

Guest Editorial

Special Issue on Artificial Intelligence and Machine Learning for Networking and Communications

Prosper Chemouil, *Fellow, IEEE*, Pan Hui, *Fellow, IEEE*, Wolfgang Kellerer, *Senior Member, IEEE*, Yong Li, *Senior Member, IEEE*, Rolf Stadler, *Senior Member, IEEE*, Dacheng Tao, *Fellow, IEEE*, Yonggang Wen, *Senior Member, IEEE*, and Ying Zhang, *Senior Member, IEEE*

I. INTRODUCTION

RESearch in large-scale networking systems has been shaped and will continue to be guided by specific characteristics of applications and the underlying platforms and infrastructures. On the one hand, applications are growing at an accelerated pace, which is fundamentally unpredictable in both breadth and depth. On the other hand, the underlying networking has been the focus of a huge transformation enabled by new models resulting from virtualization and cloud computing. This has led to a number of novel architectures supported by emerging technologies such as Software-Defined Networking (SDN), Network Function Virtualization (NFV), and more recently, edge cloud and fog networking, or network slicing [1], [2]. This evolution towards enhanced design opportunities along with increasing complexity in networking and its applications has fueled the need for improved network automation in agile infrastructures. At the same time, their complexity has dramatically increased. The networking dynamics have had the effect of making it even more important and challenging to design scalable network measurement and analysis techniques and associated tools. Critical applications such as resource allocation, network monitoring, security enforcement, or dynamic network management require real-time mechanisms for online analysis as well as efficient techniques for offline deep analysis of massive historical data.

P. Chemouil, retired, was with Convergent Network Control Laboratory, Orange Labs, 92320 Châtillon, France (e-mail: prosper.chemouil@ieee.org).

P. Hui is with the Department of Computer Science, University of Helsinki, 00014 Helsinki, Finland, and also with the Department of Computer Science and Engineering, The Hong Kong University of Science and Technology, Hong Kong (e-mail: panhui@cse.ust.hk).

W. Kellerer is with the Department of Electrical and Computer Engineering, Technical University of Munich, 80333 Munich, Germany (e-mail: wolfgang.kellerer@tum.de).

Y. Li is with the Beijing National Research Center for Information Science and Technology, Department of Electronic Engineering, Tsinghua University, Beijing 100084, China (e-mail: liyong07@tsinghua.edu.cn).

R. Stadler is with the Department of Computer Science, School of Electrical Engineering and Computer Science, KTH Royal Institute of Technology, SE-100 44 Stockholm, Sweden (e-mail: stadler@kth.se).

D. Tao is with UBTECH Sydney AI Centre, School of Computer Science, Faculty of Engineering and IT, The University of Sydney, Sydney, NSW 2008, Australia (e-mail: dacheng.tao@sydney.edu.au).

Y. Wen is with School of Computer Science and Engineering, Nanyang Technological University, Singapore 639798 (e-mail: ygwen@ntu.edu.sg).

Y. Zhang is with Network Infrastructure, Facebook, Menlo Park, CA 94025 USA (e-mail: winginsky@gmail.com).

Digital Object Identifier 10.1109/JSAC.2019.2909076

Artificial Intelligence (AI) and Machine Learning (ML) approaches, well known from scientific disciplines such as computer vision, natural language processing and speech recognition, are nowadays wide spreading to numerous areas, and they have been recently re-gaining attraction in the networking domain. AI and ML represent a different paradigm to tackle these challenges. Its data-driven nature facilitates to automatically learn the complexity of the communications and networking environment and to dynamically adjust protocols without human interactions. AI/ML techniques for network management, operations & automation are meant to improve the way we address networking today, it may require specific designs. They have been made possible for networking researchers, mainly owing to three technological trends: first, the cost of system prototyping has been reduced to an affordable level to academia. A prolific pool of open-source frameworks and technologies has helped to reduce the development effort for a system prototype with a proper reference design to a minimum level. Moreover, the cost of launching a new application for public trial has been driven to the minimum with the emergence of cloud computing technologies. Second, the emerging big-data paradigm has rendered it relatively easier for researchers to gain easy access to large datasets, which used to be heavily guarded by companies and practitioners. Via an AI engine, one can quickly obtain real-time knowledge about the system and its stakeholders. Finally, the emergence of programmable system technologies, i.e., software-defined systems, has made it feasible to realign the system design and implementation in a hot “plug-and-play” manner. Examples of programmable systems include SDN, NFV, storage virtualization and computing.

These trends have drawn attention to interdisciplinary approaches from communication networks and AI/ML research communities. On the one hand, researchers in communication networks are tapping into ML and AI techniques to optimize network architecture, control and management, leading to more automation in network operations. Interested readers are referred to a comprehensive survey on machine learning for networking [3]. On the other hand, researchers in the AI community are working with networking researchers to develop new AI/ML frameworks, able to cater for running a broad range of applications at scale.

However, in the current stage, applying AI/ML to networked systems remains inadequately understood and investigated.

Most of the proposed solutions are problem specific, in-house and difficult to benchmark. Although machine learning and big data analytic techniques that are able to characterize, detect, locate and understand complex behaviors, promise to shed light on this huge amount of data, smart and scalable approaches must be conceived to make them generally applicable in networking and communication systems. Finally, the explosion in volume and heterogeneity of data generated across the entire wireless and network stack has opened the door to innovative solutions and out-of-the-box thinking which in turn promises to improve current communication systems and networks, as well as fostering innovative solutions in new network-centric domains.

This special issue aims at addressing the current directions of research and at presenting novel contributions in the field of AI/ML applied to communications and networking, including scalable analytical techniques and frameworks capable of collecting and analyzing both online and offline massive datasets. Furthermore, its goal is to address innovative design approaches and use cases related to the application of AI/ML in communications and networking, to discuss open issues related to the application of machine learning into networking system problems, and to share new ideas and techniques for big data analysis in communication systems.

II. SPECIAL ISSUE OVERVIEW

This special issue has welcomed high-quality original contributions addressing the important challenges and presenting novel research solutions in the development of AI/ML techniques and their applications to computer and communication networks. Survey papers that offer a perspective on related work and identify key challenges for future research have been considered as well.

The timeliness and interest in AI and ML are reflected by the huge number of submissions. 152 papers were submitted by 600+ authors from over 27 countries and 6 continents. Asia is highly represented and mainland China has been the country to respond with most submissions to the call (40% excluding Hong Kong). Interestingly, most papers (90%) originated from academia. Only 4 papers have been identified out of scope and thus early rejected. The review process involved 369 individual reviewers, and each one evaluated at least one paper. The submitted papers were thoroughly reviewed and, where needed, some selected authors were given the opportunity to update and revise their papers to address in detail the reviewers' concerns. All revised manuscripts were then shepherded by one or two Guest Editors and it was finally decided to accept only twenty papers for inclusion in this special issue (an acceptance ratio of 13%).

The time between the initial submission and the online publication of the revised papers in this special issue was about 7 months.

The selected papers in this special issue are exploring how AI and ML can be used to address various areas in the design and performance management of networks and systems. It includes the following non-exhaustive list of topics, falling into three sub-categories of fundamental frameworks, network analytics, network optimization and network automation.

The topics covered include terminal identification, interference coordination, data collection, data analysis, data privacy, traffic estimation/prediction, MAC resource allocation, scheduling, resource management and allocation, anomaly detection, congestion control, quality of experience, energy efficiency in wireless systems, backhaul and backbone networks, and fog or cloud nodes. Many contributions are targeting future 5G networks and focusing on wireless networks and IoT, while a few are more focused on edge computing and multimedia networks.

While it is difficult to appropriately cluster the 20 papers into specific categories, we can distinguish various applicative trends in the proposals, even though most of them address several topics:

- A. *Descriptive AI*. It relies on a set of historical data to yield, thanks to AI techniques, insightful information and possibly prepare the data for further analysis. Potential areas include data collection and analysis, and related issues.
- B. *Predictive AI*. It attempts to understand the causes of events and behaviors. Potential areas include fault diagnostics and anomaly detection, while providing insight on performance and Key Performance Indicators (KPIs).
- C. *Prescriptive AI*. It provides ways to improve network efficiency. Potential areas include using deep learning techniques for resource allocation, that covers MAC resource allocation, scheduling, and resource management.

Among the twenty selected papers in this special issue, seven papers are mostly dealing with descriptive AI, while six papers focus on predictive approaches. Finally, seven papers are mainly related to prescriptive AI.

A. *Descriptive AI in Communications Networks*

In "Towards knowledge as a service over networks: a deep learning model communication paradigm", Chen *et al.* address the exchange of knowledge in IoT environments via neural network models [4]. They propose a deep-learning model communication paradigm based on multiple model compressions, that exploits the redundancy among multiple deep learning models in different application scenarios.

In "Deep transfer learning for intelligent cellular traffic prediction based on cross-domain big data", Zhang *et al.* focus on predicting cellular traffic, taking spatial and temporal features into account [35]. They develop a deep learning-based method which exploits transfer learning approach, thereby enabling their model to train on other available auxiliary datasets as well, in addition to main dataset, in order to make more accurate and robust prediction.

In "Idle time window prediction in cellular networks with deep spatiotemporal modeling", Luoyang *et al.* study the idle time windows (ITW) prediction in mobile networks based on network subscribers' demand and mobility behaviors observed by network operators [6]. A novel temporal-graph convolutional networks (TGCN) model is designed to characterize both the spatial and temporal relevance for the idle time

window prediction. Experiments on real mobile signal dataset demonstrated the promising performance of TGCN.

The paper “AuDI: Towards autonomous IoT device-type identification using periodic communication” by Marchal *et al.* presents a system for quickly and effectively identifying the type of a device in an IoT network by analyzing their network communications [7]. The approach models the periodic communication traffic of IoT devices using an unsupervised learning method to perform identification allowing for the definition of common policies for classes of devices based on device type.

In “Energy-efficient distributed mobile crowd sensing: a deep learning approach”, Liu *et al.* propose a concept for navigating mobile terminals’ sensing and movement around points of interest minimizing their energy consumption [8]. The resulting control algorithm integrates Convolutional Neural Network (CNN) for feature extraction, and then makes decisions under the guidance of multi-agent deep deterministic policy gradient method in a fully distributed manner.

In “Data transmission reduction schemes in WSNs for efficient IoT systems”, Jarwan *et al.* focus on the problem of reducing energy consumption of continuous sensor data collection by exploiting the spatial and temporal correlation of the generated traffic in wireless sensor networks [9]. They compare and analyze several state-of-the-art machine learning algorithms that assess improvement in energy reduction with the machine learning approach.

In “A privacy-preserving-based data collection and analysis framework for IoMT applications”, Usman *et al.* propose a data collection and analysis framework for IoMT (Internet of Multimedia Things) applications using clustering of underlying Wireless Multimedia Sensor Networks (WMSNs) into multiple clusters [10]. While cluster heads are responsible for protecting the privacy of member nodes through data and location aggregation, aggregated multimedia data is then analyzed at the cloud server using a counter-propagation artificial neural network to extract meaningful information through segmentation.

B. Predictive AI in Communications Networks

In “Dynamic TCP initial windows and congestion control schemes through reinforcement learning”, Nie *et al.* consider dynamic TCP performance control using the framework and techniques of reinforcement learning [11]. Depending on the network conditions, the initial window size and a congestion control scheme are chosen and dynamically adapted. Testbed experiments show the effectiveness of the proposed solution and gains over known control schemes.

The paper “Experience-driven congestion control: when multi-path TCP meets deep reinforcement learning” by Xu *et al.* introduces a framework for congestion control of multi-path TCP [12]. The framework is based on representation learning and includes three different neural networks to dynamically control the congestion windows of all active flows in a host. The proposed framework is implemented in a Linux environment and is evaluated against several Multi-path TCP congestion control schemes. It performs well against the

traditional schemes regarding goodput and fairness in a broad range of scenarios.

In “Learning QoE of mobile video transmission with deep neural network: A data-driven approach”, Tao *et al.* aim to develop a data-driven approach to predict the quality of experience (QoE) in mobile video transmission [13]. They first construct a dataset for QoE of mobile video transmission and then propose a method to predict subjective QoE scores. A deep-neural network (DNN) is developed to learn the relationships between the network parameters and the subjective QoE scores.

Jiang *et al.* address the problem of resource allocation in NB-IoT in their paper entitled “Reinforcement learning for real-time optimization in NB-IoT networks”. They provide several proposals using reinforcement learning to maximize the number of served IoT devices in dynamic environments [14]. In the paper, the authors show that their approach requires less training time while the improvement of their algorithm using cooperative multi-agent learning outperforms other methods and converges to efficient solutions even at large scale.

In “Wireless traffic prediction with scalable Gaussian process: Framework, algorithms, and verification”, Yue *et al.* address wireless traffic prediction using ML techniques [15]. The proposed scalable Gaussian process (GP) framework can handle large-scale wireless traffic prediction with the consideration of computational complexity. Experiments on real base station traffic data demonstrated the effectiveness of the proposed method.

In “Anomaly-tolerant network traffic estimation via noise-immune temporal matrix completion model”, Xiao *et al.* provide a method to simultaneously estimate a network traffic matrix estimation and detect network anomalies based on a novel matrix completion model that can cope with noise and network anomalies [16].

C. Prescriptive AI in Communications Networks

In “Optimal and fast real-time resources slicing with deep dueling neural networks”, Huynh *et al.* focus on network slicing by considering the availability of resources such as radio, compute and storage in real-time. They develop a reinforcement learning algorithm which is based on a deep dueling approach allowing for the convergence rate to improve in large networks [17]. Based on a semi-Markov decision process, the solution provided by the authors outperforms conventional Q-learning algorithms as well as more elaborate approaches such as a double Q-learning model.

In “Adaptive federated learning in resource constrained edge computing systems”, Wang *et al.* address the problem of federated learning in distributed systems as exemplified by current network architectures such as Multi-access Edge Computing (MEC) [18]. They derive a mathematical formulation for learning model parameters that allows accounting for limited resource capability at the edge nodes while remotely coordinating aggregates in the cloud. In the paper, the authors consider a gradient-descent approach which is common to many machine learning methods and determine the optimal

trade-off between local update and global parameter aggregate to efficiently use constrained edge and network resources.

In “A reinforcement learning approach to energy efficiency and QoS in 5G wireless networks”, Wang *et al.* focus on a game-theoretic approach to design a distributed energy-efficient bandwidth sharing mechanisms for small-cell networks [19]. They develop two reinforcement learning-based approaches to strike a balance between energy efficiency and high bandwidth utilization.

In “Spatial deep learning for wireless scheduling”, Cui *et al.* focus on scheduling interfering links in a wireless communications network using deep learning-based framework and techniques [20]. The proposed spatial deep learning network gives the near-optimal performance for sum-rate maximization and is capable of generalizing to larger deployment areas and to deployments of different link densities.

In “Deep-reinforcement learning multiple access for heterogeneous wireless networks”, Yu *et al.* investigate the use of deep reinforcement learning in a MAC protocol for heterogeneous wireless networking referred to as Deep-reinforcement Learning Multiple Access [21]. The proposed solution solves the problem of sharing time slots among a multiple of time-slotted networks that adopt different MAC protocols. Extensive simulation results show that the proposed solution can achieve near-optimal sum throughput and proportional fairness objectives, two special cases of α -fairness.

In “Online learning for energy saving and interference coordination in HetNets”, Ayala-Romero *et al.* develop a two-level algorithm to jointly control energy saving and interference coordination mechanism based on a contextual bandit formulation to optimize the energy efficiency [22]. The control framework includes a global controller, in charge of a group of macrocell, and multiple local controllers, one per macro cell. The main benefit of this two-level scheme is the drastic reduction of the dimensionality of the learning problem.

In “Joint transceiver optimization for wireless communication PHY using neural network”, Zhu *et al.* propose a novel neural network structure for jointly optimizing the transmitter and receiver in communication physical layer under fading channels [23]. They propose a convolutional auto-encoder structure that is capable to automatically design communication physical layer scheme according to different channel status. The system has no restriction on the length of input bit sequence. The experiment results give empirical evidence for the superiority of the proposed system.

III. RESEARCH CHALLENGES

In this section we outline research topics that have attracted less attention to date by the research community and lack representation in the selected papers for this issue. We believe they are of high potential and should be investigated to fully exploit AI/ML methods for networking and networked systems in general.

A. Effective Network Data Representation

Statistical learning allows us to create a model of a system from observations; the behavior of a system is learned through

monitoring it over a satisfactorily long time. This insight leads to two research directions, in which one is currently actively pursued while the other one is largely unexplored. The first direction focuses on learning effective control policies and decisions. Such works generally address complex optimization or control problems where optimal solutions are intractable to compute. The learned models provide heuristic solutions whose quality depends on the learning methods used and the input data. Characteristic of these approaches is that the structure of the input data is clearly defined by the formal problem description and includes only a small number of data types or data sources.

The second direction of research is on data representation of the networked systems. Consider the problem of predicting or forecasting end-to-end metrics in a networked system, such as service-level KPIs or QoE metrics of network services. Due to the overall complexity of such systems, a formal model-based approach is generally not feasible and statistical learning has emerged as an attractive option. Data sources that can be selected for model computation are abundant and include logs, local metrics and statistics, as well as telemetry data. The number of data types (or sources) that are available for model computation can be very large and range from several dozens for a small system to billions for a large infrastructure.

The problem thus becomes identifying and producing a data representation of the system from which efficient and accurate prediction models can be learned. (Finding such a representation is referred to as feature engineering in an AI/ML context.) In the case of networked systems, representations are built from a large set of heterogeneous and distributed data sources, often measured with various degrees of accuracy, read out at various rates, and degraded by missing or corrupted data.

An effective data representation should have low dimensionality, i.e., the number of data sources or aggregated metrics is kept low, which reduces the computation time for learning and decreases the number of observations needed for accurate prediction. How to find such representations has been thoroughly studied for cognitive tasks, such as image or voice recognition, but has not been addressed for network engineering.

Learning models based on deep architectures, such as deep neural networks, produce consecutive layers of data representation, to which semantics like increasing levels of conceptual abstractions can be attributed. Again, such representations are well understood for cognitive tasks but have not been investigated or leveraged in the context of network engineering.

B. Integrated Decision-Making Into the Networks

The decision-making process in a networked system can be modeled as three consecutive sub-processes: monitoring, i.e., for estimating the state of a networked system and its evolution over time; learning/inference, which includes estimation and forecasting derived metrics; and control actions aimed at changing the system state following given policies. These subprocesses are currently studied, designed, and optimized in isolation. The challenge is to understand them as combined

activities, develop integrated designs, and jointly optimize them.

Integrated decision-making is of particular importance in two contexts. First, in environments with limited communication or computational resources where a fundamental understanding of the tradeoffs between overhead incurred by monitoring, learning, and control on the one side and the effectiveness of decision making on the other side becomes crucial. The second context relates to large-scale systems where data sources and control points are highly distributed. Many emerging networked systems fall into this category. While for small systems (i.e. up to dozens of nodes or data sources) centralized solutions are preferable due to design simplicity, for larger systems, distributed schemes must be investigated. In the recent literature, hierarchical schemes as well as methods using more general topologies have been proposed.

From a systems point of view, the technology of softwarization within telecom networks is expected to facilitate integrated decision making [24], [25]. The concept of network function virtualization (NFV), a key aspect of softwarization, allows to place a functionality in the network infrastructure where resources are available and constraints are met. In addition, NFV facilitates the online change of functional configurations so that adaptive decision-making processes can be implemented.

C. Architectures for Learning From Network Data

Integrated decision making in networks must be supported by a dedicated architecture. As depicted in the previous section, network softwarization and NFV in particular facilitate the placement and online adaptation of (virtualized) network functions. Research challenges with respect to AI/ML that arise from such network adaptation potential are twofold. First, in a softwarized network environment, the options and their parameters for placing and chaining functions become hardly tractable in today's large and complex networks. Hence, AI/ML methods can be used as tools to tackle the complexity and provide heuristic solutions to largely complex optimization problems.

Second, the network support for online decision making is an open research question. In order to facilitate the execution of AI/ML methods in network elements or distributed over several network elements, new architectures for programmable network elements facilitating in-network processing are required. How can AI/ML be supported by network hardware and software? For example, well integrated GPU-based architectures for fast computation of large data sets could be a possible solution.

D. Network Automation

As already hinted at in the previous section, the trend to higher programmability in wired and wireless networks as described by the potential of network softwarization opens up a plethora of new options for a fully flexible network operation, control and management. The Software-Defined Networking (SDN) concept supports the adaptation of network

flows, the Network Function Virtualization (NFV) concept supports the flexible split and allocation of functions, and network virtualization/slicing supports multiple heterogeneous applications in one network substrate. Whereas the three concepts have emerged for wired networks, their application for radio networks is currently an important research topic.

The aforementioned options result in a much higher complexity for network control and management as ever before. Hence, decision making becomes extremely difficult and algorithmically challenging. AI/ML methods are considered to provide efficient solutions here. First, they support heuristics outperforming existing optimization algorithms in terms of speed. Second, compared to existing heuristic solutions, AI/ML approaches provide the possibility to adapt to the actual network state without manual adaptation.

One step further, it is now commonly considered that future networks will operate autonomously, taking into account their own state, the state of the environment and their complex parameter options. AI/ML methods provide means for decision making to facilitate network automation. One example is self-driving networks which have to deal with the uncertainty of the data input such as arrival of flows, traffic volume, applications, hardware availability, etc. The desired property of a self-driving network is being prepared for challenges and requirements that come up in the future. That means a system is robust to changes in the environment and opens for new tasks without significant performance degradation.

E. Standardized Test Cases and Datasets to Assess AI/ML Solutions

Whereas the potential of applying AI/ML methods is obvious, the evaluation and comparison of different solutions is difficult due to the lack of common test cases and datasets. Due to the heterogeneity of the problem space to be addressed by AI/ML, this is a challenging task for the research community. Nevertheless, it is of high importance to be able to assess AI/ML solutions properly to be able to understand their applicability to specific and generalized problem sets. Test cases describe a set of challenges that have to be solved by a system implementation, e.g. a trajectory for a UAV (Unmanned Aerial Vehicle), a sequence of network function embedding requests, etc. Data sets contain data that is representative and typical for a certain problem space.

We hope that the above-mentioned topics are providing useful food-for-thoughts to researchers and will result in many contributions to a future special issue of JSAC devoted to advances in artificial intelligence and machine learning for networking. The corresponding call for papers under preparation should be more focused to address areas that have not been well embraced in this current issue.

ACKNOWLEDGEMENTS

The guest editors would like to thank all authors who submitted papers to this special issue. We are grateful to all the many reviewers who have provided timely thorough reviews allowing to further improve the selected papers in the revision round. We thank Muriel Médard and Raouf Boutaba, the

former and present Editor-in-Chief of the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, as well as Philip Whiting, IEEE JSAC Senior Editor, for their support. Finally, we acknowledge the assistance of Janine Bruttin, Executive Editor of IEEE JSAC, and Lauren Briede, Editorial Support and Production Assistant, who helped with logistical and procedural issues during the SI production process.

REFERENCES

- [1] B. A. A. Nunes, M. Mendonca, X.-N. Nguyen, K. Obraczka, and T. Turetli, "A survey of software-defined networking: Past, present, and future of programmable networks," *IEEE Commun. Surveys Tuts.*, vol. 16, no. 3, pp. 1617–1634, 3rd Quart., 2014.
- [2] Y. Li and M. Chen, "Software-defined network function virtualization: A survey," *IEEE Access*, vol. 3, pp. 2542–2553, Dec. 2015.
- [3] R. Boutaba *et al.*, "A comprehensive survey on machine learning for networking: Evolution, applications and research opportunities," *J. Internet Services Appl.*, vol. 9, no. 1, p. 16, Jun. 2018.
- [4] Z. Chen *et al.*, "Towards knowledge as a service over networks: A deep learning model communication paradigm," *IEEE J. Sel. Areas Commun.*, to be published.
- [5] C. Zhang, H. Zhang, J. Qiao, D. Yuan, and M. Zhang, "Deep transfer learning for intelligent cellular traffic prediction based on cross-domain big data," *IEEE J. Sel. Areas Commun.*, to be published.
- [6] L. Fang, X. Cheng, H. Wang, and L. Yang, "Idle time window prediction in cellular networks with deep spatiotemporal modeling," *IEEE J. Sel. Areas Commun.*, to be published.
- [7] S. Marchal, M. Miettinen, T. D. Nguyen, A.-R. Sadeghi, and N. Asokan, "AuDI: Towards autonomous IoT device-type identification using periodic communication," *IEEE J. Sel. Areas Commun.*, to be published.
- [8] C. H. Liu, Z. Chen, and Y. Zhan, "Energy-efficient distributed mobile crowd sensing: A deep learning approach," *IEEE J. Sel. Areas Commun.*, to be published.
- [9] A. Jarwan, A. Sabbah, and M. Ibnkahla, "Data transmission reduction schemes in WSNs for efficient IoT systems," *IEEE J. Sel. Areas Commun.*, to be published.
- [10] M. Usman, M. A. Jan, X. He, and J. Chen, "A privacy-preserving-based data collection and analysis framework for IoMT applications," *IEEE J. Sel. Areas Commun.*, to be published.
- [11] X. Nie *et al.*, "Dynamic TCP initial windows and congestion control schemes through reinforcement learning," *IEEE J. Sel. Areas Commun.*, to be published.
- [12] Z. Xu, J. Tang, C. Yin, Y. Wang, and G. Xue, "Experience-driven congestion control: When multi-path TCP meets deep reinforcement learning," *IEEE J. Sel. Areas Commun.*, to be published.
- [13] X. Tao, Y. Duan, M. Xu, Z. Meng, and J. Lu, "Learning QoE of mobile video transmission with deep neural network: A data-driven approach," *IEEE J. Sel. Areas Commun.*, to be published.
- [14] N. Jiang, Y. Deng, A. Nallanathan, and J. A. Chambers, "Reinforcement learning for real-time optimization in NB-IoT networks," *IEEE J. Sel. Areas Commun.*, to be published.
- [15] Y. Xu, F. Yin, W. Xu, J. Lin, and S. Cui, "Wireless traffic prediction with scalable gaussian process: Framework, algorithms, and verification," *IEEE J. Sel. Areas Commun.*, to be published.
- [16] F. Xiao, L. Chen, H. Zhu, R. Hong, and R. Wang, "Anomaly-tolerant network traffic estimation via noise-immune temporal matrix completion model," *IEEE J. Sel. Areas Commun.*, to be published.
- [17] N. V. Huynh, D. T. Hoang, D. N. Nguyen, and E. Dutkiewicz, "Optimal and fast real-time resource slicing with deep dueling neural networks," *IEEE J. Sel. Areas Commun.*, to be published.
- [18] S. Wang *et al.*, "Adaptive federated learning in resource constrained edge computing systems," *IEEE J. Sel. Areas Commun.*, to be published.
- [19] Y. Wang, X. Dai, J. M. Wang, and B. Bensaou, "A reinforcement learning approach to energy efficiency and QoS in 5G wireless networks," *IEEE J. Sel. Areas Commun.*, to be published.
- [20] W. Cui, K. Shen, and W. Yu, "Spatial deep learning for wireless scheduling," *IEEE J. Sel. Areas Commun.*, to be published.
- [21] Y. Yu, T. Wang, and S. C. Liew, "Deep-reinforcement learning multiple access for heterogeneous wireless networks," in *Proc. IEEE Int. Conf. Commun.*, May 2018, pp. 1–7.
- [22] J. A. Ayala-Romero, J. J. Alcaraz, A. Zanella, and M. Zorzi, "Online learning for energy saving and interference coordination in hetnets," *IEEE J. Sel. Areas Commun.*, to be published.
- [23] B. Zhu, J. Wang, L. He, and J. Song, "Joint transceiver optimization for wireless communication PHY using neural network," *IEEE J. Sel. Areas Commun.*, to be published.
- [24] J. Xie *et al.*, "A survey of machine learning techniques applied to software defined networking (SDN): Research issues and challenges," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 1, pp. 393–430, 1st Quart., 2019.
- [25] W. Kellerer, P. Kalmbach, A. Blenk, A. Basta, M. Reisslein, and S. Schmid, "Adaptable and data-driven softwarized networks: Review, opportunities, and challenges," *Proc. IEEE*, vol. 107, no. 4, pp. 711–731, Apr. 2019.



Prosper Chemouil (F'03) received the M.Sc. and Ph.D. degrees in control theory from the École Centrale de Nantes, in 1976 and 1978, respectively. He is currently a retired Research Director on Future Networks with Orange Labs, and he remains active as an IEEE Service Volunteer. For several years, he has been focusing on cognitive management and network softwarization. His research interests include the design and management of new networks and technologies and their impact on network architecture, traffic engineering and control, and performance, with significant involvement in standardization at ITU-T for 25 years. In this context, he then investigated the potential of various artificial intelligence techniques for network management in the early 1990s. He is a fellow of SEE, the Electrical and Electronical Society of France. He was a recipient of several awards, such as the Blondel Medal in 1996, the Ampère Medal in 2003, the Salah Aidarous Memorial Award in 2014, and the Arne Jensen Lifetime Achievement Award in 2015. He was nominated as French Senior Engineer of the Year in 1995 and became a Fellow of France Telecom R&D in 1998. In 2016, he became Co-Chair of the IEEE SDN Initiative and a member of the IEEE ComSoc Industry Communities Board, representing the SDN/NFV/Cloud area. Within the IEEE SDN Initiative, he launched NetSoft, the IEEE International Conference on Network Softwarization, in 2015. He has been involved as the General or TPC Co-Chair in many events dealing with network performance and management. He has also served as a Board Member, Associate Editor, and Guest Editor for various journals, including the *IEEE Communications Magazine*, the IEEE TRANSACTIONS ON NETWORK AND SERVICE MANAGEMENT, the IEEE NETWORKS, and *Annals of Telecommunications*.



Pan Hui (F'18) received the bachelor's and M.Phil. degrees from The University of Hong Kong, and the Ph.D. degree from the Computer Laboratory, University of Cambridge. His industrial profile includes his research at Intel Research Cambridge and Thomson Research Paris from 2004 to 2006. He was a Senior Research Scientist and then a Distinguished Scientist of Telekom Innovation Laboratories (T-labs), Germany, from 2008 to 2015. He was an Adjunct Professor of social computing and networking with Aalto University from 2012 to 2016. He is currently the Nokia Chair Professor in data science and a Professor of computer science with the University of Helsinki and also the Director of the HKUST-DT System and Media Laboratory, The Hong Kong University of Science and Technology. He has published more than 250 research papers and with over 15000 citations. He has 30 granted and filed European and U.S. patents in the areas of augmented reality and mobile computing. He has founded and chaired several IEEE/ACM conferences/workshops, and he has been serving on the Organizing and Technical Program Committee of numerous top international conferences, including ACM SIGCOMM, MobiSys, the IEEE Infocom, ICNP, SECON, MASS, Globecom, WCNC, ITC, ICAI, AAI, ICWSM, and WWW. He was an Associate Editor of the IEEE TRANSACTIONS ON CLOUD COMPUTING and a Guest Editor of the *IEEE Communication Magazine* and the *ACM Transactions on Multimedia Computing, Communications, and Applications*. He has been an Associate Editor for leading journals including the IEEE TRANSACTIONS ON MOBILE COMPUTING since 2014. He is an ACM Distinguished Scientist.



Wolfgang Kellerer received the Dipl.Ing. (master's) and Dr. Ing. (Ph.D.) degrees from the Technical University of Munich, Germany, in 1995 and 2002, respectively. He was with NTT DOCOMO's European Research Laboratories for ten years in leading positions, contributing to research and standardization of LTE-A and 5G technologies. In 2001, he was a Visiting Researcher with the Information Systems Laboratory, Stanford University, CA, USA. He is currently a Full Professor, heading the Chair of Communication Networks, Department of Electrical and Computer Engineering, Technical University of Munich. His research has resulted in over 200 publications and 35 granted patents. He is a member of ACM and VDE ITG. He received an ERC Consolidator Grant from the European Commission for his research project FlexNets "Quantifying flexibility in communication networks" in 2015. He currently serves as an Associate Editor for the IEEE TRANSACTIONS ON NETWORK AND SERVICE MANAGEMENT. He is on the Editorial Board of the IEEE COMMUNICATIONS SURVEYS AND TUTORIALS and the IEEE NETWORKING LETTERS.



Dacheng Tao (F'15) is currently a Professor of computer science and an ARC Laureate Fellow with the School of Computer Science and the Faculty of Engineering and Information Technologies, and also the Inaugural Director of the UBTECH Sydney Artificial Intelligence Centre, The University of Sydney. His research in artificial intelligence is at the forefront of heralding the next generation of autonomous machines. His research results have expounded in one monograph and over 200 publications in prestigious journals and prominent conferences, such as the IEEE T-PAMI, IJCV, JMLR, AAAI, IJCAI, NIPS, ICML, CVPR, ICCV, ECCV, and ICDM, and ACM SIGKDD, with several best paper awards, such as the 2014 ICDM 10-year Highest-Impact Paper Award, the 2017 IEEE Signal Processing Society Best Paper Award, and the Distinguished Paper Award in the 2018 IJCAI. He is a fellow of the Australian Academy of Science, AAAS, IAPR, OSA, and SPIE. He received the 2015 Australian Scopus-Eureka Prize and the 2018 IEEE ICDM Research Contributions Award.



Yong Li (M'09–SM'16) received the B.S. degree in electronics and information engineering from the Huazhong University of Science and Technology, Wuhan, China, in 2007, and the Ph.D. degree in electronic engineering from Tsinghua University, Beijing, China, in 2012.

He is currently a Faculty Member with the Department of Electronic Engineering, Tsinghua University. He was recipient of the IEEE 2016 ComSoc Asia-Pacific Outstanding Young Researchers and Young Talent Program of China Association for

Science and Technology. He has served as the General Chair, the TPC Chair, and a TPC Member of several international workshops and conferences. He is on the Editorial Board of two IEEE journals. His papers have more than 5800 total citations. Among them, ten are ESI highly-cited papers in computer science, and four received Conference Best Paper (run-up) Awards.



Yonggang Wen received the Ph.D. degree in electrical engineering and computer science (minor in western literature) from the Massachusetts Institute of Technology (MIT), Cambridge, USA, in 2008. He is currently an Associate Professor with the School of Computer Science and Engineering (SCSE), Nanyang Technological University (NTU), Singapore, where he also serves as the Associate Dean (Research) of the College of Engineering. He has worked extensively in learning-based system prototyping and performance optimization for

large-scale networked computer systems. His research interests include cloud computing, green data center, distributed machine learning, blockchain, big data analytics, multimedia network, and mobile computing. His work in Multi-Screen Cloud Social TV has been featured by global media (more than 1600 news articles from over 29 countries) and received the 2013 ASEAN ICT Award (Gold Medal). His recent work on Cloud3DView, as the only academia entry, has received the 2016 ASEAN ICT Award (Gold Medal) and the 2015 Datacentre Dynamics Award—APAC (Oscar Award of the data center industry). He was the sole winner of the 2016 Nanyang Award in Innovation and Entrepreneurship at NTU. He was a co-recipient of multiple best papers awards, including the 2015 IEEE Multimedia Best Paper Award, the 2016 IEEE Globecom Award, the 2016 IEEE Infocom MuSIC Workshop Award, the 2015 EAI/ICST Chinacom Award, the 2014 IEEE WCSP Award, the 2013 IEEE Globecom Award, and the 2012 IEEE EUC Award. He also received the 2016 IEEE ComSoc MMTC Distinguished Leadership Award. He was elected as the Chair of the IEEE ComSoc Multimedia Communication Technical Committee from 2014 to 2016. He serves on the Editorial Board for multiple transactions and journals, including the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY, the *IEEE Wireless Communication Magazine*, the IEEE COMMUNICATIONS SURVEY AND TUTORIALS, the IEEE TRANSACTIONS ON MULTIMEDIA, the IEEE TRANSACTIONS ON SIGNAL AND INFORMATION PROCESSING OVER NETWORKS, the IEEE ACCESS journal, and *Ad Hoc Networks* (Elsevier).



Rolf Stadler received the M.Sc. degree in mathematics and the Ph.D. degree in computer science from the University of Zurich. He held positions at the IBM Zurich Research Laboratory, Columbia University, and ETH Zürich. In 2001, he joined the KTH Royal Institute of Technology, Stockholm, Sweden, where he is currently a Professor and also the Head of the Department of Network and Systems Engineering. His group has made contributions to real-time monitoring, resource management, and self-management for large-scale networked systems.

His current interests include advanced monitoring techniques and data-driven methods for network engineering and management. He was the Editor-in-Chief of the IEEE TRANSACTIONS ON NETWORK AND SERVICE MANAGEMENT (TNSM) from 2014 to 2017.



Ying Zhang is currently a Software Engineering Manager at Facebook. She works on large-scale network management problems, and her research interests include software-defined networks, network function virtualization, network monitoring, Internet routing, and network security. She holds over 30 granted U.S./international patents and has 50 peer-reviewed publications with about 1500 citations. She was named by Swedish media as a Mobile Network 10 Brightest Researcher. She was awarded as a Rising Star in the networking and communications area.