper, as shown in Fig. 3. It is essentially composed of three modules: anomaly detection, anomaly scoring, and feedback modules. The anomaly detection model and scoring model are trained with off-line data, using the batch computing engine and training engine in Fig. 2. Then, the KPIs data are detected online based on the streaming computing engine. The KPI data point whose anomaly score is higher than a predefined threshold will be noticed to the O&M engineer and the engineer can label it whether abnormal, providing feedback to the training module to improve the algorithm performance.

The KPIs represent varied characteristics because of the diverse characteristics of network modules. For example, some KPIs show periodicity while others do not; some KPIs have trend, while the other KPIs are stable. A two-stage modeling method is proposed in this paper to deal with the huge challenge for comprehensive modeling of all kinds of KPIs. As shown in Fig. 4, the first stage is the classification stage, where a time series clustering algorithm is formulated to classify the KPIs based on their structure characteristics. In the second

stage, the module selects an appropriate time series model for each KPI category, predicting the normal baseline at each time point for a KPI. A value would be denoted as anomaly if it exceeds the baseline of the online detection.

The time series clustering method based on structural features has been introduced in [12], which proposed a hierarchical scheme to reduce the complexity of clustering. Firstly, the time series are classified into two main categories: the significant periodicity and non-significant periodicity, based on Fourier transformation. Secondly, the k-means algorithm is used to cluster the time series in each main category base on seven features extracted from the KPI series. In the first stage, the frequency amplitude spectrum of a KPI is calculated by discrete Fourier transformation (DFT) as follows:

$$|F[k]| = \left| \sum_{n=0}^{N-1} x(n) e^{-j \frac{2\pi}{N} kn} \right|, 0 \leq k \leq N-1. \quad (1)$$

We denote the maximum, mean and standard deviation of the amplitude spectrum as $|F|_{\max}$, $|F|_{\text{mean}}$, and $|F|_{\text{std}}$. If satisfying $|F|_{\max} > |F|_{\text{mean}} + c \cdot |F|_{\text{std}}$, where c is a predefined coefficient larger than 3, the KPI would be classified as significant periodicity, otherwise non-significant periodicity. Please refer to [12] for the more detailed descriptions of the clustering process.

When a KPI is classified, a suitable time series model will be selected according to its characteristic. There are a number of candidate models available, such as density estimation, Olympic model, regression model, Holt-Winters model, and auto-regressive integrated moving average (ARIMA) [13]. For example, if a KPI contains trend and periodicity, the Holt-Win-

ters model is able to model it as following:

$$\begin{aligned} l_t &= \alpha^* (x_t - s_{t-m}) + (1 - \alpha^*) (l_{t-1} + b_{t-1}) \\ b_t &= \beta^* (l_t - l_{t-1}) + (1 - \beta^*) b_{t-1} \\ s_t &= \gamma^* (x_t - l_{t-1} - b_{t-1}) + (1 - \gamma^*) s_{t-m} \end{aligned}, \quad (2)$$

where l_t , b_t , and s_t are the level component, trend component and seasonal component respectively, and m is the period of time series. The forecasting value at h step would be:

$$\hat{x}_{t+h} = l_t + h b_t + s_{t-m+h_m^*}, \quad (3)$$

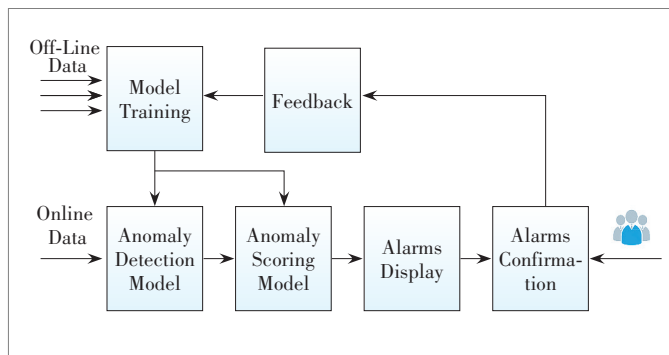
where $h_m^* = \lfloor (h-1) \bmod m \rfloor + 1$. When the prediction value and fitting errors in historical data are calculated, the normal baseline could be formulated as:

$$\begin{aligned} \hat{x}_{t+h}^L &= \hat{x}_{t+h} - z_{1-\alpha/2} \sigma_H \\ \hat{x}_{t+h}^U &= \hat{x}_{t+h} + z_{1-\alpha/2} \sigma_H \end{aligned}, \quad (4)$$

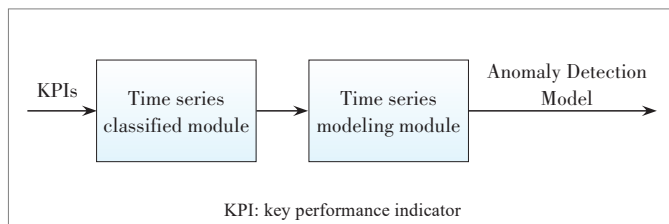
where $z_{1-\alpha/2}$ is the $1 - \alpha/2$ percentile of standard Gaussian distribution and σ_H is the standard deviation of fitting errors in historical data. A common used value for α is 0.003. Fig. 5 is an illustration of the computed thresholds for a KPI.

The other types of KPI can be modeled by other time series models. For example, the data with significant randomness could be modeled by density estimation, rather than the Holt-Winter model.

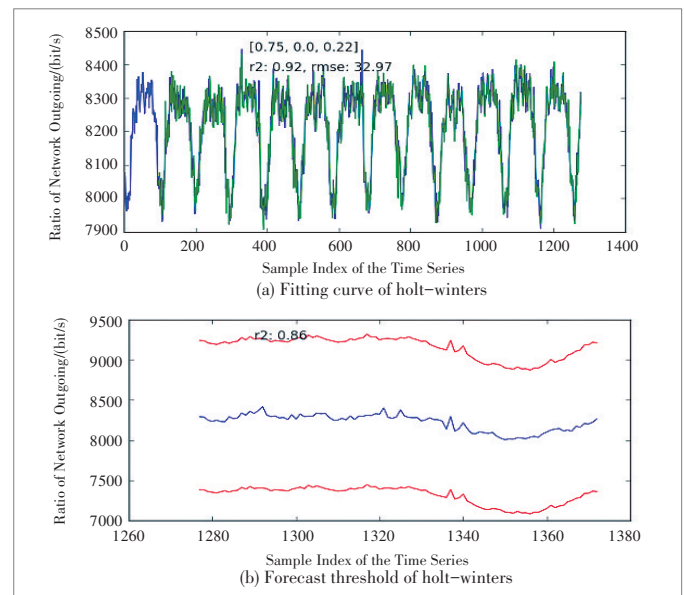
The anomaly scoring model is critical for reducing the false alarm and can facilitate the O&M engineer to focus on important events. The detailed algorithm would not be demonstrated



▲ Figure 3. An illustration of machine learning (ML)-based anomaly detection method.



▲ Figure 4. A demonstration of two-stage time series modeling method.



▲ Figure 5. An illustration of time series modeling by Holt-Winters: (a) represents the true value (blue curve) and fitting value (green curve) in historical data; (b) represents the true value (blue curve) and the predicted thresholds (red curve) in the following day.

in the paper for the sake of space limit is a planning research topic in the future.

3.2 Anomaly Diagnosis with KPIs

When a KPI anomaly is detected, it is quite worthy to define the root causes for rapid fault recover. **Fig. 6** depicts the anomaly diagnosis method developed in this paper, which combines a rule-based diagnosis module and a ML-based diagnosis module to handle a wide range of scenarios.

As shown in **Fig. 6**, when the detected anomaly is a known fault that can be explicitly diagnosed by predefined expert rules, the rule-based diagnosis module could define the root causes according to related information, such as the NE model in **Fig. 2**, which contains the network topology, the exact mathematical function between the KPI and related counter indicators (counter indicators are more basic performance data, comparing to KPIs), and expert rule library. The rule-based module can generally output exact rule causes and provide direct execution suggestion for recovering.

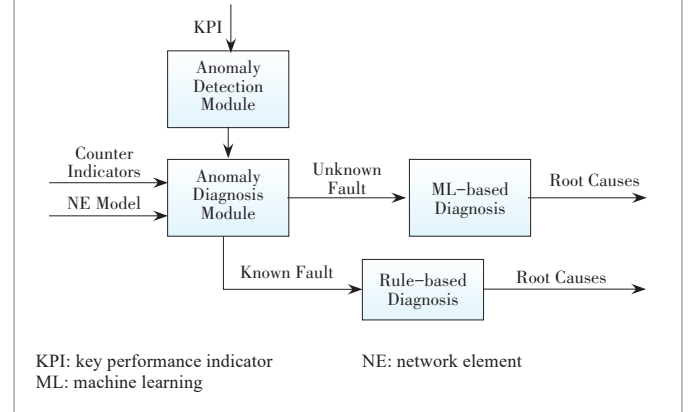
When the detected anomaly is an unknown fault, the ML-based diagnosis module would define the root causes by using the partial least squares regression (PLS) algorithm as proposed in this paper. The PLS has been used in multivariate monitoring of processing operating performance, which is almost in the same way as PCA-based monitoring [14]. Instead of only finding hyper-planes of maximum variance for independent variables, PLS finds a linear regression model by projecting the response variables and the independent variables to a new space. Compared to standard linear regression, PLS regression is particularly suitable when the dimension of response variables is more than independent variables and when there is multi-collinearity among independent variables. As illustrated in **Fig. 7**, when an abnormal KPI is detected, PLS models the KPI as a response variable and the correlated counter indicators as independent variables. Following the PLS modeling, the contribution analysis is conducted to find the top root counter indicators.

Denoting the data matrix of correlate counter indicators as X and the matrix of a KPI as Y , the PLS model between X and Y can be formulated as:

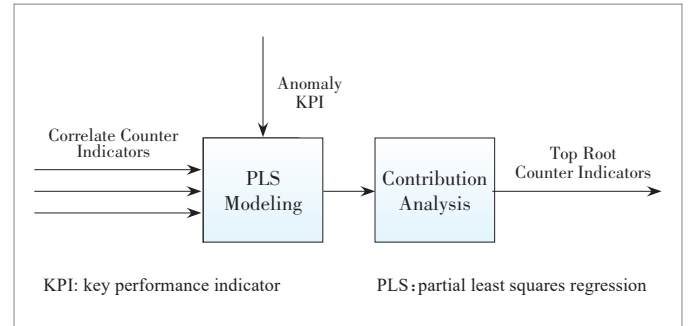
$$\begin{aligned} X &= TP^T + E \\ Y &= UQ^T + F, \end{aligned} \quad (5)$$

where T and U are projections of X (the X score, component or factor matrix) and projections of Y (the Y scores), respectively; P and Q are orthogonal loading matrices; and matrices E and F are the error terms. As the PLS model has only one response KPI, the PLS1 algorithm can be used for estimating the T , U , P and Q . And then, a T^2 statistic is used to represent the model status at each observation \mathbf{x} as in [14]:

$$T^2 = \|\Gamma \mathbf{x}\|^2, \quad (6)$$



▲ **Figure 6.** A mixed scheme that combines the rule-based and ML-based diagnosis modules for KPI anomaly diagnosis.



▲ **Figure 7.** Root cause analysis with PLS model when a KPI is abnormal.

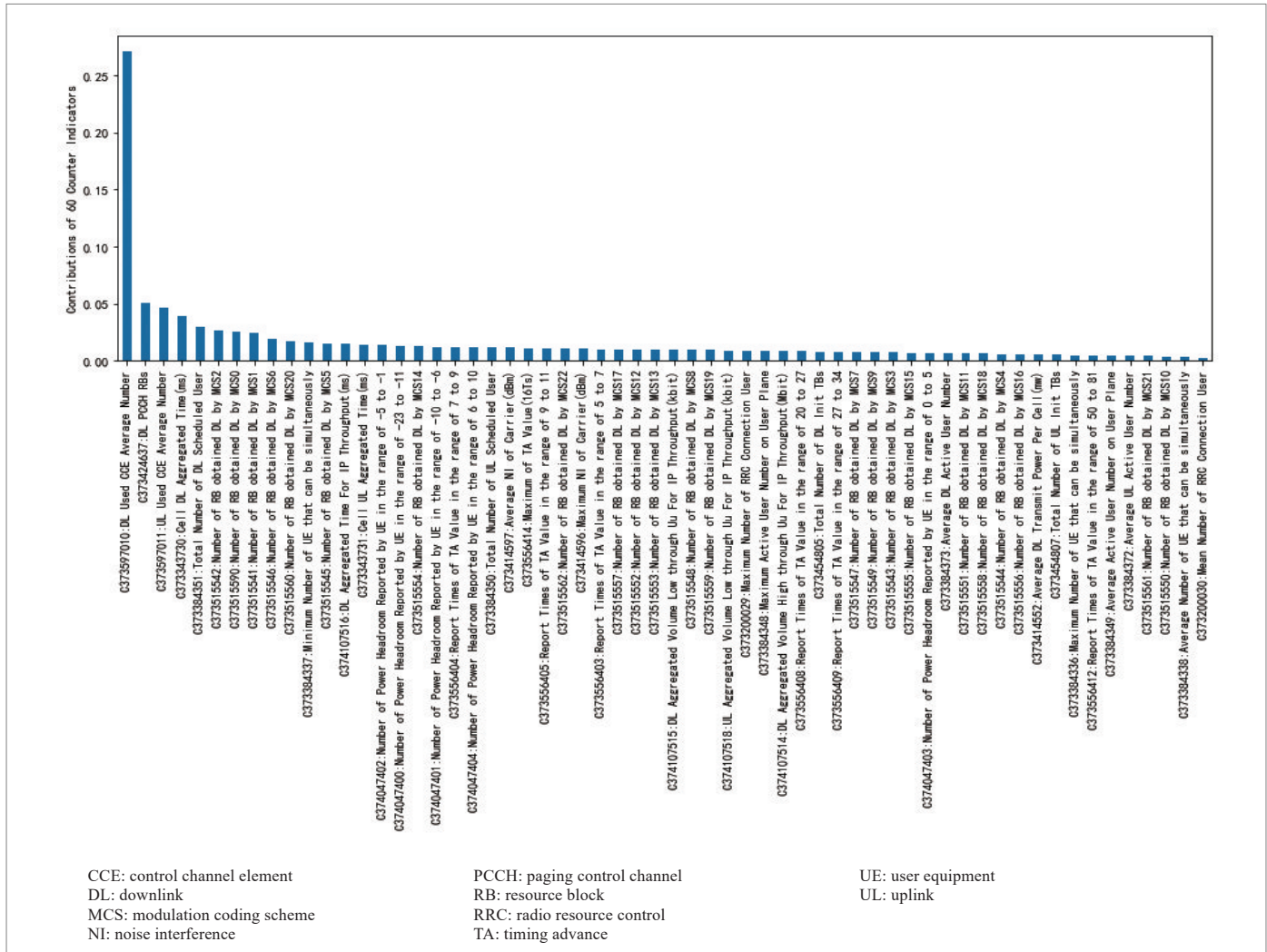
where $\Gamma = (R\Lambda^{-1}R^T)^{1/2}$, $\Lambda = \frac{1}{n-1}T^TT$ and R is the rotation matrix for X . The contribution of the i -th independent variable, i. e. counter indicator, to the T^2 statistic is calculated as:

$$C(T^2, i) = \|\gamma_i \mathbf{x}^2\|, \quad (7)$$

where γ_i is the i -th row of Γ . The total contribution of the i -th counter indicator to the variation of the KPI can be calculated as the sum of $C(T^2, i)$ from n observations. The contributions of all counter indicators are sorted, and the top- n counter indicators are output as the root causes of the anomaly KPI. **Fig. 8** shows an experimental example, illustrating the contributions of 60 counter indicators to an anomaly KPI, downlink (DL) IP Throughput. The O&M expert confirms that the top counter indicator, C373597010:DL Used Control Channel Element (CCE) Average Number, is useful for the anomaly diagnosis, demonstrating the effectiveness of the proposed algorithm.

4 Conclusions

The research of intelligent O&M has attracted extensive in-



▲ Figure 8. An experimental example of partial least squares regression (PLS) method for root cause analysis.

terest for IT system in recent years, which is known as AIOps [15]. However, this topic is relatively less discussed in wireless networks. As the evolution of wireless networks and the emerging of 5G, the networks become more complicated, emphasizing the disadvantage of manual operation and the desire to automate O&M process with intelligent analysis to handle such a challenge. In this paper, we try to formulate an intelligent operation system based on the layering concept, resulting in a flexible, scaling and manageable framework. And then, two practical use cases, the anomaly detection with KPIs data and the anomaly diagnosis of KPIs data, are studied based on the framework. A two-stage time series modeling method is proposed to construct the anomaly detection model, and a mixed scheme is proposed to the anomaly diagnosis. The real data experiments demonstrate the effectiveness of the proposed method, thus encouraging the further research for intelligent operation with ML technology. In the future, we would develop more use cases to resolve other operation issues in wireless net-

work, for example the top-n cells analysis, the automated log analysis, the prediction analysis, and the optimal parameters configuration.

References

- [1] MITRA R N, AGRAWAL D P. 5G Mobile Technology: A Survey [J]. *ICT Express*, 2015, 1(3): 132 – 137. DOI: 10.1016/j.ict.2016.01.003
- [2] C-LI, HAN S, XU Z, et al. New Paradigm of 5G Wireless Internet [J]. *IEEE Journal on Selected Areas in Communications*, 2016, 34(3): 474 – 482. DOI: 10.1109/JSAC.2016.2525739
- [3] PARK T, ABUZAINAB N, SAAD W. Learning How to Communicate in the Internet of Things: Finite Resources and Heterogeneity [J]. *IEEE Access*, 2016, 4: 7063 – 7073. DOI: 10.1109/ACCESS.2016.2615643
- [4] SOLDANI D, MANZALINI A. Horizon 2020 and Beyond: On the 5G Operating System for a True Digital Society [J]. *IEEE Vehicular Technology Magazine*, 2015, 10(1): 32 – 42. DOI: 10.1109/MVT.2014.2380581
- [5] IMRAN A, ZOHA A, ABU-DAYYA A. Challenges in 5G: How to Empower SON

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- with Big Data for Enabling 5G [J]. IEEE Network, 2014, 28(6): 27 – 33. DOI: 10.1109/MNET.2014.6963801
- [6] KIBRIA M G, NGUYEN K, VILLARDI G P, et al. Big Data Analytics, Machine Learning, and Artificial Intelligence in Next-Generation Wireless Networks [J]. IEEE Access, 2018, 6: 32328 – 32338. DOI: 10.1109/ACCESS.2018.2837692
- [7] LONG F, LI N, WANG Y X. Autonomic Mobile Networks: the Use of Artificial Intelligence in Wireless Communications [C]//2nd International Conference on Advanced Robotics and Mechatronics (ICARM). New York, USA: IEEE, 2017: 582 – 586. DOI: 10.1109/ICARM.2017.8273227
- [8] JIANG C X, ZHANG H J, REN Y, et al. Machine Learning Paradigms for Next-Generation Wireless Networks [J]. IEEE Wireless Communications, 2016, 24(2): 98 – 105. DOI: 10.1109/MWC.2016.1500356WC
- [9] FENG V - S, CHANG S Y. Determination of Wireless Networks Parameters Through Parallel Hierarchical Support Vector Machines [J]. IEEE Transactions on Parallel and Distributed Systems, 2011, 23(3): 505 – 512. DOI: 10.1109/TPDS.2011.156
- [10] XIA M, OWADA Y, INOUE M, et al. Optical and Wireless Hybrid Access Networks: Design and Optimization [J]. Journal of Optical Communications and Networking, 2012, 4(10): 749 – 759. DOI: 10.1364/JOCN.4.000749
- [11] ALNWAIMI G, VAHID S, MOESSNER K. Dynamic Heterogeneous Learning Games for Opportunistic Access in LTE-Based Macro/Femtocell Deployments [J]. IEEE Transactions on Wireless Communications, 2014, 14(4): 2294 – 2308. DOI: 10.1109/TWC.2014.2384510
- [12] MENG Z H, LIU J W, HAN J. Time Series Clustering Based on Structural Features [J]. ZTE Technology Journal, 2018, 24(03): 61 – 66. DOI: 10.3969/j.issn.1009-6868.2018.03.011
- [13] LAPTEV N, AMIZADEH S, FLINT I. Generic and Scalable Framework for Automated Time-Series Anomaly Detection [C]//Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. New York, USA: ACM, 2015: 1939 – 1947. DOI: 10.1145/2783258.2788611
- [14] LI G, QIN S-Z, JI Y-D, et al. Total PLS Based Contribution Plots for Fault Diagnosis [J]. Acta Automatica Sinica, 2009, 35(6): 759 – 765. DOI: 10.1016/S1874-1029(08)60094-4
- [15] DANG Y N, LIN Q W, HUANG P. AIOps: Real-World Challenges and Research Innovations [C]//Proceedings of the 41st International Conference on Software Engineering: Companion Proceedings. New York, USA: IEEE Press, 2019: 4 – 5. DOI: 10.1109/ICSE-Companion.2019.00023



Machine Learning for Network Slicing Resource Management: A Comprehensive Survey

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Abstract: The emerging technology of multi-tenancy network slicing is considered as an essential feature of 5G cellular networks. It provides network slices as a new type of public cloud services and therewith increases the service flexibility and enhances the network resource efficiency. Meanwhile, it raises new challenges of network resource management. A number of various methods have been proposed over the recent past years, in which machine learning and artificial intelligence techniques are widely deployed. In this article, we provide a survey to existing approaches of network slicing resource management, with a highlight on the roles played by machine learning in them.

Keywords: 5G; machine learning; multi-tenancy; network slicing; resource management

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1 Introduction

As an emerging technology, network slicing is believed to be a key enabler and essential feature of the fifth generation (5G) cellular networks. Proposed by the Next Generation Mobile Networks (NGMN) Alliance as an end-to-end (E2E) concept, network slicing is involved across the radio access network (RAN) and the core network (CN). It refers to operating and maintaining multiple logically independent virtual telecommunication networks on the top of a shared physical infrastructure, in order to provide enhanced heterogeneity, flexibility, scalability, profitability and security of future network services. This requires both the network resources and network functions to be highly countable, divisible and isolatable, which can be realized by the modern network function virtualization technologies.

Since its first proposal, network slicing has triggered extensive research interest in various topics in the broad scope of wireless networking. This includes network architecture design, E2E slice orchestration and management, slice blueprint design, slice lifecycle management, RAN virtualization, network resource management, slice isolation, mobility management, and cyber-security in network slicing.

In this article, we focus on the problems of resource management in network slicing, attempting to address the most significant challenges in this area and provide a timely and comprehensive survey to the state of the art. Especially, we will show how machine learning and artificial intelligence are applied to assist the resource management in sliced wireless networks.

2 Network Slicing and Multi-Tenancy Networks

2.1 Sliced 5G Network: Heterogeneous Services and Heterogeneous Requirements

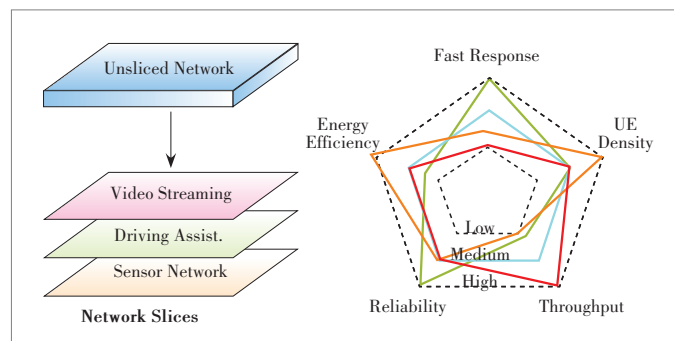
The concept of network slicing refers to creating and maintaining multiple independent logical networks, i. e. “network slices”, on the top of a shared physical network infrastructure. Every instance of the network slice, according to the definition of NGMN [1], is defined by a set of network functions and the resources to run them. These network functions and resources form a complete instantiated logical network, to meet certain network characteristics required by the service instance(s), which is realized within or by the network slice. Different network slice instances can be, fully or partially, physically or log-

ically, isolated from each other in the perspectives of control, traffic, resources, etc. Furthermore, each slice instance can be individually tailored to fulfill the requirements by its service instance(s).

The feature of individual slice specification in network slicing plays a critical role in future 5G networks, due to the high heterogeneity of different 5G service types, i. e. enhanced mobile broadband (eMBB), massive machine type communications (mMTC), and ultra-reliable and low-latency communications (URLLC) [2]. These services generally have different requirements for technical performance, each being extreme in a different aspect, e. g., throughput, access capacity, and latency, as shown in Fig. 1. This implies highly heterogeneous specifications of resources and network functions for different types of slices. Indeed, even for a certain type of 5G service, the resource requirement can also vary from one service instance to another. Aiming at fulfilling the requirements of heterogeneous service instances simultaneously, the classical one-size-fits-all architecture that has been deployed in legacy Long Term Evolution/Long Term Evolution-Advanced (LTE/LTE-A) networks exposes significant lacks of flexibility and scalability, which can lead to low resource efficiency and therewith an unaffordable resource cost. Network slicing, in this context, has become an essential enabler of 5G networks.

2.2 Slice-as-a-Service: a New Public Cloud Environment

In addition to the enhancement of resource efficiency, network slicing also makes it possible to decouple the provisions of wireless network infrastructure and network services. Instead of running and maintaining the network services by themselves, mobile network operators (MNOs) can lease network slices to multiple network slice tenants upon their requests. The tenants are therewith able to create network services and deliver them to the end customers without possessing their own network infrastructure, as illustrated in Fig. 2. The quality of service (QoS) of a leased slice is guaranteed by a service level agreement (SLA) between the MNO and the tenant, which defines the cost rate, the required minimal performances, and the penalty in case of SLA violation. This multi-tenancy network architecture introduces a new business mode that the network slices are provided as an emerging public cloud service, which



▲ Figure 1. Network slicing enables heterogeneous and highly specialized services on top of a shared network infrastructure.

is known as “slice-as-a-service” (SlaaS) [3].

Despite of the similarity in many aspects to classical public cloud environments such as software-as-a-service (SaaS), platform-as-a-service (PaaS) and infrastructure-as-a-service (IaaS), SlaaS is distinguished from them in the complexity of resource management due to the heterogeneity of network slices, while the service instances in classical cloud environments are generally homogeneous. This challenges the efficient deployment of SlaaS and has triggered dense interest of research in recent years.

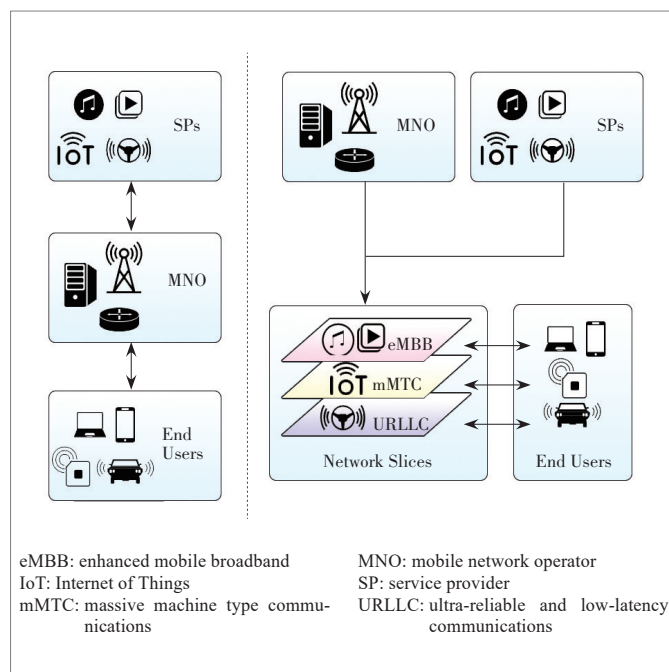
3 Resource Management in Network Slicing

3.1 Classification of Approaches

In an architectural perspective, efforts that have been made towards efficient resource management in sliced networks can be generally classified into two categories: the slice admission control and the cross-slice resource allocation (Table 1).

The former one consists of methods focusing on the issue that the limited resource pool of a MNO may be overloaded by an overwhelming amount of tenant requests for slices, whereby the MNO has to select some requests for acceptance while declining the others. It has been demonstrated that the policy of such selection, a. k. a. the slice admission strategy, has a dominant impact on the overall resource efficiency and utilization rate of sliced networks. Advanced methods are therefore proposed to find the best strategy, in order to optimize the long-term overall network performance statistically.

Approaches in the latter class, in contrast, concentrate on the active slices that have already been created and leased to tenants. The real-time traffic load of every individual slice is



▲ Figure 2. Traditional unsliced networks (left) and multi-tenancy sliced networks (right).

▼Table 1. A summary of existing works on resource management in network slicing

Reference	Slice Admission Control	Cross-Slice Resource Allocation	Policy-based	Auction-based	Note
[4]	N	Y	Y	N	User admission control on every individual slice according to tenant-specific policies to allocate resources cross slices
[5]	N	Y	Y	Y	Policy-based user admission control and user dropping on every slice to guarantee QoS; auction-based intra-slice resource allocation among users; budget-based inter-slice resource allocation. Dynamic cross-slice resource allocation not considered
[6]	N	Y	Y	N	Grouping users according to behaviors and social relationships; bio-inspired methods to update the groups; policy-based cross-slice resource allocation according to group status
[7]	Y	N	Y	N	Uniformed slice size, binary slice admission control according to the active slice set, genetic algorithm to optimize the policy
[8]	N	Y	Y	N	Deep Q-learning assisted allocation policy optimization
[9]	Y	N	Y	N	A Markov model for policy-based slice admission control
[10]	N	Y	Y	N	Jointly optimizing the base station bandwidth and the backhaul capacity as a bi-convex problem
[11]	N	Y	N	Y	Non-cooperative auction among slices for network resources, implemented with OpenFlow
[12]	Y	N	Y	N	Q-learning assisted slice admission control policy optimization
[13]	N	Y	Y	Y	A preliminary conference version of [5]
[14]	N	Y	N	Y	A two-level slicing mechanism with 1) a price competition among network chunks to determine resource prices and 2) an auction mechanism to allocate resources among slices
[15]	N	Y	N	Y	Optimizing the resource price function to maximize the total profit of slices / the net social welfare of network
[16]	N	Y	Y	N	Empirical investigation on the diversity gain in SlaaS
[17]	N	Y	Y	N	Sharing RAN resources among users according to both base station assignment and slice assignment. User admission control on every slice to shape traffic and guarantee the QoS
[18]	N	Y	Y	N	Splitting the policy optimization problem into two sub-problems, one from the MNO's perspective to maximize the revenue and the other on (every) tenant's side to minimize the cost. A distributed optimization is therefore achieved through a game-fashion iteration of price updating. Both resource constraints and service fairness are taken account of
[19]	N	Y	Y	N	Optimizing the RAN resource allocation policy taking into account of the resource-partitioning problem
[20]	Y	Y	Y	N	A two-layer framework merging slice admission control and cross-slice resource allocation
[21]	N	Y	Y	N	Allocating users to subcarriers across different MVNOs to maximize the overall network profit, assuming the cost proportional to both power and bandwidth
[22]	Y	N	Y	N	Multiple queues for different slice types, taking into account impatient behavior of tenants
[23]	N	Y	Y	N	Dynamic resource allocation based on deep neural network assisted traffic prediction. Data-driven black-box optimization
[24]	Y	Y	Y	N	Optimizing RAN resource allocation among slices and non-sliced network, where admissions to slice requests are controlled w.r.t. the demanded resource efficiency
[25]	Y	N	Y	N	Modeling MNO's revenue under policy-based slice admission control, analyzing the construction of optimal policy
[26]	Y	N	Y	N	Studying the rational behavior of impatient tenants in policy-based slice admission control with multiple queues

MNO: mobile network operator
MVNO: mobile virtual network operator

QoS: quality of service
RAN: radio access network

SlaaS: slice-as-a-service

universally time varying, exhibiting stochastic dynamics. This phenomenon, known as the slice elasticity, enables the MNO to overbook slices to tenants for a diversity gain that improves the resource efficiency and overall revenue. To realize slice overbooking and jointly maximize the short-term performance of all active slices, it calls for methods that efficiently share network resources among slices in a real-time and dynamic fashion.

On the other hand, in perspective of the decision making mechanism, for both the admission control and cross-slice resource allocation, there are two types of approaches available: 1) policy-based decision and 2) auction-based decision (Table 1).

In policy-based approaches, the MNO provides a standard list of prices for slices (in case of admission control) or resources (in case of cross-slice resource allocation), which is consistent for all tenants, and the decision of admission/allocation

is made according to the MNO's resource management policy under the current system state. In case of admission control, the system state information usually consists of the amount of idle resources, the set of current active slices, and the queuing status of awaiting requests. In case of cross-slice resource admission, on the other hand, such information usually refers to the resource pool size, and the set of current active slices along with their instantaneous resource demands and utility rates.

In auction-based approaches, the MNO does not provide universal prices, but only a list of available slices/resources. Instead, the tenants shall propose their own bids for their requested slices/resources. These bids are periodically collected and evaluated by the MNO, and the winner(s) of the auction will be granted the requested slice/resources. To guarantee a minimal revenue of operating the network infrastructure, lowest bids are

universally required by the auction-based approaches.

3.2 Key Challenges

A main and generic challenge for policy-based methods for network slicing resource management is the high computational complexity. On one hand, for both admission control and cross-slice resource allocation, the utility function is generally non-convex with regard to the MNO's policy, eliminating any analytical solution of the global optimum. On the other hand, numerical solvers are also challenged by the complexity of the problem. Policy-based admission control problems, no matter with or without queuing mechanism, are binary programming problems where the MNO's decision is always either "0" for decline or "1" for admission. The policy-based cross-slice resource allocation problems, in comparison, are integer programming problems, where the amount of resource allocated to an arbitrary slice is always integer times of some atomic resource block. Both the problems are known to be NP-hard, leading to an unaffordable computational effort to optimize the policy through exhaustive search.

In comparison to policy-based methods, auction-based approaches are proven effective to reduce the computational complexity significantly. However, it generally requires a careful design of the auction mechanism and strict regulations, in order to mitigate drawbacks and risks that intrinsically root in the procedure of auction itself, such as multi-round auction overhead, biased bidding, and cheating [27], [28].

Additionally, although slice overbooking and cross-slice resource allocation allow the MNO to benefit from the load-driven elasticity of network slices, they also lead to risk of overloading the shared resource pool when traffic peaks simultaneously occur across multiple slices. In this case, the MNO becomes incapable to deliver guaranteed QoS to all active slices and therefore have to violate some SLAs, which implies paying penalty to the involved tenants. Such a risk must be taken into account as part of the opportunity cost of maintaining slices. In an extreme case, the opportunity cost of accepting a request for new network slice instance may overwhelm the revenue generated by the corresponding slice, and therefore the greedy strategy fails in admission control.

On the other hand, being too conservative in admission control also leads to the MNO's loss, due to a two-fold reason. First, it naturally implies a low resource utilization rate and low revenue. Second, since the tenants' need for slices does not simply vanish, the declined requests will usually be either reissued later, or buffered in a queue for delayed admission. No matter which design is used, under a low admission rate, declined requests will stack to cause serious congestions, and therefore significantly raise the average delay between the issuing and the admission of a request. As we have indicated in [22], after being awaiting for too long time, tenants will eventually lose their patience and interest in the MNO's service. In a competitive SaaS market, such situation can probably lead to permanent loss of tenants.

Aiming at an optimal balance between the resource feasibility and the admission rate, the MNO must have a deep understanding in tenant behavior. This includes the characteristics of both active slices (e. g., load dynamics, lifetime distribution, etc.) and tenant requests (e. g., arriving rate, impatience, etc.). This not only calls for accurate models, but also further raises the computational complexity.

4 Machine Learning and Artificial Intelligence Methods

4.1 Reinforcement Learning

Since policy-based network slicing resource management procedures are typically Markov decision processes (MDPs) where a policy maps every specific system "state" to a corresponding "action" and therewith generates a "reward". In network slicing resource management problems, the reward function is generally non-convex over a huge policy space, as proven in [9]. Therefore, in this field people commonly choose to rely on Reinforcement Learning (RL), which is known for its high efficiency and convenient implementation in solving Markov decision problems.

A pioneering attempt of deploying RL to optimize the network slicing policy was given by [12], where the authors have demonstrated that their Q-Learning solver can efficiently approximate the optimal slice admission policy that maximizes the MNO's revenue and significantly outperform the benchmark of random policies. In comparison to the value iteration method that guarantees to achieve the optimum, the Q-Learning method is capable to be executed in an online learning fashion with a much more reasonable computation cost, with only a tradeoff of slight reduction in the revenue. Furthermore, RL algorithms can be designed model-free by appropriately selecting the reward functions, which makes them much more robust against imperfect estimations of the slicing statistics, as also demonstrated in [12].

The authors of [20] attempted to apply RL for cross-slice resource allocation, which they called cross-slice congestion control. Aiming at this, they have proposed a framework where the real-time slice elasticity is realized upon requests of every existing slice for the grant of more resource and the MNO makes policy-based decisions with regard to both the current resource availability and the slice priorities. In this way, the cross-slice resource allocation task is accomplished by an admission-control-like mechanism, where a Q-Learning method is proven to bring a significant gain in slice elasticity.

Cross-slice resource allocation was achieved in a more straightforward manner in [8], where the authors defined an "action" of the system as a specific allocation of radio resource to all existing slices instead of a binary decision like in slice admission. This design simplifies the system design, but leads to a significantly huger policy space and a high non-linearity of the reward function about the action. To cope with this issue,

the authors adopted deep neural networks, as we will introduce later in Section 4.2.

4.2 Artificial Neural Networks

As the most important part of modern artificial intelligence technologies, artificial neural networks (ANN) are known to be efficient in modeling non-linear systems. This can be used to enhance RL methods into deep reinforcement learning (DRL) methods, such the deep Q-Learning method reported in [8].

Another common application of ANN is the model estimation and prediction of complex non-linear processes. The authors of [23] have given a typical example of ANN-based prediction in the field of network slicing resource management. In this work, they stacked three layers of three-dimensional convolutional neural networks (3D-CNN) to compose an encoder, which is cascaded with a decoder implemented by multi-layer perceptrons (MLPs). This encoder-decoder structured cognitive network is proven capable to predict service capacity requirement in a data-driven fashion with high accuracy, which helps the slice orchestrator to make decisions in slice admission control and cross-slice resource allocation. In contrast, legacy methods are only able to predict the mean traffic.

4.3 Evolutionary Algorithms

There are various methods, which rely on statistical evolutions based on learning from the system feedbacks to random strategies. They are commonly referred to as evolutionary algorithms, which is an important category of machine learning techniques.

One example of evolutionary algorithms' application in cross-slice resource allocation is given by [6], where the social relationship between different users attached to multiple network slices are updated in a dynamic and evolutionary manner. Based on these social relationships, users are clustered into groups in such a way that all users in the same group have similar characteristics in service requirement. This process helps in degrading and simplifying the complex model of resource requirement in a large-size sliced network, and therefore supports to optimize the resource allocation strategy.

In context of slice admission control, on the other hand, we have shown in our previous work [7] the effectiveness of genetic algorithms (GAs). By encoding every slice admission policy into a chromosome, i. e. a binary sequence, and applying a classical GA on a population of randomly generated chromosomes, it will recursively generate new generations of chromosomes (policies) that statistically converge towards an optimum. Furthermore, by manually introducing (an arbitrary) benchmark policies into the first generation, this GA-based mechanism is guaranteed to outperform the benchmark. It also shows good robustness against dynamic environments.

4.4 Distributed Learning

While all the aforementioned cases generally invoke a cen-

tralized learning process, some efforts have been made to distribute the learning process over different participators in the network slicing process, i. e. the mobile network operator and different tenants/slices, in order to reduce the computational complexity.

A typical example is [11], where a RL process is executed simultaneously at every bidder (slice) to recursively update its bid for network resources. This so-called Exponential Reinforcement Learning (XL) algorithm is proven to converge to the unique Nash equilibrium of the auction game.

Similarly, the authors of [18] decomposed the cross-slice resource allocation problem into a revenue-maximizing problem of the MNO and a cost-minimizing problem of every slice. This sets up a game where a distributed evolutionary algorithm converges to the equilibrium.

Another instance is provided by [21], which invokes the famous Binary Particle Swarm Optimization (BIPSO) algorithm, which allows to jointly update the resource assignments to different users in a distributed cross-learning manner, i. e. in each iteration, the resource assignment to every specific user will be updated according to the resource assignments to other users in the last iteration. Such iterative update continues until the utility requirement is satisfied. The authors have shown that the BIPSO is computationally efficient in solving the policy-based cross-slice radio resource allocation optimization problem.

5 Future Challenges

Beyond the successes that have already been made, there are still many open issues and potentials for further successes of machine learning in the field of network slicing resource management, as we will name some of them below.

5.1 AI-Enhanced Optimization in More Complex Admission Control Scenario

As it has been pointed out, complex features of slices/tenants, such as elasticity [20] and impatience [22], will lead to challenges in modeling their behavior, even under ideal assumptions such as Poisson arrivals of traffic/service requests. In realistic scenarios, the request arrivals and slice/resource release are usually non-Markovian. This calls for a deeper understanding in the system behavior and better policy optimizers, which shall be provided by a better integration of artificial neural networks with RL methods, like the authors of [23] have done.

5.2 Cooperative Game with Distributed Learning

While existing applications of distributed learning in this field generally consider non-cooperative games where the Nash equilibriums are achieved, there is a great potential to adopt the concept of cooperative game, where tenants/slices can learn to make decisions in an organized and cooperative way, in order to maximize the global social welfare instead of their own interests. In this way, a Pareto optimum can be expected

instead of the Nash equilibrium.

6 Conclusions

In this survey, we have discussed the resource management problem in multi-tenancy network slicing, introduced different types of approaches in this field, and extensively reviewed the existing works. Especially, we have shown how the modern techniques of machine learning and artificial intelligence could be applied in this field, and have named some open issues for potential future work.

References

- [1] AllianceNGMN. Description of Network Slicing Concept [R]. 2016
- [2] ITU-R. Minimum Requirements Related to Technical Performance for IMT-2020 Radio Interface(s) [R]. Report ITU-R M.2410-0, 2017
- [3] SCIANCALEPORE V, CIRILLO F, COSTA - PEREZ X. Slice as a Service (SlaaS): Optimal IoT Slice Resources Orchestration [C]//2017 IEEE Global Communications Conference (GLOBECOM). Singapore, Singapore, 2017: 1 - 7. DOI: 10.1109/GLOCOM.2017.8254529
- [4] SALLENT O, PÉREZ-ROMERO J, FERRÚS R, et al. On Radio Access Network Slicing from a Radio Resource Management Perspective [J]. IEEE Wireless Communications, 2017, 24(5): 166 - 174. DOI: 10.1109/MWC.2017.1600220WC
- [5] CABALLERO P, BANCHS A, DE VECIANA G, et al. Network Slicing for Guaranteed Rate Services: Admission Control and Resource Allocation Games [J]. IEEE Transactions on Wireless Communications, 2018, 17(10): 6419 - 6432. DOI: 10.1109/TWC.2018.2859918
- [6] WU D, ZHANG Z, WU S, et al. Biologically Inspired Resource Allocation for Network Slices in 5G-Enabled Internet of Things [J]. IEEE Internet of Things Journal, 2018. DOI: 10.1109/JIOT.2018.2888543
- [7] HAN B, JI L, SCHOTTEN H D. Slice as an Evolutionary Service: Genetic Optimization for Inter-Slice Resource Management in 5G Networks [J]. IEEE Access, 2018, 6: 33137 - 33147. DOI: 10.1109/ACCESS.2018.2846543
- [8] LI R, ZHAO Z, SUN Q, et al. Deep Reinforcement Learning for Resource Management in Network Slicing [J]. IEEE Access, 2018, 6: 74429 - 74441. DOI: 10.1109/ACCESS.2018.2881964
- [9] HAN B, FENG D, SCHOTTEN H D. A Markov Model of Slice Admission Control [J]. IEEE Networking Letters, 2019, 1(1): 2 - 5. DOI: 10.1109/LNET.2018.2873978
- [10] VO P L, NGUYEN M N H, LE T A, et al. Slicing the Edge: Resource Allocation for RAN Network Slicing [J]. IEEE Wireless Communications Letters, 2018, 7(6): 970 - 973. DOI: 10.1109/LWC.2018.2842189
- [11] D'ORO S, GALLUCCIO L, MERTIKOPOULOS P, et al. Auction-Based Resource Allocation in OpenFlow Multi-Tenant Networks [J]. Computer Networks, 2017, 115: 29 - 41. DOI: 10.1016/j.comnet.2017.01.010
- [12] BEGA D, GRAMAGLIA M, BANCHS A, et al. Optimising 5G Infrastructure Markets: The Business of Network Slicing [C]//2017 IEEE Conference on Computer Communications (INFOCOM). Atlanta, USA, 2017: 1 - 9. DOI: 10.1109/INFOCOM.2017.8057045
- [13] CABALLERO P, BANCHS A, DE VECIANA G, et al. Network Slicing Games: Enabling Customization in Multi-Tenant Networks [C]//2017 IEEE Conference on Computer Communications (INFOCOM). Atlanta, USA: 1 - 9. DOI: 10.1109/INFOCOM.2017.8057046.
- [14] JIANG M, CONDOLUCI M, MAHMOODI T. Network Slicing in 5G: An Auction-Based Model [C]//2017 IEEE International Conference on Communications (ICC), Paris, France, 2017: 1 - 6. DOI: 10.1109/ICC.2017.7996490
- [15] WANG G, FENG G, Tan W, et al. Resource Allocation for Network Slices in 5G with Network Resource Pricing [C]//2017 IEEE Global Communications Conference (GLOBECOM). Singapore, Singapore, 2017: 1 - 6. DOI: 10.1109/GLOCOM.2017.8254074
- [16] MARQUEZ C, GRAMAGLIA M, FIORE M, et al. How Should I Slice My Network?: A Multi-Service Empirical Evaluation of Resource Sharing Efficiency [C]//24th Annual International Conference on Mobile Computing and Networking (MobiCom'18). New Delhi, India, 2018: 191 - 206. DOI: 10.1145/3241539.3241567
- [17] ZHENG J, CABALLERO P, DE VECIANA G, et al. Statistical Multiplexing and Traffic Shaping Games for Network Slicing [C]//15th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt). Paris, France, 2017: 1 - 8. DOI: 10.23919/WIOPT.2017.7959883
- [18] LECONTE M, PASCHOS G S, MERTIKOPOULOS P, et al. A Resource Allocation Framework for Network Slicing [C]//2018 IEEE Conference on Computer Communications (INFOCOM). Honolulu, USA, 2018: 2177 - 2185. DOI: 10.1109/INFOCOM.2018.8486303
- [19] CHANG C-Y, NIKAEIN N, SPYROPOULOS T. Radio Access Network Resource Slicing for Flexible Service Execution [C]//2018 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS). Honolulu, USA, 2018: 668 - 673. DOI: 10.1109/INFCOMW.2018.8407021
- [20] HAN B, DE DOMENICO A, DANDACHI G, et al. Admission and Congestion Control for 5G Network Slicing [C]//2018 IEEE Conference on Standards for Communications and Networking (CSCN). Paris, France, 2018: 1 - 6. DOI: 10.1109/CSCN.2018.8581773
- [21] OLADEJO S O, FALOWO O E. Profit-Aware Resource Allocation for 5G Sliced Networks [C]//2018 European Conference on Networks and Communications (EuCNC). Ljubljana, Slovenia, 2018: 43 - 47. DOI: 10.1109/Eu-CNC.2018.8442661
- [22] HAN B, SCIANCALEPORE V, FENG D, et al. A Utility-Driven Multi-Queue Admission Control Solution for Network Slicing [C]//2019 IEEE Conference on Computer Communications (INFOCOM). Paris, France, 2019: 56 - 63. DOI: 10.1109/INFOCOM.2019.8737517
- [23] BEGA D, GRAMAGLIA M, FIORE M, et al. DeepCog: Cognitive Network Management in Sliced 5G Networks with Deep Learning [C]//2019 IEEE Conference on Computer Communications (INFOCOM). Paris, France, 2019: 280 - 288. DOI: 10.1109/INFOCOM.2019.8737488
- [24] SCIANCALEPORE V, DI RENZO M, COSTA-PERÉZ X. STORNS: Stochastic Radio Access Network Slicing [C]//2019 IEEE International Conference on Communications (ICC). Shanghai, China, 2019: 1 - 7
- [25] HAN B, FENG D, JI L, et al. A Profit-Maximizing Strategy of Network Resource Management for 5G Tenant Slices [EB/OL]. (2017-09-26). <https://arxiv.org/abs/1709.09229>
- [26] HAN B, FENG D, SCIANCALEPORE V, et al. Rational Impatience Admission Control in 5G-Sliced Networks: Shall I Bide My Slice Opportunity? [EB/OL]. (2018-10-31). <https://arxiv.org/abs/1809.06815>
- [27] CHATTERJEE K, SAMUELSON W F (eds). Game Theory and Business Applications [M]. Boston, USA: Springer, 2002: 339 - 370
- [28] KRISHNA V. Auction Theory [M]. Cambridge, USA: Academic Press, 2009

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Machine Learning Based Unmanned Aerial Vehicle Enabled Fog–Radio Access Network and Edge Computing

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Abstract: The emerging unmanned aerial vehicle (UAV) technology and its applications have become part of the massive Internet of Things (mIoT) ecosystem for future cellular networks. Internet of things (IoT) devices have limited computation capacity and battery life and the cloud is not suitable for offloading IoT tasks due to the distance, latency and high energy consumption. Mobile edge computing (MEC) and fog radio access network (F-RAN) together with machine learning algorithms are an emerging approach to solving complex network problems as described above. In this paper, we suggest a new orientation with UAV enabled F-RAN architecture. This architecture adopts the decentralized deep reinforcement learning (DRL) algorithm for edge IoT devices which makes independent decisions to perform computation offloading, resource allocation, and association in the aerial to ground (A2G) network. Additionally, we summarized the works on machine learning approaches for UAV networks and MEC networks, which are related to the suggested architecture and discussed some technical challenges in the smart UAV-IoT, F-RAN 5G and Beyond 5G (6G).

Keywords: unmanned aerial vehicle; machine learning; F-RAN; edge computing

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1 Introduction

In the recent past, cellular technologies have become more dynamic and improved the network infrastructure to the satisfaction of end users. There are a number of ultra-dense heterogeneous devices from individuals and organizations, which are always generating and storing a huge amount of data via sensors (edge Internet of Things (IoT) devices) and applications [1]. When the massive Internet of Things (mIoT) devices emerge, the data generated by various sensors will increase exponentially. Due to the huge volume of the data produced and different forms of conventional databases (with structured and unstructured data), big data analysis has attracted much attention in recent years and many organizations have focused on the analysis of collected data to extract useful data for making appropriate decisions [2]. The data generated from

billions of heterogeneous IoT sensors are sent to the cloud for processing computing tasks, with a high cost of processing delay and energy consumption. However, some IoT sensors data need to be processed faster than the current processing capability of clouds. To solve this problem, fog and edge computing (FEC) is proposed to enable computing tasks processed at the network edge of IoT [3] – [5]. Edge computing is a new emerging paradigm to solve IoT computation and resource allocation problem in localized manner [5]. Fog computing is decentralized computing paradigm, where a number of smart devices which have a computational capacity are utilized [6], [7]. In this paradigm, key issues were discussed about the requirement and deployment of fog connectivity environment due to the existence of ultra-dense heterogeneous devices. Several technical issues on fog computing such as deployment, simulation, resource management, fault tolerance and services have

been studied in [6], [8] – [13]. Even though fog computing and edge computing both move the computation and storage to the edge of the network, closer to end-nodes, their paradigms are not identical [14]. The rapid development of diverse mIoT devices such as wireless sensors, smart machines, and mobile users' applications enable the users to enjoy high quality of experience (QoE) and high quality of service (QoS) [5], [15], [16]. However, most of these applications are delay sensitive or real-time applications, which need high computational capacity. The edge devices could not compute each task due to the limitation of battery and low computation capability, so it is difficult for them to implement these applications [17]. The FEC can compute tasks of IoT devices and interplay with the cloud server to provide better QoS and QoE to end users. Some works were done on computation offloading to mobile edge computing (MEC) servers and on resource allocation of the IoT devices to maximize network performance and optimize the problem in ultra-dense heterogeneous network [18] – [20]. For ultra-dense IoT network system, a game theory computation offloading framework was designed in [21] and [22], to minimize the overall computation overhead of the task on edge IoT devices.

Radio access network (RAN) provides connectivity to the wireless terminals through wireless access points (base stations) and may use one or more radio access technologies (RATs). The fog radio access network (F-RAN) is composed of F-RAN nodes connected through a single or multiple RATs. The F-RAN has a unique feature better than the cloud radio access network (CRAN) and heterogeneous cloud radio access network (H-CRAN), which helps maximize the use of edge IoT devices of the network and improve network management and optimization mechanisms [5], [23], [24].

Based on the report from Federal Aviation Administration (FAA) [25], the fleet of drones will be more than doubled from estimated 1.1 million vehicles in 2017 to 2.4 million units by 2022. Benefitting from connecting unmanned aerial vehicles (UAVs) to cellular networks for better control and communications, the growth of the UAV market is expected to bring new promising business opportunities for cellular operators. Millions of UAVs have been used to perform various services such as public protection, disaster relief operation, surveillance applications, traffic management, commercial services, extending the cellular-network coverage to remote areas, and acting as flying base stations [26], [27]. The Third Generation Partnership Project (3GPP) is exploring the challenges and opportunities for serving UAVs as a new type of User Equipment (UE), called aerial UE. UAVs can facilitate the development of IoT ecosystems for mIoT applications [28]. UAVs will be the future of IoT because UAVs, at the beginning, efficiently replace the connected sensors at rest with one device that is deployable to different locations, capable of carrying flexible payloads, re-programmable in mission, able to measure anything from anywhere, easily deployed, and cost effective. In recent years, a number of works have been done on either UAVs net-

works or their integration with cellular networks. Those works focused on computation offloading, maximization of energy efficiency, optimization of UAV trajectory and path planning, throughput maximization of UE in UAV network, and terrestrial heterogeneous devices.

The authors of [29] summarized the journey of machine learning in the last thirty years and the roles machine learning played in the next-generation wireless network (NGWN) as a road for achieving the ambitious goal of NGWN and as a tool for managing the network complexity. The authors of [30] emphasized the role of diverse machine learning algorithms in different key issues of networking across different network technologies. Machine learning techniques are applied for fundamental problems in networking, including routing and classification, traffic prediction, congestion control, QoS and QoE management, resource and fault management, and network security. In [31], the authors studied the advanced machine learning application in wireless communication for mobility management in the network layer, resource management in the MAC layer, and networking and localization in application layer. The paper [32] discussed the future cellular networks or wireless networks which support ultra-reliable and low-latency communications, as well as the intelligent management for mIoT devices in dynamic environment. Deep reinforcement learning (DRL) approaches for cellular networks, next generation wireless networks and self-organization cellular networks were reviewed in [29] – [34]. Recently, DRL has become one of the mostly popular machine learning algorithms for edge computing resource management and a suitable optimization technique for radio access networks. DRL has recently been used as an emerging tool for effectively solve various problems and challenges in modern networks that are more decentralized, ad-hoc, and autonomous in nature, such as heterogeneous networks (HetNets), IoT, vehicle to vehicle (V2V) system, machine to machine (M2M) system, vehicle to everything (V2I) system, self-organization cellular networks, and UAV networks [31].

Different non-deterministic polynomial-time hardness (NP-hard) problems of UAV networks and UAV connected cellular networks were optimized by adopting traditional optimization techniques [35] – [38], [40] – [43]. However, traditional optimization techniques are difficult to be applied for complex network infrastructure and not suitable for the current and future intelligent wireless networks. Recently, machine learning algorithms have been used to easily optimize different problems in UAV networks and UAV connected cellular networks [63] – [66], [68], [69]. However, there are still challenges to using machine learning algorithms for UAV networks which assist the mIoT, public safety communication (PSC), and edge computing.

The main contributions of this work are summarized as follows:

- We suggest a new orientation with UAV enabled F-RAN ar-

chitecture. This architecture adopts the decentralized DRL algorithm for edge IoT devices, which enables decision independently made for offloading, resource allocation, and association in the A2G network.

- We summarize the works on machine learning approaches for UAV networks and MEC networks, which are related to the suggested architecture.

- We discuss some technical challenges in the smart UAV-IoT, F-RAN 5G, and B5G (6G).

The rest of the paper is organized as follows. We provide a brief overview of UAV in wireless cellular networks and the use of UAV for emergency situation and computation offloading in Section 2. In Section 3, we review machine learning and its classification. In Section 4, we present our orientation with UAV-enabled F-RAN in MEC, which adopts the machine learning algorithm. In Section 5, we present the works on computation offloading and resource allocation using DRL in MEC and UAV networks. In Section 6, we discuss technical challenges and future research directions of intelligent UAV enabled F-RAN at the edge level. We conclude the paper in Section 7.

2 UAV in Wireless Cellular Networks

Currently, the use of flying UAV platform is popular; this rapidly growing technology has attractive attributes such as mobility, flexibility, and adaptive attitude, and has key potential applications in wireless system. UAVs can be used as aerial base stations (ABS) to enhance coverage, capacity, reliability, and energy efficiency of wireless networks, as well as flying mobile terminals in cellular network infrastructure. UAV can be connected with cellular networks as new user equipment and help increase the revenues for network operators.

The authors of [35] summarized the current state of UAV in cellular communication system from different points of view. Different types and characteristics of UAVs are available. A number of industry-led initiatives depend on the standards of cellular communications which support low-altitude UAVs for enabling beyond Line of Sight (LoS) control and establishing a

reliable communication. The deployment of flying UAV base stations is better than that of ground base stations for reducing cost and minimizing electronics equipment of base stations. The deployment of ABS faces different practical challenges such as placement and mobility, but UAV flying base stations can be easily deployed at optimum locations in 3D space; they can potentially provide much better performance in different parameters such as coverage, load balancing, spectral efficiency, and user experience, compared to existing terrestrial based solutions. UAV can act as flying base stations in the heterogeneous 5G environment and also support millimeter wave (mmW) communications; it is collectively viewed as the nexus of next-generation 5G cellular systems. UAV-enabled mmW communications is a proposing application of UAVs, which can establish LoS communication links to users [27]. UAVs can also assist various terrestrial network infrastructure such as mMTC, cellular, and vehicular networks (V2V, V2X, V2I) in different ways; for example, UAVs can improve the reliability of wireless connection and scalability, replace destroyed bases stations, compute different tasks of edge IoT devices, and relay the data or signal into central network controller. **Table 1** compares terrestrial networks with base stations and UAV networks with bases stations.

UAV at the edge level in cellular networks has a major impact on 5G and beyond. A single or multiple UAVs can compute the tasks of edge IoT devices. The UAV used as relaying and ABS which connect terrestrial smart mobile users with edge servers in MEC have been studied in [36]. To minimizing the average weighted energy consumption of the smart mobile devices and the UAV, the authors of [37] studied the multi-cell edge which is three adjacent cells served by three base stations; at the multi-cell edge, some of the users out of the radius of the base stations are connected with UAV. The problems are how to optimize the maximal sum rate of edge users by avoiding the interference and how to improve QoS and optimize UAV trajectory for the users who are out of network coverage and served by UAV.

The recent literature works on UAV network and UAV as-

▼ **Table 1. Comparison between UAV networks with base stations and terrestrial networks with base stations**

Terrestrial Networks	UAV Networks
Insufficient spectrum	Insufficient spectrum
Well defined energy constraints and models	Elaborate and stringent energy constraints and models
Mainly static association	Varying cell association
No timing constraints, with BS being always there	Hover and flight time constraints
Terrestrial BS	UAV BS
Typical two-dimensional deployment	By nature, three-dimensional deployment
Mostly long-term and permanent deployments	Short-term and frequently changing deployments
Few and selected locations	Mostly unrestricted locations
Fixed and static	Mobility dimension
Not suitable for mobility tracking	Suitable for mobility tracking

BS: base station

UAV: unmanned aerial vehicle

sisted cellular user or IoT focused on computation offloading, resource allocation and path planning, and trajectory optimization of either a single UAV or multi-UAV network. In all cases, the UAV assists the terrestrial users or IoT devices in offloading tasks and in requesting resources such as power, computational resources and bandwidth. LIU et al. [38] designed UAV-Edge-Cloud computing hybrid computing architecture to jointly optimize the computation offloading and routing problem for swarms of multi-UAV which are connected in D2D forms. The architecture in [38] aims to minimize the transmission delay and increase the computing capability between UAVs and mobile users. TI et al. [39] designed UAV based Fog-Cloud-Computing (FCC) to minimize the computation and power consumption of all users, which can jointly optimize the computation offloading, user-cloud/cloudlet association, transition power allocation, and path planning of mobile users. The UAV acts as a small distributed cloud and the local BS as micro cloud server; both users and UAV are movable.

When the terrestrial network infrastructure encounters a natural disaster such as earthquake, volcano, landslide and avalanche, UAVs can act as a network life saver, especially for emergency situations. One of the popular communication technologies is PSC, which plays a critical role in saving lives, property, and national infrastructure during natural or man-made emergency [40]. This technology is developed for delivering critical real-time streams (video, voice) using predefined spectrums. The UAV base station (UAVBS) or ABS, with LTE-advanced capabilities, can be utilized for emergency restoration and temporary expansion of public safety for disaster recovery [41]. ZHAO et al. [42] proposed a UAV-assisted emergency network to replace the destroyed base station by establishing multi-hop D2D users in different cells and relay the signal for emergency vehicular communication. And it is a promising method for establishing emergency networks. The authors of [43] studied how to replace destroyed base stations by UAV base stations after creating multi-hop D2D communications. They also designed a UAV transceiver for managing UAV uplink and downlink, extending the wireless coverage and guaranteeing the QoS of UAV communications for IoT in disasters.

3 Machine Learning: Overview

Machine learning is an application of artificial intelligence (AI), which provides systems with the ability to automatically learn and improve themselves from experience without being explicitly programmed. It is essentially based on the premise that machines should be furnished with AI that enables them to learn from previous computations and adapt to their environment through experience [32], [44]. Machine learning began to flourish in the 1990s. Before 1990s, logic-and knowledge-based schemes, such as inductive logic programming and expert systems dominated the AI scene relying on high-level hu-

man-readable symbolic representations of tasks and logic. Researchers in 2000s gradually renewed their interest on deep learning (DL) with the aid of advanced hardware-based computational capacity and the machine learning paradigm became popular at that time, supporting a wide range of services and applications in different areas [32], [44], [45].

3.1 Various Types of Machine Learning

Machine learning algorithms can be classified into three groups based on training data: supervised learning, unsupervised learning, and reinforcement learning (RL)

The supervised learning algorithm enables machines to be trained using labeled data. When dealing with labeled data, both the input data and its desired output data are known to the system. Supervised learning is commonly used in applications that have enough historical data. The algorithm is used to infer a function that maps the input data to the output label relying on the training of sample data-label pairs. Practically, considering a set of N sample data label pairs in the form of $\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$, where x_n is the n -th sample input data and y_n represents its label. Let $X = \{x_1, x_2, \dots, x_N\}$ denotes the input data set and $Y = \{y_1, y_2, \dots, y_N\}$ denotes the output label set. The sample pairs are independent and identically distributed (i. i. d.). The learning algorithms aim for seeking a function $g(x)$ that yields the highest value of the score function $f(x, y)$, hence we have $g(x) = \operatorname{argmax}_y f(x, y)$. Supervised learning algorithms can be widely used in the context of classification, regression and prediction.

The unsupervised learning algorithm enables machines to be trained without labeled data. Unsupervised learning is typically about finding structure hidden in collections of unlabeled data. By analyzing N input data $X = \{x_1, x_2, \dots, x_N\}$, a pair of popular methods have been conceived for revealing the underlying unknown features of N input data, namely density estimation and feature extraction.

RL enables machines to learn what to and how to map situations to actions so as to maximize a numerical reward signal. It is different from the above two algorithms and is currently the most popular research topic in the field of machine learning. There are elements which are necessary for reinforcement learning such as agent, state, action in a given environment. At each episode, the environment is in some state S and the agent selects a legitimate action A . The system responds at the next episode by moving into a new state S' with a certain probability influenced both by the specific action chosen and by the inherent transitions of the system. Meanwhile, the agent receives a corresponding reward $r(S, A)$ from the system, as time evolves. RL, an important branch of machine learning, is an effective tool and widely used Markov Decision Process (MDP) method [46]. In RL process, an agent can learn its optimal policy through interaction with its environment. Q-learning is the most effective method and widely used algorithm for RL. One

of the most popular and widely used learning techniques is deep learning which allows the computer to build complex concepts out of simpler concepts. It is a set of algorithms and techniques that attempt to find important features of data and to model its high-level abstractions [40]. However, the learning process of RL takes a lot of time to reach optimal policy or generate best policy by exploring and generating knowledge of an environment, and this circumstance is not suitable and inapplicable for complex large problems. An artificial neural network (ANN) is a computational nonlinear model based on the neural structure of the brain, which is able to learn to perform tasks such as classification, prediction, decision-making, and visualization. The basic model of a neuron is mathematically expressed as follows:

$$Z_n(w_n, b_n, x_n) = f\left(b_n + \sum_{i=k}^J x_{nk} \cdot w_{nk}\right), \quad (1)$$

where x_{nk} is an input signal from a given neuron n to neuron i , $x_n = [x_{n1}, x_{n2}, x_{n3}, \dots, x_{nJ}]$ is a vector of the input signal of neuron n , w_{nk} is the corresponding input weight value, $w_n = [w_{n1}, w_{n2}, w_{n3}, \dots, w_{nJ}]$ is a vector of input weight of neuron n , Z_n is the output signal of neuron n , b_n is the bias of neuron n , and $f(\cdot)$ is a nonlinear activation function. A bias value can shift the activation function, which is critical for successful learning. The activation function in a neural network will represent the rate of action potential ring in the cell of a neuron. An ANN constructed using linear activation functions in (1) cannot reach a stable state after training, and this problem can be controlled by normalizing different activation functions such as sigmoid function, tanh function, and rectified linear unit (ReLU) function.

3.2 Deep Reinforcement Learning

Deep learning was recognized as the first among the top ten AI technology trends for 2018 [45] and is already the leading machine learning technique successfully used in many scientific fields such as image recognition, text recognition, speech recognition, audio and language processing, and robotics [32], [44], [45]. Deep learning models are based on an ANN. As we mentioned above, the application of RL is insufficient for the current complicated problems. The combination of RL and deep learning, known as deep reinforcement learning (DRL), can break the limitation of RL in different areas. The DRL takes the advantage of deep neural networks (DDN) to train the learning process, improving the learning efficiency and performance of RL algorithms.

Q-learning is one of the most common used RL algorithms. It is an attempt to learn the value $Q(s, a)$ of a specific action given to the agent in a particular state. Considering a table where the number of rows represents the number of states, the RL agent interacts with the environment to learn the Q-values,

based on which the agent takes an action. The Q-value is defined as the discounted accumulative reward starting at a tuple of a state and an action. Once the Q-values are learned after a maximum episode, the agent can make a quick decision under the current state by taking the action with the largest Q-value and the number of columns represents the number of actions which is called a Q-table [45], [47]. A large amount of state and action space in the environment makes the Q-table unmanageable. In current real-world examples like cellular edge computing, the state space is infinitely large. In order to eliminate the shortcoming of Q-learning, a neural network is used to predict the Q-values. One popular DRL algorithm is deep Q-network (DQN), which uses DNN to approximate the values. DQN is much more capable of generalization compared to the Q-network. DQN inherits and promotes advantages of both reinforcement and deep learning techniques, and thus it has a wide range of applications in practice such as game development, transportation, and robotics [44], [45], [47]. The study of DQNs has let too many improvements; new architectures have been designed for better performance and stability, including double DQN (DDQN), dueling DQN, and another asynchronous DRL algorithms studied on this articles [47]–[49].

4 System Architecture of UAV Enabled F-RAN

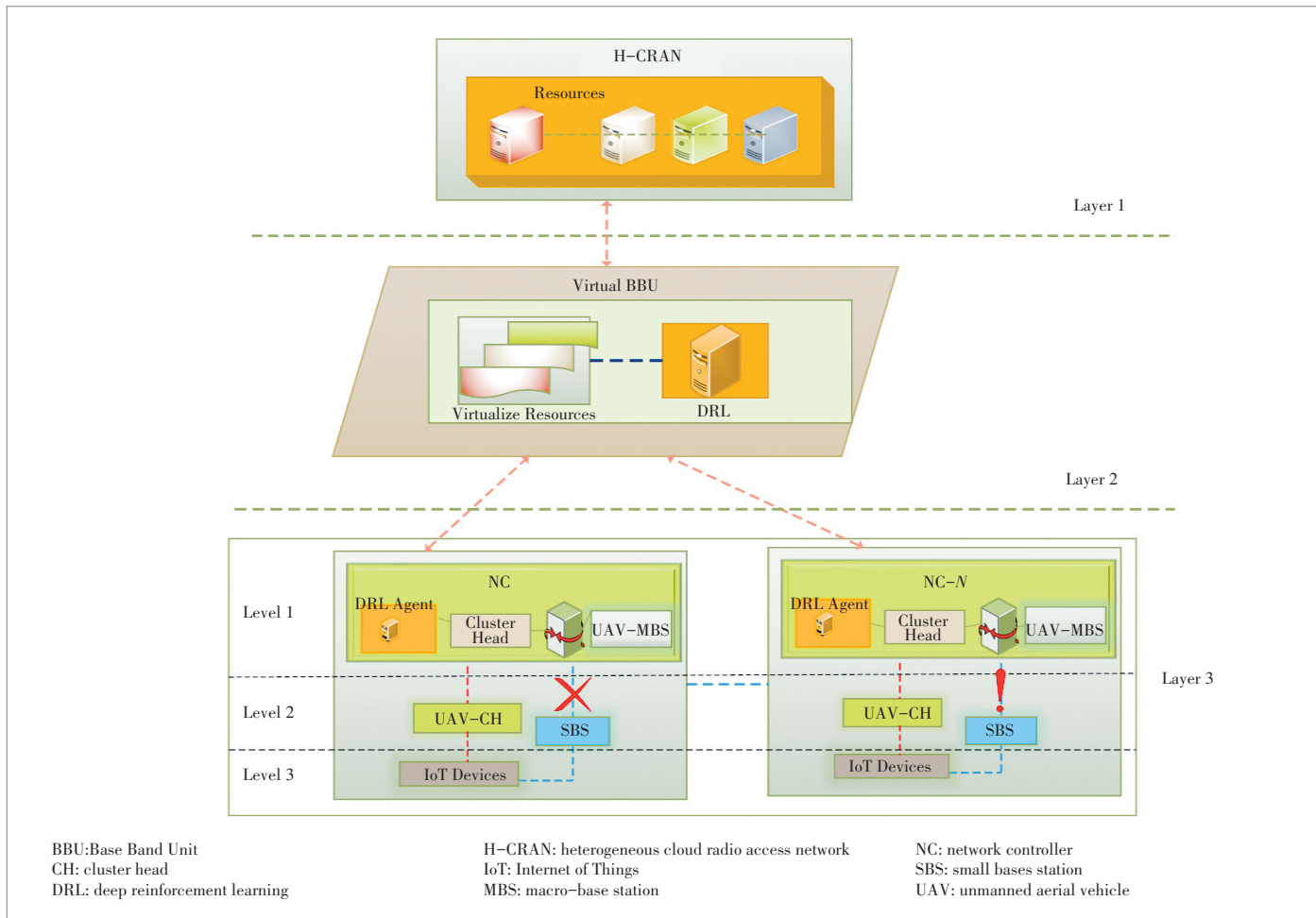
In the future, the ABS infrastructure will play a great role in 5G and beyond 5G communications. The ML algorithms applied in the current and future cellular technologies and aerial networks will be used to manage the dynamic network environment. **Figs. 1** and **2** depict the integration of UAV networks and terrestrial networks, where resources from cloud networks are accessed through the virtualized base band unit (VBBU). In VBBU, the network resources which are used for both aerial and terrestrial network infrastructures are virtualized in intelligent manner. The resources are allocated in the infrastructures, depending on the network demands. We categorize the architecture into three layers.

4.1 Layer 1

The H-CRAN that has cloud computing resources is delivered by server-based applications through digital networks or the public Internet itself. The resources which are available on cloud are far from edge IoT devices. Due to this, the edge IoT devices need localized computational nodes and resources to achieve features of 5G and B5G such as ultra-reliability, low-latency and massive (ubiquitous) connectivity.

4.2 Layer 2

The virtual BBU pool is located at the data center and multiple BBU nodes dynamically allocate resources to different network operators. The resources are allocated to aerial networks and terrestrial networks based on current network demands.



▲ Figure 1. UAV enabled fog radio access network (F-RAN) system architecture.

On this layer, the resources are virtualized into N network slices which are found on cloud. The network virtualization allows network resources to be sliced and granted to multiple tenants. We assume the DRL is in decentralized manner and the fog-edge network can make decisions independently based on the local learning environment and inputs. The resulting decision will then be sent to the central controller.

4.3 Layer 3

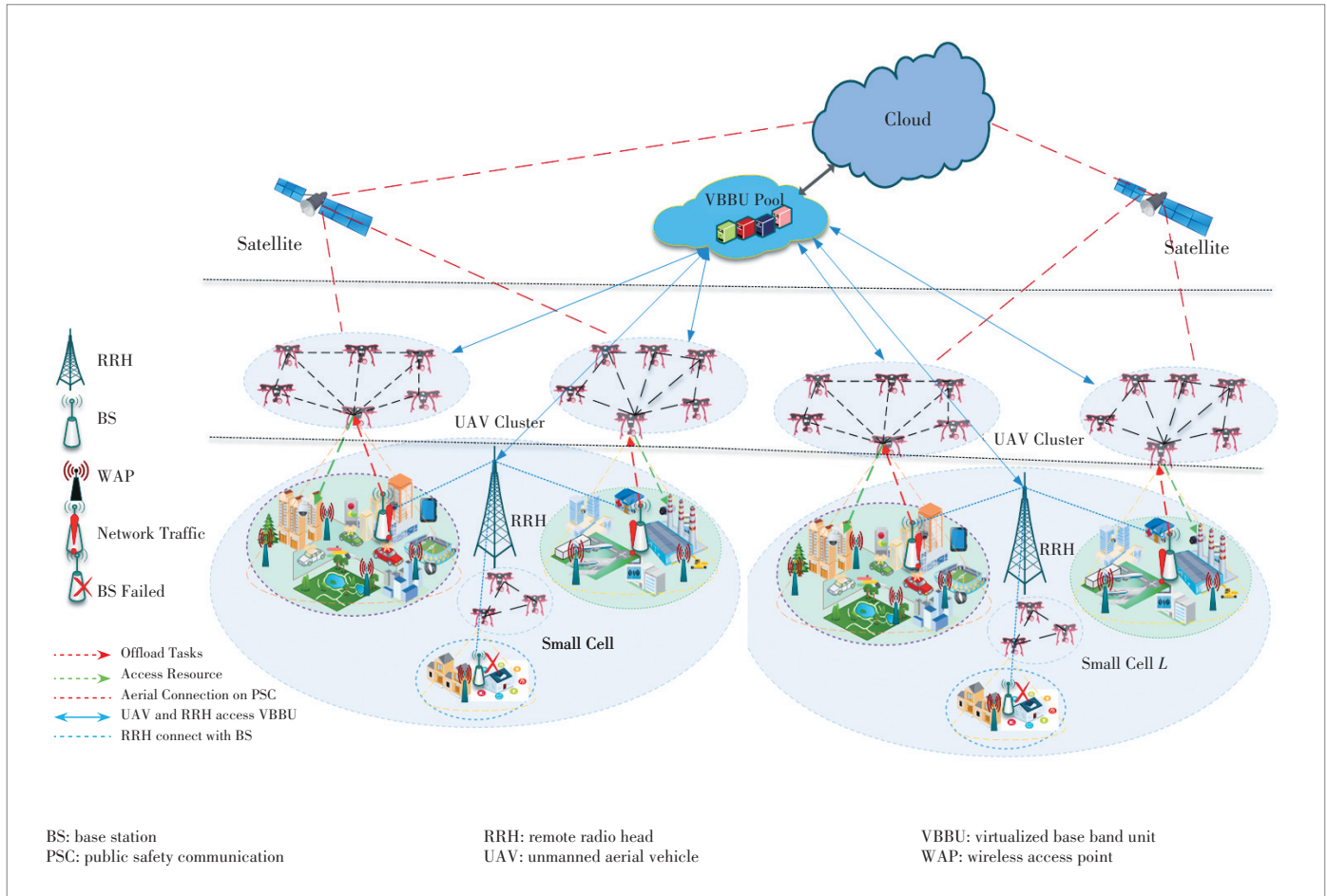
The main network operations such as DRL, resource management and computation offloading are performed at this layer. It has three levels which are network controller, UAV-small bases stations (SBS) and Edge IoT devices.

1) **Level 1:** The network controller (NC) is a central controller of the two network infrastructures and a communication platform where the aerial networks assist the terrestrial networks and DRL makes an intelligent coordination depending on network traffic, emergency and resource scarcity. A macro base station (MBS) with MEC server is used to manage resources which are allocated by the VBBU, allocate these resources to different network operators, and make a decision about the

network condition for using DRL approach. To satisfy QoS and QoE of heterogeneous connected edge devices in each slice, the network will be assisted by UAV network in intelligent manners. Under MBS there are a number of SBSs with local servers in each small cell which are used to connect ultra-dense heterogeneous devices.

2) **Level 2:** UAV and SBS at this level are used to assist the communication in a given small cell mainly when the network is congested at specific time and in emergency situations; UAV acts as a flying base station to replace the destroyed BS and perform computational tasks and recharge of edge IoT devices. At this time the edge IoT devices are mainly wireless sensors, wearable devices and surveillance cameras, which offload the collected data into UAV for further analysis and decision making. Therefore, we consider UAV enabled F-RAN in which the UAV is considered as a flying remote radio head (RRH) or base station with computation capability to assist the edge IoT device. The UAV is part of cellular network; it recharges IoT sensor batteries and also sends collected data to MBSs.

3) **Level 3:** Edge IoT devices at this level are ultra-dense heterogeneous devices (mIoT devices), which are connected



▲ Figure 2. UAV enabled fog radio access network (F-RAN) and edge computing system model in public safety communication (PSC).

with each other and SBSs. These devices share common resources, exchange information with the nearest devices, and have different interests. The MEC server may be crowded or even damaged when the devices request resources and need to offload their own tasks at the same time. The layer three has more network traffic than other layers and the cooperation of aerial network with terrestrial network is needed. The UAV assists the edge IoT network when either the network coverage is far from base station or some natural disaster has affected the network.

5 Machine Learning Algorithms in Edge Computing and UAV

In the current edge technology era, there is the spright of direct communication between devices which are connected with the network infrastructures without travelling to base stations or core networks. D2D communication system is one of the most common networks and has been widely used in recent years; it is a milestone on the road towards self-organization and peer-to-peer (P2P) collaboration. Currently most of edge

IoT devices need computing latency-sensitive support, which is not tolerable at the cloud level. In 2012, a group of researchers from Cisco proposed a new paradigm known as fog computing. Fog computing and edge computing appear similar since they both involve bringing intelligence and processing closer to UE. Most of the edge IoT devices have shortage of computational capacity and limitation of battery life. Due to this limitation, the edge IoT devices may fail to perform different operations properly. However, using the emerging MEC paradigm, the edge device can offload computation intensive tasks to the MEC server in different ways. The study of computation offloading and resource allocation in MEC and fog computing is complicated system analysis because of mobility patterns, radio access interfaces, strong couplings among mobile users with heterogeneities in application demands, QoS provisioning, and wireless resources. A machine learning approach specially using RL is a promising candidate to manage huge state space and optimization variables, especially by using different types of ANN.

DRL is an emerging tool for sophisticated problems in communication and networking in IoT, MEC, HetNet, and UAV networks. The network unities such as IoT devices, mobile us-

ers, and UAVs need to make local and autonomous decisions, like spectrum access, data rate selection, transmit power control, computation offloading decision, and base station association, to achieve the goals of different networks including throughput maximization, delay minimization, energy consumption minimization, and UAV deployment. The main problem is an uncertain and stochastic environment but the MDP model can solve the problem using dynamic programming, value iteration and RL [45]. LUONG et al. [31] studied the role of DRL in communication and networking. DRL minimizes the complexity of optimization and solves the problem in different perspectives. DRL allows network entities to learn and build knowledge about the communication and networking environment. By using DRL algorithms, mobile users can learn optimal policies for base station selection, channel selection, handover decision, caching and offloading decisions, UAV deployment, path planning, and trajectory optimization without knowing channel model and mobility pattern. In [31], different topics of the research works related to DRL were shown in percentages, for example, as the research in space communication is 13%, Ad-hoc 19%, cellular network 31%, IoT network 9%, and others 31%; the related issues to be solved were also presented in percentages, for example, the issues of wireless capacity is 19%, computation offloading 13%, rate control 8%, network access 13%, data collection 9%, resource scheduling 9%, connectivity preservation 8%, and network security 12%. Although there are a number of works on machine learning approaches for wireless communication networks [29], [31], [34], there is no research focus on machine learning based UAV enabled F-RAN infrastructures yet.

5.1 Machine Learning Based Computation Offloading in MEC

Edge IoT devices such as sensors and wearable devices have a limited computational capacity, short life time of battery, and storage. Due to this limitation, the IoT devices do not support advanced applications such as face recognition and online gaming (VR/AR). To tackle the problems in edge IoT devices and also in the network, an offloading mechanism is used to offload computational tasks and data to the nearest computational nodes (MEC server, UAV, or local servers). The offloading of data and computation tasks of the IoT devices can minimize the processing delay and energy consumption, and may enhance security. Under this circumstance, there are some critical challenges to computation offloading, such as choosing a computational node from multiple computational nodes and determining the offloading rate. Selection of an overloaded computational node also affects the computation time and energy consumption of IoT devices. The previous works on computation offloading and resources allocation used heuristic or iteration algorithms, but they have high complexity. Alternatively, machine learning is a promising tool used for solving the complex problem of computation offloading and resource allocation.

tion.

Recently, machine learning algorithms have been applied in fog edge computing to minimize the optimization problems. The authors of [50] proposed SDN NFV based DQN framework for caching and computation offloading to achieve energy efficiency in the network. The authors of [51] proposed a deep learning-based offloading framework to minimize the offloading cost for MEC networks. A deep supervised learning was also modeled to obtain the optimal offloading policy for mobile users. The authors of [52] tried to solve the resource allocation problems by joint optimization of caching, networking and computation for video content compressing and encoding, using feedforward neural network (FNN) based DQN. DDQN and dueling DQN approaches were proposed to improve the stability and performance of the DQN algorithm [53]. A DQN framework was also proposed for smart city applications, which is a dynamic orchestration of caching, bandwidth and computation to achieve QoS for different services [54].

The authors of [55] proposed offloading cellular traffic for WLAN by adopting the DQL algorithm and MDP model to minimize energy consumption and mobile user cost. The MEC server has a limitation of resources to allocate for all edge devices; due to this, the MEC server also minimize cost and energy. In a vehicular network, there is a huge action space and high complexity due to the vehicles' mobility and service delay. In [56], a multi-time scale DQN framework is proposed to minimize the system cost through jointly designing caching, communication and computing. The authors of [57] proposed DQN based joint optimization for computation offloading and resource allocation in MEC-enabled cellular networks. And the cost of delay and power consumption is accordingly minimized for all mobile users. In cellular networks, a DQL based optimal offloading policy was proposed to minimize the mobile users' cost and energy consumption [58]. In [59], a virtualized computation offloading framework using DRL was designed and a DDQN based DQL algorithm was proposed for an agent to learn the optimal offloading policy without prior knowledge of the network environment in a dynamic manner. This work also focused on the utility function by decomposing Q-function and combining with DDQN; a novel online SARSA-based DRL algorithm was proposed [59]. Besides, the computation offloading of multiple MEC servers have been considered [60] – [62]. The authors of [60] designed Q-learning and fast DQL offloading scheme to achieve optimal policy for IoT devices and energy harvesting capacity.

In [61], a two-layered DQL algorithm for offloading to maximize the utilization of cloud resources was studied; the first layer uses a convolutional neural network (CNN)-based DQL framework to estimate an optimal cluster for each computational task and the second layer uses Q-learning to determine the optimal serving physical machine in cluster. The authors of [62] proposed distributed deep learning-based offloading (DDLO) for multi-computing servers, users and tasks in MEC

networks to minimize wireless device (WD) energy consumption by offloading WD tasks to the MEC server or cloud and allocating bandwidth. **Table 2** shows different machine learning algorithms in vehicular networks and cellular networks.

5.2 Machine Learning Based UAV Connected Cellular Networks

The application of machine learning for UAV is known as the drone system. Over the past years, many studies were conducted on either the integration of UAV networks with terrestrial networks or UAV networks in different application streams such as energy efficiency, computation offloading, resource allocation, and network coverage extension. However, Most of the previous works solved the existed problems using heuristic algorithm. The current research is focusing more on using machine learning algorithms to solve the aerial and terrestrial network integration for UAV assisted cellular networks, IoT, BSs and others to achieve a specific goal in the network. The cellular connected UAV will be a future hot research topic because it can integrate with future cellular networks and machine learning approaches to create a new intelligent aerial mobile user.

Many studies have been conducted on machine learning algorithms used in UAV or cellular connected UAV networks for optimizing UAV deployment, path planning, and trajectory as well as improving energy efficiency, UAV coverage, throughput, and resource allocation. GHANAVI et al. [63] proposed the optimal 3D UAV deployment to implement UAV-BSs which use RL to assist or serve the terrestrial network of mobility equipment for keeping the reliability of connection and increasing the QoS of users. The authors of [64] proposed an efficient 3D ABS positioning solution, in which DQN with DRL is used to assist the terrestrial BS in a small cell where the BS is overloaded and none of LoS exists for maximizing the spectra efficiency of the system. In [65], proposed a novel framework was proposed to deploy ABSs to assist overloaded or congested base stations in small cells. Researchers also adopted the machine learning approach to tackle the problem of predicting the traffic demand of each base station through previous histories,

based on which ABSs are deployed for serving users in small cells and applying contract theory to jointly maximize the individual utility of each BS and UAV. In [66], an ANN based opportunistic computation offloading framework was proposed, the clustered UAV network assists a vehicular traffic network and the ground controller predicts the response time of each clustered UAV to offload intensive tasks. A clustered UAV network can compute intensive tasks by itself or borrow the resources from another cluster UAV network [66]. The authors of [67] studied the model free RL algorithm using Q-learning to optimize the trajectory of an UAV acting as a flying BS that serves multiple terrestrial network users. And the UAV also acts as an autonomous agent in the environment, learning the trajectory for maximize the sum rate of transmission during UAV flying time from one location to another location. CUI et al. [68] studied a multi-agent RL using Q-learning and stochastic game theory model for dynamic resource allocation in multi-UAV connected multi-users. Each UAV acts as an agent to make a decision independently for maximizing long-term rewards of each agent to provide reliable communications. Users, power levels and sub-channel selection strategies were also jointly studied in [68]. For cellular connected UAVs in beyond 5G system, a DRL algorithm was proposed based on the echo state network (ESN) for an interference aware path planning and management [69]. Each UAV acts as an agent that uses deep ESN to learn optimal path, transmission power level and cell association in each location of path and minimize sequence of time-dependent utility function. Authors of [69] also studied energy efficiency, the control of UAVs, and the fair covering of the active areas where the users are available and the UAVs are required to act as base stations by the DRL algorithm. In this work, the fairness index algorithm was applied to control UAV network coverage to minimize UAV energy consumption and improve UE QoS.

6 Challenges and Future Research Directions

According to the recent studies of various issues for future

▼ **Table 2. Machine learning algorithms for computation offloading and resource allocation in vehicular networks and cellular networks**

Paper	Network	Agent	Model	Learning Algorithm
[50]	CRN	Base station	MDP	DQN using FNN
[52]	Vehicular Network	Service Provider	MDP	DQN using FNN
[53]	Vehicular Network	Service Provider	MDP	DQN using CNN
[55]	Cellular System	Base Station	MDP	DQN using CNN
[56]	Cellular System	Mobile User	MDP	DQN using CNN
[57]	Cellular System	Base Station	MDP	DQN using FNN
[58]	Cellular System	Mobile User	MDP	DQN using FNN
[59]	Cellular System	Mobile User	MDP	DDQN, SARSA
[60]	Cellular System	Mobile User	Game theory	DQN using CNN, Q-learning

CNN: convolutional neural network
CRN: cognitive radio network

DDQN: double deep Q-network
DQN: deep Q-network

FNN: feedforward neural network
MDP: Markov Decision Process

SARSA: state action reward state action

generation network infrastructures, we outline some challenges and future research directions for the integration of aerial networks and terrestrial networks with machine learning approaches in F-RAN, NFV and MEC paradigms.

6.1 Challenges

1) Machine learning used in virtualized UAV enabled F-RAN: RL (commonly DQN, Q-Learning and others) in virtualized MEC system has been used to tackle many issues at different layers of cellular networks. Deploying the machine learning algorithms at different layers of virtualized H-CRAN of UAV-enabled F-RAN will create the intelligence of the future network infrastructure of 5G and beyond. However, in this scenario there are a number of network infrastructure and concepts. Handling this multi-paradigm concept is complex in the current 5G technology and future 6G network.

2) Multi-agent in multi-layer UAV enabled F-RAN: Most of the current studies of cellular mobile networks or MEC system and UAV network focus on efficient resource allocation, energy efficiency, computation offloading, and caching to minimize delay and energy consumption or maximize revenue. The machine learning (commonly RL) algorithms have been used to tackle these issues, but most of them use a single agent at the base station or service providers. The recent years have witnessed the rapid evolution of network infrastructure and technologies from one generation to another generation every ten years. In the era of 5G, ultra-dense heterogeneous networks, which consist of different layers of IoT or fog network that supports ultra-low-latency (ULL) devices, are connected to each other at a given time step. In the future, beyond 5G or 6G (5G+AI) will support intelligent Personal Edge (IPE), genome database, autonomous health, sensors to AI fusion block-chain, etc. [70] – [72]. To perform complex multi-dimensional tasks in these networks, a multi-agent decentralized DRL approach needs to be adopted. Adopting this concept in the UAV-enabled F-RAN multi-agent at each layer is somehow complex and needs clear framework modeling.

3) Determination of the state of network traffic in different small cells: In 5G and beyond 5G era, there is ultra-dense heterogeneous network with massive IoT devices and smart mobile users which generate a huge amount of traffic in different circumstances. These ultra-dense devices will be assisted by UAV-cluster networks to satisfy the QoS and QoE rather than terrestrial base stations. In the UAV connected cellular network at lower layers such as fog or edge computing level, a single UAV or multi-UAVs are deployed and heuristic algorithms are used to identify network traffic in small cells, depending on the UAV capacity and coverage area. However, such application of machine learning in the dynamic network is unpredictable, has a large and continuous state space for making the determination of the network traffic state in different cells, and faces complex deployment of UAV-clusters.

4) Handover for transmitting data and task of mIoT devices

for emergency situations: One of the attractive and promising paradigms of the UAV connected cellular network is acting as a flying base station to assist the emergency service. In this situation, the mIoT devices would send computational tasks and huge amount of request data traffic to the local base station at a specific time step. However, after the occurrence of a natural disaster, a good and intelligent handover framework is needed to manage the handovers in a terrestrial network environment in a disaster area. The application of machine learning algorithms in the handover process is much suitable.

6.2 Future Research Directions

1) Distributed machine learning based virtualized UAV enabled F-RAN: One of the popular machine learning algorithm frameworks in wireless communication and network is RL with deep neuron network, which requires large amount of training. Most of the time the large DNN is implemented at the central network controller which has sufficient resources such as computational capacity and is capable of training a large continuous state space and action space in the dynamic network environment. The central controller minimizes the burden of aerial mobile users and IoT devices by considering the limitation of capacities and capabilities. The main functionalities of UAV networks and terrestrial or cellular networks can be integrated with the central network controller. The virtualized DRL framework for UAV enabled F-RAN or UAV connected cellular system is an open issue. The network traffic exchanges from one layer to another and from aerial mobile users to terrestrial mobile users (mIoT devices) are efficient.

2) Dynamic deployment of multi-UAV cluster in F-RAN: In UAV networks, one of the open issues is UAV deployment in optimal 3D placement for different dynamic terrestrial network infrastructure. A number of previous works focused on UAV deployment with optimization of trajectory, path planning, and maximizing energy efficiency. Due to the dynamical network infrastructure in 5G and beyond 5G (6G), such as the rapid changes in coverage, the number of connected devices and network platforms, the DRL based approach for optimal 3D placement of UAV will be a necessity, with the integration of the cellular or IoT network. Under this consideration, there are other issues such as resource management (aerial mobile users and terrestrial network devices), optimal computation offloading, network coverage area, minimizing energy consumption of network, and cell association to maximize flight time.

3) Machine learning based resource management in UAV-Enabled F-RAN: A number of studies have been conducted on resource management at different layers in cellular networks, vehicular networks, and UAV networks to solve complex problems such as optimization, maximizing energy efficiency, resource allocation for UAV and bandwidth management. These studies aim to maximize the revenue or minimize the cost of delay and energy in the system. Other works that used heuristic algorithms to tackle the complex problems in cellular net-

works, vehicular networks, and fog and edge computing are now adopting machine learning, commonly RL (DQN, Q-learning, DDQN, DDGP, Actor-critics) for resource management and computation offloading. However, in the mixed network infrastructures such as UAV-enabled F-RAN, need to design a machine learning based joint resource management and computation offloading framework.

4) Machine learning for dynamic deployment of ABS in emergency (PSC): UAV plays a potential role in the future promising paradigm for emergency situations known as PSC. The current communication era heavily relies on the backbone networks. For the failure of base stations due to natural disaster or malevolent attacks, PSC is able to use machine learning to deploy a group of multi-UAVs in ultra-dense HetNet architecture as ABSs that can dynamically replace the destroyed or over-headed base stations in the terrestrial network. The UAVs are used to support the reliable connection for edge IoT devices, extend the network coverage, control the end user devices, etc. from the communication perspective. If a destroyed BS has the computational resource (local server), MEC server, and power source that cannot be accessed by edge IoT devices, the intelligent ABSs also replace the destroyed terrestrial BS to conduct computing task and allocate transmission power to satisfy the QoS and QoE of end users/IoT devices at the fog/edge level of RAN networks.

5) Machine learning based mobility control of multi-UAV connected cellular network/F-RAN: In a multi-UAV assisted cellular network/F-RAN, the UAV flies from one location to another location within the given time frame. At the time of UAV's flying over the terrestrial network, mobile users/IoT devices will wait for long time to get access to the UAV terminal. Due to this, the QoS and QoE of the network could be degraded. To tackle this issue, an intelligent machine learning based model is designed for multi-UAV mobility management, where the agents learn by themselves to adjust the mobility in the predicted location in the terrestrial network infrastructure. Besides, the model also considers the terrestrial network connected devices such as mobile users, vehicle, and other mobility environments. In this scenario, the management of resources (computational, bandwidth, and energy) is also considered in the mixed network infrastructures.

7 Conclusions

This paper presents a short review of the machine learning used to solve complex problems in modern network infrastructures and suggests the machine learning based multi UAV-enabled F-RAN. First, we introduce F-RAN and UAV for the current and future network technologies. Second, we discuss UAV in cellular networks and its replacement of base stations in terrestrial networks. Third, we review machine learning algorithms and RL and suggest the machine learning based UAV-enabled F-RAN framework architecture in H-CRAN net-

work infrastructure for computation offloading and resource allocation. We also mention some previous works on edge computing and UAV using RL with DNN to solve different problems such as resource allocation, computation offloading and base station replacement in different networks. Finally, we outline the challenges and future research directions.

References

- [1] ASSUNÇÃO M D, CALHEIROS R N, BIANCHI S, et al. Big Data Computing and Clouds: Trends and Future Directions [J]. *Journal of Parallel and Distributed Computing*, 2015, 79 – 80: 3 – 15. DOI: 10.1016/j.jpdc.2014.08.003
- [2] ALHADDADIN F, LIU W, GUTIERREZ J A. A User Profile - Aware Policy - Based Management Framework for Greening the Cloud [C]//IEEE Fourth International Conference on Big Data and Cloud Computing, Sydney, Australia, 2014: 682 – 687. DOI: 10.1109/bdcloud.2014.116
- [3] DASTJERDI A V, GUPTA H, CALHEIROS R N, et al. Fog Computing: Principles, Architectures, and Applications [M]//Internet of Thing Principles and Paradigms, Burlington, USA: Morgan Kaufmann, 2016. DOI: 10.1016/b978-0-12-805395-9.00004-6
- [4] CHIANG M, ZHANG T. Fog and IoT: an Overview of Research Opportunities [J]. *IEEE Internet of Things Journal*, 2016, 3(6): 854 – 864. DOI: 10.1109/jiot.2016.2584538
- [5] YU W, LIANG F, HE X, HATCHER W G, et al. A Survey on the Edge Computing for the Internet of Things [J]. *Mobile Edge Computing*, 2017, 6(88): 6900 – 6919. DOI: 10.1109/access.2017.2778504
- [6] MAHMUD R, KOTAGIRI R, BUYYA R. Fog Computing: A Taxonomy, Survey and Future Directions [M]//Internet of Things. Singapore, Singapore: Springer, 2017: 103 – 130. DOI: 10.1007/978-981-10-5861-5_5
- [7] GAO L X, LUAN T H, YU S, et al. FogRoute: DTN-Based Data Dissemination Model in Fog Computing [J]. *IEEE Internet of Things Journal*, 2016, 4(1): 225 – 235. DOI: 10.1109/jiot.2016.2645559
- [8] YI S, LI C, LI Q. A Survey of Fog Computing: Concepts, Applications and Issues [C]//Proc. 2015 Workshop on Mobile Big Data, New York, USA: Association for Computing Machinery, 2015: 37 – 42. DOI: 10.1145/2757384.2757397
- [9] HU P F, DHELM S, NING H S, et al. Survey on Fog Computing: Architecture, Key Technologies, Applications and Open Issues [J]. *Journal of Network and Computer Applications*, 2017, 98: 27 – 42. DOI: 10.1016/j.jnca.2017.09.002
- [10] BACCARELLI E, NARANJO P G V, SCARPINITI M, et al. Fog of Everything: Energy - Efficient Networked Computing Architectures, Research Challenges, and a Case Study [J]. *IEEE Access*, 2017, 5: 9882 – 9910. DOI: 10.1109/access.2017.2702013
- [11] VARSHNEY P, SIMMHAN Y. Demystifying Fog Computing: Characterizing Architectures, Applications and Abstractions [C]//IEEE 1st International Conference on Fog and Edge Computing (ICFEC), Madrid, Spain, 2017: 115 – 124. DOI: 10.1109/icfec.2017.20
- [12] MOURADIAN C, NABOULSI D, YANGUI S M, et al. A Comprehensive Survey on Fog Computing: State-of-the-Art and Research Challenges [J]. *IEEE Communications Surveys & Tutorials*, 2018, 20(1): 416 – 464. DOI: 10.1109/comst.2017.2771153
- [13] PERERA C, QIN Y R, ESTRELLA J C, et al. Fog Computing for Sustainable Smart Cities [J]. *ACM Computing Surveys (CSUR)*, 2017, 50(3): 1 – 43. DOI: 10.1145/3057266
- [14] YOUSEFPOUR A, FUNG C, NGUYEN T, et al. All One Needs to Know about Fog Computing and Related Edge Computing Paradigms: A Complete Survey [J]. *Journal of Systems Architecture*, 2019, 98: 289 – 330. DOI: 10.1016/j.sysarc.2019.02.009
- [15] FRENCH A M, SHIM J P. The Digital Revolution: Internet of Things, 5G and Beyond [J]. *Communications of the Association for Information Systems (CAIS)*, 206, 38(40): 40. DOI: 10.17705/1CAIS.03840

- [16] MACH P, BECVAR Z. Mobile Edge Computing: A Survey on Architecture and Computation Offloading [J]. *IEEE Communications Surveys & Tutorials*, 2017, 19(3): 1628 – 1656. DOI: 10.1109/comst.2017.2682318
- [17] BUYYA R, SRIRAMA S N. *Fog and Edge Computing: Principles and Paradigms* [M]. Hoboken, USA: John Wiley & Sons, 2019. DOI: 10.1002/9781119525080
- [18] ALNOMAN A, SHARMA S K, EJAZ W, et al. Emerging Edge Computing Technologies for Distributed IoT Systems [J]. *IEEE Network*, 2019, 33(6): 140 – 147. DOI: 10.1109/mnet.2019.1800543
- [19] HUSAIN S, KUNZ A, PRASAD A, et al. Mobile Edge Computing with Network Resource Slicing for Internet-of-Things [C]//*IEEE 4th World Forum on Internet of Things (WF-IoT)*. Singapore, Singapore, 2018: 1 – 6. DOI: 10.1109/wf-iot.2018.8355232
- [20] BESHLEY H, BESHLEY M, MAKSYMUK T, et al. Method of Centralized Resource Allocation in Virtualized Small Cells Network with IoT Overlay [C]//*14th International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (TCSET)*. Lviv-Slavske, Ukraine, 2018: 1147 – 1151. DOI: 10.1109/tcset.2018.8336397
- [21] GUO H Z, LIU J J, ZHANG J, et al. Mobile-Edge Computation Offloading for Ultra-dense IoT Networks [J]. *IEEE Internet of Things Journal*, 2018, 5(6): 4977 – 4988. DOI: 10.1109/jiot.2018.2838584
- [22] PARK Y, KIM S. Game-Based Data Offloading Scheme for IoT System Traffic Congestion Problems [J]. *EURASIP Journal on Wireless Communications and Networking*, 2015, 2015(1): 192. DOI: 10.1186/s13638-015-0418-y
- [23] ZHANG H J, QIU Y, CHU X L, et al. Fog Radio Access Networks: Mobility Management, Interference Mitigation, and Resource Optimization [J]. *IEEE Wireless Communications*, 2017, 24(6): 120 – 127. DOI: 10.1109/mwc.2017.1700007
- [24] TRAN T X, HAJISAMI A, PANDEY P, et al. Collaborative Mobile Edge Computing in 5G Networks: New Paradigms, Scenarios, and Challenges [J]. *IEEE Communications Magazine*, 2017, 55(4): 54 – 61. DOI: 10.1109/mcom.2017.1600863
- [25] ZENG Y, WU Q Q, ZHANG R. Accessing from the Sky: A Tutorial on UAV Communications for 5G and Beyond [J]. *Proceedings of the IEEE*, 2019, 107(12): 2327 – 2375. DOI: 10.1109/jproc.2019.2952892
- [26] HOSSEIN MOTLAGH N, TALEB T, AROUK O. Low-Altitude Unmanned Aerial Vehicles-Based Internet of Things Services: Comprehensive Survey and Future Perspectives [J]. *IEEE Internet of Things Journal*, 2016, 3(6): 899 – 922. DOI: 10.1109/jiot.2016.2612119
- [27] MOZAFFARI M, SAAD W, BENNIS M, et al. A Tutorial on UAVs for Wireless Networks: Applications, Challenges, and Open Problems [J]. *IEEE Communications Surveys & Tutorials*, 2019, 21(3): 2334 – 2360. DOI: 10.1109/comst.2019.2902862
- [28] FENG W, WANG J C, CHEN Y F, et al. UAV-Aided MIMO Communications for 5G Internet of Things [J]. *IEEE Internet of Things Journal*, 2019, 6(2): 1731 – 1740. DOI: 10.1109/jiot.2018.2874531
- [29] WANG J J, JIANG C X, ZHANG H J, et al. Thirty Years of Machine Learning: The Road to Pareto - Optimal Next - Generation Wireless Networks [EB/OL]. (2019-01-24). <https://arxiv.org/abs/1902.01946>
- [30] BOUTABA R, SALAHUDDIN M A, LIMAM N, et al. A Comprehensive Survey on Machine Learning for Networking: Evolution, Applications and Research Opportunities [J]. *Journal of Internet Services and Applications*, 2018, 9(1): 16. DOI: 10.1186/s13174-018-0087-2
- [31] LUONG N C, HOANG D T, GONG S M, et al. Applications of Deep Reinforcement Learning in Communications and Networking: A Survey [J]. *IEEE Communications Surveys & Tutorials*, 2019, 21(4): 3133 – 3174. DOI: 10.1109/comst.2019.2916583
- [32] CHEN M Z, CHALLITA U, SAAD W, et al. Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial [J]. *IEEE Communications Surveys & Tutorials*, 2019, 21(4): 3039 – 3071. DOI: 10.1109/comst.2019.2926625
- [33] KLAINE P V, IMRAN M A, ONIRETI O, et al. A Survey of Machine Learning Techniques Applied to Self-Organizing Cellular Networks [J]. *IEEE Communications Surveys & Tutorials*, 2017, 19(4): 2392 – 2431. DOI: 10.1109/comst.2017.2727878
- [34] SUN Y H, PENG M G, ZHOU Y C, et al. Application of Machine Learning in Wireless Networks: Key Techniques and Open Issues [J]. *IEEE Communications Surveys & Tutorials*, 2019, 21(4): 3072 – 3108. DOI: 10.1109/comst.2019.2924243
- [35] FOTOUHI A, QIANG H R, DING M, et al. Survey on UAV Cellular Communications: Practical Aspects, Standardization Advancements, Regulation, and Security Challenges [J]. *IEEE Communications Surveys & Tutorials*, 2019, 21(4): 3417 – 3442. DOI: 10.1109/comst.2019.2906228
- [36] ZHANG J, ZHOU L, TANG Q, et al. Stochastic Computation Offloading and Trajectory Scheduling for UAV-Assisted Mobile Edge Computing [J]. *IEEE Internet of Things Journal*, 2018, 6(2): 3688 – 3699. DOI: 10.1109/jiot.2018.2890133
- [37] CHENG F, ZHANG S, LI Z, et al. UAV Trajectory Optimization for Data Offloading at the Edge of Multiple Cells [J]. *IEEE Transactions on Vehicular Technology*, 2018, 67(7): 6732 – 6736. DOI: 10.1109/tvt.2018.2811942
- [38] LIU B C, HUANG H W, GUO S, et al. Joint Computation Offloading and Routing Optimization for UAV - Edge - Cloud Computing Environments [C]//*IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, Guangzhou, China, 2018: 1745 – 1752. DOI: 10.1109/smartworld.2018.00295
- [39] TI N T, LE L B. Joint Resource Allocation, Offloading Computation, and Path Planning for UAV Based Hierarchical Fog-Cloud Mobile Systems [C]//*IEEE Seventh International Conference on Communications and Electronics (ICCE)*, Hue, Vietnam, 2018: 373 – 378. DOI: 10.1109/icc.2018.8465572
- [40] MERWADAY A, GUVENC I. UAV Assisted Heterogeneous Networks for Public Safety Communications [C]//*IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*, New Orleans, USA, 2015: 329 – 334. DOI: 10.1109/wcncw.2015.7122576
- [41] HAINZL M. Integrating UAVs into Public Safety LTE Networks [R]. Tech. Rep., 2014.
- [42] ZHAO N, LU W D, SHENG M, et al. UAV-Assisted Emergency Networks in Disasters [J]. *IEEE Wireless Communications*, 2019, 26(1): 45 – 51. DOI: 10.1109/mwc.2018.1800160
- [43] LIU X N, LI Z, ZHAO N, et al. Transceiver Design and Multi-Hop D2D for UAV IoT Coverage in Disasters [J]. *IEEE Internet of Things Journal*, 2018, 6(2): 1803 – 1815. DOI: 10.1109/jiot.2018.2877504
- [44] MOHRI M, ROSTAMIZADEH A, TALWALKAR A. *Foundations of Machine Learning* [M]. Cambridge, USA: MIT press, 2012
- [45] SUTTON R S, BARTO A G. *Reinforcement Learning: An Introduction* [M]. Cambridge, USA: MIT press, 1998. DOI: 10.1109/tnn.1998.712192
- [46] HOWARD R A. *Dynamic Programming and Markov Processes* [M]. New York, USA: Technology Press of the Massachusetts Institute of Technology, 1960. DOI: 10.2307/2312519
- [47] MNH V, KAVUKCUOGLU K, SILVER D, et al. Human-Level Control through Deep Reinforcement Learning [J]. *Nature*, 2015, 518(7540): 529 – 533. DOI: 10.1038/nature14236
- [48] MNH V, BADIA A P, MIRZA M, et al. Asynchronous Methods for Deep Reinforcement Learning [C]//*International Conference on Machine Learning*, New York, USA, 2016: 1928 – 1937
- [49] LILLICRAP T P, HUNT J J, PRITZEL A, et al. Continuous Control with Deep Reinforcement Learning [EB/OL]. (2015-09-09). <https://arxiv.org/abs/1509.02971>
- [50] HE Y, ZHANG Z, ZHANG Y H. A Big Data Deep Reinforcement Learning Approach to Next Generation Green Wireless Networks [C]//*IEEE Global Communications Conference*, Singapore, Singapore, 2017: 1 – 6. DOI: 10.1109/glocom.2017.8254717
- [51] YU S, WANG X, LANGAR R. Computation Offloading for Mobile Edge Computing: A Deep Learning Approach [C]//*IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*. Montreal, Canada, 2017: 1 – 6. DOI: 10.1109/pimrc.2017.8292514
- [52] HE Y, LIANG C C, ZHANG Z, et al. Resource Allocation in Software-Defined and Information-Centric Vehicular Networks with Mobile Edge Computing [C]//*IEEE 86th Vehicular Technology Conference (VTC-Fall)*, Toronto, Canada, 2017: 1 – 5. DOI: 10.1109/vtcfall.2017.8288203
- [53] HE Y, ZHAO N, YIN H X. Integrated Networking, Caching, and Computing for Connected Vehicles: A Deep Reinforcement Learning Approach [J]. *IEEE Transactions on Vehicular Technology*, 2018, 67(1): 44 – 55. DOI: 10.1109/

- tv.2017.2760281
- [54] HE Y, YU F R, ZHAO N, et al. Software-Defined Networks with Mobile Edge Computing and Caching for Smart Cities: A Big Data Deep Reinforcement Learning Approach [J]. *IEEE Communications Magazine*, 2017, 55(12): 31 – 37. DOI: 10.1109/mcom.2017.1700246
- [55] ZHANG C, LIU Z, GU B, et al. A Deep Reinforcement Learning Based Approach for Cost- and Energy-Aware Multi-Flow Mobile Data Offloading [J]. *IEEE Transactions on Communications*, 2018, E101.B(7): 1625 – 1634. DOI: 10.1587/transcom.2017cqp0014
- [56] TAN L T, HU R Q. Mobility-Aware Edge Caching and Computing in Vehicle Networks: A Deep Reinforcement Learning [J]. *IEEE Transactions on Vehicular Technology*, 2018, 67(11): 10190 – 10203. DOI:10.1109/tvt.2018.2867191
- [57] LI J, GAO H, LV T, et al. Deep Reinforcement Learning Based Computation Offloading and Resource Allocation for MEC [C]//2018 IEEE Wireless Communications and Networking Conference (WCNC). Barcelona, Spain, 2018: 1 – 6. DOI:10.1109/wcnc.2018.8377343
- [58] CHEN X F, ZHANG H G, WU C, et al. Performance Optimization in Mobile-Edge Computing Via Deep Reinforcement Learning[C]//2018 IEEE 88th Vehicular Technology Conference (VTC-Fall). Chicago, USA, 2018. DOI: 10.1109/vtcfall.2018.8690980
- [59] CHEN X F, ZHANG H G, WU C, et al. Optimized Computation Offloading Performance in Virtual Edge Computing Systems Via Deep Reinforcement Learning [J]. *IEEE Internet of Things Journal*, 2019, 6(3): 4005 – 4018. DOI:10.1109/iot.2018.2876279
- [60] MIN M H, XIAO L, CHEN Y, et al. Learning-Based Computation Offloading for IoT Devices with Energy Harvesting [J]. *IEEE Transactions on Vehicular Technology*, 2019, 68(2): 1930 – 1941. DOI: 10.1109/tvt.2018.2890685
- [61] QUAN L, WANG Z L, REN F J. A Novel Two-Layered Reinforcement Learning for Task Offloading with Tradeoff Between Physical Machine Utilization Rate and Delay [J]. *Future Internet*, 2018, 10(7): 60. DOI: 10.3390/fi10070060
- [62] HUANG L, FENG X, ZHANG L X, et al. Multi-Server Multi-User Multi-Task Computation Offloading for Mobile Edge Computing Networks [J]. *Sensors*, 2019, 19(6): 1446. DOI: 10.3390/s19061446
- [63] GHANAVI R, KALANTARI E, SABBAGHAN M, et al. Efficient 3D Aerial Base Station Placement Considering Users Mobility by Reinforcement Learning [C]//IEEE Wireless Communications and Networking Conference (WCNC), Barcelona, Spain, 2018: 1 – 6. DOI: 10.1109/wcnc.2018.8377340
- [64] WU J, YU P, FENG L, et al. 3D Aerial Base Station Position Planning Based on Deep Q-network for Capacity Enhancement [C]//FIP/IEEE Symposium on Integrated Network and Service Management (IM), Arlington, USA, 2019: 482 – 487
- [65] ZHANG Q Q, SAAD W, BENNIS M, et al. Predictive Deployment of UAV Base Stations in Wireless Networks: Machine Learning Meets Contract Theory [EB/OL]. (2018–11–03). <https://arxiv.org/abs/1811.01149>
- [66] VALENTINO R, JUNG W S, KO Y B. A Design and Simulation of the Opportunistic Computation Offloading with Learning-Based-Prediction for Unmanned Aerial Vehicle (UAV) Clustering Networks [J]. *Sensors*, 2018, 18(11): 3751. DOI: 10.3390/s18113751
- [67] BAYERLEIN H, DE KERRET P, GESBERT D. Trajectory Optimization for Autonomous Flying Base Station via Reinforcement Learning [C]//IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Kalamata, Greece, 2018: 1 – 5. DOI:10.1109/spawc.2018.8445768
- [68] CUI J J, LIU Y W, NALLANATHAN A. Multi-Agent Reinforcement Learning Based Resource Allocation for UAV Networks [J]. *IEEE Transactions on Wireless Communications*, 2019: 1. DOI:10.1109/twc.2019.2935201
- [69] LIU C H, CHEN Z Y, TANG J, et al. Energy-Efficient UAV Control for Effective and Fair Communication Coverage: A Deep Reinforcement Learning Approach [J]. *IEEE Journal on Selected Areas in Communications*, 2018, 36(9): 2059 – 2070. DOI:10.1109/jsac.2018.2864373
- [70] NAWAZ S J, SHARMA S K, WYNE S, et al. Quantum Machine Learning for 6G Communication Networks: State-of-the-Art and Vision for the Future [J]. *IEEE Access*, 2019, 7: 46317 – 46350. DOI: 10.1109/access.2019.2909490
- [71] LETAIEF K B, CHEN W, SHI Y M, et al. The Roadmap to 6G: AI Empowered Wireless Networks [J]. *IEEE Communications Magazine*, 2019, 57(8): 84 – 90. DOI: 10.1109/mcom.2019.1900271
- [72] O'BRIEN C. Why 6G Research Is Starting Before We Have 5G [EB/OL]. (2019–7–1). <https://venturebeat.com/2019/03/21/6g-research-starting-before-5g>

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A Survey on Machine Learning Based Proactive Caching

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Abstract: The world today is experiencing an enormous increase in data traffic, coupled with demand for greater quality of experience (QoE) and performance. Increasing mobile traffic leads to congestion of backhaul networks. One promising solution to this problem is the mobile edge network (MEN) and consequently mobile edge caching. In this paper, a survey of mobile edge caching using machine learning is explored. Even though a lot of work and surveys have been conducted on mobile edge caching, our efforts in this paper are rather focused on the survey of machine learning based mobile edge caching. Issues affecting edge caching, such as caching entities, caching policies and caching algorithms, are discussed. The machine learning algorithms applied to edge caching are reviewed followed by a discussion on the challenges and future works in this field. This survey shows that edge caching can reduce delay and subsequently the backhaul traffic of the network; most caching is conducted at the small base stations (SBSs) and caching at unmanned aerial vehicles (UAVs) is recently used to accommodate mobile users who dissociate from SBSs. This survey also demonstrates that machine learning approach is the state of the art and reinforcement learning is predominant.

Keywords: mobile edge caching; reinforcement learning; unmanned aerial vehicle

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<http://kns.cnki.net/kcms/detail/34.1294>.

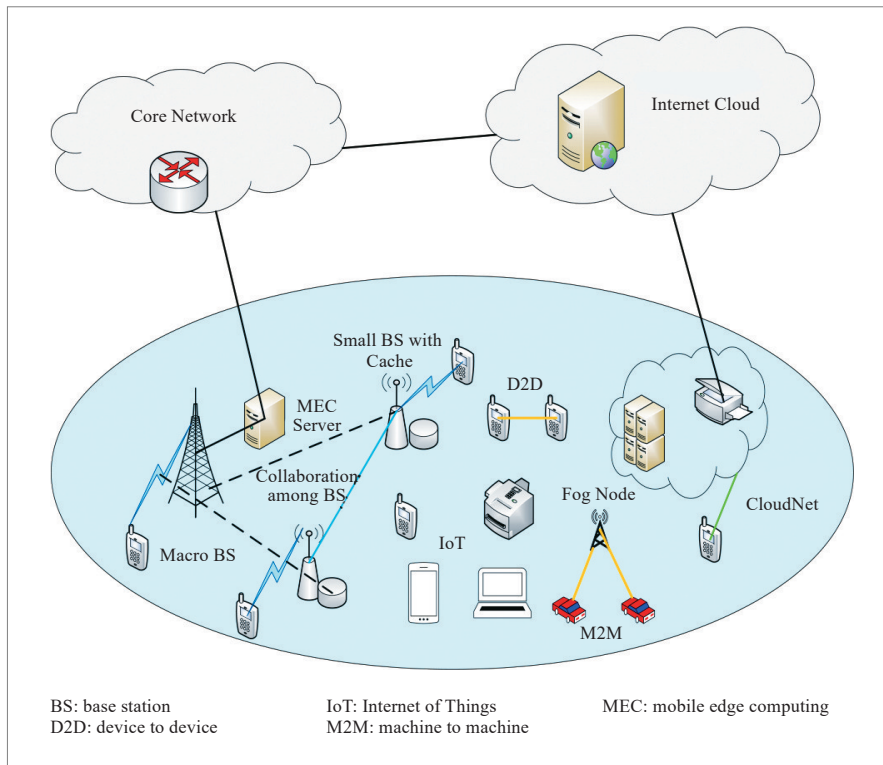
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1 Introduction

The world is witnessing an astronomical growth of mobile traffic and an ever-increasing demand from end users for high bandwidth and quality of experience (QoE) because they do almost everything and share vast amounts of data, documents, media, etc. on their mobile devices. Mobile data traffic grew fast between 2011 and 2016 and is estimated to increase to 49.0 exabytes per month by 2021 [1]. Increasing mobile traffic leads to congestion of backhaul networks, which further leads to a higher cost of operation and maintenance, a lower quality of service (QoS), and inhibits data delivery. The increasing demand for bandwidth coupled with greater QoE and performances is beyond the current fourth generation (4G) technologies, and new solutions such as the fifth generation (5G) technologies have emerged. In order to meet

the increasing data demands, small-cell networks will be widely deployed, which can achieve much higher throughput and energy efficiency [2]. Mobile edge networks (MENs), as shown in **Fig. 1**, are a promising solution to address the above issues (increasing demand for bandwidth, congestion of backhaul networks, higher cost of operation and maintenance, a lower QoS, demand for greater QoE and performance, etc.). By moving the network functions and resources closer to end users (i.e., the network edge), many benefits can be obtained, such as high data rates, low delay, improved energy efficiency, and flexible network deployment and management [3]. One innovative proposal to overcoming these challenges is caching the content. While the two common locations for caching the content are at the evolved packet core (EPC) and the radio access network (RAN) [4]. Certain popular contents (e.g., on-the-air TV series



▲ Figure 1. Architecture of a mobile edge network.

and popular music) are frequently requested; such contents can be cached during off-peak times at the network edge, such as at base stations (BSs) and even user devices [5]. Then the contents are distributed to requesters through high-rate and low-cost mobile edge networks rather than transmitted through the backhaul network repeatedly.

There is an emerging paradigm shift towards the use of unmanned aerial vehicles (UAVs) to assist the traditional cellular networks in wireless communications to provide connectivity from the sky to ground users. Such communication from the sky is expected to be a major component of beyond 5G cellular networks. When mobile users move outside the cell coverage areas, the cached contents may not be effectively distributed to the users. In addition, when a user hands over to a new cell, the contents requested may not be cached, leading to extra delay and bandwidth consumption due to the caching in the new BS or long-distance fetch from the content server. Also, in drone cells, the limited fronthaul capacity can hardly satisfy the demands of data-craving services [6]. To alleviate the pressure of small cells and reduce the cost of densely deployed small base stations (SBSs), UAVs can be exploited to assist small cells in providing high-speed transmission due to their low cost and high mobility. UAV-aided wireless networks can establish wireless connections without infrastructure, realize larger wireless coverage, and achieve higher transmission rate. This makes it suitable for many practical applications, such as terrestrial BS offloading [7], emergency response and public

safety [8], Internet of Things (IoT) communications [9], [10], and massive machine type communications [11]. A lot of surveys have been conducted on edge caching over the years. In [12], various cache management systems were suggested to enhance the performance of mobile Ad hoc networks (MANETs). The authors of [13] presented a comprehensive overview of the recently proposed in-network caching mechanisms for information centric networks (ICNs). They described each caching mechanism in detail, presented examples to illustrate how it works and extensive simulations, and discussed the remaining research challenges. The authors of [14] provided a review of the caching problems in ICNs, with a focus on on-path caching. To this end, a detailed analysis of the existing caching policies and forwarding mechanisms that complement these policies were given in [14]. The paper [15] grouped the most interesting caching techniques with regard to different architectures, considering the cases and the quality of the solutions.

Additionally, the survey [12] outlined various cooperative caching schemes in wireless sensor networks (WSN) and classified them in distinct categories based on type of approach applied. Maintaining cache consistency is as important as caching data. This paper also gave a brief overview of various cache consistency models. GLASS et al. [16] developed a unique taxonomy for cache discovery, surveyed a representative set of MANET-based cooperative caching schemes, and classified the associated cache discovery techniques within the taxonomy. Using this classification, they then highlighted the various cache discovery techniques that have been utilized, analyzed their potential in addressing the specific challenges that occur when deploying non-safety applications within vehicular Ad hoc networks (VANETs), and identified general pitfalls that should be avoided. In [17], a survey of cache management strategies in ICNs was presented along with their contributions and limitations, and their performance was evaluated in a simulation network environment with respect to cache hit, stretch ratio, and eviction operations. Some unresolved ICN caching challenges and directions for future research in this networking area were also discussed.

The paper [18] provided a systematical survey of the state-of-the-art caching techniques that were recently developed in cellular networks, including macro-cellular networks, heterogeneous networks, device-to-device networks, cloud-radio access networks, and fog-radio access networks. In particular, its authors gave a tutorial on the fundamental caching techniques and introduced caching algorithms from three aspects, i. e. ,

content placement, content delivery, and joint placement and delivery. They also provided comprehensive comparisons among different algorithms in terms of different performance metrics, including throughput, backhaul cost, power consumption, and network delay; finally, they summarized the main research achievements in different networks and highlighted main challenges and potential research directions. A detailed survey on the emerging technologies to achieve low latency communications was presented in [19], considering three different solution domains: RAN, core network, and caching; a general overview of major 5G cellular network elements such as software defined network (SDN), network function virtualization (NFV), caching, and mobile edge computing (MEC) capable of meeting latency and other 5G requirements was also presented. Finally, [20] presented an overview of caching in wireless networks and then provided a detailed comparison of traditional and popularity-based caching. The attributes of videos and the evaluation criteria of caching policies were discussed, some of the recent works on proactive caching, focusing on prediction strategies, were summarized, and an insight into the potential opportunities and challenges as well as some open research issues enabling the realization of efficient deployment of popularity-based caching as part of the next-generation mobile networks were provided.

- Even though a lot of work and surveys have been done on mobile edge caching [13] – [15], this survey is focused on the study of machine learning based mobile edge caching.

- We discuss the issues that affect caching in mobile edge networks in general and the use of UAVs to cache contents introduced.

- We discuss learning techniques applied to caching in mobile edge networks.

The rest of the paper is organized as follows. Section 2 outlines some of the issues that affect edge caching. Section 3 discusses learning based caching schemes and Section 4 analyzes the challenges and future directions. Conclusions are drawn in Section 5.

2 Mobile Edge Caching

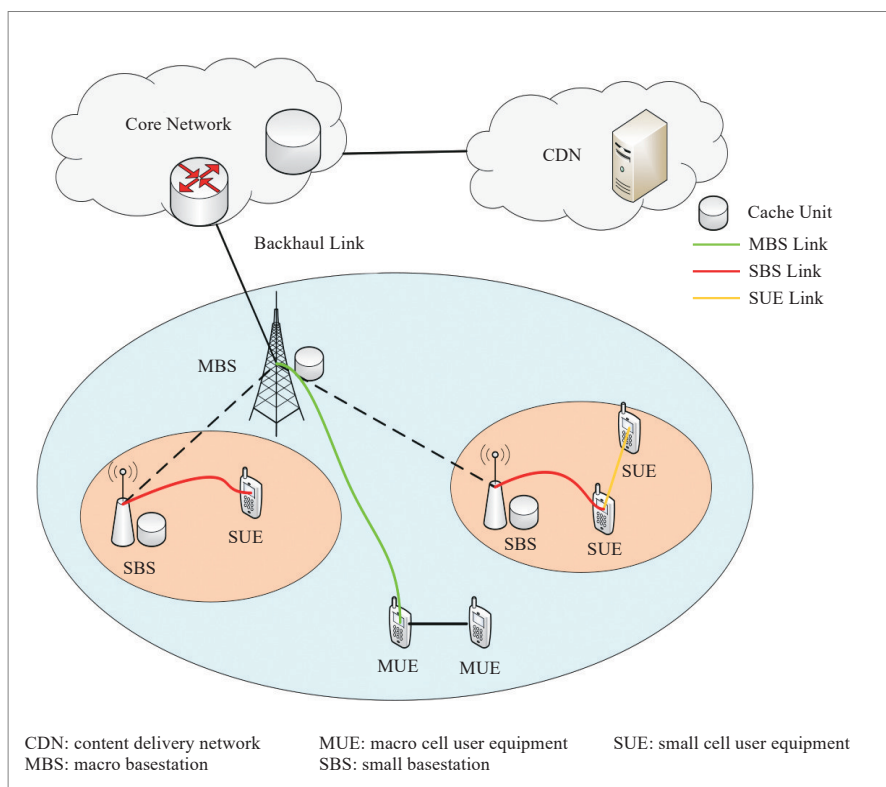
Many caching schemes pose such questions as where to cache, what to cache, and how to cache. Answers to these questions provide us with better caching solutions. A lot of research work has been done in trying to answer some of the above questions using various methods. Heuristic, stochastic and various optimization techniques have been applied on caching solutions. As the network gets so dynamic and com-

plex, such methods become too difficult and complex to be implemented, hence the introduction of machine learning in the caching solutions to mobile edge caching (architecture shown in Fig. 2). In this section, we will survey the research efforts that have been made in the mobile edge networks. The related issues include caching entities, content description, caching policies, content delivery, and so on.

2.1 Caching Entities

Caching units can be deployed in many places of a mobile network, such as the core network, RAN, user devices and current UAVs, to cater for mobile users. Currently the widely deployed places of caching is the EPC [4]. By caching content at the mobile core network, the mobile traffic can be reduced. The caching places at the edge network are discussed as follows.

1) Macro BS (MBS) caching: In heterogeneous networks, MBSs have more coverage areas and can serve more users. Caching at the MBS can obtain better cache hit probability. CAO and CAI in [21] investigated a context-aware proactive caching problem in a heterogeneous network consisting of a single MBS with grid power supply and multiple small-cells with energy harvesting, aiming to maximize the service ratio at the SBSs. The authors of [22] presented Wolpertinger architecture for content caching at the macro base station. The proposed framework aims at maximizing the long-term cache hit rate and it requires no knowledge of the content popularity dis-



▲ Figure 2. Architecture of edge caching.

tribution. Furthermore, Context-aware data caching in the heterogeneous small cell networks (HSCNs) with MBS caching was proposed in [23], [35] to reduce the service delay for end users.

2) SBS caching: SBSs are densely deployed in next generation heterogeneous networks. Therefore, caching at SBSs is another good choice since the SBSs are more close to end users and usually provide higher data rates. Many researchers [18], [21], [24] have studied the performance of caching at SBSs.

3) Device caching: device-to-device (D2D) communication is one of the key technologies in 5G networks. The storage resources in mobile devices can be exploited. The QoE of users can be greatly improved by caching contents in mobile devices if the caching strategy is carefully designed. In [25], the D2D caching problem was modeled as a multi-agent multi-armed bandit problem and Q-learning was used to learn how to coordinate the caching decisions. Several D2D caching schemes with the application of learning techniques have been proposed [26] – [29].

4) UAV caching: A new trend of caching entity is the use of UAVs as a flying BS to cache popular contents that would be able to serve mobile users. The authors of [6] solved the problem of content caching with multi UAVs while considering the user mobility by using a novel algorithm based on the machine learning framework of conceptor-based echo state networks. In this framework, the agent is able to learn the mobility patterns and request distributions of the users; based on that, it can predict the contents for caching at the UAVs and the location of the UAVs, and can effectively deliver the contents to the users. Additionally, the liquid state machine is used to maximize the queue stability requirements of users while caching the contents at the UAV [30].

2.2 Caching Policies and Algorithms

To decide what to cache, the caching policies and algorithms are used in the edge networks and the popularity of content should be considered to maximize the hit probability of cache, i. e., the probability that the content requested by users is cached in the edge networks. Even though content popularity can be grouped into Static [31] and Dynamic [28], [32], the static ones cannot reflect the real content popularity which is time varying so the dynamic one is more realistic and suitable for the learning based caching schemes. The commonly used popularity model is the Zipf model observed in web caching [33].

A host of caching policies and algorithms have been proposed in mobile caching. Some of the conventional caching policies in wired networks are also applicable in wireless networks. In addition, new schemes such as learning based policies and cooperative caching policies are also proposed. The literature [16] reviews in detail the conventional caching policies and forwarding mechanism in information centric networks.

1) Conventional versus learning based caching policies: Content replacement policies such as the least frequently used (LFU) and least recently used (LRU) have been adopted in a large number of caching policies [16]. These strategies are simple and efficient with uniform size objects. However, these policies ignore the download latency and size of objects. Another proactive caching policy used in content delivery networks is the most popular video (MPV) policy, which caches the most popular videos based on the global video popularity distribution [34]. However, the cache size of the RAN is very limited compared to that of CDN. The hit probability achieved by MPV policy could be too low for RAN caches. On the other hand, the content popularity is time-varying and is not known in advance. Therefore, the track and estimation of timely content popularity is an important issue. Based on machine learning technology, learning based caching policies were proposed in [35]. The authors in [35] solved the problem of distributed caching in SBSs from a reinforcement learning view. By adopting coded caching, the caching problem is reduced to a linear program that considers the network connectivity and the coded caching scheme performs better than the uncoded scheme. The authors in [36] solved the cache replacement problem with a Q-learning based strategy.

2) User preference based policies: In [34], the authors proposed a user preference profile (UPP) based caching policy. It is observed that local video popularity is significantly different from national video popularity and users may show strong preferences toward specific video categories. The UPP of each user is defined as the probability that a user requests videos of a specific video category.

3) Non-cooperative versus cooperative caching: Some of the existing caching policies decide the content to cache at each base station without considering the cooperation among BSs. In [34], the proposed scheme makes caching decision based on the UPP of active users in a specific cell without considering the impact of caches in other cells. In [36], the cache replacement problem modeled as Markov Decision Process (MDP) is solved in a distributed way using Q-learning method, without exchanging extra information about cached data between the BSs. This strategy outperforms the conventional ones such as the LFU, LRU and randomized strategy. However, a lot of existing works have studied the cooperation among cache entities when designing the caching policies [26], [37] – [40].

2.3 Caching of Different File Types

The most common file types for caching is multimedia files such as popular videos and audio files [26], [38], [41]. One essential trait of multimedia data is that many users have the same affinity for popular contents, thus caching of such contents aid in improving the hit rate. The Internet of Things is one of the main use cases of the next generation 5G networks. IoT refers to a large number of “things” (devices, objects, humans and animals with unique IDs) connected via the Internet

that can share data. Thus the caching of IoT data (sensory and any kind of data including multimedia data) is also important for reducing the total traffic load as the IoT data volume is increasing and IoT data have different characteristics such as short lifespan of the data as compared to multimedia data [42], [43].

2.4 Mobility versus Static User Awareness

User mobility is a unique feature of wireless networks, thus it should be considered in caching at the network edge. Many works have been done on this issue. The authors in [44] proposed a temporal-spatial recommendation policy, which can guide mobile users to request their preferred files in proper time and place, so as to make local popularity peakier. Here the assumption was that the user preference, the impact of the recommendation on request probability, and the mobility pattern are unknown. Hence, they resorted to deep reinforcement learning to optimize the recommendation and caching policy. User mobility in the caching policies was also considered in [29] and [45].

2.5 Impact on System Performance

1) Capacity: Existing works on edge caching have proved that caching at the network edge can significantly improve system capacity. For example, the solution proposed in [34] can improve capacity by 3 times compared to having no cache in the RAN.

2) Delay: Caching at the network edge can significantly reduce content delivery delay due to the proximity of caches to end users. In [26], the reinforcement learning cooperative content caching scheme significantly reduced content download-

ing latency and improved content cache hit rate when compared with other popular caching schemes. In [39], the authors investigated a delay minimization problem by jointly considering the spatiotemporal variation of content variation, the cost of content sharing between user devices, and the cost of cooperative caching among BSs, using a two-stage multi-armed bandit learning based online cooperative algorithm.

3) Spectral efficiency: a deep reinforcement learning (DRL) based algorithm was developed for coded caching enabled Fog RAN (F-RANs) in [46] to provide high spectral and energy efficiency. With the help of new designed fog access points (F-APs), F-RANs can take the full advantage of local caching capabilities, which relieves the load of fronthaul and reduces transmission delay. In [47], a cache content management policy was proposed, which exploited the popularity of the contents in order to increase the chances of D2D communications. With extensive simulations in [47], it was observed that the proposed Q-learning algorithm indeed learns by reserving near-optimal number of resource blocks (RBs) to serve the data rate requirement at each distributed D2D controller (DDC) and that the one-and two-hop modes of D2D transfer effectively reduces the load on eNB by transferring a maximum 49% of the required data to the user equipment (UE). A summary of the issues affecting edge caching is shown in **Table 1**.

3 Learning Based Caching

The traditional optimization techniques become complex and difficult to solve due to the complex nature of the caching problems. Therefore, the machine learning approaches are introduced into solving these kinds of problems. Machine learn-

▼ **Table 1. Summary of literatures on edge caching**

Work Area	Literature	Key Points
Caching entities	[15], [21], [23], [31], [37], [47], [49], [51] – [53]	Macro base station (MBS)
	[18], [21] – [25], [28], [29], [31], [35] – [38], [41], [43], [44], [46], [49], [50], [52] – [54]	Small base station (SBS)
	[25] – [29], [39], [47], [51], [55]	Device
	[6], [30], [55], [56]	Unmanned aerial vehicle (UAV)
Content popularity	[31]	Static model
	[6], [21], [22], [24], [26] – [29], [32], [34] – [36], [39] – [41], [44], [45], [49], [50] – [52], [54] – [57]	Dynamic model
Caching policies and algorithms	[16], [34], [48]	Conventional caching policies
	[28], [29], [34], [44], [52], [58]	User preference based policies
	[6], [21] – [30], [35] – [41], [43] – [47], [49] – [51], [53] – [57]	Learning based policies
	[34]	Non-cooperative policies
	[22], [23], [26], [28], [30], [37] – [40], [51], [54], [55], [57]	Cooperative policies
Caching file types	[6], [21] – [24], [26] – [30], [32], [34] – [41], [44] – [47], [49] – [51], [53], [55], [57] – [59]	Multimedia data
	[42], [43], [48], [59]	Internet of Things (IoT) data
Mobility awareness	[6], [29], [30], [44], [45], [48], [49], [51], [52]	Spatial and temporal properties of user mobility
Problem	[23], [24], [26], [27], [34], [37] – [39], [41], [43], [46], [50], [52], [55], [58]	Delay
	[22] – [26], [37], [44]	Hit rate
	[35], [36], [39] – [41], [45] – [47]	Backhaul/fronthaul
	[6], [34], [49], [58]	Quality of experience (QoE)

ing techniques are generally grouped into the supervised learning, unsupervised learning, and reinforcement learning. This section will discuss the application of these learning techniques in caching.

3.1 Supervised Learning Based Caching

The majority of practical machine learning uses supervised learning. Supervised learning uses an algorithm to learn the mapping from input variables X to the output variable ($Y = f(X)$) based on example input-output pairs. The goal would be a model that would approximate the mapping function so well that when you have new input data (X), you can predict the output variables (Y) for that data.

VARANASI and CHILUKURI [48] proposed a differentiated edge caching scheme called FlexiCache for vehicle to anything (V2X) communication, aiming at increasing the QoS of the network; kernel ridge regression (KRR) is used to predict the proportion of cache to be allocated to each traffic type, for a desired QoS parameter.

CHEN, et al. [30] used the liquid state machine to solve the problem of joint caching and resource allocation in a network of cache-enabled UAVs that serve wireless ground users over the Long Term Evolution (LTE) licensed and unlicensed bands.

SHEN et al. [49] considered caching selected contents of SBSs in an ultra-dense network (UDN). The cache efficiency problem is formulated as a system backhaul load minimization problem, which is hard to be solved for the highly random content demands. Therefore, the cache strategies based on machine learning (K-means and K-Nearest Neighbour (K-NN)) were proposed to tackle this difficult problem from the perspective of exploiting the potential of mobile traffic data. Other machine learning schemes include [23], [38], [40], [50], etc.

3.2 Unsupervised Learning Based Caching

For unsupervised learning, you only have input data (X) and no corresponding output variables. The goal of unsupervised learning is to learn more about data by modeling the underlying structure or distribution in the data. The algorithms are left to their own devices to discover and present the interesting structure in the data. Examples are found in the literatures [27], [28], [32], and [49].

In [49], the K-means clustering algorithm was used to fully uncover hidden spatio-temporal patterns of content requests at SBSs, and achieve personalized inter-cluster cache and predictive intra-cluster cache. Then, the K-NN classification algorithm was introduced to categorize the constantly emerging new contents and cache them in the corresponding cluster periodically with high accuracy and low complexity.

The authors in [27] proposed an efficient learning-based caching algorithm operating together with a non-parametric estimator to minimize the average transmission delay in D2D-enabled cellular networks. It is assumed that the system does not have any prior information regarding the popularity of the files, and the non-parametric estimator is aimed at learning the in-

tensity function of the file requests. An algorithm was devised to determine the best <file,user> pairs that provide the best delay improvement in each loop to form a caching policy with very low-transmission delay and high throughput. This algorithm was also extended to address a more general scenario, in which the distributions of fading coefficients and the values of system parameters potentially change over time.

In order to learn user preference, the authors of [28] modeled the user request behavior resorting to probabilistic latent semantic analysis and the model parameters are learned by the expectation maximization algorithm. They found that the user preferences are less similar and the activity level and topic preference of each user change slowly over time. Based on this observation, they introduced a prior knowledge-based learning algorithm for user preference, which can shorten the learning time.

Based on SDN, the authors of [32] proposed a deep-learning-based content popularity prediction (DLCPP) to achieve the popularity prediction. DLCPP adopts the switch's computing resources and links in the SDN to build a distributed and reconfigurable deep learning network. For DLCPP, they initially determine the metrics that can reflect changes in content popularity. Each network node collects the spatial-temporal joint distribution data of these metrics. Then, the data are used as input to stacked auto-encoders (SAE) in DLCPP to extract the spatiotemporal features of popularity. Finally, the popularity prediction is transformed into a multi-classification problem through discretizing the content popularity into multiple classifications. The Softmax classifier is used to achieve the content popularity prediction.

3.3 Reinforcement Learning Based Caching

In reinforcement learning, an agent is able to learn from its environment and take some action so as to maximize some notion of cumulative reward with or without a model. The authors of [22], inspired by the success of DRL in solving complicated control problems, presented a DRL-based framework with Wolpertinger architecture for content caching at the base station. The proposed framework is aimed at maximizing the long-term cache hit rate, and it requires no knowledge of the content popularity distribution. SUNG et al. [37] applied reinforcement learning (Q-learning) to the content replacement problem in a wireless content delivery network (WCDN) with cooperative caching to maximize the hit ratio based on a multi-agent Q-learning scheme.

CHENG et al. [52] proposed a novel localized deterministic caching framework, based on machine learning techniques. By introducing the concept of the rating matrix, they first proposed a new Bayesian learning method to predict personal preferences and estimate the (individual content request probability) ICRP. This crucial information was then incorporated into their caching strategy for maximizing the system throughput, or equivalently, minimizing the download latency, where a deter-

ministic caching algorithm based on reinforcement learning was proposed to optimize the content placement. The authors of [42] presented fundamentals of caching, major challenges, relevant state of the art, and a description of their current approaches. They showed directions of using machine learning for caching in the IoT.

Additionally, the authors of [58] proposed a multi-agent reinforcement learning (MARL)-based cooperative content caching policy for the MEC architecture when the users' preference is unknown and only the historical content demands can be observed. They formulated the cooperative content caching problem as a multi-agent multi-armed bandit problem and proposed a MARL-based algorithm to solve the problem. In [26], the D2D caching problem is modeled as a multi-agent multi-armed bandit problem and use Q-learning to learn how to coordinate the caching decisions. The user devices can be independent learners if they learn the Q-values of their own actions, or joint action learners if they learn the Q-values of their own actions in conjunction with those of other UEs. The authors of [25] presented Stimulable Neural Network (SNN)-Cache that leverages SNN to utilize the inter-relationships among sequenced requests in caching decision, evaluated SNN-Cache using an ICN simulator, and showed that it decreases the load of content servers significantly compared to a recent size-aware cache replacement algorithm (up to 30.7%) as well as the traditional cache replacement algorithms.

Furthermore, SADEGHI et al. [57] introduced a novel approach to account for space-time popularity of user requests by casting the caching task in a reinforcement learning (RL) framework for heterogeneous networks (Hetnets). HE et al. [51] formulated an optimization problem to maximize the network operator's utility while considering the trust-based social

networks specifically with MEC, in-network caching and D2D communications under the umbrella of a 3C framework using a deep reinforcement learning approach. An integrated framework that can enable dynamic orchestration of networking, caching and computing resources to improve the performance of next generation vehicular networks was studied in [60] and in this framework, the resource allocation strategy is formulated as a joint optimization problem and DRL is used for problem solving. The authors of [61] dealt with an information-centric virtualized network for smart cities with a deep Q learning approach for caching. There are other reinforcement based caching schemes proposed in [26], [29], [43], [44], [46], [50], and [59]. **Table 2** summarizes some of the machine learning techniques applied to mobile edge caching.

4 Challenges and Future Directions

Like traditional networks, wireless networks are faced with similar challenges like communication cost, storage and computation. The major challenge of caching is the limited storage space. Because of this, a caching scheme must carefully consider the caching decision and replacement techniques to overcome the challenge and improve the performance such as backhaul traffic, latency, and throughput of the network.

4.1 Online Caching

Caching has the content placement phase during which the content is placed in the caching unit and the content delivery phase during which the content is actually delivered to the end user (entity). At some point in the life span of the content, the content may require updating. One efficient caching update is update during the content delivery phase rather

▼ **Table 2. A summary of machine learning techniques applied to edge caching**

Type of Machine Learning	Literature	Algorithm
Supervised learning	[6]	Eco state network
	[30]	Liquid state network
	[22], [49]	K-Nearest Neighbour (KNN)
	[48]	Kernel ridge regression (KRR)
	[38], [40], [50]	Deep learning
	[23]	Convolutional neural network (CNN)
	[25]	Stimulable neural network (SNN)
Unsupervised learning	[27], [28], [32], [49]	K-means
	[27], [28]	Greedy based algorithm
	[32]	Stacked auto encoders (SAEs) deep learning
Reinforcement learning	[57]	Q-learning
	[44] - [46], [51]	Deep Q-learning
	[60]	Double-dueling-deep Q-network
	[22], [34], [37], [43]	Actor critic
	[26], [58]	Multi agent Q-learning
	[21]	Post decision state based approximate RL (PDS-ARL)
	[52]	Discrete learning automata (DLA)

than the content placement phase. This is known as online caching. Online caching together with machine learning presents itself as an important direction in the future cache research.

4.2 UAV Caching

A major problem of mobile edge caching is the mobility of users. Mobile users tend to dissociate themselves from their associated base stations. The advent of UAV caching and machine learning techniques in the future 5G networks would help to solve this bottleneck by employing UAVs as flying base stations to help to proactively cache content for such mobile users. The UAV can assist cellular networks or can be a complete UAV network on their own depending on the application.

4.3 Context Awareness

The mobile edge networks are advantageous in exploiting context information (user location, other surrounding users, and resources in the environment). The real time context aware applications could be accomplished with the use of machine learning by collaborations among MEC platforms.

4.4 Virtualization

In the future 5G networks, different service providers would be providing different services with different QoS and QoE. Network infrastructure are expensive, so there is the need for the research into providing virtual networks that would be able to efficiently share and utilize the underlying physical infrastructure.

4.5 Integration

The architecture of mobile edge networks involves resources such as computing, storage and communications. The efficient integration of these resources to achieve the optimal performance for all users and applications is an ongoing research direction that is not concluded. More comprehensive resource allocation schemes need to be developed.

5 Conclusions

This paper surveys and summarizes the research efforts made on the mobile edge caching and communication resources. The related issues of caching are discussed. Additionally, machine learning based caching schemes are discussed and summarized. In this survey, we group the machine learning based caching into reinforcement learning and other learning techniques. We realize that reinforcement learning is more widely used because of its ability to interact and learn from the environment with or without a model. The more recent UAV caching is also introduced which is able to deal with mobile users that request content. Finally, the challenges and future works on mobile edge caching are discussed.

References

- [1] IndexC. V. N. Cisco Visual Networking Index : Global Mobile Data Traffic Forecast, 2016 – 2021 [R]. CISCO, PapWhite. Feb. 2017
- [2] WANG N, HOSSAIN E, BHARGAVA V K. Backhauling 5G Small Cells: A Radio Resource Management Perspective [J]. IEEE Wireless Communications, 2015, 22(5): 41 – 49. DOI: 10.1109/MWC.2015.7306536
- [3] WANG S, ZHANG X, ZHANG Y, et al. A Survey on Mobile Edge Networks: Convergence of Computing, Caching and Communications [J]. IEEE Access, 2017, 5: 6757 – 6779. DOI: 10.1109/ACCESS.2017.2685434
- [4] WANG X, CHEN M, TALEB T, et al. Cache in the Air: Exploiting Content Caching and Delivery Techniques for 5G Systems [J]. IEEE Communications Magazine, 2014, 52(2): 131 – 139. DOI: 10.1109/MCOM.2014.6736753
- [5] SU Z, XU Q, HOU F, et al. Edge Caching for Layered Video Contents in Mobile Social Networks [J]. IEEE Transactions on Multimedia, 2017, 19(10): 2210 – 2221. DOI: 10.1109/TMM.2017.2733338
- [6] CHEN M, MOZAFFARI M, SAAD W, et al. Caching in the Sky: Proactive Deployment of Cache-Enabled Unmanned Aerial Vehicles for Optimized Quality-of-Experience [J]. IEEE Journal on Selected Areas in Communications, 2017, 35(5): 1046 – 1061. DOI: 10.1109/JSAC.2017.2680898
- [7] LYU J, ZENG Y, ZHANG R. UAV-Aided Offloading for Cellular Hotspot [J]. IEEE Transactions on Wireless Communications, 2018, 17(6): 3988 – 4001. DOI: 10.1109/TWC.2018.2818734
- [8] MERWADAY A, GUVENC I. UAV Assisted Heterogeneous Networks for Public Safety Communications [C]//IEEE Wireless Communications and Networking Conference Workshops (WCNCW), New Orleans, USA, 2015: 329 – 334. DOI: 10.1109/WCNCW.2015.7122576
- [9] MOZAFFARI M, SAAD W, BENNIS M, et al. Mobile Internet of Things: Can UAVs Provide an Energy-Efficient Mobile Architecture? [C]//IEEE Global Communications Conference, Washington DC, USA, 2016: 4 – 8. DOI: 10.1109/GLOCOM.2016.7841993
- [10] ZHAN C, ZENG Y, ZHANG R. Energy-Efficient Data Collection in UAV Enabled Wireless Sensor Network [J]. IEEE Wireless Communications. Letters, 2018, 7(3): 328 – 331. DOI: 10.1109/LWC.2017.2776922
- [11] SOORKI M N, MOZAFFARI M, SAAD W, et al. Resource Allocation for Machine-to-Machine Communications with Unmanned Aerial Vehicles [C]//IEEE Globecom Workshops, Washington, USA, 2016: 1 – 6. DOI: 10.1109/GLOCOMW.2016.7849026
- [12] GUPTA S, SHARMA T P. Cooperative Data Caching in MANETs and WSNs: A Survey [C]//International Conference on Intelligent Computing, Instrumentation and Control Technologies, Kannur, India, 2018: 6 – 7. DOI: 10.1109/ICICICT1.2017.8342787
- [13] ZHANG M, LUO H, ZHANG H. A Survey of Caching Mechanisms in Information-Centric Networking [J]. IEEE Communications Surveys & Tutorials, 2015, 17(3): 1473 – 1499. DOI: 10.1109/COMST.2015.2420097
- [14] IOANNOU A, WEBER S. A Survey of Caching Policies and Forwarding Mechanisms in Information-Centric Networking [J]. IEEE Communications Surveys & Tutorials, 2016, 18(4): 2847 – 2886. DOI: 10.1109/COMST.2016.2565541
- [15] ABOUAMAR A, FILALI A, KOBANE A. Caching, Device-to-Device and Fog Computing in 5th Cellular Networks Generation: Survey [C]//International Conference on Wireless Networks and Mobile Communications, Rabat, Morocco, 2017: 1 – 4. DOI: 10.1109/WINCOM.2017.8238174
- [16] GLASS S, MAHGOUB I, RATHOD M. Leveraging MANET-Based Cooperative Cache Discovery Techniques in VANETs: A Survey and Analysis [J]. IEEE Communications Surveys & Tutorials, 2017, 19(4): 2640 – 2661. DOI: 10.1109/COMST.2017.2707926
- [17] DIN I U, HASSAN S, KHAN M K, et al. Caching in Information-Centric Networking: Strategies, Challenges, and Future Research Directions [J]. IEEE Communications Surveys & Tutorials, 2018, 20(2): 1443 – 1474. DOI: 10.1109/COMST.2017.2787609
- [18] LI L, ZHAO G, BLUM R S. A Survey of Caching Techniques in Cellular Networks: Research Issues and Challenges in Content Placement and Delivery Strategies [J]. IEEE Communications Surveys & Tutorials, 2018, 20(3): 1710 – 1732. DOI: 10.1109/COMST.2018.2820021
- [19] PARVEZ I, RAHMATI A, GUVENC I, et al. A Survey on Low Latency Towards 5G: RAN, Core Network and Caching Solutions [J]. IEEE Commun. Surv. Tutorials, 2018, 20(4): 3098 – 3130. DOI: 10.1109/COMST.2018.2841349
- [20] GOIAN H S, AL-JARRAH O Y, MUHAIDAT S, et al. Popularity-Based Video

- Caching Techniques for Cache-Enabled Networks: A Survey [J]. IEEE Access, 2019, 7: 27699 – 27719. DOI: 10.1109/ACCESS.2019.2898734
- [21] CAO H, CAI J. Context-Aware Proactive Caching for Heterogeneous Networks with Energy Harvesting: An Online Learning Approach [C]//IEEE International Congress on Cybermatics, Halifax, Canada, 2018. DOI: 10.1109/Cybermatics_2018.2018.00073
- [22] ZHONG C, GURSOY M C, VELIPASALAR S. A Deep Reinforcement Learning-Based Framework for Content Caching [C]//52nd Annual Conference on Information Sciences and Systems, Princeton, USA, 2018. DOI: 10.1109/CISS.2018.8362276
- [23] TSAI K C, WANG L, HAN Z. Mobile Social Media Networks Caching with Convolutional Neural Network [C]//IEEE Wireless Communications and Networking Conference Workshops (WCNCW), Barcelona, Spain, 2018: 83 – 88. DOI: 10.1109/WCNCW.2018.8368988
- [24] BLASCO P, GUNDUZ D. Learning-Based Optimization of Cache Content in a Small Cell Base Station [C]//IEEE International Conference on Communications (ICC), Sydney, Australia, 2014: 1897 – 1903. DOI: 10.1109/ICC.2014.6883600
- [25] IM Y, PRAHLADAN P, KIM T H, et al. SNN-Cache: A Practical Machine Learning-Based Caching System Utilizing the Inter-Relationships of Requests [C]//52nd Annual Conference on Information Sciences and Systems, Princeton, USA, 2018. DOI: 10.1109/CISS.2018.8362281
- [26] JIANG W, FENG G, QIN S, et al. Multi-Agent Reinforcement Learning for Efficient Content Caching in Mobile D2D Networks [J]. IEEE Transactions on Wireless Communications, 2019, 18(3): 1610 – 1622. DOI: 10.1109/TWC.2019.2894403
- [27] LI Y, ZHONG C, GURSOY M C, et al. Learning-Based Delay-Aware Caching in Wireless D2D Caching Networks [J]. IEEE Access, 2018, 6: 77250 – 77264. DOI: 10.1109/ACCESS.2018.2881038
- [28] CHEN B, YANG C. Caching Policy for Cache-Enabled D2D Communications by Learning User Preference [J]. IEEE Transactions on Communications, 2018, 66(12): 6586 – 6601. DOI: 10.1109/TCOMM.2018.2863364
- [29] WANG C, WANG S, LI D, et al. Q-Learning Based Edge Caching Optimization for D2D Enabled Hierarchical Wireless Networks [C]//IEEE 15th International Conference on Mobile Ad Hoc and Sensor Systems (MASS), Chengdu, China, 2018: 55 – 63. DOI: 10.1109/MASS.2018.00019
- [30] CHEN M, SAAD W, YIN C. Liquid State Machine Learning for Resource Allocation in a Network of Cache-Enabled LTE-U UAVs [C]//IEEE Global Communications Conference, Singapore, Singapore, 2018: 1 – 6. DOI: 10.1109/GLOCOM.2017.8254746
- [31] PASCHOS G, BASTUG E, LAND I, et al. Wireless Caching: Technical Misconceptions and Business Barriers [J]. IEEE Communications Magazine, 2016, 54(8): 16 – 22. DOI: 10.1109/MCOM.2016.7537172
- [32] LIU W X, ZHANG J, LIANG Z W, et al. Content Popularity Prediction and Caching for ICN: A Deep Learning Approach with SDN [J]. IEEE Access, 2017, 6: 5075 – 5089. DOI: 10.1109/ACCESS.2017.2781716
- [33] BRESLAU L, CAO P, FAN L, et al. Web Caching and Zipf-Like Distributions: Evidence and Implications [C]//IEEE INFOCOM, New York, USA, 1999: 126 – 134. DOI: 10.1109/INFCOM.1999.749260
- [34] AHLEHAGH H, DEY S. Video-Aware Scheduling and Caching in the Radio Access Network [J]. IEEE/ACM Transactions on Networking, 2014, 22(5): 1444 – 1462. DOI: 10.1109/TNET.2013.2294111
- [35] SENGUPTA A, AMURU S, TANDON R, et al. Learning Distributed Caching Strategies in Small Cell Networks [C]//11th International Symposium on Wireless Communications Systems, Barcelona, Spain, 2014: 917 – 921. DOI: 10.1109/ISWCS.2014.6933484
- [36] GU J, WANG W, HUANG A, et al. Distributed Cache Replacement for Caching-Enable Base Stations in Cellular Networks [C]//IEEE International Conference on Communications (ICC), Sydney, Australia, 2014: 2648 – 265. DOI: 10.1109/ICC.2014.6883723
- [37] SUNG J, KIM K, KIM J, et al. Efficient Content Replacement in Wireless Content Delivery Network with Cooperative Caching [C]//IEEE International Conference on Machine Learning and Applications, Anaheim, USA, 2016. DOI: 10.1109/ICMLA.2016.0096
- [38] PANG H, LIU J, FAN X, et al. Toward Smart and Cooperative Edge Caching for 5G Networks: A Deep Learning Based Approach [C]//IEEE/ACM 26th International Symposium on Quality of Service, Banff, Canada, 2018: 1 – 6, 2019. DOI: 10.1109/IWQoS.2018.8624176
- [39] NIU Y, QIN X, ZHANG Z. A Learning-Based Cooperative Caching Strategy in D2D Assisted Cellular Networks [C]//24th Asia-Pacific Conference on Communications, Ningbo, China, 2018: 269 – 274. DOI: 10.1109/APCC.2018.8633483
- [40] SAPUTRA Y M, HOANG D T, NGUYEN D N, et al. Distributed Deep Learning at the Edge: A Novel Proactive and Cooperative Caching Framework for Mobile Edge Networks [J]. IEEE Wireless Communications Letters, vol. 8, no. 4, pp. 1220 – 1223, 2019. DOI: 10.1109/LWC.2019.2912365
- [41] THAR K, OO T Z, TUN Y K, et al. A Deep Learning Model Generation Framework for Virtualized Multi-Access Edge Cache Management [J]. IEEE Access, 2019, 7: 62734 – 62749. DOI: 10.1109/ACCESS.2019.2916080
- [42] PAHL M O, LIEBALD S, WUSTRICH L. Machine-Learning Based IoT Data Caching [C]//IFIP/IEEE Symposium on Integrated Network and Service Management, Arlington, USA, 2019
- [43] WEI Y, YU F R, SONG M, et al. Joint Optimization of Caching, Computing, and Radio Resources for Fog-Enabled IoT Using Natural Actor-Critic Deep Reinforcement Learning [J]. IEEE Internet of Things Journal, 2019, 6(2): 2061 – 2073. DOI: 10.1109/JIOT.2018.2878435
- [44] GUO K, YANG C. Temporal-Spatial Recommendation for Caching at Base Stations via Deep Reinforcement Learning [J]. IEEE Access, 2019, 7: 8519 – 58532. DOI: 10.1109/ACCESS.2019.2914500
- [45] TAN L T, HU R Q. Mobility-Aware Edge Caching and Computing in Vehicle Networks: A Deep Reinforcement Learning [J]. IEEE Transactions on Vehicular Technology, 2018, 67(11): 10190 – 10203. DOI: 10.1109/TVT.2018.2867191
- [46] ZHOU Y, PENG M, YAN S, et al. Deep Reinforcement Learning Based Coded Caching Scheme in Fog Radio Access Networks [C]//IEEE/CIC International Conference on Communications in China, Beijing, China, 2018: 309 – 313. DOI: 10.1109/ICCChinaW.2018.8674478
- [47] KUMAR N, SWAIN S N, SIVA RAM MURTHY C. A Novel Distributed Q-Learning Based Resource Reservation Framework for Facilitating D2D Content Access Requests in LTE-A Networks [J]. IEEE Transactions on Network and Service Management, 2018, 15(2): 718 – 731. DOI: 10.1109/TNSM.2018.2807594
- [48] VARANASI V S, CHILUKURI S. Adaptive Differentiated Edge Caching with Machine Learning for V2X Communication [C]//International Conference on Communication Systems and Networks, Bengaluru, India, 2019. DOI: 10.1109/COMSNETS.2019.8711328
- [49] SHEN G, LI P, PAN Z W, et al. Machine learning based small cell cache strategy for ultra dense networks [C]//9th International Conference on Wireless Communications and Signal Processing, Nanjing, China, 2017: 1 – 6. DOI: 10.1109/WCSP.2017.8170936
- [50] LEI L, YOU L, DAI G, et al. A Deep Learning Approach for Optimizing Content Delivering in Cache-Enabled HetNet [C]//International Symposium on Wireless Communication Systems, Bologna, Italy, 2017: 449 – 453. DOI: 10.1109/ISWCS.2017.8108157
- [51] HE Y, YU F R, ZHAO N, et al. Secure Social Networks in 5G Systems with Mobile Edge Computing, Caching, and Device-to-Device Communications [J]. IEEE Wireless Communications, 2018, 25(3): 103 – 109. DOI: 10.1109/MWC.2018.1700274
- [52] CHENG P, MA C, DING M, et al. Localized Small Cell Caching: A Machine Learning Approach Based on Rating Data [J]. IEEE Transactions on Communications, 2019, 67(2): 1663 – 1676. DOI: 10.1109/TCOMM.2018.2878231
- [53] SUN G, AL-WARD H, BOATENG G O, et al. Autonomous Cache Resource Slicing and Content Placement at Virtualized Mobile Edge Network [J]. IEEE Access, 2019, 7(c): 84727 – 84743. DOI: 10.1109/ACCESS.2019.2923021
- [54] QIU C, YAO H, YU F R, et al. Deep Q-Learning Aided Networking, Caching, and Computing Resources Allocation in Software-Defined Satellite-Terrestrial Networks [J]. IEEE Transactions on Vehicular Technology, 2019, 68(6): 5871 – 5883. DOI: 10.1109/TVT.2019.2907682
- [55] XU X, ZENG Y, GUAN Y L, et al. Overcoming Endurance Issue: UAV-Enabled Communications with Proactive Caching [J]. IEEE Journal on Selected Areas in Communications, 2018, 36(6): 1231 – 1244. DOI: 10.1109/JSAC.2018.2844979
- [56] JIANG B, YANG J, XU H, et al. Multimedia Data Throughput Maximization in Internet-of-Things System Based on Optimization of Cache-Enabled UAV [J]. IEEE Internet of Things Journal, 2019, 6(2): 3525 – 3532. DOI: 10.1109/JIOT.2018.2886964
- [57] SADEGHI A, SHEIKHOLESLAMI F, GIANNAKIS G B. Optimal and Scalable Caching for 5G Using Reinforcement Learning of Space-Time Popularities [J].

- IEEE Journal of Selected Topics in Signal Processing, 2018, 12(1): 180 – 190. DOI: 10.1109/JSTSP.2017.2787979
- [58] JIANG W, FENG G, QIN S, et al. Multi-Agent Reinforcement Learning Based Cooperative Content Caching for Mobile Edge Networks [J]. IEEE Access, 2019, 7: 61856 – 61867. DOI: 10.1109/ACCESS.2019.2916314
- [59] ZHU H, CAO Y, WEI X, et al. Caching Transient Data for Internet of Things: A Deep Reinforcement Learning Approach [J]. IEEE Internet of Things Journal, 2019, 6(2): 2074 – 2083. DOI: 10.1109/IIOT.2018.2882583
- [60] HE Y, ZHAO N, YIN H. Integrated Networking, Caching, and Computing for Connected Vehicles: A Deep Reinforcement Learning Approach [J]. IEEE Transactions on Vehicular Technology, 2018, 67(1): 44 – 55. DOI: 10.1109/TVT.2017.2760281
- [61] HE Y, RICHARD Y F, ZHAO N, et al. Software-Defined Networks with Mobile Edge Computing and Caching for Smart Cities: A Big Data Deep Reinforcement Learning Approach [J]. IEEE Communications Magazine, 2017, 55(12): 31 – 37. DOI: 10.1109/MCOM.2017.1700246

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A Survey on Network Operation and Maintenance Quality Evaluation Models

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Abstract: The evaluation of network operation and maintenance quality is an important reference for carriers to improve their service. However, the traditional evaluation methods involve so much human participation that it cannot cope with the explosive amount of data. Therefore, both the major carriers and researchers are trying to find solutions to evaluate the quality of network operation and maintenance more objectively and accurately. In this paper, we analyze the general process of quality evaluation models for network operation and maintenance. The process has four steps: 1) selection of evaluation indicators; 2) data process for chosen indicators; 3) determination of indicator weights; 4) establishment of evaluation models. We further describe the working principle of each step, especially the methods for indicator selection and weight determination. Finally, we review the recently proposed evaluation models and the international standards of network operation and maintenance quality evaluation.

Keywords: quality evaluation; network operation and maintenance; quality of service; indicator selection; weight determination

1 Introduction

Great progress has been made in the research of communication technologies. The coverage of voice network has been expanding, the 4G network has been widely put into use, and the 5G technology is continuously developing [1]. With the popularity of mobile communication devices, the number of users has also been increasing explosively, which makes the competition among major carriers become fiercer [2]. In order to take up more market share, the carriers utilize various approaches such as market research, user questionnaire, drive test, and network quality evaluation. Network quality evaluation is a comprehensive approach, involving quality of service evaluation, the efficiency of maintenance evaluation, etc. Quality evaluation is also utilized in education, economics, management and other fields. It is a good way to assess work results and improve work methods.

In the process of network quality evaluation, we usually use indicators to measure the quality of network in different aspects. These indicators come from drive test data, ticket data or alarm data supplied by the carriers. However, with the expansion of communication networks and services, various device types and the huge number of devices bring difficulties to

traditional evaluation methods for the quality evaluation of operation and maintenance. First of all, it is impossible to take all of the original indicators into the evaluation process, since the traditional indicator selection methods need too much resource and lacks objectivity and comprehensiveness. Second, data heterogeneity caused by different types of devices from different manufacturers makes data integration a challenge. In addition, the expansion of user groups and network scopes, as well as the use of automatic drive test technology, has also brought a surge of data, which inevitably has an impact on the efficiency of calculation.

How to establish a proper and accurate quality evaluation model for network operation and maintenance has become an important issue. The international standard organizations, such as International Telecommunications Union (ITU) and Telecom Management Forum (TMF), have defined the quality of service (QoS) models and the related parameters [3] - [8]. Many researchers at home and abroad have proposed their quality evaluation models or methods. This paper conducts a survey on the research about how to evaluate the quality of network operation and maintenance and sums up the general construction process of the evaluation model.

2 Construction Process of Quality Evaluation Model

The methods for obtaining the condition of a network in-

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clude custom survey, alarm systems, ticket records, drive tests, etc. The alarm systems record the data, such as fault elements, fault occurrence time, failure time, which is the primary reference for carriers to predict and resolve the emergent problems. The ticket records include handling time, reply delay, failure cause, solving methods and influence, which is always used for evaluating maintenance efficiency. The drive test is the most common method in the industry to test the wireless signal. It can provide the signal strength, voice quality, business establishment success rate, average throughput of uplink and downlink, and some other crucial data. The automatic drive test system has been popular in recent years, making it possible to expand the scope and increase the frequency of the test, therefore get more accurate data and reduce the costs. The explosive growth of the data mentioned above, which is derived from various sources and has different formats, brings challenges to the traditional manual evaluation methods.

Many researchers have proposed their quality evaluation models and methods, and have improved the key technologies. We summarized the general process of constructing the quality evaluation model of network operation and maintenance by taking a survey on the state-of-the-art technologies in detail. The process can be divided into the following four steps:

1) Evaluation indicator selection: In this step, we pick up important indicators from the original indicator set to reduce the difficulty of data processing and calculation. At the stage of choosing the indicators, an important principle is that the indicators should be as comprehensive as possible without information overlap.

2) Data process for chosen indicators: The major task is to change data into a unified format which can make it easy to calculate and integrate. First we quantify the qualitative data, that is, change the natural language data into numerical terms. And then we process all the data of chosen indicators in a normalized way, so that the data will have the same units of measurement for mathematical operations, such as adding or multiplying.

3) Determination of indicator weights: In this step, we utilize the weight to reflect the importance of the chosen indicator. Then we do some mathematical operations according to the weight of indicators to enhance the accuracy of the evaluation result. Although there are many studies relying on expert experience to specify the weight, those methods may result in different evaluations for different experts. In this article, we sum up the objective weight determination methods which could reduce human participation as far as possible to ensure the accuracy and objectivity of a quality evaluation model.

4) Establishment of evaluation model: The final step is to determine the proper evaluation formula. We study on how to combine weights and data and how to combine the scores of each indicator to get the final evaluation results.

When a quality evaluation model is constructed, these four steps are in a linear order. We select the crucial indicator first to reduce the amount of data, which will make the following

processes easier. And only the data are standardized to the same dimension can they be utilized to weight calculation and the final integration operation.

3 Evaluation Indicators Selection

The evaluation indicators indicate the evaluation content and the evaluation result is obtained by statistical analysis of the evaluation indicators. With the progress of communication technology, the communication network is becoming complex, and the service provided by carriers diverse, which leads to the increase of the number of relevant indicators. Evaluating all the indicators will result in great computation complexity and information overlap. So we should obtain a smaller indicator set of network operation and maintenance quality evaluation model by filtering the original indicator set. The selected indicator set should be concise enough without missing the information of the original indicator.

Traditionally, the indicator selection is usually completed by experts based on subjective experience. Although the indicator set obtained in this way is concise and specific, it cannot guarantee the comprehensiveness and non-overlapping of the indicator information. Several international standard organizations have proposed some general models and the related terminology definitions, but has not given the concrete appraisal target. Therefore, we surveyed the literature [9] – [11] and summed up a number of commonly used indicator selection methods.

LI et al. [9] proposed an indicator classification method which requires multiple data sets to compute the cross-correlation coefficients of indicators in different datasets. The cross-correlation coefficient is usually used in the signal domain to indicate the similarity between two signal curves. We utilize the absolute value form of the cross-correlation coefficient for analyzing. The greater the absolute values of two indicators indicate, the more similar they are. The data sequence of an indicator is a kind of time series data, which is similar to the discrete signal data. The correlation coefficient could be utilized to represent the similarity between two indicators. Suppose two indicators x and y are time series data with m samples respectively, then the formula of the correlation between the two indicators could be represented as r_{xy} :

$$r_{xy} = \frac{\sum_{i=1}^m (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^m (x_i - \bar{x})^2 \cdot \sum_{i=1}^m (y_i - \bar{y})^2}}, \quad (1)$$

where x_i and y_i represent the i -th sample of indicators x and y respectively, and \bar{x} and \bar{y} are the mean values of these two indicators.

According to the law of correlation, two indicators are highly correlated when the absolute value of the correlation number is greater than 0.7 [9]. The paper takes many different data sets into account, and calculates the correlation of the chosen indi-

cators respectively. Two indicators are similar if they are highly correlated in most datasets. Then we can use one of them to represent this class of indicators.

DENG et al. [10] made a detailed description of the conditional generalized minimum variance method, which is similar to the method mentioned above. But this method does not involve correlation coefficient in judging the similarity between indicators. In this paper, if the value of an indicator set is constant meanwhile the amplitude variation of another indicator set is very small, the two indicator sets have a strong correlation. If we delete one of it, there will be tiny information loss. This method arranges the data sequences of the chosen indicator set as a matrix. The length of each data sequence should be the same. Then it uses the determinant of the matrix, that is, the generalized variance to reflect the change of the indicators. The range of generalized variance is between 0 and 1. The larger the generalized variance is, the more independent the indicator data series is. If the data sequences of two indicators are linearly related, the generalized variance is 0.

After using the method mentioned in literature [9] to divide the indicator set into several classes, the next step is to choose the appropriate indicators in each class to represent the entire class. Similarly, when the two indicator sets have similar information, we need to determine which one to be deleted in the method in [10]. In the industry there is no appropriate method now, but we can use the expert experience to choose the more commonly used and more representative indicators. This method is not only objective and accurate, but also takes the key indicators of carriers concerned into account, which accords with economic benefit.

Another method, principal component analysis is mentioned in the literature [11]. This method changes a given set of related variables into another set of uncorrelated variables by linear transformation and keeps the total variance of the variables constant. The new variables are arranged according to the descending order of variance. The variable with the largest variance is called the first principal component, the variable with the second variance the second principal component, and so on. The preceding variable has more significant influence on the result of the evaluation and should be retained while the latter variable has less influence and should be discarded. We use the method of characteristic root to determine whether a variable should be retained; that is, if the characteristic root of a variable is greater than 1, it will be retained and vice versa. Although this method is just a rule of thumb, many examples have proved it very simple and reliable.

The indicator classification method based on correlation and the conditional generalized minimum variance method are same in concept. Both the methods remove the indicators which have similar information from the original indicator set. The difference between the two methods is that different parameters are utilized to calculate the similarity between the indicators. The principal component analysis can also get the importance of in-

dicators, but it may need a great amount of computation.

4 Data Process for Chosen Indicators

The indicator set may contain some qualitative indicators, which need to be quantified, and then can be combined with other quantitative indicators. Quantitative indicators are indicators which have numerical values while qualitative indicators are indicators whose member is the evaluation or description of the subjects. Qualitative indicators usually include categorical and sequential indicators [12]. We can use the mean or the median method to quantify the sequential indicators, which has a clear order or degree of relationship between the indicators. Literature [10] uses a median approach. Assuming that an indicator has n values, a_1, a_2, \dots, a_n , after the quantization process the value becomes X_1, X_2, \dots, X_n . Assuming a_i as a normal distribution, we divided the X_i value into n segments according to a probability distribution, and X_i is the median of each segment, where X follows the $N(0, 1)$ distribution. By querying the normal distribution table, we can get the value of X_i .

The value of categorical indicators usually is unstructured and disordered. It is challenging to use objective methods to quantify categorical indicators. Most of the examples rely on expert experience for a rough estimate. This type of data usually appears in coal mining, water conservancy, finance and services industries. In the network operation and maintenance quality evaluation, this data mainly appears in the manual fill-in ticket data, such as "business impact", "troubleshooting results" and other indicators. ZHANG et al. [13] used a statistical figure collecting method, which is a subjective quantification approach for qualitative indicators. In this method, the experts give their prediction about the range of the evaluation. The range given by different experts on the same indicators may be different. A smaller range indicates greater accuracy of prediction and vice versa, and thus determines the weight of each expert. By combing the weight, we can get the comprehensive quantification value, according to statistical figure collecting principles.

In addition, the selected indicator data needs to be normalized. Normalized processing refers to the elimination of the impact of the magnitude by changing the actual value of the indicators to a normalized form that can be integrated with other indicators, which makes it possible to integrate the evaluation of indicators. The normalized processing methods commonly used are the Z-score normalization method and min-max normalization method [14]. When normalizing the data, we need to divide the indicators into negative indicators and positive indicators. The negative indicator means that the increase of indicator value has a negative impact on the object, while the positive indicator is the indicator that has a positive impact when its value increases. Assume that the indicator I has the data sequence d_1, d_2, \dots, d_n , where the maximum value is d_{\max} and the minimum value is d_{\min} . Using the min-max normaliza-

tion method, the data can be transformed as a normalized value between $[0, 1]$ as s_1, s_2, \dots, s_n . If the data sequence is all the same, the data will be processed as 1, otherwise, the formula is as follows:

$$s_j = \begin{cases} \frac{d_j - d_{\min}}{d_{\max} - d_{\min}}, & I \text{ is positive indicators} \\ \frac{d_{\max} - d_j}{d_{\max} - d_{\min}}, & I \text{ is negative indicators} \end{cases}. \quad (2)$$

5 Determination of Indicator Weights

The weight determination is the most important step in the construction of an evaluation model. A reasonable weight set will enhance the accuracy of the evaluation results. Traditionally, the weight determination relies on expert experience which requires a lot of human resources and lacks objectivity, and makes it difficult to reflect the differences between indicators. We have investigated and summed up the following several objective ways to determine the weight of indicators [10], [15] – [18].

The Analytic Hierarchy Process (AHP) is used to determine the weight [10], [16]. There are four methods of AHP: the geometric mean method, arithmetic mean method, eigenvector method, and least squares method. The basic principles and steps of these four methods are almost the same, which can be divided into three steps:

1) First of all, construct a hierarchical structure model that can be divided into three levels: the target layer, the criterion layer and the program layer. The number of hierarchical levels is related to the complexity of the problem. In general, the number of layers is not limited, but each element of the level should be less than nine.

2) Construct the judgment matrix for each level mentioned above. And conduct the single level ranking and take consistency test.

3) Finally, make the overall ranking and consistency test. And calculate the weight of each level, then integrate all the weights to a comprehensive one.

This method can be used to systematically analyze the problem with a little quantitative data. However, it will result in too many qualitative conclusions and makes it difficult to cope with the situation when there are excessive indicators.

One of the easiest ways is the standard deviation method [15], which uses the standard deviation of the indicator data to measure the degree of deviation of the data from the mean value. If the standard deviation of the data is larger, the variation of the indicator is larger between the different evaluation objects. That is to say, the indicator will provide the greater amount of information and make the greater effect in the evaluation, thus it should be given greater weight. The standard deviation method is used to calculate the i -th indicator's weight w_i in the selected n indicators with the formula as follows:

$$w_i = S_i / \sum_{k=1}^n S_k, \quad (3)$$

where S_i is the standard deviation of the data of the i -th indicator. In addition, regardless of which method is used, the sum of the weights of all the calculated indicators should be constant as 1.

The entropy method [17] is a thermodynamics concept, introduced by Shannon, which is used to measure the uncertainty. There is a similarity between the idea of the entropy method and the standard deviation method. The information entropy of a certain indicator is smaller, the degree of variation of the data is greater, which reflect the indicator and will provide more information therefore should be given greater weight. Suppose there are n indicators, each indicator has m data. The i -th indicator information entropy formula is as follows:

$$E_i = -(\ln m)^{-1} \sum_{j=1}^m p_{ij} \ln p_{ij}, \quad i = 1, 2, \dots, n, \quad (4)$$

where $p_{ij} = d_{ij} / \sum_{j=1}^m d_{ij}$, in which d_{ij} is the j -th data record of the i -th indicator, then the weight of the i -th indicator is:

$$w_i = \frac{1 - E_i}{n - \sum_{i=1}^n E_i}, \quad i = 1, 2, \dots, n. \quad (5)$$

The last weight determination method was proposed in [18]. The degree of similarity is expressed by introducing the conflict between the indicators. The greater the conflict between indicators, the higher the amount of information reflected when the indicators change, and vice versa. The conflict of i -th indicator is calculated as follows:

$$c_i = \sum_{j=1, j \neq i}^n (1 - r_{ij}), \quad i = 1, 2, \dots, n, \quad (6)$$

where r_{ij} is the correlation coefficient between the i -th and j -th indicators. The calculation method of the correlation coefficient can refer to the formula in the indicator selection step. This method combines the aforementioned weights and conflict to obtain the final weight. The weight with conflict of the i -th indicator is determined by w_i and c_i . The formula for calculating the weight with conflict of the indicator W_i is:

$$W_i = \frac{w_i \cdot c_i}{\sum_{i=1}^n w_i \cdot c_i}, \quad i = 1, 2, \dots, n. \quad (7)$$

LUO et al. [15] compared the effects of the aforementioned objective weight determination methods. It turned out that combining the standard deviation method and conflict as above form performs best. In the selection of indicators, we need to pay attention to select the non-overlapping information between the indicators as much as possible. The aforementioned

weight determination method with conflict is one way to achieve this effect.

6 Establishment of Evaluation Model

The last step of building the model is to determine the evaluation formula, combined with the indicator data and the weight to get the final evaluation results. Commonly used evaluation formulas are the linear weighted sum, logarithmic linear weighted sum, mixed weighting, and so on, among which linear weighting is the simplest and easiest. Assuming that n indicators are selected, and the weights of each indicator are w_1, w_2, \dots, w_n . These indicators data sequence is d_1, d_2, \dots, d_n , then the evaluation formula of linear weighting method is:

$$R = d_1 \cdot w_1 + d_2 \cdot w_2 + \dots + d_n \cdot w_n. \quad (8)$$

After the calculation, we will get the score, a value within the range $[0, 1]$, of the object at a certain moment. In this way, the results of the same object at different times will be calculated; hence the fractional curve with time and the mass fluctuation of the object can be obtained. One can also use the top-N algorithm [19] to compare the scores of different objects at the same time and select the first N best or worst objects for analysis. Top-N analysis can narrow the scope of the problem, which is more suitable for carriers to improve prominent problems.

There are some problems existing in the quality evaluation model using the method mentioned above. It is difficult to explain the mean of each time node's fraction, since it can only be explained by comparing with before and after time nodes' fraction. So here a fuzzy comprehensive evaluation method [20] – [22] is introduced to evaluate the quality of network operation and maintenance. The method applies to the case that cannot clearly explain the "good" or "bad" quality, such as the quality of an object at any time node. The fuzzy comprehensive evaluation method also needs to complete indicator selecting, data processing and weight determining, and then needs to determine the membership function and establish the fuzzy evaluation matrix. There are many ways to determine the membership function, such as various types of F distribution. The comprehensive weight can function as a fuzzy evaluation matrix, shown in **Table 1**. The rows of the matrix are the various factors of the evaluation object and the columns are different grades. Each cell in this matrix is the degree of membership of the factor for the grade. If we synthesize all the columns, for

example, taking an averaging operation, we will get the degree of membership to this grade of this object. By calculating the degree of membership to all grades, we choose the largest grade as the final evaluation of the object. We establish the fuzzy evaluation matrix as Table 1, where the data in this table are manually fill-in. We take three factors into account as "Call completing rate", "Reconstruction success rate" and "Uplink user average rate". And we evaluate each factor in three grades as "Good", "Medium" and "Bad". As shown in Table 1, the first cell is 47.6%, which means that the possibility of the call completing rate to be good is 47.6%. After synthesizing each column, we could get the degree of membership of each grade. Then we choose the largest grade as the final evaluation; in this example, the object has the largest possibility to be perfect.

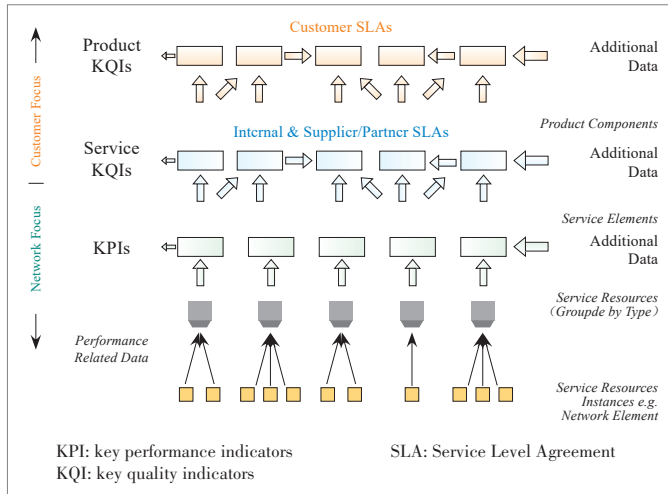
7 International Standards

To deal with the large amounts of heterogeneous data, the standardization of network operation and maintenance quality evaluation methods has become a focus of attention in the industry. The International Organization for Standardization has proposed some general models for assessing network quality, which can serve as a reference for carriers to evaluate network performance, quality of service and so on. In the GB923 handbook [3], the Telecom Management Forum (TMF) proposed a mapping model of key performance indicators (KPIs) and key quality indicators (KQIs). KPI is a measure of performance and KQI is an indicator of the quality of service, which is the integration and supplementation of KPI indicators. In both cases, KPI is based on network performance and KQI is a direct response to the business service performance of the end to end network. In GB923, two kinds of KQIs are defined. One is the product quality KQI, reflecting the quality of the agreement between the carrier and the user. The other is the quality of service KQI, reflecting the quality of a single service. The relationship between these two KQIs is that the quality of service KQI consists of a number of service elements of the KPI composition while the product quality KQI consists of a number of quality of service KQI composition, which ultimately forms as hierarchical structure of the key indicators (**Fig. 1**).

The International Telecommunication Union (ITU) also presents a general model for business performance in the E. 802 standard document [8]. The goal of this model is to analyze the performance issues in detail by a structured approach that facilitates the transformation of identified quality criteria into QoS parameters and can be described with easy-to-understand technical data. The model is expressed in the form of a matrix, where Y-axis is the performance factor of service, and X-axis is the criterion to measure service quality. These elements can cover most aspects of a telecommunication service. The models mentioned in these standard documents cannot be used directly in practice, considering the ac-

▼Table 1. Examples of fuzzy evaluation matrices

	Good	Medium	Bad
Call completing rate	47.6%	32.2%	20.2%
Reconstruction success rate	58.7%	25.6%	15.7%
Uplink user average rate	38.6%	37.7%	23.7%



▲ Figure 1. Key indicator hierarchy [3].

tual situation.

8 Conclusions

In this paper, we summarize the general process of evaluating network operation and maintenance quality, and divide the evaluation process into four steps: selecting the evaluation indicators, processing the data of chosen indicators, determining the weight of indicators, and establishing the evaluation model. The process can also be used in any quality evaluation model of other areas. We introduce each processing step, especially the objective methods which do not rely on expert experience. The general process above has been utilized to establish a network performance quality evaluation model for the Shanxi Branch of China Mobile. The experiment confirmed that this evaluation model has a good predictive effect on performance alerts.

A future direction could be developing a fully unsupervised method, such as clustering, for indicator selection. In addition, the question how to provide a reasonable explanation of the evaluation results and how to properly display the issues still calls for many efforts. Finally, in the actual scenarios of the network, different periods such as working days or weekends may follow different evaluation criteria, which also needs to be explored.

References

- [1] LUO F L. 5G New Radio (NR): Standard and Technology [J]. ZTE Communications, 2017, 15(S1): 1 – 2, 2017
- [2] SU Y Q. M-ICT 2.0: Exploring the Way of Digitalized Transformation [J]. ZTE Technology Journal, 23(1): 53 – 57, 2017. DOI: 10.3969/j.issn.1009-6868.2017.01.013
- [3] TMFORUM. Wireless Service Measurements Handbook GB923 Approved Version 3.0 [Z]. 2004
- [4] ITU-T E.800. Recommendation Definitions of Terms Related to Quality of Service [S]. 2008
- [5] ITU-T E.803. Recommendation Quality of Service Parameters for Supporting Service Aspects [S]. 2011
- [6] ITU-T. How to Increase QoS/QoE of IP-Based Platform(s) to Regionally Agreed Standard [R]. ITU-T Technical Report. 2013
- [7] ITU-T G.1020. Recommendation: Performance Parameter Definitions for Quality of Speech and Other Voiceband Applications Utilizing IP Networks [S]. 2006

- [8] ITU-T E.802. Recommendation: Framework and Methodologies for the Determination and Application of QoS Parameters [S]. 2007
- [9] LI H Z, YUAN C W. The Method of KPI Classification of Mobile Communication Network [J]. Netinfo Security, 2014, (12): 56 – 60
- [10] DENG X, LI J M, ZENG H J, et al. Research on Computation Methods of AHP Weight Vector and Its Applications [J]. Mathematics in Practice & Theory, 2012, 42(7): 93 – 100. DOI: 10.3969/j.issn.1000-0984.2012.07.012
- [11] JOLLIFFE I T. Principal Component Analysis [M]. Berlin, Germany: Springer-Verlag, 1986
- [12] TAKAYAMA K. Journal of Financial and Quantitative Analysis [J]. Annual Review of Fluid Mechanics, 2004(36): 347 – 379. DOI: 10.1146/annurev.fluid.36.050802.121954
- [13] ZHANG W H, WANG J J. The Study of Quantifying Method of Qualitative Index in the Evaluation of Coal Enterprise Logistics Information System [J]. Logistics Sci-Tech, 2007(7)
- [14] MA L P. Standardization of Statistical Data-Dimensionless Method [J]. Beijing Statistics, 2000(3): 34 – 35. DOI: CNKI:SUN:BJTJ.0.2000-03-029
- [15] LUO Y Q, XIA J B, CHEN T P. Comparison of Objective Weight Determination Methods in Network Performance Evaluation [J]. Journal of Computer Applications, 2009, 29(10): 2624 – 2626. DOI: 10.3724/SP.J.1087.2009.02624
- [16] SAATY T L. Analytic Hierarchy Process [M]//Encyclopedia of Biostatistics. Hoboken, USA: John Wiley & Sons, Ltd, 2013:19 – 28
- [17] ZOU Z H, YUN Y, SUN J N. Entropy Method for Determination of Weight of Evaluating Indicators in Fuzzy Synthetic Evaluation for Water Quality Assessment [J]. Journal of Environmental Sciences, 2006, 18(5): 1020 – 1023. DOI: 10.1016/s1001-0742(06)60032-6
- [18] ZHANG H T, MAO H P. Comparison of Four Methods for Deciding Objective Weights of Features for Classifying Stored-Grain Insects Based on Extension Theory [J]. Transactions of the Chinese Society of Agricultural Engineering, 2009, 25(1): 132 – 136. DOI: 10.1306/972009-1549
- [19] CREMONESI P, KOREN Y, TURRIN R. Performance of Recommender Algorithms on Top-N Recommendation Tasks [C]//ACM Conference on Recommender Systems. Copenhagen, Denmark, 2010: 39 – 46. DOI: 10.1145/1864708.1864721
- [20] ZHAO H, TANG X. Evaluation Model of Network Service Performance Based on Fuzzy Analytic Hierarchy Process [J]. Journal of Computer Applications, 2013, 33(11): 3035 – 3038
- [21] JIN J L, WEI Y M, JING D. Fuzzy Comprehensive Evaluation Model Based on Improved Analytic Hierarchy Process [J]. Journal of Hydraulic Engineering, 2004(2): 144 – 147
- [22] HUANG L M, WANG H. Multilevel Fuzzy Comprehensive Evaluation Method of Network Security [J]. Journal of Liaoning Technical University, 2004(23): 510 – 513

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An Improved Non-Geometrical Stochastic Model for Non-WSSUS Vehicle-to-Vehicle Channels

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Abstract: A novel non-geometrical stochastic model (NGSM) for non-wide sense stationary uncorrelated scattering (non-WSSUS) vehicle-to-vehicle (V2V) channels is proposed. This model is based on a conventional NGSM and employs a more accurate method to reproduce the realistic characteristics of V2V channels, which successfully extends the existing NGSM to include the line-of-sight (LoS) component. Moreover, the statistical properties of the proposed model in different scenarios, including Doppler power spectral density (PSD), power delay profile (PDP), and the tap correlation coefficient matrix are simulated and compared with those of the existing NGSM. Furthermore, the simulation results demonstrate not only the utility of the proposed model, but also the correctness of our theoretical derivations.

Keywords: vehicle-to-vehicle; non-WSSUS channels; non-geometrical stochastic model; LoS component; statistical properties

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1 Introduction

Vehicle-to-vehicle (V2V) communication plays a key role in intelligent transportation systems (ITS), which aims at improving the traffic efficiency, minimizing traffic accidents and enabling some new applications [1]. As a newly emerging communication technique, V2V communication faces research challenges and standardization problems, which limit its further development. Therefore, much research attention has been attracted to V2V channel modeling for facilitating the analysis and design of V2V communication systems [2], [3].

As addressed in [4], [5], V2V channel models can be categorized as geometry-based deterministic model (GBDM) [6] and stochastic model, and the latter can be further classified as non-geometrical stochastic model (NGSM) [7], [8] and geometry-based stochastic model (GBSM). The GBDM is characterized by V2V physical channel parameters in a completely de-

terministic approach, whereas its computational complexities increase with the accuracy requirement. Compared with GBDM, stochastic models have better tradeoff between accuracy and complexity, and thus have been widely used currently in V2V channel modeling. The authors in [9] – [15] proposed several GBSMs, which used the simplified ray tracing principle and equivalent scatterer concept to simulate propagation environment. Though the GBSM can be easily adapted to diverse scenarios, it is more complex than the NGSM. The NGSM determines physical parameters of the V2V channel in a completely stochastic manner without presuming any underlying geometry. In the literature [7], [8], two conventional wideband NGSMs were proposed and are both based on the tapped delay line (TDL) structure.

The wideband NGSM developed in [7] is a conventional channel model standardized by IEEE 802.11p. The NGSM in [7] includes the line-of-sight (LoS) component and has variable types of Doppler spectra for different delays. Specifically, due to the short distance of V2V communication, it often includes the LoS component, especially for the scenario with low vehicular traffic density (VTD). In order to identify the presence of LoS component, the model employs the Ricean fading. Moreover, in the NGSM [7], each tap contains several unresolvable

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subpaths, and subpaths with different delays have different types of Doppler spectra, e. g. , flat shape, round shape, classic 3 dB shape, and classic 6 dB shape. However, for simplicity, the NGSM [7] is based on the wide sense stationary uncorrelated scattering (WSSUS) assumption and only employs the Ricean fading, which cannot mimic the severe fading in V2V channels.

In the wideband NGSM [8], two characteristics of the V2V channels not considered in [4] are taken into account, i. e. , non-stationarity and severe fading. Due to unpredictable traffic and changes in the size, location, as well as velocity of scatterers, the number of multipath components and strengths alter frequently, resulting in the non-stationarity in both time and frequency domains for V2V channels. The NGSM [8] employs the first-order two-state Markov chains and generates correlated stochastic variables to describe the non-stationarity in both time and frequency domains, respectively. Moreover, in V2V channels, the fading of multipath component is often worse than Rayleigh fading due to severer delay dispersion and Doppler dispersion. Hence, the model also describes the severe fading by means of the Weibull distribution, in which the tap amplitudes follow the Weibull distribution, with the fading parameter determining fading severity. However, since the NGSM [8] considers both non-stationarity and severe fading, it is difficult to further identify the existence of LoS component and possess variable types of Doppler spectra for different delays.

Based on the measurement data presented in above two conventional NGSMs, we can summarize four important and unique characteristics that exist in V2V channels, i. e. , non-stationarity, severe fading, the existence of LoS component, and variable types of Doppler spectra for different delays. However, both NGSMs implement only half of the above four characteristics. Therefore, neither of the two conventional NGSMs can meet the requirements. Motivated by this, a new NGSM is desirable to be developed for non-WSSUS V2V channels.

To fill the aforementioned gap and accurately describe the characteristics of the V2V channel, we propose an improved model based on the NGSM [8] for non-WSSUS V2V channels. The proposed model not only considers the non-stationarity but also describes the severe fading in V2V channels, keeping the advantages of the NGSM [8]. Moreover, to mimic the V2V channel non-stationarity in frequency domain, channel models should generate correlated taps, which consist of the amplitude part and phase part. Since the amplitude and phase of taps are independent, the distribution of amplitude and phase should be properly modeled respectively. Specifically, the tap amplitude statistics can be modeled as Weibull distribution to mimic the severe fading. For simplicity, most papers defined a uniformly distributed phase over the interval as shown in [8] and [16]. However, the uniformly distributed phase leads to the corresponding channel taps having no ability to include the LoS component. To include the LoS component, the authors in [17] proposed a Laplace distributed phase. However, the La-

place distributed phase cannot mimic the scenarios without the LoS component. To further fill the gap, we propose a non-uniformly distributed phase, which is properly combined with the fading parameter used in the severe fading modeling. By changing value of the fading parameter, the proposed model can flexibly mimic different V2V scenarios with and without LoS components. The main contributions of this paper can be summarized as follows.

1) For the first time, we prove that it is inappropriate to impose a uniformly distributed tap phase, which causes the absence of LoS component.

2) We propose an improved NGSM with the non-uniformly distributed phase for non-WSSUS V2V channels, which extends the NGSM [8] to identify the presence of the LoS component. Therefore, the proposed model has the ability to mimic the aforementioned first three unique characteristics of V2V channels. The simulation results demonstrate that the LoS component is successfully added into Doppler power spectral density (PSD).

3) The effectiveness and accuracy of the proposed V2V channel model are validated by extensive simulations.

The rest of this paper has the following structure. In Section 2, we describe the constriction steps of the NGSM in [8] and propose an improved NGSM. The simulation results of the proposed model for different scenarios, including Doppler PSDs, power delay profile (PDP), and the tap correlation coefficient matrix are provided and analyzed in Section 3 in comparison with the NGSM [8]. Finally, conclusions are drawn in Section 4.

2 Channel Models for Non-WSSUS V2V Channels

In this section, we first review the constriction steps of the NGSM in [8] and prove that imposing a uniformly distributed tap phase is inappropriate. Then, an improved NGSM with non-uniformly distributed tap phase is proposed.

2.1 Conventional NGSM with Uniform Phase Distribution

The constriction steps of existing NGSM [8] include three parts: non-WSS modeling, non-US modeling, and severe fading modeling. In this section, we will briefly describe the constriction steps of the model and prove that it is too restrictive to impose a uniform phase distribution in the NGSM [8].

2.1.1 Non-WSS Modeling

Due to unpredictable traffic and changes in the size, location, and velocity of scatterers, the number of multipath components and strengths alter frequently. Based on the literature [18], the NGSM in [8] represents the non-WSS characteristic by employing the “birth and death” process with persistence process $Z_k(t) = \{0, 1\}$ in V2V channel model, where tap “off” means below 25-dB threshold from the main tap.

Such thresholding methods [19] – [21] are widely used in the literature to limit the number of taps to those that have the non-negligible energy [8].

In addition, the state transition process of the on/off process can be described by first-order two-state Markov chains, and the transition (TS) matrix and the steady-state (SS) matrix [8] can be given by

$$TS = \begin{bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{bmatrix} \quad SS = \begin{bmatrix} P_0 \\ P_1 \end{bmatrix}, \quad (1)$$

where each element P_{ij} in matrix TS is defined as the probability of going from state i to state j , and each SS element P_j gives the “steady-state probability” associated with the j th state.

Then, the channel impulse response (CIR) of the NGSM in [8] can be expressed as

$$h(t, \tau) = \sum_{k=1}^N z_k(t) c_k(t) \delta(\tau - \tau_k) \times \exp\left\{j2\pi \left[f_{D,k}(t - \tau_k) - f_c \cdot \tau_k \right]\right\}, \quad (2)$$

where $Z_k(t) = \{0, 1\}$ is a persistence process used to account for the finite “lifetime” of the propagation paths. $h(t, \tau)$ denotes the channel output at time t due to an impulse input at time $t - \tau$. $c_k(t)$ represents the k -th received amplitude, the exponential term represents the k -th received phase, and the k -th echo path has a time-varying propagation delay τ_k . The δ function is a Dirac delta (impulse), and f_c is the carrier frequency in Hz. The term $f_{D,k}$ represents the Doppler shift, which is associated with the k -th received multipath echo.

2.1.2 Non-US Modeling

Non-US characteristic reflects the impacts of correlation on different paths/taps, which represents the delay domain characteristics. To accurately represent correlated scattering (non-US) characteristic, the model generates complex Gaussian stochastic variables. As shown in Fig. 1, the correlated complex Gaussian stochastic variables can be generated with any desired correlation coefficients.

The process to generate correlated complex Gaussian stochastic variables with correlation ρ^G from pairs of uncorrelated Gaussian stochastic variables is as follows: 1) Generate uncorrelated complex Gaussian stochastic variables V through the independent Gaussian stochastic variables; 2) using Cholesky decomposition of the correlation matrix $LL^H = \rho^G$ to determine the coloring matrix V , where L^H is the Hermitian transpose of L ; 3) Generate correlated complex Gaussian stochastic variables by means of $W = LV$.

2.1.3 Severe Fading Modeling

In V2V channels, due to more severe delay dispersion, Dop-

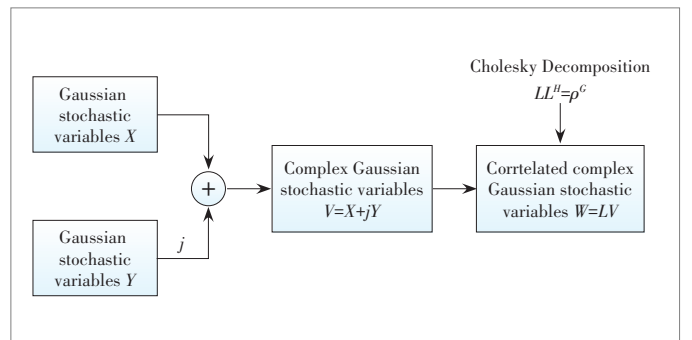
pler dispersion, and non-stationarity characteristics, the fading of multipath component is often worse than Rayleigh fading. As addressed in [22], overall, the best fit for the largest number of taps is obtained by means of the Weibull distribution. Therefore, in the NGSM [8], the tap amplitude statistics are modeled as the flexible Weibull distribution, which can be written as

$$p_W(x) = \frac{\beta}{a^\beta} x^{\beta-1} \exp\left[-\left(\frac{x}{a}\right)^\beta\right], \quad (3)$$

where $\alpha = \sqrt{E(x^2)/\Gamma[(2/\beta) + 1]}$ denotes a scale parameter and β is a fading parameter to represent fading severity. When $\beta = 2$, the Weibull distribution can be transformed to the well-known Rayleigh distribution, and as β increases, the situation in which the signal becomes more deterministic. When β is large enough, it means that the LoS component will exist in the V2V communications. However, when $\beta < 2$, the severe fading will exist in the V2V channel.

As can be seen from the above analysis, severe fading modeling can be implemented by the Weibull stochastic process, whereas Weibull stochastic process can be obtained by a complex Gaussian stochastic process [23]. Specifically, the detail construction steps of the NGSM in [8] is shown in Fig. 2. As can be readily observed from the figure, the time correlated domain of the model is implemented by means of the linear convolution for the Gaussian stochastic process. In order to maintain the type of Doppler spectra, the NGSM in [8] employs the separation of amplitude and phase, in which only the amplitude is transformed with complex exponentiation $2/\beta$. Whereas, the phase is not be transformed, which is directly separated from the complex Gaussian stochastic variables.

The phase is gained directly from the complex Gaussian stochastic process and if we do not consider the time correlation, the phase will follow a uniform distribution over $[-\pi, \pi]$. Consequently, the tap amplitude follows the Weibull distribution and the tap phase follows the uniform distribution. Thus, the stochastic variables can be expressed as



▲ Figure 1. Generating correlated complex Gaussian stochastic variables.

$$\tilde{W}_k = |\tilde{W}_k| e^{j\tilde{\phi}_k} = |\tilde{V}_k|^{2/\beta} e^{j\tilde{\phi}_k}, \tilde{\phi}_k \in [-\pi, \pi], \quad (4)$$

where the number of taps is assumed to be K and $\tilde{\phi}_k$ is the tap phase of the NGSM [8].

Due to the phase $\tilde{\phi}_k$ with a uniformly distributed over $[-\pi, \pi]$, the mean of the NGSM [8] can be calculated as

$$E(\tilde{W}_k) = \frac{1}{2\pi} \int_{-\pi}^{\pi} |\tilde{V}_k|^{2/\beta} e^{j\tilde{\phi}_k} d\varphi_k = 0. \quad (5)$$

The uniformly distributed tap phase denotes zero-mean in-phase and quadrature components, which causes the absence of LoS component in NGSM [8]. However, based on the aforementioned analysis, the existence of LoS component is one of the important and unique characteristics of V2V channels. Consequently, we can conclude that it is inappropriate to impose a uniformly distributed tap phase. To fill up the aforementioned gaps and accurately describe the characteristics of the V2V channel, an improved model with a non-uniform phase distribution is described thereafter.

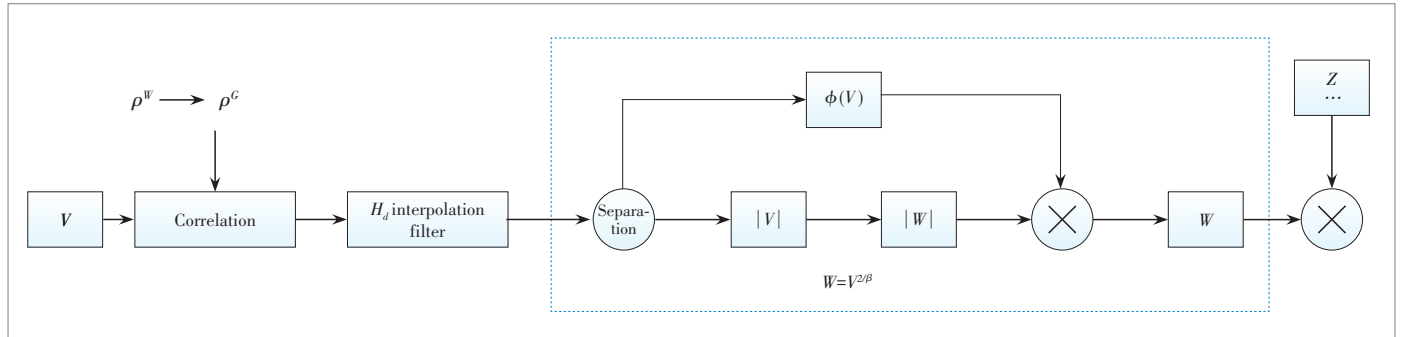
2.2 Improved NGSM with Non-Uniform Phase Distribution

In this section, an improved NGSM with non-uniformly distributed tap phase is proposed, which is based on the existing

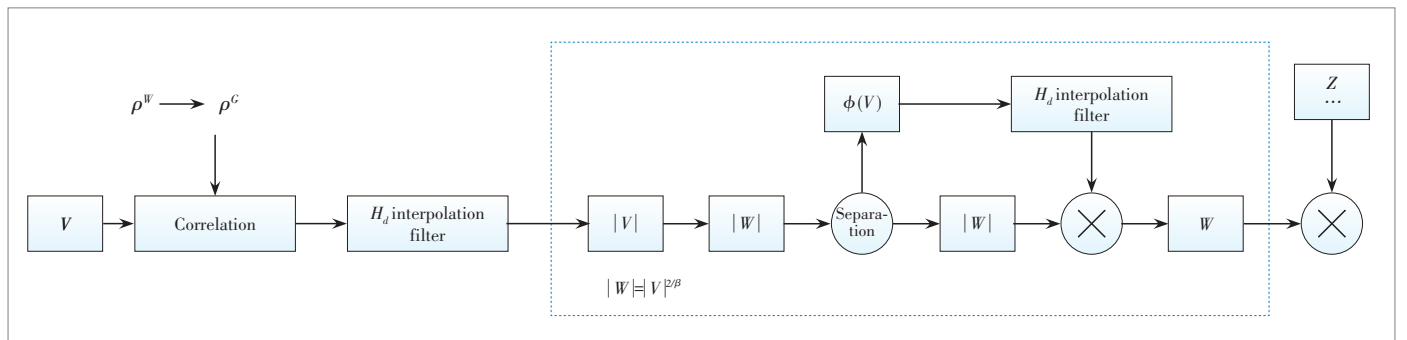
NGSM [8]. The process to develop the improved model also consists of three parts: non-WSS modeling, non-US modeling, and severe fading modeling. However, the proposed model employs a more accurate method to represent the characteristics of V2V channels, which extends the NGSM [8] to have the ability to include the LoS component.

As can be seen from the above analysis, LoS component cannot be included in the NGSM [8]. This is because the tap phase is directly gained from the separation from Gaussian stochastic process and follows a uniform distribution in the interval $[-\pi, \pi]$, which causes the absence of the LoS component. Thus, the uniformly distributed tap phase must be changed. Specifically, in the Weibull stochastic process, the amplitude and the phase of complex Gaussian stochastic variables are both transformed with complex exponentiation $2/\beta$, and then the complex Gaussian stochastic variables are separated into the amplitude part and the phase part since the amplitude and phase of the complex stochastic variables are independent on each other. As a result of the above transformation, β affects equivalently the amplitude part and the phase part. Consequently, the tap amplitude follows the Weibull distribution and the tap phase follows non-uniform distribution. Above all, the constriction steps of the improved model are shown in Fig. 3.

With β being increased, the resulting tap phase concentrates within a smaller phase range, as expected. Consequently, an impulse at zero occurs as $\beta \rightarrow \infty$. Also, when $\beta = 2$, a uni-



▲ Figure 2. The constriction steps of the NGSM [8] (V is an independent and identical complex Gaussian stochastic variable, and Z is a post-operation such as a persistence process).



▲ Figure 3. The constriction steps of the improved model (V is an independent and identical complex Gaussian stochastic variable, and Z is a post-operation such as a persistence process).

formly distributed phase occurs, and the stochastic variables of the improved model can be expressed as

$$\begin{aligned}\tilde{W}'_k &= \tilde{V}_k^{2/\beta_k} = \left(|\tilde{V}_k| \cdot e^{j\tilde{\phi}_k} \right)^{2/\beta_k} = |\tilde{V}_k|^{2/\beta_k} e^{j\tilde{\phi}'_k}, \\ \tilde{\phi}_k &\in [-\pi, \pi], \tilde{\phi}'_k \in [-2\pi/\beta, 2\pi/\beta],\end{aligned}\quad (6)$$

where the number of taps is assumed to be K and $|\tilde{V}_k|$ is the tap amplitude, which follows the Weibull distribution. $\tilde{\phi}'_k$ is the tap phase of the improved model and follows the non-uniform distribution, which is a linear function of the uniformly distributed phase. Specifically, the tap phase of the improved model can be given by

$$\tilde{\phi}'_k = \tilde{\phi}_k \cdot 2/\beta_k. \quad (7)$$

Similarly, the mean of the improved model can be calculated as

$$\begin{aligned}E(\tilde{W}'_k) &= \frac{1}{2\pi} \int_{-2\pi/\beta_k}^{2\pi/\beta_k} |\tilde{V}_k|^{2/\beta_k} e^{j\tilde{\phi}'_k} d\tilde{\phi}'_k \Big|_{\beta_k > 2} = \frac{|\tilde{V}_k|^{2/\beta_k}}{\pi} \left(1 - \cos \frac{4\pi}{\beta_k} \right) e^{j\frac{4\pi}{\beta_k}} \Big|_{\beta_k > 2} \neq 0.\end{aligned}\quad (8)$$

Equation (8) shows that as β increases, the tap phase concentrates within a smaller range, resulting in $E(\tilde{W}'_k) \neq 0$. Furthermore, on comparing (5) and (8), we can conclude that the improved model with non-uniformly tap phase no longer denotes zero-mean in-phase and quadrature components, the Doppler PSD will show a dominant frequency component, which is able to describe the existence of LoS component [24]. Thus, the results demonstrate the advantage of our proposed method.

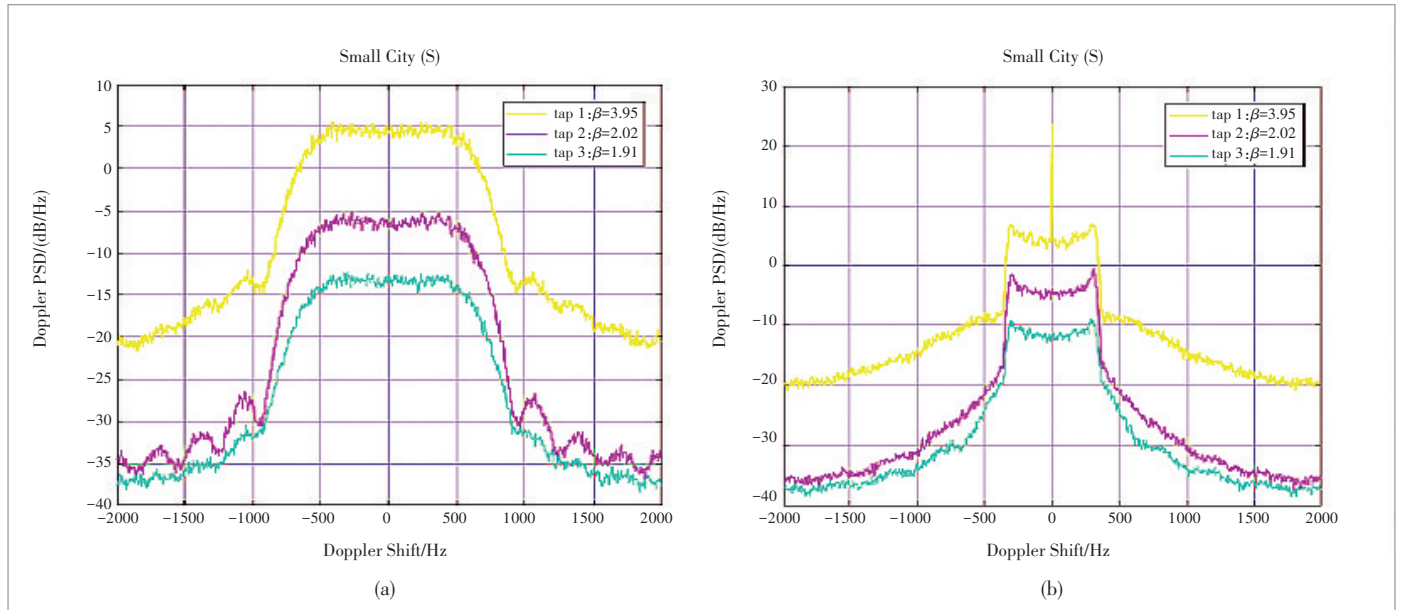
Further analysis shows that each tap of V2V channels exhibits serious Doppler spread due to the high mobility of vehicles, and the phase distribution ranged from $[-\pi, \pi]$ is not enough to represent the serious Doppler environment adequately. The non-uniformly distributed tap phase that derived from the conventional definition of the fading parameter β is more accurately used to describe the characteristics of V2V channels. Equation (8) allows further observations: the $E(\tilde{W}')$ and β is positively correlated, which means that with β being increased, the signal becomes more deterministic and the LoS component is also larger [24].

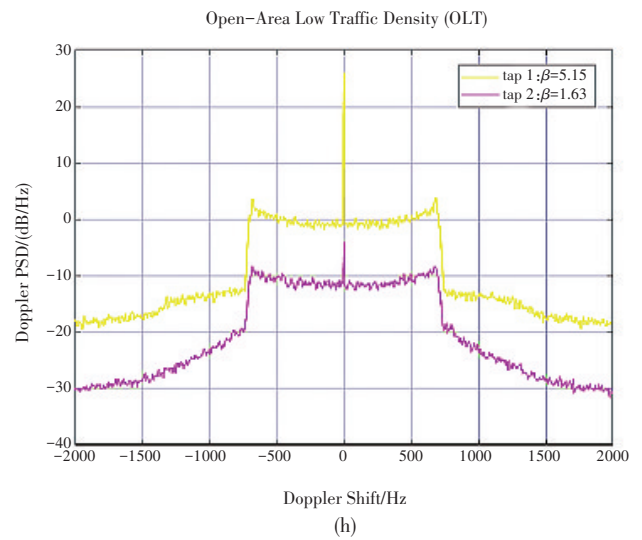
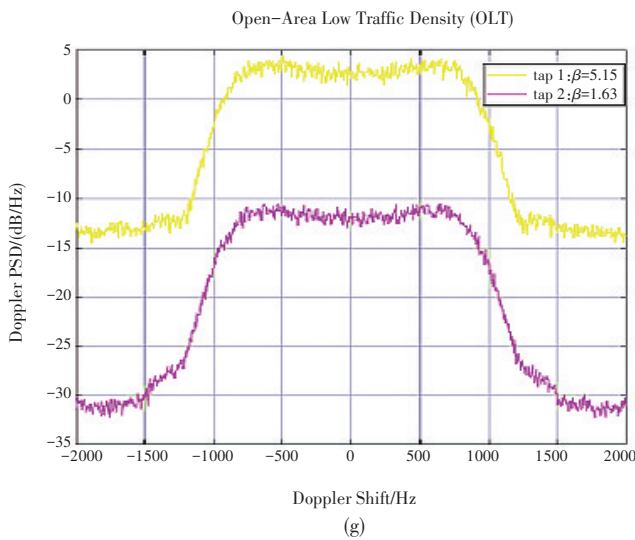
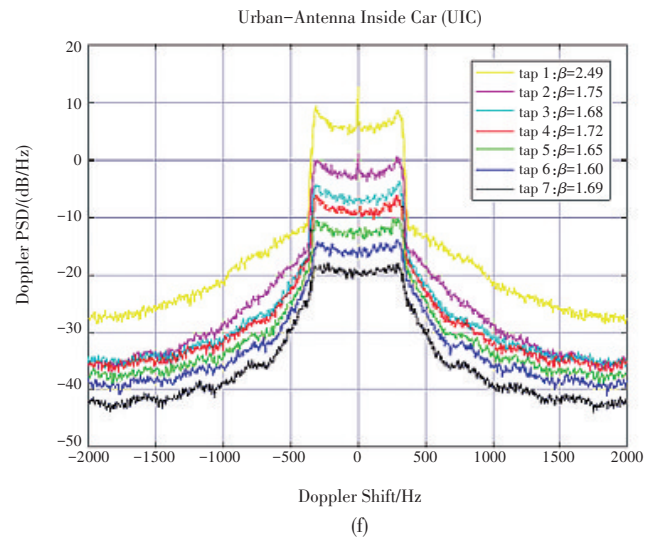
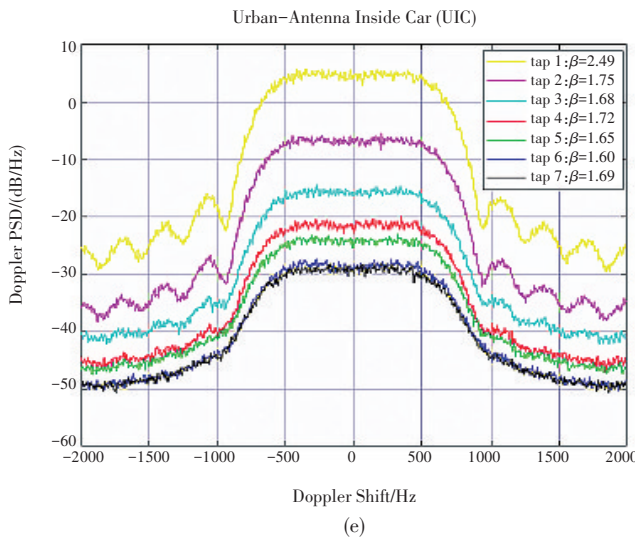
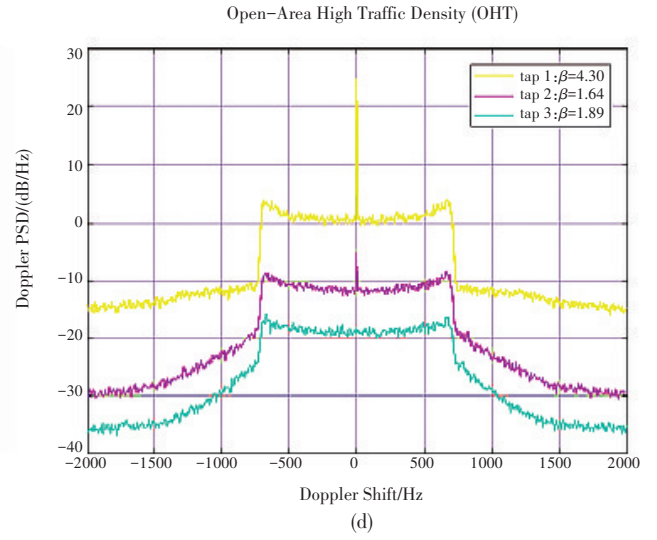
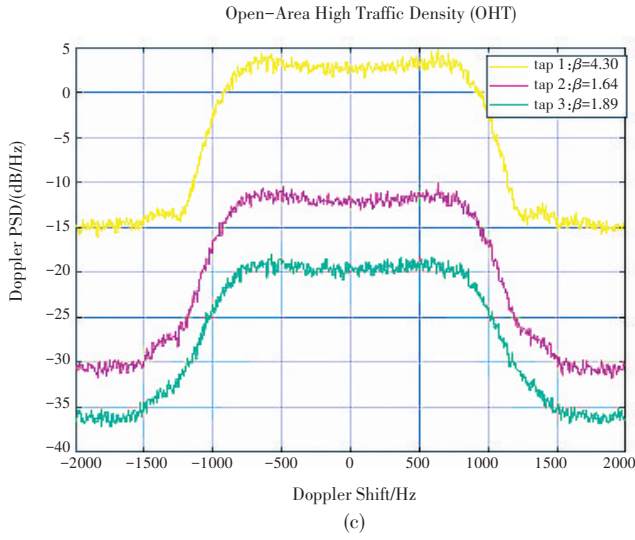
It is also worth noting that the transformation of phase does not influence the amplitude of complex Gaussian stochastic variables, so that this improvement does not have impact on the type of Doppler spectra and the tap correlation coefficient matrix.

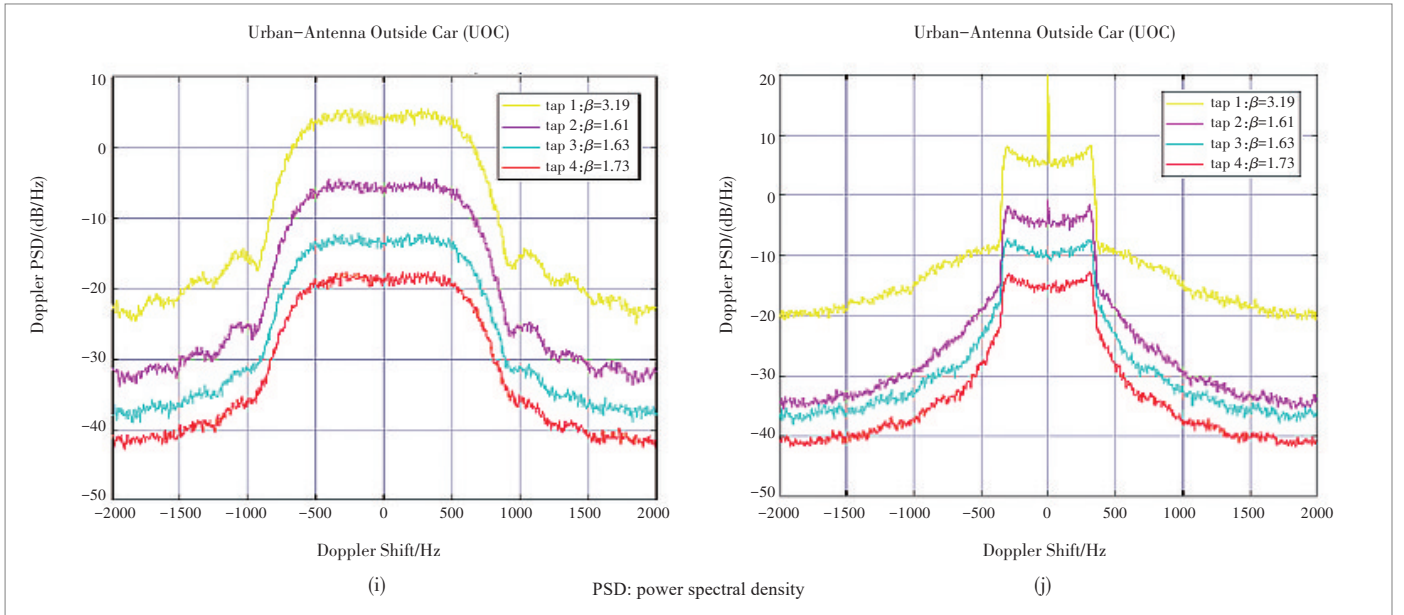
3 Simulation Results and Analysis

In this section, the statistical properties of the proposed model in different scenarios, including Doppler PSD, PDP, and the tap correlation coefficient matrix are simulated and compared with those of the NGSM in [8]. To better compare the performance of the two models, the following key parameters are utilized to obtain the simulation results, which are the same as those in [8]. Specifically, the key parameters can be set as the carrier frequency $f_c = 5.12$ GHz, the bandwidth $BW = 10$ MHz, and the duration of each “birth and death” process state (i. e., the coherence time of the channel) $T_c = 0.0005 \sim 0.001$ s. Moreover, all the simulation scenarios are also the same as those in [8], including Small City (S), Urban-Antenna Outside Car (UOC), Urban-Antenna Inside Car (UIC), Open-Area High Traffic Density (OHT), and Open-Area Low Traffic Density (OLT).

Fig. 4 provides the comparison between the Doppler PSD of







▲ Figure 4. The Doppler PSD of different models for different scenarios. (a) Doppler PSD of the model in [8] for S scenario; (b) Doppler PSD of the improved model for S scenario; (c) Doppler PSD of the model in [8] for OHT scenario; (d) Doppler PSD of the improved model for OHT scenario; (e) Doppler PSD of the model in [8] for UIC scenario; (f) Doppler PSD of the improved model for UIC scenario; (g) Doppler PSD of the model in [8] for OLT scenario; (h) Doppler PSD of the improved model for OLT scenario; (i) Doppler PSD of the model in [8] for UOC scenario; (j) Doppler PSD of the improved model for UOC scenario.

the model in [8] and the improved model. Due to the similar Doppler PSD for each scenario, for simplicity, we select scenario S to analyze the simulation results. As can be readily observed from Fig. 4a, for scenario S, the maximum Doppler shift $f_{D,\max}$ is about 500 Hz and the type of Doppler PSD is “classic 3dB”. Specially, we notice that Doppler PSD of the NGSM [8] shows no dominant LoS component. In Fig. 4b, we show the simulation results of the improved model for scenario S. It is obvious that maximum Doppler shift $f_{D,\max}$ is still 500 Hz and the Doppler PSD is also “classic 3 dB”. As expected, Doppler PSD of the improved model has a strong narrow peak in the middle, which is characteristic to communications in presence of LoS component [25] – [27]. Moreover, the energy of taps with fading parameter $\beta < 2$ is obviously lower than that of other taps, which is consistent with the model in [8]. This is because in the improved model, we also employ $\beta < 2$ to describe the severe fading in V2V channels. The excellent agreement between the theoretical and measured Doppler PSD confirms the utility of the improved model. Therefore, the simulation results demonstrate that the improved model also has the ability to mimic the severe fading, keeping the advantages of the model in [8].

To further validate the utility of the proposed model, we compare our model with measurement data and model in [7] as shown in Fig. 5. It is clear that Doppler PSD of the model in [7] has a dominant narrow peak in the middle to identify the presence of LoS component, which is consistent with that of the improved model. Therefore, we can conclude that on the basis

of maintaining the merits of the model in [8], the improved model can mimic the existence of LoS component and better mimic the characteristics of V2V channels.

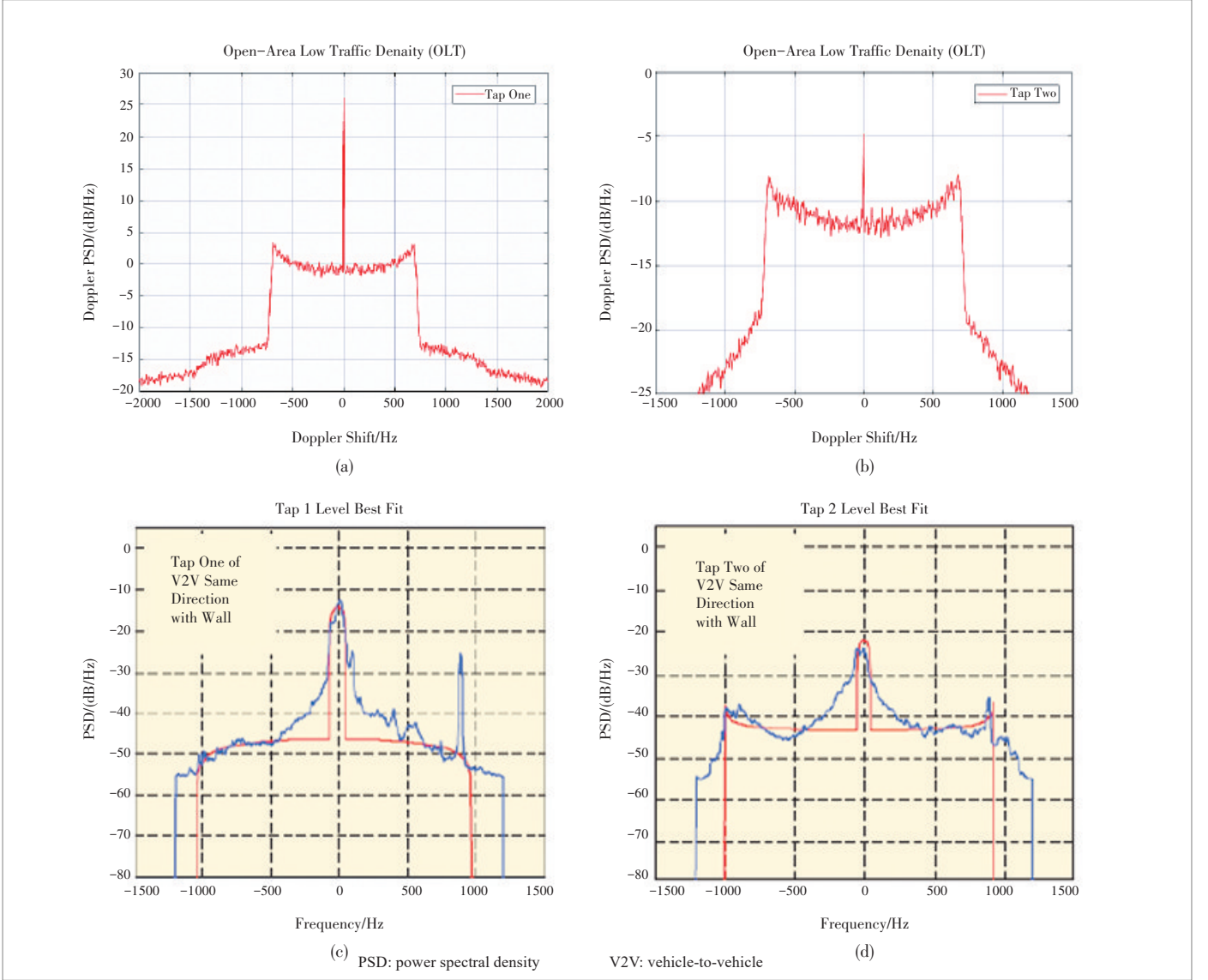
In Table 1, we show the tap correlation coefficient matrix of the NGSM in [8] and the improved model for scenario UIC, respectively. The tap correlation coefficient matrix is defined as

$$\rho = [r_{ij}] = \frac{\text{cov}(\alpha_i, \alpha_j)}{\sqrt{\text{var}(\alpha_i)\text{var}(\alpha_j)}} \text{ where } [r_{ij}] \text{ is the coefficient between tap } i \text{ and } j, \text{ var}(\cdot) \text{ denotes variance and cov}(\cdot) \text{ denotes covariance.}$$

Since the correlation coefficient matrix is symmetric about the diagonal, we only need to specify the upper or lower triangular part; for brevity, the lower triangular part corresponds to correlations between taps for the improved model, whereas the upper triangular part corresponds to correlations between taps for the model in [8].

▼ Table 1. Correlation matrices of the non-geometrical stochastic model (NGSM) in [8] and improved model for scenario UIC (lower/upper triangular part: improved model/ NGSM in [8])

i, j	1	2	3	4	5	6	7
1	1.0000	0.1989	0.0555	0.0481	0.0977	0.1074	0.3504
2	0.1965	1.0000	0.1477	0.1495	0.0974	0.2329	0.1999
3	0.0573	0.1411	1.0000	0.2298	0.0106	0.1368	0.1496
4	0.0474	0.1350	0.2342	1.0000	0.2189	0.2088	0.1143
5	0.1066	0.0976	0.0152	0.2092	1.0000	0.1600	0.0000
6	0.1159	0.2363	0.1512	0.1977	0.1524	1.0000	0.2600
7	0.3249	0.1938	0.1442	0.1211	0.0012	0.2600	1.0000



▲ Figure 5. The Doppler PSD of different models. (a) (b) Doppler PSD of the improved model; (c) (d) Doppler PSD of the model in [7].

lations between taps for the NGSM in [8]. Through comparison between the corresponding parameters under scenario UIC, we can observe that the corresponding parameters of the improved model only fluctuate with a few correlation coefficient values, but most of them remain consistent. This is because the change of phase distribution does not influence the amplitude of complex Gaussian stochastic process, so this improvement does not have impact on the tap correlation coefficient matrix. The excellent agreement between the simulation results and measured data confirms the utility of the improved model. Therefore, the improved model also has the ability to implement the non-stationarity in frequency domain, maintaining the advantages of the NGSM [8].

Fig. 6 shows a comparison between the PDP of the NGSM in [8] and the improved model in each scenario: UIC, UOC, OHT, S, and OLT [8]. As can be seen from the figure, both in the

NGSM [8] and the improved model, the spread delay in UIC scenario is more severe than others. This is because in the UIC scenario, antenna is inside the vehicles, resulting in more obstacles in channel propagation. We can also notice that in OLT scenario, the scattering and reflection caused by moving vehicles are less than other scenarios with short spread delay, and the energies are concentrated in the first tap, which is also confirmed in the literature [27]. Furthermore, it is obvious that PDP of two models for each scenario has some difference. The cause for this difference is the presence of the dominant LoS component in the improved model. Comparatively speaking, the LoS component is successfully added in the improved model and the energy is more centered in the first path. In this way, the proportion of energy in other paths has a visible decline and the fading is more obvious, which means multipath effect is more apparent as well. Therefore, the comparison of

PDP also validates that the improved model properly includes the LoS component.

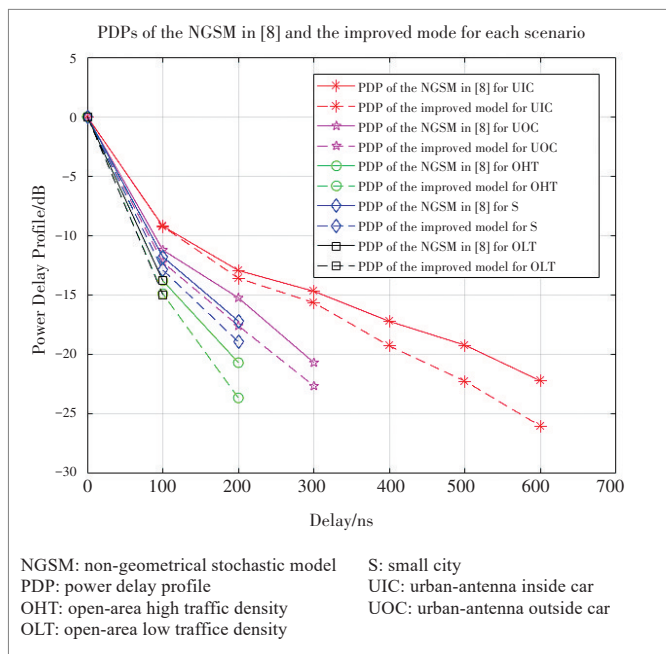
As can be seen from the above analysis, we compare the NGSM in [8] with the improved model, and the results can be shown in Table 2.

Table 2. shows the comparison results between the NGSM in [8] and the improved model. We can readily observe that both models are based on the assumption of non-WSSUS and describe the severe fading by means of Weibull distribution. In addition, the improved model remains the tap correlation coefficient matrices of the NGSM [8] fortunately, realizing the

correlated scattering between each tap. Moreover, from the simulation results of the PDP, it is also obvious that both models implement delay dispersion well. However, compared with the NGSM [8], the improved model includes a dominant LoS component into the Doppler PSD and thus has the ability to describe the presence of LoS component. Consequently, we can conclude that the improved model fills the aforementioned gap and is more accurate to describe the characteristics of V2V channels.

4 Conclusions

In this paper, a novel NGSM for non-WSSUS V2V channels has been proposed, which is based on a conventional NGSM in [8]. The proposed NGSM employs a method of generating non-uniformly distributed phase in the Weibull distribution, which extends the NGSM [8] to include the LoS component. It also has been demonstrated by the simulation results that compared with the NGSM [8], the proposed model has added a dominant LoS component into Doppler PSD and thus has explicitly identified the presence of LoS component. Furthermore, the comparison of the PDP has shown that the energy is more centered in the first path in the proposed model. Therefore, it has been verified by the simulation results that the proposed model is more accurate to describe the characteristics of V2V channels.



▲ Figure 6. PDP of the NGSM in [8] and the improved model for each scenario.

▼ Table 2. Comparison of the NGSM in [8] and the improved model

NGSM in [8]	Improved model
non-WSSUS	non-WSSUS
severe fading (achieved)	severe fading (achieved)
good implementation of delay dispersion	good implementation of delay dispersion
the number of taps determined based on the RMS of delay time	the number of taps determined based on the RMS of delay time
no description of LoS component	a good description of the LoS component

LoS: line-of-sight

NGSM: non-geometrical stochastic model

RMS: root-mean-square

WSSUS: wide sense stationary uncorrelated scattering

Note: By comparing with the model in [8] as shown in Table 1 and Fig. 4, it is clear that the proposed model can properly mimic the non-stationarity and severe fading. While comparing with the model in [7] as shown in Fig. 5, one can see that the proposed model can mimic the existence of LoS component.

References

- [1] CHENG X, CHEN C, ZHANG W, et al. 5G-Enabled Cooperative Intelligent Vehicular (5GenCIV) Framework: When Benz Meets Marconi [J]. IEEE Intelligent Systems, 2017, 32(3): 53 – 59. DOI: 10.1109/mis.2017.53
- [2] CHENG X, ZHANG R-Q, YANG L-Q. 5G-Enabled Vehicular Communications and Networking [M]. Cham, Switzerland: Springer Press, 2018
- [3] WANG C X, CHENG X, LAURENSEN D I. Vehicle-to-Vehicle Channel Modeling and Measurements: Recent Advances and Future Challenges [J]. IEEE Communications Magazine, 2009, 47(11): 96 – 103. DOI: 10.1109/mcom.2009.5307472
- [4] YIN X F, CHENG X. Propagation Channel Characterization, Parameter Estimation, and Modeling for Wireless Communications [M]. Singapore, Singapore: John Wiley & Sons, 2016. DOI: 10.1002/9781118188248
- [5] YUAN Y, WANG C-X, HE Y, et al. 3D Wideband Non-Stationary Geometry-Based Stochastic Models for Non-Isotropic MIMO Vehicle-to-Vehicle Channels [J]. IEEE Transactions on Wireless Communications, 2015, 14(2): 6883 – 6895. DOI: 10.1109/twc.2015.2461679
- [6] MAURER J, FUGEN T, POREBSKA M. A Ray-Optical Channel Model for Vehicle to Vehicle Communications [M]. Berlin, Germany: Springer-Verlag, 2004
- [7] MARUM G A, INGRAM M. Six Time- and Frequency-Selective Empirical Channel Models for Vehicular Wireless LANs [J]. IEEE Vehicular Technology Magazine, 2007, 2(4): 4 – 11. DOI: 10.1109/MVT.2008.917435
- [8] SEN I, MATOLAK D W. Vehicle-Vehicle Channel Models for the 5-GHz Band [J]. IEEE Transactions on Intelligent Transportation System, 2008, 9(2): 235 – 245. DOI: 10.1109/tits.2008.922881
- [9] ZAJI A G, STUBER G L, PRATT T G, et al. Wideband MIMO Mobile-to-Mobile Channels: Geometry-Based Statistical Modeling with Experimental Verification [J]. IEEE Transactions on Vehicular Technology, 2009, 58(2): 517 – 534. DOI: 10.1109/tvt.2008.928001
- [10] AKKI A S, HABER F. A Statistical Model for Mobile-to-mobile Land Communi-

- cation Channel [J]. *IEEE Transactions on Vehicular Technology*, 1986, 35(1): 2 – 7. DOI: 10.1109/t-vt.1986.24062
- [11] ZAJIC A G, STUBER G L. Space-Time Correlated Mobile-to-Mobile Channels: Modelling and Simulation [J]. *IEEE Transactions on Vehicular Technology*, 2008, 57(2): 715 – 726. DOI: 10.1109/tvt.2007.905591
- [12] CHENG X, WANG C-X, LAURENSEN D I, et al. An Adaptive Geometry - Based Stochastic Model for Non-Isotropic MIMO Mobile-to-Mobile Channels [J]. *IEEE Transactions on Wireless Communications*, 2009, 8(8): 4824 – 4835. DOI: 10.1109/twc.2009.081560
- [13] CHENG X, WANG C-X, AI B, et al. Envelope Level Crossing Rate and Average Fade Duration of Nonisotropic Vehicle-to-Vehicle Ricean Fading Channels [J]. *IEEE Transactions on Intelligent Transportation System*, 2014, 15(1): 62 – 72. DOI: 10.1109/tits.2013.2274618
- [14] CHENG X, YAO Q, WEN M, et al. Wideband Channel Modeling and ICI Cancellation for Vehicle-to-Vehicle Communication Systems [J]. *IEEE Journal on Selected Areas in Communications*, 2013, 31(9): 434 – 448. DOI: 10.1109/jsac.2013.sup.0513039
- [15] KAREDAL J, TUFVESSON F, CZINK N, et al. A Geometry-Based Stochastic MIMO Model for Vehicle-to-Vehicle Communications [J]. *IEEE Transactions on Wireless Communications*, 2009, 8(7): 3646 – 3657. DOI: 10.1109/twc.2009.080753
- [16] CHEN J, YU C, CHUNG Y, et al. On the Impact of CFO for OFDM Systems with Un-equal Gain Diversity Schemes over Small-Term Fading [C]//CROWNCOM. Singapore, Singapore, 2008: 1 – 5. DOI: 10.1109/crowncom.2008.4562552
- [17] LI Y, AI B, CHENG X, et al. A TDL Based Non-WSSUS Vehicle-to-Vehicle Channel Model [J]. *International Journal of Antenna and Propagation*, 2013, 103461:1 – 8. DOI: 10.1155/2013/103461
- [18] SCHWARTZ M, BENNETT W R, STEIN S. *Communication Systems and Techniques* [M]. New York, America: McGraw-Hill Press. 1966
- [19] KIVINEN J, ZHAO X, VAINIKAINEN P. Empirical Characterization of Wideband Indoor Radio Channel at 5.3 GHz [J]. *IEEE Transactions on Antennas and Propagation*, 2001, 49(8): 1192 – 1203. DOI: 10.1109/8.943314
- [20] DABIN J, HAIMOVICH A, GREBEL H. A Statistical Ultra-Wideband Indoor Channel Model and the Effects of Antenna Directivity on Path Loss and Multipath Propagation [J]. *IEEE Journal on Selected Areas in Communications*, 2006, 24(8): 752 – 758. DOI: 10.1109/jsac.2005.863824
- [21] ITU-R M.1225. Guidelines for Evaluation of Radio Transmission Technologies for IMT-2000 Systems [S]. 1998
- [22] PAPOULIS A, PILLAI U. *Probability, Random Variables, and Stochastic Processes* [M]. New York, USA: McGraw-Hill Press. 2001
- [23] ZAJIC A G, STUBER G L. Three-Dimensional Modeling, Simulation, and Capacity Analysis of Space-Time Correlated Mobile-to-Mobile Channels [J]. *IEEE Transactions on Vehicular Technology*, 2008, 57(4): 2042 – 2054. DOI: 10.1109/tvt.2007.912150
- [24] IVAN I, BESNIER P, BUNLON X, et al. On the Simulation of Weibull Fading for V2X Communications [C]//ITST. St. Petersburg, Russia, 2011: 86–91. DOI: 10.1109/itsst.2011.6060167
- [25] MATOLAK D W, ATHENS O. Channel Modeling for Vehicle-to-Vehicle Communications [J]. *IEEE Communication Magazine*, 2008, 46(5): 76 – 83. DOI: 10.1109/mcom.2008.4511653
- [26] LI Y, AI B, MICHELSON D G, et al. A Method for Generating Correlated Taps in Stochastic Vehicle-to-Vehicle Channel Models [C]//81st IEEE Vehicular Technology Conference. Glasgow, Scotland, 2015: 1–5. DOI: 10.1109/vtc-spring.2015.7145621
- [27] PAPAFAEIROPOULOS A K, KOTSOPoulos S A. Generalized Phase Crossing Rate and Random FM Noise for α - μ Fading Channels [J]. *IEEE Transactions on Vehicular Technology*, 2010, 59(1): 494 – 499. DOI: 10.1109/tvt.2009.2029861

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Fiber–Wireless Integrated Reliable Access Network for Mobile Fronthaul Using Synclastic Uniform Circular Array with Dual–Mode OAM Multiplexing

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Abstract: We propose an access network that integrates fiber and wireless for mobile fronthaul (MFH) with simple protection capabilities, using dual-mode orbital angular momentum (OAM) multiplexing. We experimentally demonstrate a 3.35 Gbit/s DMT-32QAM pre-equalized system with 10 km and 15 km fiber links in the 5.9 GHz band; then there is a link of two channels with a 0.5 m wireless link.

Keywords: OAM; fiber-wireless integrated access network

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1 Introduction

Driven by emerging mobile devices and mobile multimedia, mobile data traffic is exponentially increasing. Different multiplexing technologies are researched and discussed. In order to provide end users with multi-gigabit wireless link rates, fiber-wireless integrated access networks have proven their potential for more efficient traffic offload and flexibility [1] – [5]. Millimeter wave (MMW) that provides a friendly infrastructure for high-throughput wireless services with low cost, abundant bandwidth, and rapid deployment is an efficient physical link for mobile fronthaul (MFH), which has been extensively studied. Photonics-aided MMW generation for the MFH that can leverage existing fiber to the home (FTTH), passive optical network (PON), and wavelength division multiplexing (WDM) PON in the future [2] – [6]. However, tree-based network topologies lack simple and cost-effective protection or recovery capabilities.

At the same time, orbital angular momentum (OAM) has been proposed as an emerging multiplexing technique to further improve spectral efficiency and channel capacity in radio communications due to mutual orthogonality of different modes [7] – [9]. In principle, many orthogonal modes of OAM can be used

for multiplexing and demultiplexing with low crosstalk. Therefore, using various antennas to generate OAM beams in the radio domain has been extensively studied in the research community. By simultaneously transmitting different OAM modes, synclastic uniform circular array (UCA) has attracted increasing interest. Based on the multi-layer design, a synclastic UCA is proposed for OAM generation and dual mode communication [8] – [10]. The integration of OAM in the low-frequency radio domain and optical fiber for MFH is an attractive alternative.

In this paper, we propose a fiber-wireless reliable access network for MFH, which integrates fiber and wireless with dual-mode OAM multiplexing to verify the performance of an optical OAM transmission architecture based on DMT technology. Two modes from one synclastic UCA are assigned two different fiber links that may have simple protection capabilities. We experimentally demonstrate a 3.35 Gbit/s DMT-32QAM fiber-wireless integrated system with pre-equalization (Pre-EQ) in the 5.9 GHz band. After 10 km and 15 km fiber transmission, the two modes are transmitted simultaneously through a 0.5 m wireless link respectively.

2 Principle of Antenna

The synclastic UCA, in which the elements are placed in a circular ring and have the same orientation, is an array configuration of very practical interest. A typical synclastic UCA mod-

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el with eight elements is presented in **Fig. 1** and the corresponding free space propagation geometry with synclastic UCAs is also illustrated. In **Fig. 1b**, we assume that N isotropic elements are equally placed on the $x - y$ plane along a circular ring with radius of a . The normalized field of the whole array can be written as

$$\begin{aligned} E_n &= \sum_{n=1}^N a_n \cdot /R_n \\ a_n &= I_n e^{j\varphi_n} = I_n e^{j(\varphi_0 + n \cdot 2\pi l/N)} \\ E_{nn'} &= \frac{e^{(-jkr)}}{r} \sum_{n=1}^N a_n I_n e^{j[k\sin\theta\cos(\phi_{n'} - \phi_n) + \varphi_{n'} + \varphi_n]}, \end{aligned} \quad (1)$$

where k is the Boltzmann constant, R_n is the distance from the n th array element to the n' -th observation element, and a_n is the

$$a_n = I_n e^{j\varphi_n} = I_n e^{j(\varphi_0 + n \cdot 2\pi l/N)}, \quad (2)$$

where I_n is the amplitude excitation and φ_n is the phase excitation of the n -th element. And φ_0 is the assumed system reference phase, N is the number of the elements of an array, and l is the mode of the OAM.

Assuming that $r \gg a$ and $R_n \approx r$, the electric field of the n' -th element in the receiving array transmitted by the n -th element in the transmitting array is

$$E_{nn'} = \frac{e^{(-jkr)}}{r} \sum_{n=1}^N a_n I_n e^{j[k\sin\theta\cos(\phi_{n'} - \phi_n) + \varphi_{n'} + \varphi_n]}, \quad (3)$$

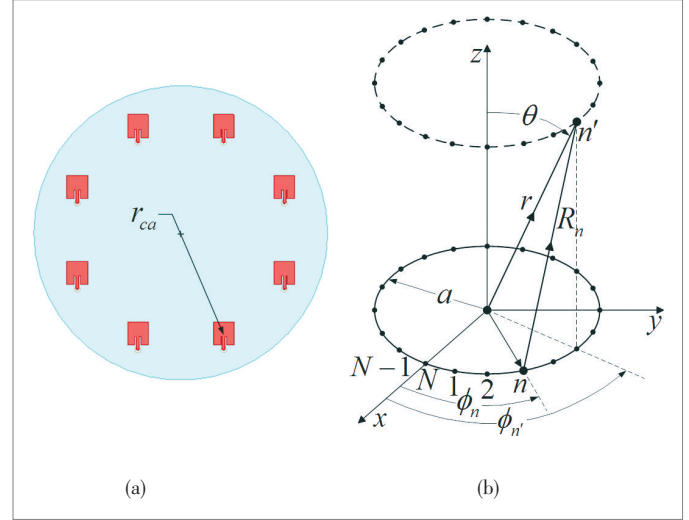
where $\varphi_{n'}$ is the phase of the element in the receiving array. Thus, the electric field of the n' -th element in the receiving array can be derived as

$$\begin{aligned} E_{n'} &= \frac{e^{(-jkr)}}{r} \sum_{n=1}^N a_n I_n e^{j[k\sin\theta\cos(\phi_{n'} - \phi_n) + \varphi_{n'} + \varphi_n]} = \\ &= \left[\frac{e^{(-jkr)}}{r} \sum_{n=1}^N I_n e^{j[k\sin\theta\cos(\phi_{n'} - \phi_n) + 2\varphi_0 + n \cdot 2\pi l/N]} \right] \cdot e^{jn' \cdot 2\pi l/N}. \end{aligned} \quad (4)$$

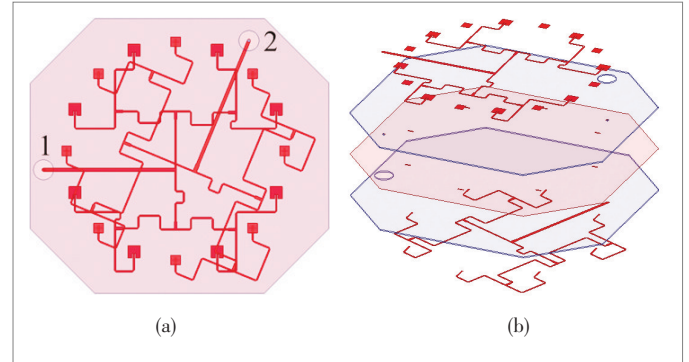
Finally, the phase factor of $e^{jn' \cdot 2\pi l/N}$ is extracted from Equation (4), which proves the OAM generation from these equal phase and equal amplitude UCAs theoretically.

To verify the correctness of the theory, a dual-mode OAM multiplexing antenna is designed and fabricated (**Fig. 2**). And the near field phase front of the OAM antenna is simulated and the result is shown in **Fig. 3**, which indicates the reliable generation of the OAM beams.

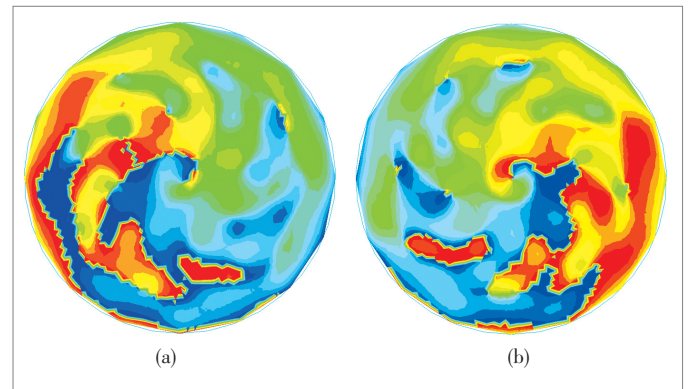
While OAM has unlimited range of achievable states which are mutually orthogonal, it is quite promising to combine it with optical fiber for MFH to achieve high spectrum efficiency transmission. The wireless OAM multiplexing is achieved by the synclastic UCAs with N independent OAM modes. The



▲ **Figure 1.** Synclastic UCA model: (a) Top view; (b) schematic diagram (the upper array is the receiving array and the lower array is the transmitting array).



▲ **Figure 2.** Dual-mode OAM antenna: (a) Top view; (b) explosive view.



▲ **Figure 3.** Near field phase front of the dual mode OAM antenna: (a) +1 mode; (b) +2 modes.

various OAM beams can be considered as a form of spatial division multiplexing (SDM). The OAM beams multiplexed with different modes propagate along the same spatial axis in free space. The coaxially propagating OAM beams lead to inherently low crosstalk between OAM channels and reduce the need for signal processing to eliminate OAM channel interference af-

ter demultiplexing.

As we can see, OAM provides another degree of freedom to carry information with multi-level amplitude/phase modulation. It shows potential possibility to integrate OAM with the current fiber-based MFH infrastructure for further increase of system capacity.

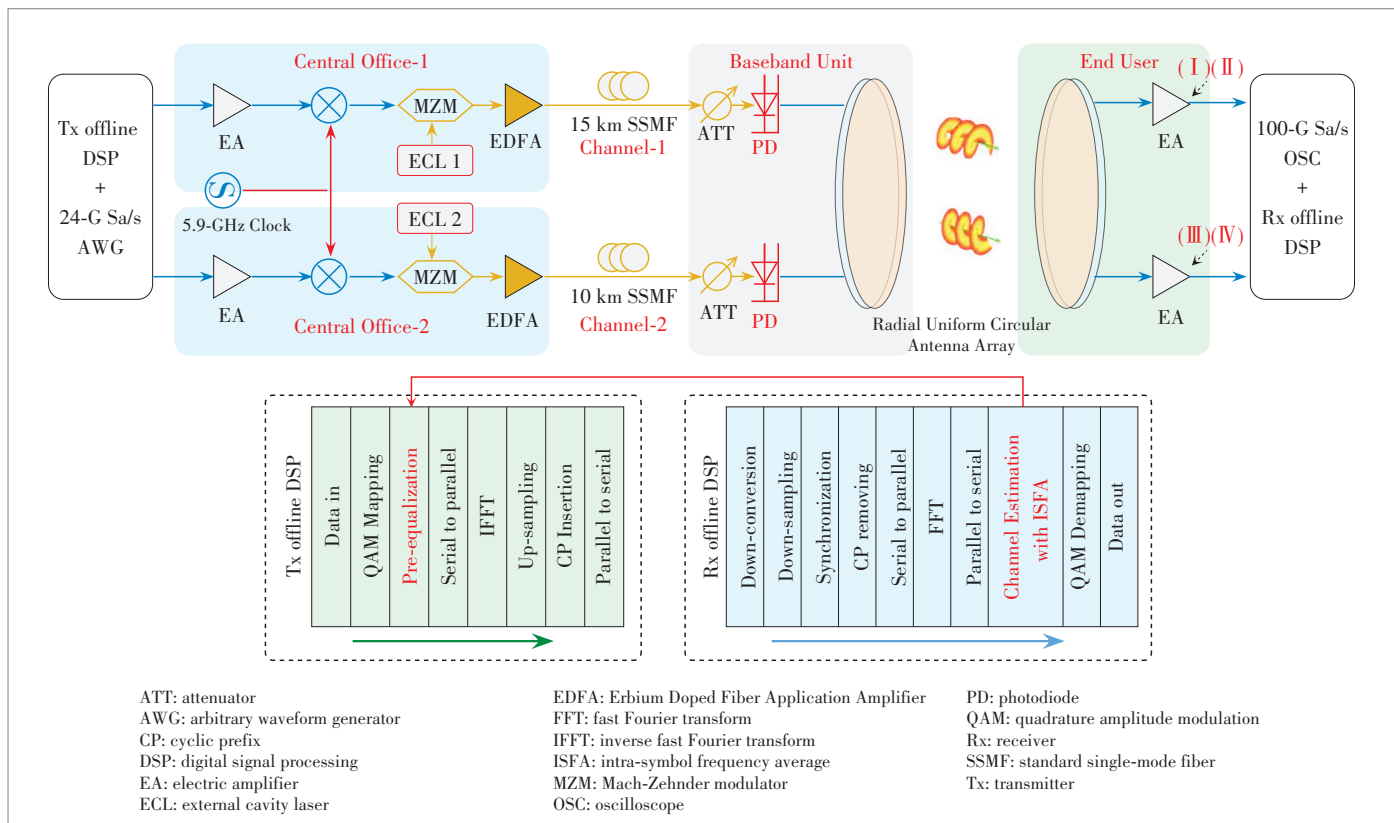
3 Experimental Setup

An experimental setup for intensity modulation and direct detection (IM-DD) DMT-32QAM signal transmission based on the Mach-Zehnder modulator (MZM) [9-10] is shown in Fig. 4. The DMT signal is generated offline in Matlab in a 32-QAM modulation format. We estimate the channel using 256 subcarriers loaded with data and 10 training sequences. We use 1/32 subcarriers as the cyclic prefix (CP) to avoid inter-symbol interference (ISI) as well. For Rx offline digital signal processing (DSP), data without Pre-EQ are first sent for channel estimation with intra-symbol frequency domain averaging (ISFA), and then Pre-EQ is operated using the estimated reverse channel [11].

The experimental system consists of two independent central offices (COs) with MZM modulators that convert the signal to optical domain. The baseband unit (BBU) is used for dual-mode OAM beams transmission and the end user side is used to receive signals. Two COs are connected to both sides of a synclastic UCA array using the 15-km and 10-km SSMF links

as Ch-1 and Ch-2 respectively. These different fiber links may have simple protection features. The 200 Mbit/s baseband DMT-32QAM signal is uploaded into an arbitrary waveform generator (AWG) with 1.2 - 2.4 GSa/s sample rate for Ch-1 and Ch-2. The amplified signal is then mixed with a 5.9 GHz clock and up-converted into two intermediate frequency (IF) signals. The modulated signal through the MZM is then amplified by the Erbium Doped Fiber Application Amplifier (EDFA) prior to fiber transmission. After transmission, an optical attenuator (ATT) is applied to adjust the received optical power maintained at 0 dBm before power is injected into the photodiode (PD). Then, the converted electrical signals are injected into the synclastic UCA and performed in two orthogonal OAM modes respectively. After 50-cm free space transmission, radio beams with different OAM modes are detected by the according received antenna. Finally, the received signals are amplified and sent into an oscilloscope (OSC) at a 12.5 GSa/s sample rate, which is then processed by the Rx offline DSP.

In another experiment, the arbitrary waveform generator (AWG, Tektronix 7122C) is used to generate a 1.6 GSa/s DMT signal with a carrier frequency of 5.9 GHz. A 1550 nm external cavity laser (ECL) is used as an optical carrier and fed into the intensity modulator. The signal is converted into optical domain via a MZM. The optical power is controlled by a variable optical attenuator (VOA) before transmitting the signal through standard single mode fiber (SSMF). At the receiver

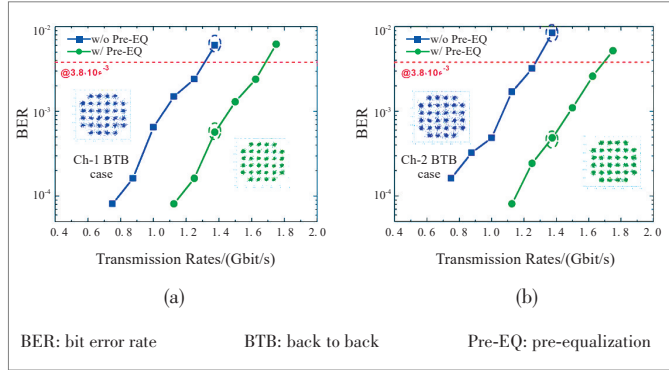


▲ Figure 4. Experimental setup for intensity modulation and direct detection (IM-DD) DMT-32QAM signal transmission based on the MZM.

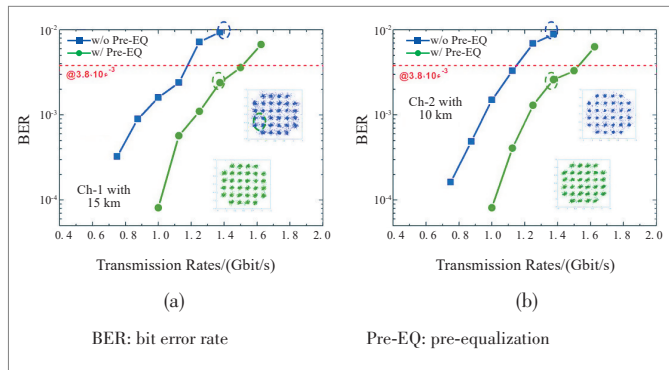
side, the optical signal is detected by a PD to achieve photo-electric conversion. The electrical signal is amplified before being transmitted to the synclastic UCA. After 40 cm free space transmission, the electrical signal is received by the antenna of the receiver. The received signal is then sampled using a 12.5 GSa/s digital storage oscilloscope (DSO Tektronix DSA73304D) and the off-line DSP is processed.

4 Results and Analysis

For the first experiment, Figs. 5a and 5b show the bit error rate (BER) of Ch-1 and Ch-2 versus transmission rates in the case of back to back (BTB). The blue lines indicate the signal without Pre-EQ and the green lines represent the signal with Pre-EQ. We observe that the BER performance of Ch-1 and Ch-2 at the same transmission rate is similar with or without Pre-EQ. As can be seen from Figs. 5a and 5b, the BER increases as the rate increases. A DMT-32QAM signal exceeding 1.125 Gbit/s can be delivered below the BER of 3.8×10^{-3} per channel without Pre-EQ. In addition, the use of Pre-EQ can effectively increase the transmission rate to over 1.625 Gbit/s. In the case of BTB with Pre-EQ, both the channels can realize a total rate of 3.35 Gbit/s. Figs. 6a and 6b show the BER of Ch-1

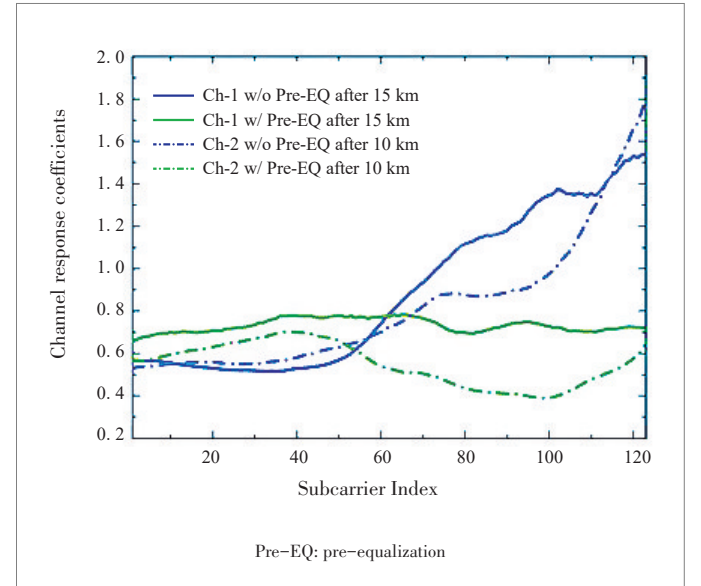


▲ Figure 5. (a) The BER of Ch-1 vs. transmission bit rates under BTB case without and with Pre-EQ; (b) the BER of Ch-2 vs. transmission bit rates under BTB case without and with Pre-EQ.

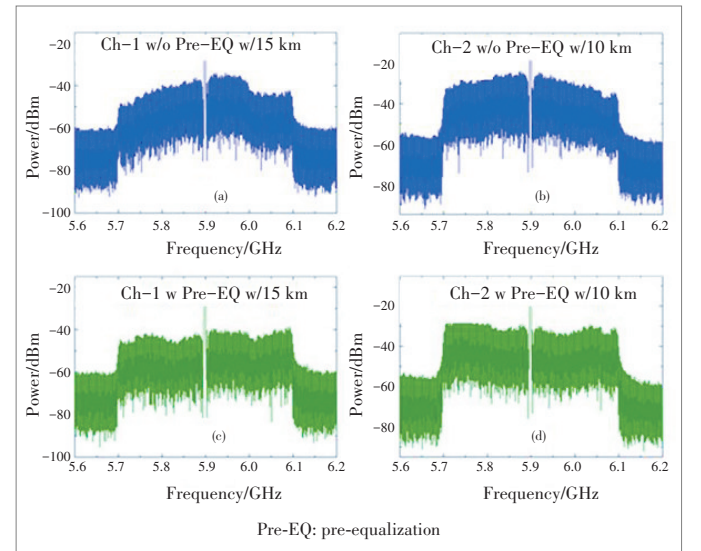


▲ Figure 6. (a) The BER of Ch-1 vs. transmission bit rates after 15 km fiber without and with Pre-EQ; (b) the BER of Ch-2 vs. transmission bit rates after 10 km fiber without and with Pre-EQ.

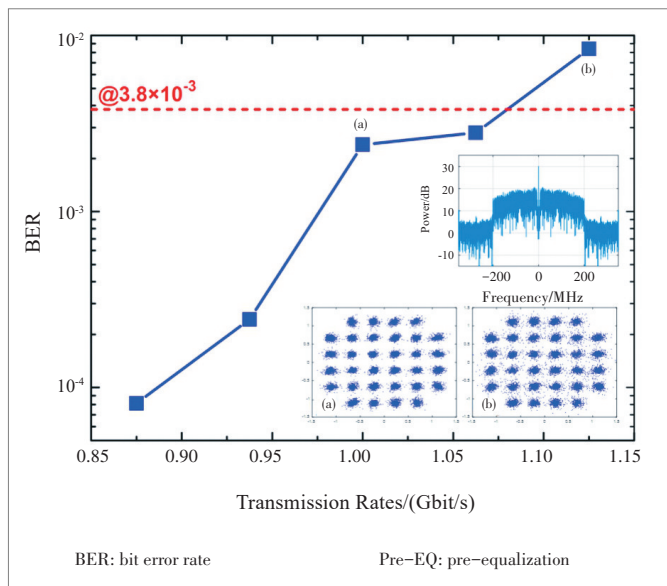
and Ch-2 versus the transmission rate after 15 km and 10 km fiber transmission respectively. With Pre-EQ, the transmission rate of both channels can be effectively increased from 1.125 Gbit/s to 1.5 Gbit/s. For dual-mode OAM multiplexing, a total 3 Gbit/s rate can be achieved. Constellations of DMT-32QAM signal at 1.375 Gbit/s without or with Pre-EQ are shown in the insets with blue and green markers respectively. The channel responses of Ch-1 and Ch-2 are shown in Fig. 7, which shows that the channel response coefficients can be flattened with Pre-EQ. As can be seen from Fig. 8, the channel response coefficients after 15 km transmission exceed the channel response coefficients after 18 km transmission with subcarrier index increasing.



▲ Figure 7. The channel response coefficients of Ch-1 and Ch-2 without and with Pre-EQ.



▲ Figure 8. The electrical spectra of the received DMT-32QAM signal without and with Pre-EQ.



▲ Figure 9. BER versus transmission bit rates for integrated fiber and OAM wireless transmission links.

Figs. 8a – d are the spectra of the received DMT-32QAM signals with and without Pre-EQ respectively. It indicates that the spectrum can be flush with the Pre-EQ as well. In this experiment, Ch-1 and Ch-2 were simultaneously transmitted. However, if one of the fiber links fails, the other link will not be affected. Therefore, data switching protection can be implemented based on service priority.

For the second experiment, the BER vs. transmission rates (Fig. 9) indicates that the signal transmission of 1.0625 Gbit/s can reach the 7% Forward error correction (FEC) threshold ($\text{BER} = 3.8 \times 10^{-3}$), which is even worse if the transmission rate is increased. The electrical spectrum of the down-converted 200 Mbaud DMT-32QAM signal and the constellations of 1 Gbit/s and 1.125 Gbit/s are shown in the insets respectively.

5 Conclusions

In this paper, a fiber-wireless reliable access network for MFH is proposed through the integration of fiber and wireless with dual-mode OAM multiplexing. We experimentally demonstrated a 3 Gbit/s DMT-32QAM fiber-optic wireless integrated system with a synclastic UCA. The system has Pre-EQ in the 5.9 GHz band, and both channels after 10 km and 15 km fiber transmission are transmitted over a 0.5-m wireless link simultaneously. The fiber-wireless reliable access network can alternatively be used for MFH.

References

- [1] CHANG G K, CHENG L, XU M, et al. Integrated Fiber-Wireless Access Architecture for Mobile Backhaul and Fronthaul in 5G Wireless Data Networks [C]// IEEE Avionics, Fiber-Optics and Photonics Technology Conference (AVFOP), Atlanta, USA, 2014. DOI:10.1109/avfop.2014.6999461

- [2] YU J J, HUANG M F, JIA Z S, et al. Polarization-Insensitive All-Optical Upconversion for Seamless Integration Optical Core/Metro/Access Networks with ROF Systems Based on a Dual-Pump FWM Scheme [J]. *Journal of Lightwave Technology*, 2009, 27(14): 2605 – 2611. DOI:10.1109/jlt.2009.2013364
- [3] YU J J, CHANG G-K, JIA Z S, et al. Cost-Effective Optical Millimeter Technologies and Field Demonstrations for very High Throughput Wireless-Over-Fiber Access Systems [J]. *Journal of Lightwave Technology*, 2010, 28(16): 2376 – 2397. DOI:10.1109/jlt.2010.2041748
- [4] ZHANG J W, WANG J, XU Y M, et al. Fiber-Wireless Integrated Mobile Backhaul Network Based on a Hybrid Millimeter-Wave and Free-Space-Optics Architecture with an Adaptive Diversity Combining Technique [J]. *Optics Letters*, 2016, 41(9): 1909 – 1912. DOI:10.1364/ol.41.001909
- [5] CHENG L, ZHU M, MUHAMMAD U G, et al. Adaptive Photonics-Aided Coordinated Multipoint Transmissions for Next-Generation Mobile Fronthaul [J]. *Journal of Lightwave Technology*, 2014, 32(10): 1907 – 1914
- [6] GOU P Q, KONG M, YANG G M, et al. Integration of OAM and WDM in Optical Wireless System by Radial Uniform Circular Array [J]. *Optics Communications*, 2018, 424: 159 – 162. DOI:10.1016/j.optcom.2018.04.059
- [7] FANG Y, YU J J, ZHANG J W, et al. Ultrahigh-capacity Access Network Architecture for Mobile Data Backhaul Using Integrated W-band Wireless and Free-space Optical Links with OAM Multiplexing [J]. *Optics Letters*, 2014, 39(14): 4168 – 4171. DOI:10.1364/ol.39.004168
- [8] BAI Q, TENNANT A, ALLEN B. Experimental Circular Phased Array for Generating OAM Radio Beams [J]. *Electronics Letters*, 2014, 50(20): 1414 – 1415. DOI:10.1049/el.2014.2860
- [9] YAO A M, PADGETT M J. Orbital Angular Momentum: Origins, Behavior and Applications [J]. *Advances in Optics and Photonics*, 2011, 3(2): 161 – 204. DOI: 10.1364/aop.3.000161
- [10] LI F, YU J J, FANG Y, et al. Demonstration of DFT-Spread 256QAM-OFDM Signal Transmission with Cost-effective Directly Modulated Laser [J]. *Optics Express*, 2014, 22(7): 8742 – 8748. DOI:10.1364/oe.22.008742

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ZTE Communications

Table of Contents, Volume 17, 2019

Volume-Number-Page

Special Topic

Quality of Experience for Emerging Video Communications

Editorial	CHEN Changwen, ZHAO Tiesong, and CHEN Zhibo	17-01-01
Recent Advances and Challenges in Video Quality Assessment	LI Dingquan, JIANG Tingting, and JIANG Ming	17-01-03
Quality Assessment and Measurement for Internet Video Streaming	ZHANG Xinggong, XIE Lan, and GUO Zongming	17-01-12
Automating QoS and QoE Evaluation of HTTP Adaptive Streaming Systems	Christian TIMMERER and Anatoliy ZABROVSKIY	17-01-18
Quality of Experience Effects in Video Delivery	CHEN Jinling, XU Yiwen, LIU Yisang, HUANG Huiwen, and ZHUANG Zhongwen	17-01-25
Visual Attention Modeling in Compressed Domain: From Image Saliency Detection to Video Saliency Detection	FANG Yuming and ZHANG Xiaoqiang	17-01-31
Perceptual Quality Assessment of Omnidirectional Images: Subjective Experiment and Objective Model Evaluation	DUAN Huiyu, ZHAI Guangtao, MIN Xiongkuo, ZHU Yucheng, FANG Yi, and YANG Xiaokang	17-01-38
Quality-of-Experience in Human-in-the-Loop Haptic Communications	LIU Qian and ZHAO Tiesong	17-01-48

Machine Learning for Wireless Networks

Editorial	WANG Zhengdao	17-02-01
A Framework for Active Learning of Beam Alignment in Vehicular Millimetre Wave Communications by Onboard Sensors	Erich ZÖCHMANN	17-02-02
Novel Real-Time System for Traffic Flow Classification and Prediction	YE Dezhong, LV Haibing, GAO Yun, BAO Qiuxia, and CHEN Mingzi	17-02-10
A Network Traffic Prediction Method Based on LSTM	WANG Shihao, ZHUO Qinzhen, YAN Han, LI Qianmu, and QI Yong	17-02-19
Potential Off-Grid User Prediction System Based on Spark	LI Xuebing, SUN Ying, ZHUANG Fuzhen, HE Jia, ZHANG Zhao, ZHU Shijun, and HE Qing	17-02-26
Detecting Abnormal Start-Ups, Unusual Resource Consumptions of the Smart Phone: A Deep Learning Approach	ZHENG Xiaoqing, LU Yaping, PENG Haoyuan, FENG Jiangtao, ZHOU Yi, JIANG Min, MA Li, ZHANG Ji, and JI Jie	17-02-38

Data Intelligence in New AI Era

Editorial	XU Chengzhong and QIAO Yu	17-03-01
A Lightweight Sentiment Analysis Method	YU Qingshuang, ZHOU Jie, and GONG Wenjuan	17-03-02
Big Data-Driven Residents' Travel Mode Choice: A Research Overview	ZHAO Juanjuan, XU Chengzhong, and MENG Tianhui	17-03-09
Face Detection, Alignment, Quality Assessment and Attribute Analysis with Multi-Task Hybrid Convolutional Neural Networks	GUO Da, ZHENG Qingfang, PENG Xiaojiang, and LIU Ming	17-03-15
RAN Centric Data Collection for New Radio	GAO Yin, LI Dapeng, HAN Jiren, LIU Zhuang, and LIU Yang	17-03-23

Computational Radio Intelligence: One Key for 6G Wireless

Editorial	JIANG Wei and LUO Fa-Long	17-04-01
To Learn or Not to Learn: Deep Learning Assisted Wireless Modem Design		17-04-01
	XUE Songyan, LI Ang, WANG Jinfei, YI Na1, MA Yi, Rahim TAFAZOLLI, and Terence DODGSON	17-04-03
A Machine Learning Method for Prediction of Multipath Channels	Julian AHRENS, Lia AHRENS, and Hans D. SCHOTTEN	17-04-12
A Case Study on Intelligent Operation System for Wireless Networks	LIU Jianwei, YUAN Yifei, and HAN Jing	17-04-19
Machine Learning for Network Slicing Resource Management: A Comprehensive Survey	HAN Bin and Hans D. SCHOTTEN	17-04-27
Machine Learning Based Unmanned Aerial Vehicle Enabled Fog-Radio Access Network and Edge Computing		
	Mohammed SEID, Stephen ANOKYE, and SUN Guolin	17-04-33
A Survey on Machine Learning Based Proactive Caching	Stephen ANOKYE, Mohammed SEID, and SUN Guolin	17-04-46

Review

Comparison Analysis on Feasible Solutions for LTE Based Next- Generation Railway Mobile Communication System		
	SUN Bin, DING Jianwen, LIN Siyu, WANG Wei, CHEN Qiang, and ZHONG Zhangdui	17-01-56
Cooperative Intelligence for Autonomous Driving	CHENG Xiang, DUAN Dongliang, YANG Liuqing, and ZHENG Nanning	17-02-44
Standardization of Fieldbus and Industrial Ethernet	CHEN Jinghe and ZHANG Hesheng	17-02-51
Reinforcement Learning from Algorithm Model to Industry Innovation: A Foundation Stone of Future Artificial Intelligence		
	DONG Shaokang, CHEN Jiarui, LIU Yong, BAO Tianyi, and GAO Yang	17-03-31
A Survey on Network Operation and Maintenance Quality Evaluation Models	LIU Lixia, WU Muyang, JI Feng, and LIU Zheng	17-04-56

Research Paper

SRSC: Improving Restore Performance for Deduplication-Based Storage Systems		
	ZUO Chunxue, WANG Fang, TANG Xiaolan, ZHANG Yucheng, and FENG Dan	17-02-59
A Low-Cost Outdoor Fingerprinting Localization Scheme For Wireless Cellular Networks		
	PEI Dengke, XU Xiaodong, QIN Xiaowei, LIU Dongliang, and ZHAO Chunhua	17-03-42
High Speed Polarization-Division Multiplexing Transmissions Based on the Nonlinear Fourier Transform		
	WANG Jia, ZHAO Yilong, HUANG Xin, and HE Guangqiang	17-03-50
A Service-Based Intelligent Time-Domain and Spectral-Domain Flow Aggregation in IP-over-EON Based on SDON		
	NI Dong, LI Hui, JI Yuefeng, LI Hongbiao, and ZHU Yinan	17-03-56
Data-Driven Joint Estimation for Blind Signal Based on GA-PSO Algorithm	LIU Shen, QIN Yuannian, LI Xiaofan, ZHAO Yubin, and XU Chengzhong	17-03-63
An Improved Non-Geometrical Stochastic Model for Non-WSSUS Vehicle-to-Vehicle Channels	HUANG Ziwei, CHENG Xiang, and ZHANG Nan	17-04-62
Fiber-Wireless Integrated Reliable Access Network for Mobile Fronthaul Using Synclastic Uniform Circular Array with Dual-Mode OAM Multiplexing		
	XU Yusi, WU Xingbang, YANG Guomin, and CHI Nan	17-04-72

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