Machine Learning for 5G and Beyond: From Model-Based to Data-Driven Mobile Wireless Networks

Tianyu Wang[1,2], Shaowei Wang[1,2], Zhi-Hua Zhou[1,*]

[1] National Key Laboratory for Novel Software Technology, Nanjing University, Nanjing 210023, China
[2] School of Electronic Science and Engineering, Nanjing University, Nanjing 210023, China
* The corresponding author, email: zhouzh@nju.edu.cn

Abstract: During the past few decades, mobile wireless communications have experienced four generations of technological revolution, namely from 1G to 4G, and the deployment of the latest 5G networks is expected to take place in 2019. One fundamental question is how we can push forward the development of mobile wireless communications while it has become an extremely complex and sophisticated system. We believe that the answer lies in the huge volumes of data produced by the network itself, and machine learning may become a key to exploit such information. In this paper, we elaborate why the conventional model-based paradigm, which has been widely proved useful in pre-5G networks, can be less efficient or even less practical in the future 5G and beyond mobile networks. Then, we explain how the data-driven paradigm, using state-of-the-art machine learning techniques, can become a promising solution. At last, we provide a typical use case of the data-driven paradigm, i.e., proactive load balancing, in which online learning is utilized to adjust cell configurations in advance to avoid burst congestion caused by rapid traffic changes.

Keywords: mobile wireless networks; data-driven paradigm; machine learning

I. INTRODUCTION

Mobile wireless communication is one of the most rapidly growing discipline, which has experienced four generations of technological revolution during the past few decades. The first 5G standard (3GPP Release 15) which defines the 5G new radio specifications for both non-standalone and standalone operations is frozen in July 2018, officially announcing the coming of 5G mobile wireless communications. In 5G era, three major use scenarios are considered, referred to as enhanced Mobile Broadband (eMBB), massive Machine Type Communications (mMTC) and Ultra-Reliable and Low Latency Communications (URLLC) [1]. The eMBB scenario is an extension of today's mobile broadband applications, including the emerging ultra-HD video, 360-degree video and AR/VR applications, in which 10 Gbps peak data rate is required. The mMTC scenario is an enhancement of today's low power wide area technologies, such as NB-IoT, in which 1 million connections per square kilometer is required. The URLLC scenario is developed to support mission critical applications that are extremely sensitive to reliability and latency, such as self-driving cars, industri-

Received: Sep. 17,2018
Revised: Oct. 28,2018
Editor: Rongpeng Li

In this paper, we analyzed the potential deficiencies of the conventional model-based paradigm in mobile wireless communications, such as the difficulty of defining accurate model and getting system parameters, the prohibitive computational complexity, the infeasibility of producing lossless block decomposition.

al 4.0 and smart grid. In current early phase of 5G, only the eMBB scenario is specified while the mMTC and URLLC ones are expected to be added progressively in future 3GPP specifications.

To address the challenging scenarios of 5G networks, a series of candidate technologies have been proposed [2]. In the physical layer, massive antenna technologies are utilized to provide diversity gain and support increased capacity, new waveforms are considered to flexibly accommodate services and applications with different quality of service requirements, and multiple radio access schemes are proposed to address different types of connections, e.g., the 5G new radio for broadband connections, non-orthogonal multiple access technologies for massive IoT connections and millimeter wave for spectrum above 6 GHz. Besides, dynamic spectrum access and cognitive radio are also extensively discussed to enhance system throughput and support diverse emerging services [3-6]. And recently, artificial intelligence is introduced to empower the 5G networks [7].

In the network layer, ultra-dense network architecture is proposed to increase the system-level capacity by providing the ultimate spatial reuse of radio spectrum. Heterogeneous radio access technologies, such as relay, device-to-device communications, vehicular ad hoc networks, self-organizing networks and unmanned aerial vehicle assisted networks, are introduced to provide extra degrees of freedom for specific use scenarios. Network slicing, together with software-defined networking, network function virtualization and mobile edge computing, is proposed to partition the entire network into different slices with different configurations such that network operators can efficiently utilize their network resources while satisfying the quality of service requirements of different users. As we can see, modern mobile wireless networks have become a “hodgepodge” of technologies that cannot be fully described by a uniform theoretic model.

The lack of a uniform theoretic model of mobile wireless communications is possibly due to the hardness of analyzing general network-level capacity from an information theory point of view. Thus, most of the proposed communication technologies are built on high-level models with clear abstractions and simplifications, which are reasonable when we focus on different facets of the network. For example, inter-cell interference management is usually considered as a network layer problem, in which the underlying user traffic is abstracted by stochastic graph models, and interferences from different access points are treated as indistinguishable noises, even though the interference signal can be further utilized by using physical layer interference alignment technologies.

In this paper, we will show that the conventional divide-and-conquer manner is rapidly losing its “magic” as the mobile wireless network is evolving into an extremely complex and sophisticated system whose components are tightly coupled with each other, and the conventional *model-based* paradigm should be reevaluated in contrast with the novel *data-driven* paradigm, in which communication technologies are directly built on the data produced by the network, instead of pure mathematical models with artificial assumptions. Some initial studies have shown the potential of the data-driven paradigm in both physical layer and network layer [8,9]. A key of data-driven mobile wireless networks is the use of state-of-the-art machine learning technology. In contrast to the optimization technologies widely applied in communication systems, the solution of machine learning can automatically improve itself through data-based training, which does not fully rely on artificial models of the communication systems as prior knowledge. With the progress in new learning algorithms and the ongoing decrease in storage and computation cost, machine learning methods have been adopted by a variety of fields in science, technology and commerce [10].

Among the massive learning algorithms, supervised learning is the most popular method, which have been widely utilized in spam classifiers, image recognition, and medical diagnosis. In supervised learning problems, the training sample is described in the form of a feature-label pair (x, y), in which x represents the available features such as text content of an email, RGB values of an image and medical symptoms of a patient, y represents the labels that we care about, such as whether an email is a spam, what objects a picture contains, and the probability of having diseases for a patient. These sample data can be utilized to learn a mapping $f(x)$, which produces a predicted label y for an unknown sample with feature x, such that new samples can be automatically labeled by the supervised learning system. There exist many different forms of mapping f, including decision tress, logistic regression, support vector machines, Bayesian classifiers, boosting methods that combine multiple learning algorithms [11], and well-known deep learning methods [12,13]. However, data with fully ground-truth labels is generally difficult to obtain due to the high cost of the data-labeling process in many mobile wireless communication scenarios, where weakly supervised learning is likely to be a promising technique to deal with such kind of problems [14].

Unsupervised learning is another classical paradigm that focuses on unlabeled data. Dimension reduction methods, including principle components analysis, manifold learning and random projections, are often utilized to identify low-dimensional structures from high-dimensional data, which helps to reveal the underlying properties of raw data. Clustering is another unsupervised learning problem, in which a proper partition is needed to divide unlabeled samples into multiple clusters such that samples within a cluster is “similar” to each other. Based on specific understandings of “similarity”, different clustering methods have been developed, such as hierarchical clustering, K-means clustering and distribution-based clustering. In unsupervised learning, computational complexity is always the paramount concern.

Reinforcement learning [15,16] is a special machine learning paradigm, in which the training data neither explicitly indicates the correct output for a given input as in supervised learning, nor provides some information about the correct partition as in unsupervised learning. In fact, reinforcement learning allows an agent to interact with the environment by exploring different policies, to maximize the expected reward over time. Reinforcement learning can be seen as an extension of the classic Markov decision process (MDP), and similar ideas such as policy iteration and value iteration are adopted. The main difference is that most of the information that is assumed to be known in MDP problems (e.g., probability transfer matrix) is no longer available, and reinforcement learning can address problems with much larger scales.

The rest of the paper is organized as follows: In Section II, we review the conventional model-based paradigm and elaborate why it can be less efficient and less practical in future 5G and beyond networks. In Section III, we explain why the data-driven paradigm is promising to address the new challenges that cannot be solved by the model-based paradigm. In Section IV, we provide a typical use case of the data-driven paradigm. Finally, we conclude the paper in Section V.

II. Limitation of Model-Based Paradigm

Mathematical modelling, which is the use of mathematical language to describe the behavior of a system, has been proved to be the foundation of modern science and technology in many fields. In the development of mobile wireless communications, mathematical modelling has provided interpretability, computability and verifiability for a large number of technical problems, which makes it a standard research process in pre-5G networks. However, this model-based paradigm exhibits serval inherent limitations that may restrict further development of mobile wireless networks. In this section, we provide a discussion about these drawbacks.

2.1 Hard to get accurate models

The success of model-based paradigm depends on its accuracy in representing the behavior of mobile wireless networks. With the evolution of cellular networks, the underlying mathematical models become more and more complex for exploiting more sophisticated technologies. For example, the network topology model has evolved from the classic hexagon model into stochastic graph models with multiple layers of access points, such that heterogeneous networks can be introduced to increase capacity in specific hot spots. For another example, the radio resource scheduling model has evolved from the basic queueing model into sophisticated Markov decision processes, to enable the system to support multiple types of data services with different rate and delay requirements.

Unfortunately, there exist some extremely complex problems that cannot be accurately described by statistic models. For example, interference management in traditional mobile networks is an extremely complex problem, which is affected by a large number of underlying technical details, such as traffic distribution, user mobility and even load balancing strategies, and may affect multiple performance indicators that contradict against each other. To address such intractable problems, empirical parameters and formulas based on highly simplified models are always used, in which iterative measurement and tuning are employed to adjust the network in practical deployment. Other examples may include coverage management and handover strategies, in which statistical models cannot provide an accurate description due to the complexity of the problem. These problems will become more complex with the introduction of new features in 5G and beyond networks, such as multi-RAT, multi-service and multi-connectivity, making the conventional model-based paradigm inefficient, unreliable or even impractical.

Also, statistic models are also incapable of addressing extremely detailed information due to the lack of statistics, which however may be the key information for some of the most challenging scenarios in 5G and beyond networks. For example, in ultra-dense networks where the number of access points and users are comparable, the exact mobility information of each user can seriously influence the network performance, in terms of virtual cell formation, user association, transmission mode selection and handover strategies. However, there exists no mobility model for a single mobile user, and the best way to describe its mobility is the raw data of location and speed information. Other examples may include the cell-specific content request information in mobile edge caching, and channel parameters in complicated propagation environments. Therefore, for some of the most challenging scenarios that require the most detailed information, statistical models may lose their "magic" due to the sparsity and diversity of target data.

2.2 Difficult to get solutions with reasonable complexity

Due to the homogeneity and uniformity of pre-5G networks, many problems formulated by statistic models can be efficiently solved by classical optimization techniques. In some cases, even closed-form solutions exist. For example, the optimal power allocation of an OFDMA system can be given with water-filling algorithm. However, there are a large number of NP-hard problems in mobile wireless networks whose optimal solutions cannot be worked out in polynomial computational time, e.g., optimal user association and resource allocation in heterogeneous networks, and optimal cell placement and coverage management. To avoid exponential computational complexity, these NP-hard problems are generally decomposed into tractable subproblems that can be solved separately or sequentially, or by using heuristics that can produce suboptimal solutions. However, even suboptimal solutions may require a huge amount of computational resources due to the scale of these problems.

The computational complexity is further increased by the heterogeneity and diversity brought by the new features of 5G and beyond networks, e.g., multiple radio access technologies and multiple connectivity of each user, multiple types of services supported by the network in different use scenarios, and diversity of QoS requirement of multiple types of user equipment. The huge number of user equipment and access points also greatly increases the computational complexity. It is expected that 5G will support up to 1 million connected devices per km ^{2}, and the distance between access points is only a few meters in ultra-dense scenarios. The management of these user devices and access points are tightly coupled due to their geographical proximity, and thus, should be jointly considered, which dramatically increases the complexity. Therefore, the computational complexity generated by model-based paradigm becomes a bottleneck in 5G and beyond mobile networks.

2.3 Hard to get system parameters

To provide an explicit model for mobile wireless networks, the model-based paradigm needs to define a large number of system parameters. For example, massive MIMO systems may require the real-time channel parameters of different users in different frequencies and antennas to form the optimal beams; vehicular networks may require the exact location and speed information of each vehicle such that the optimal clustering can be calculated; ultra-dense networks may require the inter-cell interference power between nearby access points to optimize user association; network slicing may require the customized traffic pattern such that the radio resources can be efficiently shared by different slices; and mobile edge computing may require the whole profile of computational resource consumption of each service. However, due to insurmountable technical challenges and unbearable huge amount of radio resource consumption, these parameters may not be available. Also, the network devices of different types and manufacturers limit the number of common parameters in the network. Therefore, the conventional model-based paradigm may not be feasible due to the lack of available parameters in practical networks.

2.4 Hard to get lossless block decomposition

In conventional mobile wireless networks, the network is divided into multiple layers, each of which is composed of separate blocks with specific network functions. This structure decomposes the complex communication system that is difficult to handle into multiple subproblems/subsystems that can be formulated by mathematical models, which greatly accelerates the technical progress as different groups of researchers can focus on specific layers and blocks. For example, in the physical layer, the communication process is divided into a series of signal processing blocks, such as channel coding, modulation, and detection, each of which is optimized independently in pre-5G networks. For another example, the radio resource management problem is divided into inter-cell interference management, user association, and intra-cell resource scheduling, which are optimized separately by using different mathematical models.

However, this divide-and-conquer manner corresponding to the model-based paradigm does not necessarily provide the optimal solution. In fact, it always comes at the cost of losing the optimality of the original problem, as the decomposed subproblems may not be fully independent. For example, the performance of channel coding can be seriously influenced by the modulation scheme in different channel conditions. Also, the performance of inter-cell interference management can be directly influenced by the user association strategy and intra-cell resource scheduling strategy used by each access point. In 5G and beyond networks, the coupling among different network function blocks are greatly tightened by the increasing density of user devices and access points, as well as the diversity of communication scenarios and service types. For example, the inter-cell interference management, user association strategy and intra-cell radio resource scheduling can highly influence each other in ultra-dense networks. Therefore, in order to further improve the network performance, the conventional block structure should be reconsidered in 5G and beyond networks.

III. ADVANTAGES OF DATA-DRIVEN PARADIGM

As discussed above, the conventional model-based paradigm has difficulty getting accurate models, system parameters and lossless block decomposition, as well as obtaining solutions to the formulated optimization tasks with an acceptable complexity. This model-based paradigm may be less efficient or less practical in future 5G and beyond networks. In this section, we discuss about the data-driven paradigm for mobile wireless networks, in which network functions are directly built on the data produced by the network instead of artificial models about communication system, and we show how it can cover up the deficiencies of the conventional model-based paradigm.

3.1 Architecture of data-driven networks

As seen in figure 1, the data-driven networks need to monitor the huge volume of data produced by the network, including local data produced by distributed units (e.g., channel parameters and interference level) as well as global data from centralized units (e.g., total energy consumption). The data is then properly utilized by both edge and cloud computing platforms, on which a variety of learning-based network functions are deployed to manage and control the network.

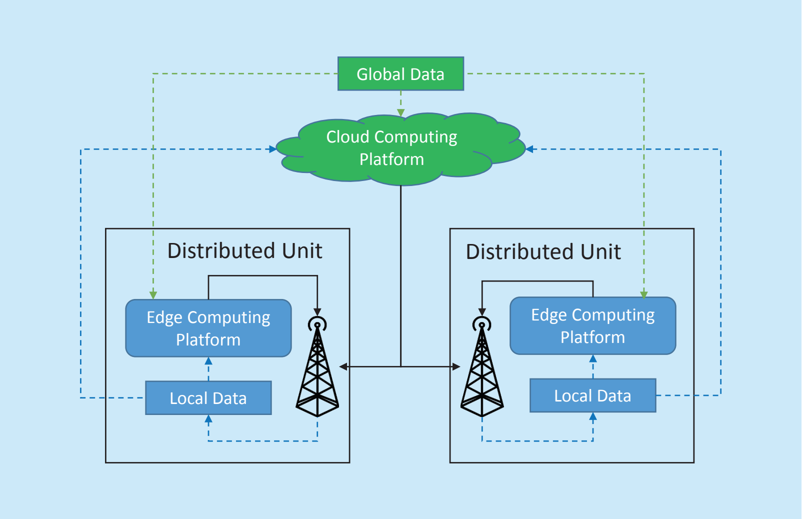

Fig. 1. *Architecture of data-driven mobile wireless networks. The dotted lines represent the global data flow, the dashed lines represent the local data flow, and the solid lines represents control flow of data-driven network functions.*

One of the key characteristic of data-driven networks is that all network functions are fundamentally built on same data foundation, while in conventional model-based networks, the network functions adopt mathematical models with different assumptions and simplifications. This uniform architecture ensures that sophisticated network functions proposed in different times will not deviate from the original problems as mobile networks evolve into more and more complex systems. Another characteristic is that there exist no explicit boundaries for different layers of the network, and a data-driven network function can be in charge of tasks over multiple layers of the conventional networks. Generally speaking, edge computing platforms can provide smaller latency for the "low-level" network functions (e.g., channel coding and modulation), while cloud computing platforms can provide global information for "high-level" network functions (e.g., inter-cell interference management).

3.2 No requirement of accurate models

To deal with complex and incalculable network scenarios in practical mobile communication environment, prior assumptions and simplifications are usually required so as to characterize the target problems explicitly in the conventional model-based mobile networks. As discussed above, it becomes harder and harder to get such kind of models in the future. In contrast with the model-based paradigm, the data-driven paradigm does not need an accurate model to resolve the target problem since the solution to the problem can be directly learned from the data produced by the mobile network. This brings a great advantage of dealing with the extremely detailed information and extremely complex problems arising from the forthcoming 5G and beyond mobile communication systems. In fact, for supervised learning problems, we can compute an arbitrary function by using a neural network with a single hidden layer. This universality property of machine learning methods provides an extremely powerful tool to describe the problems without accurate mathematical models, e.g., radio resource scheduling and transmission mode selection in ultra-dense networks, interference management and admission control in heterogeneous networks, and handover configuration in vehicular networks.

3.3 Possible to cope with intractable problem with acceptable complexity

The computational complexity of machine learning algorithms can be divided into two parts: induction complexity and deduction complexity. The former usually requires a large amount of computational resource, e.g., the backpropagation algorithm in neural networks, such that the learning model can be properly trained using the huge volumes of data. This part of computation is usually performed offline in large data centers with adequate computation and storage resources. Notice that the offline computation does not influence the operation of the mobile networks since only the output produced by the induction is needed at the deduction stage. In other words, the deduction part is performed online to predict the behavior of new data, and thus, determines the effective complexity of machine learning algorithms employed to tackle the target problems in mobile wireless networks.

Compared with the conventional model-based algorithms, in which the computational complexity of many optimization tasks increases exponentially with the scale of the network parameters, the online complexity of machine learning algorithms is directly determined by the scale of learning model, which is decided and bounded by supper parameters, e.g., the layers and number of nodes in deep neural networks. Thus, the computational complexity of the used machine learning algorithms is controllable and independent from the scale of the network parameters, which is extremely crucial for practical communication networks with rigorous execution time. Therefore, it becomes possible to address those NP-hard communication problems in the model-based paradigm using machine learning algorithms with acceptable computational complexity.

3.4 Less sensitive to system parameters

In the data-driven paradigm using machine learning techniques, we can exploit any data that is available and considered to be related to the problem. For example, in model-based networks, reference signal receiving power is often utilized to calculate the inter-cell interference, and other details that may highly affect the interference condition, e.g., the traffic load of each access point, the distribution of cell-edge users and the mobility pattern of mobile users, are usually not considered so as to maintain a tractable model for the problem. However, in the data-driven paradigm, all related information can be involved by using learning-based algorithms, and even incomplete data can be utilized in a uniform manner. In many other cases, the raw data produced by the network is first extracted to give some of the most related features, and then new these features are utilized to increase the efficiency of learning models.

The flexibility of available parameters highly improves the feasibility of data-driven paradigm in mobile wireless networks. For example, in Massive MIMO systems, partial channel parameters can be treated as the input parameters, which avoids the inaccuracy introduced by the linear interpolation procedure for complete channel parameters. Also, for networks with heterogeneous access points, common features can be defined and extracted in each access point such that a uniform machine learning algorithm can be applied in the entire network. The data-driven paradigm requires only available data produced by the network, which fills the gap between practical parameters and artificial parameters as in the model-based paradigm.

3.5 No need to do block decomposition

In the model-based paradigm, a complex problem is always decomposed into several less complex subproblems that are lightly coupled with each other. Then, these subproblems are studied independently in the literature, which forms different research fields in mobile wireless networks. As we have mentioned, the coupling between different network functions is not negligible in future 5G and beyond networks. In the data-driven paradigm, due to the unlimited model space, tightly coupled problems can be jointly considered in a uniform technical framework, e.g., coding and modulation in the physical layer, inter-cell interference management and user association in the network layer, and even radio resource allocation problems across all layers. In such problems, data-driven methods can provide a uniform technical structure, which avoids the unnecessary decomposition and simplification as in the conventional model-based paradigm.

IV. Proactive Load Balancing Using Online Learning

Due to the uncertainties of mobile user behaviors and wireless propagation environment, traffic load in mobile wireless networks can be highly uneven in space and highly dynamic in time, which leads to inefficient utilization of radio resources and unexpected traffic congestions in access points [17]. This issue is further aggravated by the decreasing cell range and increasing heterogeneity in 5G and beyond networks. Therefore, load balancing has become one of the most active and emerging fields of research in mobile wireless networks.

4.1 Conventional load balancing techniques

Traditionally, load balancing is an expensive, time consuming and error prone process that requires frequent manual configuration and management of cell parameters. For example, engineers may adjust the transmit power of reference signal and the electrical tilt of antennas based on drive tests and customer complaints. To overcome the drawbacks of manual load balancing, automatic load balancing schemes have been proposed, in which all configurations and adjustments are performed automatically and periodically to address real-time traffic imbalance. In each period of automatic load balancing, the load of a cell is evaluated in terms of the usage of multiple resources and the performance of multiple indicators, e.g., total transmit power, radio resource usage, interference level, downlink/uplink throughput and handover failure ratio. Then, cell parameters such as reference signal power, antenna tilt, cell reselection thresholds and handover offsets, are adjusted periodically according to the real-time reports from the network, such that the cell load does not exceed certain threshold.

To maintain the stability of mobile networks, each practical parameter adjustment should be limited within a certain range. Thus, it may take multiple times of parameter adjustments to reach the optimal cell configuration for a given period. Therefore, for burst congestions caused by fast moving users (e.g., a bus of broadband users with speed 30 km/h passing through a small cell with radius 500 m may cause a 10 Gbps data burst for 10 seconds), the reactive paradigm of current load balancing techniques may not provide the optimal cell configuration in time. To address such burst congestions, the cell parameters need to be adjusted before the traffic burst is observed by the target cell, which we refer to proactive load balancing in this paper. The key technique of proactive load balancing is to accurately predict when and where such traffic bursts may happen, for which we adopt online learning to address complicated use scenarios.

4.2 Proactive load balancing based on online learning

In figure 2, we illustrate proactive load balancing by considering a bus passing through three access points a, b and c along the road. As seen in figure 2(a), access points a, b and c cover equal areas when there is no vehicle moving along the road. When the bus passes through the area, as seen in figure 2(b), access points a and c reshape their coverage areas to serve vehicular users, and access point b reshapes its coverage area to serve pedestrian users. Note that the corresponding parameter adjustments are completed before the bus entering the target area. Therefore, potential congestions caused by traffic burst in access points a, b and c can be alleviated and handover overhead for vehicular users can be minimized.

To accurately predict the arrivals of traffic bursts, we can employ the emerging online learning techniques, which is a learning process consisting of a sequence of consecutive predictions [18]. In any round t, the learner needs to provide an answer p_t to a prediction task, given the current information $x_t \in \mathcal{X}$ as the input. In the next round $t+1$, the correct answer to the previous task is revealed, which is denoted by $y_t \in \mathcal{Y}$, and the learner suffers a loss given by $l(p_t, y_t)$. The ultimate goal of online learning is to minimize the total loss caused by incorrect predictions, which is given by $\sum_{i=1}^{T} l(p_t, y_t)$ for T rounds. Classic statistical methods can address such problems if there are strong statistical correlation between past and present, e.g., $x_1, x_2, \ldots, x_T$ are independent and identically distributed, and the loss function is given explicitly in an analytical form. However, these assumptions are usually not satisfied in practical online learning problems.

Instead of focusing on minimizing the actual loss, most online learning algorithms focus on minimizing the *regret* compared with hypothesises $h: \mathcal{X} \to \mathcal{Y}$ from a finite hypothesis space $\mathcal{H}$. Formally, the regret of an algorithm

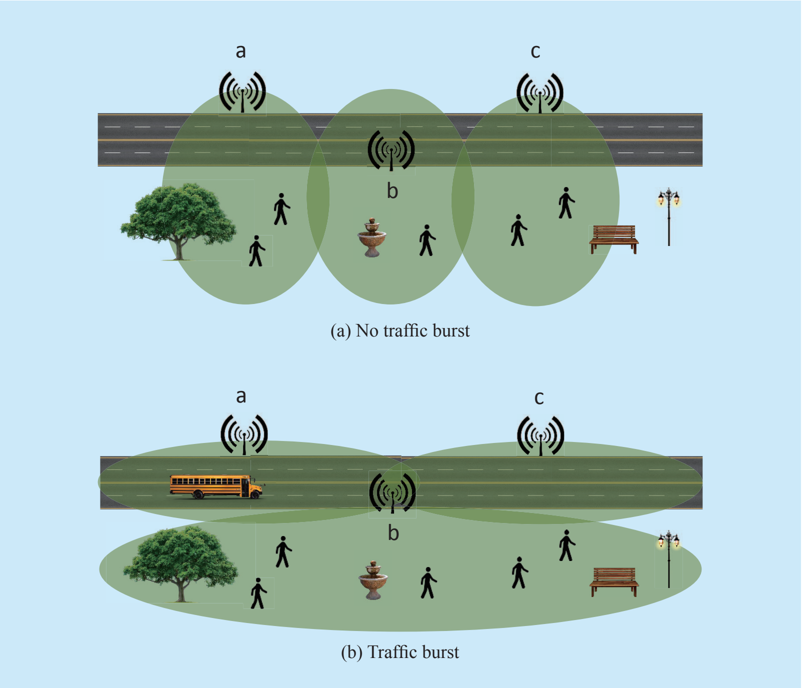

Fig. 2. *Proactive load balancing for traffic burst in 5G and beyond networks. The cells along the road are reshaped before the bus passes through, such that the passengers on the bus can experience the highest data rates and the minimum number of handovers.*

relative to hypothesis $h \in \mathcal{H}$ is defined as

$$\mathrm{Regret}_{\mathrm{T}}(h) = \sum_{t=1}^{T} l(p_t, y_t) - \sum_{t=1}^{T} l(h(x_t), y_t),$$

and the regret to the entire hypothesis space is defined as

$$\mathrm{Regret}_{\mathrm{T}}(\mathcal{H}) = \max_{h \in \mathcal{H}} \mathrm{Regret}_{\mathrm{T}}(h).$$

Therefore, a variety of "low-regret" algorithms have been proposed (e.g., the Follow The Leader algorithm), in which the regret increases sub-linearly with T. These "low-regret" algorithms guarantee that the average loss in each round will be as good as the best hypothesis in $\mathcal{H}$ when T goes to infinity. When the prediction domain $\mathcal{Y}$ is a convex set and the loss function $l: \mathcal{Y} \to \mathbb{R}$ is convex, online convex optimization techniques can be applied to accelerate the learning process.

Thus, we propose a proactive load balancing architecture based on online learning, as shown in figure 3. In the proposed architecture, each access point performs an independent traffic predictor based on online learning and a central coordinator performs a global

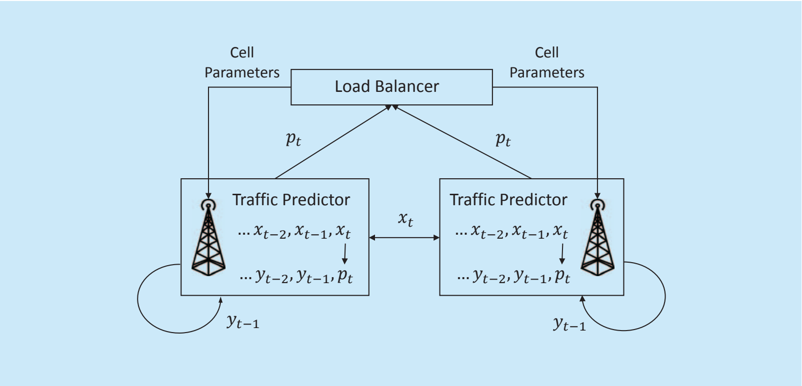

Fig. 3. *Architecture of proactive load balancing in 5G and beyond networks.*

load balancer to adjust cell parameters in the target area. In each round t, the predictors collect relative information x_t from neighboring cells, e.g., historical data rates and association information of neighboring users. And they make predictions p_t on whether a traffic burst will arrive in the next round. The load balancer collects the prediction information and returns the optimal cell configurations that can alleviate the traffic congestion in the next round. Then, the access points start to adjust their cell parameters before the traffic burst arrives. By using the prediction-action-observation loop, burst congestions caused by rapid traffic changes can be effectively alleviated.

V. Conclusions

In this paper, we analyzed the potential deficiencies of the conventional model-based paradigm in mobile wireless communications, such as the difficulty of defining accurate model and getting system parameters, the prohibitive computational complexity, the infeasibility of producing lossless block decomposition. We have shown how the data-driven paradigm using state-of-the-art machine learning technology can relax such pressures facing the future mobile networks by building the networks directly on the data produced by itself. At last, we presented a typical use scenario of the data-driven paradigm, in which online learning methods are utilized to realize proactive load balancing, so as to avoid burst congestions for rapid traffic changes. We believe that the data-driven paradigm is with great potential to push forward the development of mobile wireless communications, and a great number of research problems related should be studied in the future.

Acknowledgment

This work was partially supported by the National Natural Science Foundation of China (61751306, 61801208, 61671233), the Jiangsu Science Foundation (BK20170650), the Postdoctoral Science Foundation of China (BX201700118, 2017M621712), the Jiangsu Postdoctoral Science Foundation (1701118B), and the Fundamental Research Funds for the Central Universities (021014380094).

References

[1] ITU-R, "ITU-R M.[IMT-2020.TECH PERF REQ] - Minimum Requirements Related to Technical Performance for IMT2020 Radio Interface(s)," Report ITU-R M.2410-0, Nov. 2017.

[2] M. Shafi, A. F. Molisch, P. J. Smith, T. Haustein, P. Zhu, P. D. Silva, F. Tufvesson, A. Benjebbour and G. Wunder, "5G: A Tutorial Overview of Standards, Trials, Challenges, Deployment, and Practice," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 6, pp. 1201-1221, Jun. 2017.

[3] J. Dai and S. Wang, "Clustering-Based Spectrum Sharing Strategy for Cognitive Radio Networks," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 1, pp. 228-237, Jan. 2017.

[4] T. Wang, L. Song, Z. Han, and W. Saad, "Distributed Cooperative Sensing in Cognitive Radio Networks: An Overlapping Coalition Formation Approach," *IEEE Trans. Commun.*, vol. 62, no. 9, pp. 3144-3160, Sep. 2014.

[5] S. Wang, Z.-H. Zhou, M. Ge, and C. Wang, "Resource Allocation for Heterogeneous Cognitive Radio Networks with Imperfect Spectrum Sensing," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 3, pp. 464-475, Mar. 2013.

[6] G. Ding, J. Wang, Q. Wu, Y. Yao, R. Li, H. Zhang, and Y. Zou, "On the limits of predictability in real-world radio spectrum state dynamics: from entropy theory to 5G spectrum sharing," *IEEE Commun. Mag.*, vol. 53, no. 7, pp. 178-183, Jul. 2015.

[7] R. Li, Z. Zhao, X. Zhou, G. Ding, Y. Chen, Z. Wang, and H. Zhang,"Intelligent 5G: When Cellular Networks Meet Artificial Intelligence," *IEEE Wireless Commun.*, vol. 24, no. 5, pp. 175-183, Oct. 2017.

[8] T. Oshea and J. Hoydis, "An Introduction to

Deep Learning for the Physical Layer," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 563-575, Oct. 2017.

[9] H. Ye, L. Liang, G. Y. Li, J. Kim, L. Lu, and M. Wu, "Machine Learning for Vehicular Networks: Recent Advances and Application Examples," *IEEE Veh. Tech. Mag.*, vol. 13, no. 2, pp. 94-101, Apr. 2018.

[10] M. I. Jordan and T. M. Mitchell, "Machine learning: Trends, Perspectives, and Prospects," *Science*, vol. 349, no. 6245, pp. 255-260, Jul. 2015.

[11] Z.-H. Zhou," Ensemble Methods: Foundations and Algorithms", Boca Raton, FL: Chapman & Hall/CRC, 2012.

[12] Y. LeCun, Y. Bengio, G. Hinton, "Deep Learning," *Nature*, vol. 521, no. 7553, pp. 436-444, May 2015.

[13] Z.-H. Zhou and J. Feng, "Deep forest," *National Science Review*, http://doi.org/10.1093/nsr/nwy108, Oct. 2018.

[14] Z.-H. Zhou, "A brief introduction to weakly supervised learning," *National Science Review*, vol. 5, no. 1, pp. 44-53, Jan. 2018.

[15] L. P. Kaelbling, M. L. Littman, and A. W. Moore, "Reinforcement Learning: A Survey," *J. Artific. Intell. Res.*, vol. 4, pp. 237-285, May 1996.

[16] K. Arulkumaran, M. P. Deisenroth, M. Brundage, and A. A. Bharath,"Deep Reinforcement Learning: A Brief Survey," *IEEE Signal Process*. Mag., vol. 34, no. 6, pp. 26-38, Nov. 2017.

[17] Y. Zhong, X. Ge, H. H. Yang, T. Han, and Q. Li, "Traffic Matching in 5G Ultra-Dense Networks," *IEEE Commun. Mag.*, vol. 56, no. 8, pp. 100-105, Aug. 2018.

[18] S. Shalev-Shwartz, "Online Learning and Online Convex Optimization," *Foundations and Trends in Machine Learning*, vol. 4, no. 2, pp.107-194, Mar. 2012.

Biographies

Tianyu Wang, received his BSc, MSc and PhD degrees from Peking University, China. He is currently an associate researcher in the School of Electronic Science and Engineering at Nanjing University, China. He has published more than 30 IEEE journal and conference papers, and received the Best Paper Award from the IEEE ICC'15, IEEE GLOBECOM'14, and ICST ChinaCom'12. His current research interest includes network slicing, load balancing and machine learning in wireless networks.

Shaowei Wang, received his BSc, MSc and PhD degrees from Wuhan University, China. He is currently a full professor in the School of Electronic Science and Engineering at Nanjing University, Nanjing, China. His research interests mainly include telecommunication systems, operations research and machine learning. He is on the editorial board of IEEE Communications Magazine, IEEE Transactions on Wireless Communications, and Springer Journal of Wireless Networks. He serves/served on the technical or executive committee of reputable conferences including IEEE INFOCOM, IEEE ICC, IEEE GLOBECOM, IEEE WCNC .

Zhi-Hua Zhou, received his BSc, MSc and PhD degrees in computer science from Nanjing University, China. He is currently a professor and head of the Department of Computer Science and Technology, and Dean of the School of Artificial Intelligence, Nanjing University, China. His research interests mainly include artificial intelligence, machine learning and data mining. He is a foreign member of the Academy of Europe, and Fellow of ACM, AAAI, AAAS, IEEE, IAPR, CCF and CAAI. Email: zhouzh@nju.edu.cn.