

AI-assisted Network-slicing based Next-generation Wireless Communications

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Abstract

The integration of communications with different scales, diverse radio access technologies, and various network resources renders next-generation wireless networks highly heterogeneous and dynamic. Emerging use cases and applications, such as machine to machine communications, autonomous driving, and factory automation, have stringent requirements in terms of reliability, latency, etc. Such requirements pose new challenges to architecture design, network management, and resource orchestration in next-generation wireless networks. Starting from illustrating these challenges, this paper targets at providing an understanding of the overall architecture of next-generation wireless networks and three specific research directions under this overall architecture. First, we introduce a network-slicing based architecture and explain why and where artificial intelligence (AI) should be adopted into this architecture. Next, the motivation, research challenges, existing works, and potential future directions related to applying AI-based approaches in three research problems are described in detail, i.e., flexible radio access network slicing, automated radio access technology selection/user association, and mobile edge caching and content delivery. Overall, this paper highlights the benefits and potentials of AI-based approaches in the research of next-generation wireless networks.

Index Terms

next-generation wireless networks, heterogeneous networks, network slicing, machine learning, RAN slicing, RAT selection, content placement and delivery.

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I. INTRODUCTION

A. *Next-generation Wireless Networks: Visions & Challenges*

The evolution of mobile communications from the first to the fifth generation (5G) has revolutionized many aspects of human society in the past four decades. Expediting this evolution, the next-generation wireless communication networks are envisioned to be the cornerstone for a vast number of novel applications, ranging from remote surgery to smart cities. Following the classification of services into enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable and low-latency communications (URLLC) [1], the next-generation wireless networks will support even more diversified services with various throughput, latency, and reliability requirements [2]. Meanwhile, thanks to improved reliability and connection density, the next-generation wireless networks are expected to attract enterprise users, in addition to conventional mobile communication users, by supporting use cases such as autonomous driving and factory automation [3], [4].

The above evolution has been shaping wireless networks towards becoming increasingly heterogeneous and dynamic [5]. For instance, next-generation wireless networks will incorporate various components such as device-to-device (D2D), vehicle-to-everything (V2X), etc., with different radio access technologies including cellular, Wi-Fi, and dedicated short-range communications (DSRC), as well as different access points such as cellular base stations (BSs), road-side units (RSUs), and unmanned aerial vehicles (UAVs). Each component in the integrated heterogeneous communication networks may have a unique focus and a corresponding set of performance metrics. For example, V2X communications must handle highly dynamic communication channels and rapidly changing network topology, while D2D communications request decentralized channel access control and communication resource allocation with high energy efficiency. While the heterogeneous and dynamic characteristics are inevitable results of supporting ever-growing demands for increasingly-diverse communication services, they impose significant challenges in the architecture design, network deployment, and network management in next-generation wireless networks.

Designing the architecture for next-generation wireless networks that can handle diversified services and maximize infrastructure and resource utilization efficiency is the first major challenge. Achieving the target of increasing network capacity and accommodating highly diverse services with stringent quality of service (QoS) requirements necessitates innovations in network

architecture. Network densification via deploying ultra-dense small cells can improve network capacity [6]. However, network densification does not provide a solution to scalable management of heterogeneous networks, but creates additional challenges such as extra infrastructure deployment cost, low cell utilization efficiency, and inter-cell interference. The integration of terrestrial and satellite networks has been proposed for providing seamless communication coverage [7]. Such integration, however, poses a further challenge in network management considering the dynamic trajectory of UAVs, the orbits of satellites, and the resulting impact on the service range and communication channels. Cloud/Fog-radio access network (RAN) based architecture, which incorporates the paradigm of cloud and fog computing into wireless networks, has also been proposed [8]. However, such an architecture focuses on improving energy efficiency, reducing cost, and alleviating data traffic on the fronthaul rather than satisfying diversified service requirements in complex heterogeneous networks.

The second challenge is designing scalable and intelligent network management that can adapt to a dynamic network environment. Network environments can change rapidly due to user mobility, time-varying channel conditions, dynamically changing traffic load distribution, and temporal variations of content popularity. Up to the current generation of wireless communications, the problem of handling a dynamic environment has been studied mostly on a small scale, i.e., from the perspective of individual or several mobile users or base stations. One example is opportunistic spectrum access that targets individual secondary mobile users for them to access channels in a dynamic network environment [9], [10]. Another example is the dynamic deployment of virtual machines in cloud-fog computing systems based on computing task arrivals [11]. Nevertheless, managing next-generation wireless networks requires the development of scalable and adaptive models and approaches that suit large-scale problems and heterogeneous network architectures, which should include both centralized and decentralized network control components.

Last but not least, effective real-time network resource orchestration in the presence of multiple resources, many service types, and unknown traffic models is another challenge. The next-generation wireless networks will integrate functionalities of networking, caching, computing, sensing, and control [12]. Correspondingly, the resources in next-generation wireless networks will extend beyond the conventional communication resources (i.e., bandwidth, time, and/or transmit power), and include computing and caching resources. As a result, adaptive and flexible network resource orchestration becomes crucial in next-generation wireless networks, considering the surging growth in data traffic and increasingly diversified and stringent QoS requirements.

Conventional centralized resource allocation can become inadequate in certain parts of next-generation wireless networks. For example, resource allocation in microcells and D2D communications may need to be decided locally in order to reduce signaling overhead and response time. In addition, conventional approaches that rely on instantaneous network information, such as channel state information, and focus on optimizing an instantaneous performance metric, such as instantaneous data rate, can become inapplicable when such information is unknown. In next-generation wireless networks, exploiting the spatial-temporal traffic patterns while achieving service differentiation and maintaining massive connectivity would be a major challenge for network resource orchestration.

B. Network-Slicing based Architecture

Network slicing is an important network architecture innovation in 5G that is also expected to be inherited in the next generation [13]–[15]. Network slicing enables the coexistence of multiple isolated and independent virtual (logical) networks, i.e., slices, on the same physical network infrastructure. The advantages of network slicing are multifold. First, through the multiplexing of the virtual networks, network slicing supports multi-tenancy, i.e., multiple virtual network operators (VNOs) sharing the same physical network infrastructure [16]. This reduces capital expense in network deployment and operation. Second, network slicing provides the potential to create customized slices for different service types with various QoS requirements, which can achieve service differentiation and guarantee service level agreement (SLA) for each service type. Third, as slices can be created on-demand and modified or annulled as needed, network slicing increases the flexibility and adaptability of network management [17].

The enabling techniques for implementing network slicing are software-defined networking (SDN) and network function virtualization (NFV). SDN leverages the cloud computing paradigm in network management so that the network has a centralized controller to dynamically steer and manage traffic flow and orchestrate network resource allocation for performance optimization [18]. An SDN controller provides the abstract set of resources and control logic for setting up slices, and a slice can be viewed as an SDN client context [19]. Therefore, SDN facilitates the pre-defining of slice blueprints as well as the on-demand creation of slice instances based on the corresponding service and resources. NFV implements network functions, e.g., firewall, load balancing, address translation, etc., as software instances, known as virtual network functions (VNFs), running on virtual machines on top of general servers without requiring specialized

hardware [20], [21]. Thus, a network service in NFV can be considered as a component of a network slice, while a network slice contains one or more virtualized network functions [22]. NFV complements SDN in implementing network slicing since SDN establishes control plane functions that enable slicing while NFV provisions services and manages the life cycle of network slices and orchestrates slice resources through realizing VNFs [23].

Despite its popularity in both academia and industry, the slicing of RANs faces several challenges. For example, determining the optimal slicing granularity, i.e., whether or not there should be a slice for each type of service, each set of QoS requirements, each VNO, or some combination of the aforementioned, is an open problem [24]. In addition, effective admission control that strikes a balance among infrastructure utilization, service provisioning in each slice, and the revenue of network operator calls for further investigation [25]. Last, the monitoring of slice SLA and the slice adaption based on traffic dynamics can be challenging, considering that the resource allocation among slices aims at slice isolation. The aforementioned challenges, generally involving making optimal decisions in a dynamic environment with unknown information, may not be solved following conventional model-based methods. Therefore, although network slicing will continue to be an important part of the next-generation wireless networks, additional innovations in the network architecture are necessary for addressing the above challenges.

C. Integrating Artificial Intelligence

The past decade has witnessed remarkable progress in the research and applications of artificial intelligence (AI). As one of the most powerful AI tools, machine learning (ML) has been advancing rapidly to embrace a wide range of applications including voice recognition, image processing, and self-driving vehicles. The rapid advances in ML, boosted by the progress in hardware technology specialized to support AI, paves the path for applying AI in next-generation wireless communication networks [26]. A major advantage of ML is its ability to handle complicated problems, which renders ML a powerful tool that suits the dynamic, heterogeneous, and decentralized features of next-generation wireless networks. Applying ML could yield benefits such as improved performance and faster convergence in network management automation and performance optimization in large-scale systems.

ML methods include supervised learning, unsupervised learning, and RL. Each suits a different group of research problems in wireless communications. Supervised learning relies on labeled data to learn the mapping from the input to the output, and can be used to analyze network

data, learn network characteristics, and estimate network parameters [27]. Applications of supervised learning in the communications and networking include traffic classification [28], smart offloading [29], sub-6 GHz to millimeter wave (mmWave) frequency handover [30], mmWave beam alignment [31], etc. Unsupervised learning identifies patterns and attributes hidden in data for inference and prediction without using labeled data. Potential applications in communication networks include spectrum sensing [32], traffic volume prediction [33], etc. RL iteratively learns the best set of actions based on the feedback of network state information to maximize a cumulative reward in the long term. RL methods are particularly suitable for decision making in a dynamic environment. The applications of RL include protocol design [34], user scheduling and resource allocation [35], etc.

From the above applications, it can be seen that there is a trend of applying ML methods in the research and development (R&D) of communication networks to enhance system performance, flexibility, and scalability. For network data analysis, ML can handle the heterogeneity and spatial-temporal diversity in the data for network design and management [36]. For user mobility management, ML provides tools for analyzing the mobility pattern of mobile users for location-based services [37]. For network resource management, ML-based methods can be applied to model and study the joint allocation of communication, caching, and computing resources [38] or the joint problem of content caching and delivery [39].

As mentioned earlier, the heterogeneous and dynamic characteristics of next-generation wireless networks demand powerful tools to automate and optimize network slicing. From existing studies in literature, it can be seen that ML has the potential to be a promising tool for this purpose. Applying ML in network slicing can provide the innovations required to address the aforementioned challenges in the network architecture and resource orchestration and, thereby, help fulfill the great prospect of next-generation wireless communications.

The rest of the report is organized as follows. Section II provides a description of the overall architecture. Sections III to V cover three research problems in a network-slicing based architecture, as well as related research efforts and, in particular, AI-based approaches. Section III introduces a framework for RAN slicing. In Section IV, we present radio access technology (RAT) selection and user association automation. Section V investigates content caching and content delivery. Section VI concludes this paper. Table I gives a list of acronyms used in this paper.

TABLE I: List of Acronyms.

3GPP	3rd Generation Partnership Project	5G	Fifth Generation
ABC	Always Best Connected	AI	Artificial Intelligence
AP	Access Point	AR	Augmented Reality
BBU	Baseband Unit	BRNN	Bidirectional Deep Recurrent Neural Network
BS	Base Station	CapEx	Capital Expenditure
CNN	Convolution Neural Network	CRAN	Cloud Radio Access Network
D2D	Device-to-device	DNN	Deep Neural Network
DCF	Distributed Coordination Function	DL	Downlink
DSRC	Dedicated Short-range Communications	eMBB	Enhanced Mobile Broadband
FTP	File Transfer Protocol	HARQ	Hybrid Automatic Repeat-request
HNN	Hopfield Neural Network	IoT	Internet of Things
LFU	Least Frequently Used	LRU	Least Recent Used
LSTM	Long Short-Term Memory	LTE	Long Term Evolution
MADM	Multiple Attribute Decision Making	MDP	Markov Decision Process
MEC	Mobile Edge Computing	ML	Machine Learning
mMTC	Massive Machine-type Communications	MV	Monocular Video
NFV	Network Function Virtualization	OpEx	Operational Expenditure
POMDP	Partially Observable Markov Decision Process	QoS	Quality of Service
RAN	Radio Access Network	RAT	Radio Access Technology
RL	Reinforcement Learning	RNN	Recurrent Neural Network
RSU	Road-side Unit	SDN	Software-defined Networking
SLA	Service Level Agreement	SV	Stereoscopic Video
UAV	Unmanned Aerial Vehicle	UE	User Equipment
UL	Uplink	URLLC	Ultra-reliable and Low-latency Communications
V2X	Vehicle-to-everything	VNF	Virtual Network Function
VNO	Virtual Network Operator	VR	Virtual Reality

II. OVERALL ARCHITECTURE

This section presents the overall network architecture based on network slicing and discusses where and how AI can be applied. Following the challenges mentioned in the introduction, the architecture of next-generation wireless networks is expected to have the following properties [40]:

- Flexible and scalable, to support a wide range of service types and QoS requirements, and to support scalable slice management after the deployment of slices;
- Automated and adaptive, to support automated RAN and cloud network resource allocation

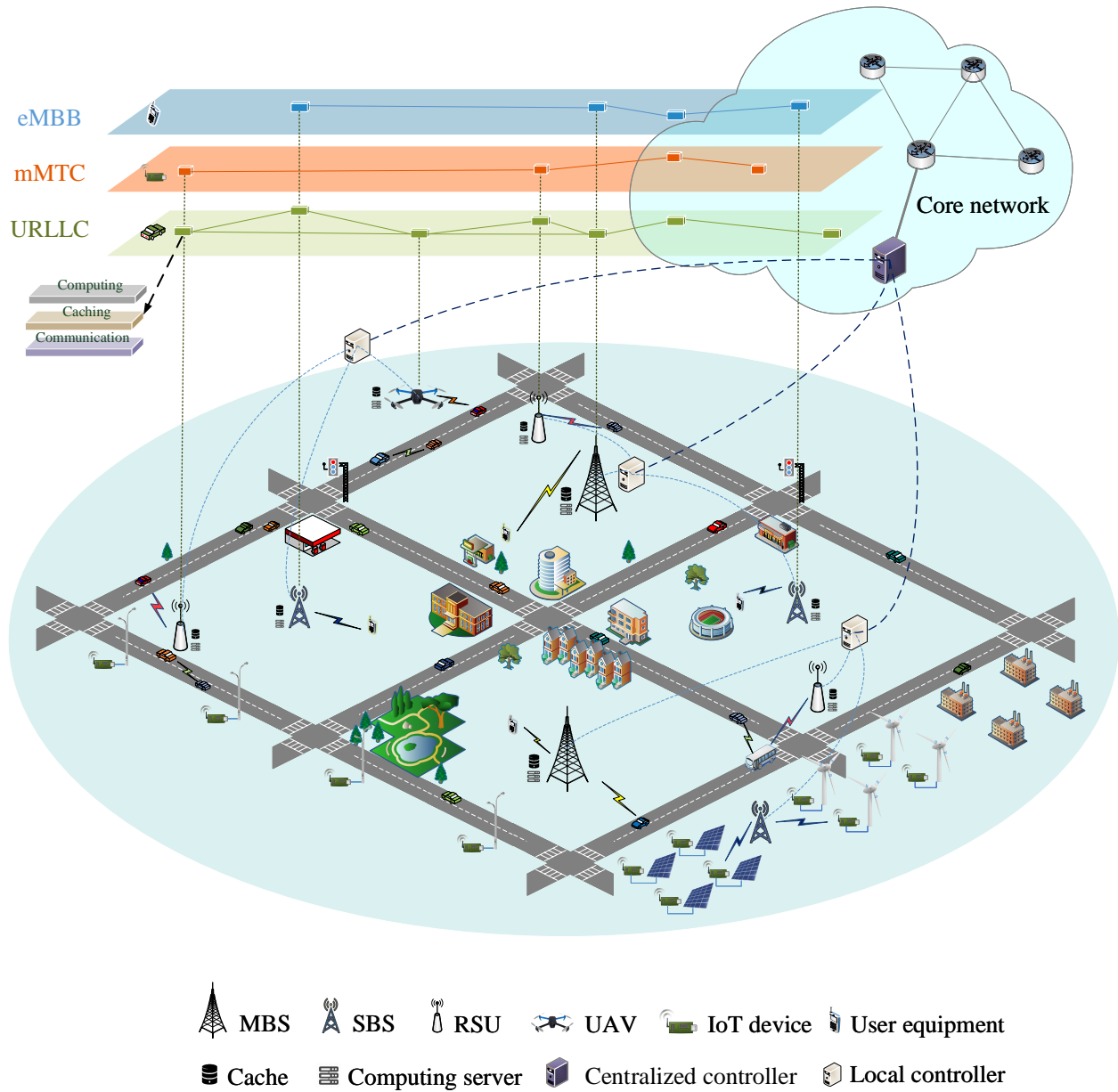


Fig. 1: The architecture of network-slicing based next-generation wireless networks, in which three network slices are illustrated.

and adaptation based on data traffic and network performance, and to support automated slice creation, slice performance monitoring, and slice adaption;

- Open and modularized, to support customized slices defined or operated by VNO, and to open certain network management functions to third parties.

A network slicing-based AI-assisted network architecture satisfying the above properties is

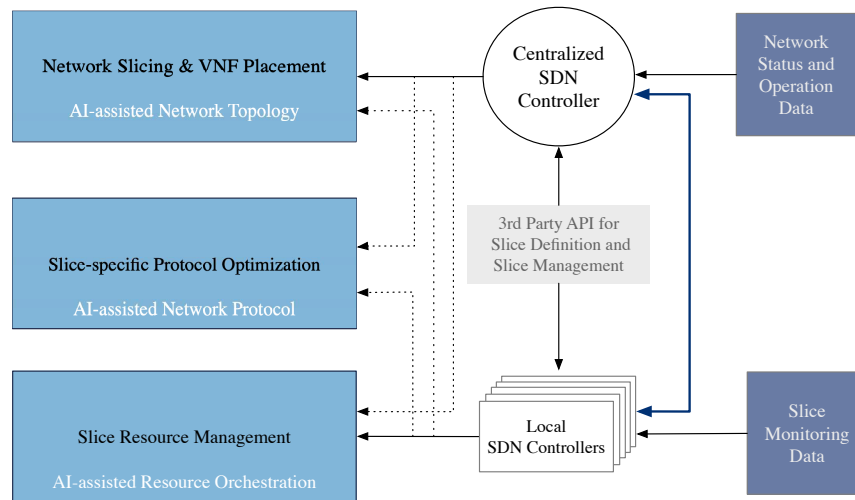


Fig. 2: The functional architecture of network-slicing based AI-assisted next-generation wireless RAN.

illustrated in Fig. 1. In this architecture, a centralized SDN controller is placed at the central cloud, while local SDN controllers are placed at individual RANs. Each local controller is connected to the infrastructure in its corresponding RAN and responsible for collecting the network information. VNFs are deployed at servers connected to radio heads, access points, storage facilities, local data servers, etc. In the context of RAN, VNFs consist of baseband unit (BBU) functions, e.g., compression and encryption procedures and hybrid automatic repeat-request (HARQ) [41], [42]. Accordingly, network slicing translates to the placement of VNFs into various slices (subject to physical infrastructure constraints and QoS requirements), the establishment of the logical topology of the VNFs in each slice, and the mapping from the VNFs to the underlying physical infrastructure. In this architecture, computing becomes especially important due to the virtualization of network functions since the placement of VNFs in the slices is essentially the allocation of computing resources.

The key functional components and their relations corresponding to the architecture in Fig. 1 are shown in Fig. 2. While end-to-end (E2E) connections span both wireless segment(s) and the core network, this illustration focuses on the wireless domain. The centralized SDN controller is responsible for slice blueprint definition and end-to-end slicing based on the information collected

from local controllers. Local controllers are responsible for assisting the centralized controller in the slicing of their corresponding RAN. After a slice is deployed, the corresponding local controller is responsible for orchestrating slice resources among end users as well as monitoring slice status for resource utilization and QoS violations. In addition, local controllers can also be involved in slice monitoring and slice adaption, while the centralized SDN controller may or may not be involved depending on the service type and the use case. The network status and operation data, aggregated from all slices, are collected by local controllers and either processed locally or forwarded to the centralized SDN controller for analysis. The analysis results will be used to update slice deployment and slice adaption. The above relation between centralized and local controllers introduces an important question: whether and when should the centralized controller be involved in specific network management and resource allocation tasks under this network architecture? Evidently, involving the centralized SDN controller in such tasks can take advantage of the global network information for making optimal network management and resource allocation decisions. However, decision making via the centralized SDN controller can incur significant signaling overhead. Therefore, a balance between the tasks for the centralized and local controllers, which depends on the type of tasks and the type of a slice, should be investigated.

The three blocks in Fig. 2, i.e., network topology, network protocol, and network resource orchestration, form a closed loop, which reflects the interplay between the two levels of network management: network planning and network resource scheduling [43]. Network planning, including the initial resource reservation for all slices, corresponds to the block of network topology in Fig. 2. Meanwhile, network resource scheduling consists of the network protocol and network resource orchestration blocks in Fig. 2, where the resource orchestration applies within each slice. As shown in Fig. 3, network planning admits slice requests, reserves resources for the admitted slices, and determines the placement of required VNFs in each slice. Based on the result of network planning, network resource scheduling further allocates various resources in a slice to individual network users dynamically. The resulting SLA and resource utilization in the admitted slices are monitored, based on which the network planning may be adjusted in the future.

The role of AI in the network architecture includes exploiting the slice SLA monitoring data and the slice resource utilization data to facilitate slice deployment, slice adaption, and slice update. Due to the heterogeneous and dynamic features of next-generation wireless networks,

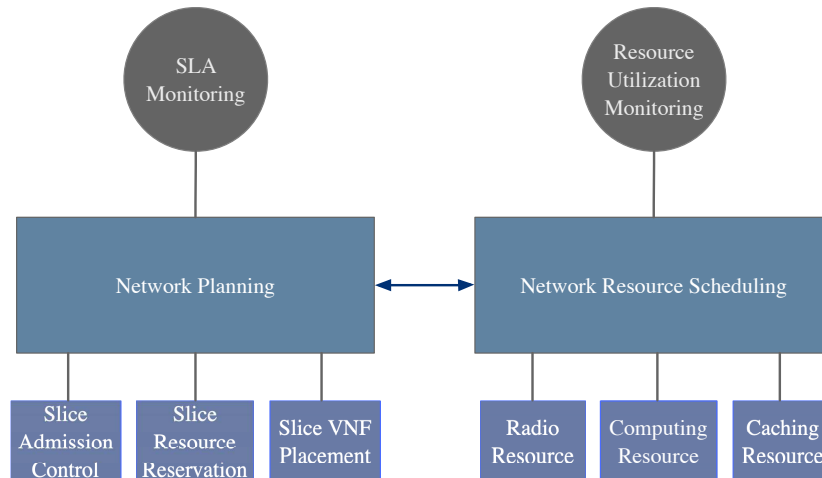


Fig. 3: The interplay between network planning and network resource scheduling in the slicing-based architecture.

conventional optimization approaches based completely on statistical models are likely to become intractable or too slow, if not both. By contrast, ML-based approaches can potentially make use of the aforementioned monitoring data for both slice and network performance optimization. Through the application of ML for data analysis and decision making in both the centralized and local SDN controllers, the slicing based architecture in Fig. 1 can be empowered by AI.

In the following sections, we investigate the RAN slicing framework, RAT selection automation, and content caching and delivery, respectively, under this AI-assisted slicing based network architecture.

III. RAN SLICING FRAMEWORK

RAN slicing is deemed as the most promising technology in 5G networks and beyond, by providing a flexible and scalable network architecture to support a variety of services attached to manifold QoS requirements. By slicing the shared physical wireless networks into multiple isolated logical networks, RAN slicing can dynamically and elastically allocate network resources to provide tailored services for isolated logical networks. Building on the shared physical network infrastructure, RAN slicing is a cost-effective solution of network management. A study reported that RAN slicing can save capital expenditure (CapEx) and operational expenditure (OpEx) up to 60 billion dollars worldwide within the next five years [44]. These benefits motivate the study on RAN slicing for next-generation wireless networks. Extensive industry efforts

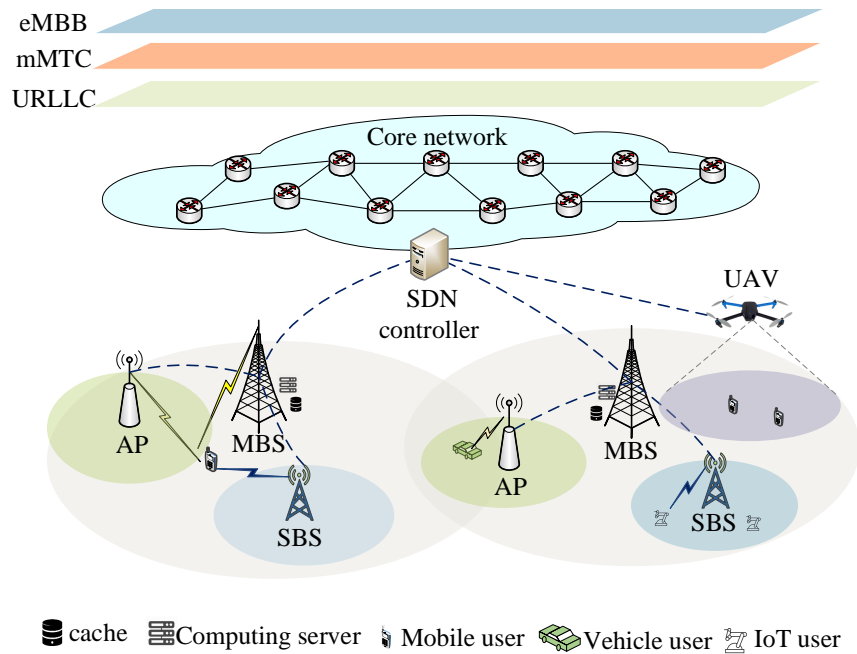


Fig. 4: A RAN slicing framework provides differentiated services for various types of users in heterogeneous networks.

have been devoted to RAN slicing framework ratification. For example, network slicing has been introduced as one of key features of international mobile telecommunication (IMT)-2020 network [45]. 3rd generation partnership project (3GPP) also conducts extensive studies on the slicing-based architecture for 5G networks [46], [47]. Multiple proof-of-concept systems on RAN slicing have been developed and evaluated based on real world network traffic data [48], [49]. Interested readers can refer to a detailed survey paper in [50]. Next-generation wireless networks become more complicated due to diverse network resources, dynamic and heterogeneous network topology, and differentiated QoS requirements. These characteristics create new challenges for RAN slicing to support various kinds of applications. In this section, we first present the research challenges of RAN slicing. Then, existing works on RAN slicing are reviewed, which are summarized in Table II. Finally, potential benefits and challenges of emerging AI-based RAN slicing are discussed.

A. Research Challenges in RAN Slicing

The next-generation wireless networks have the following characteristics: 1) Heterogeneous network architecture - The network architecture consists of multiple network infrastructures,

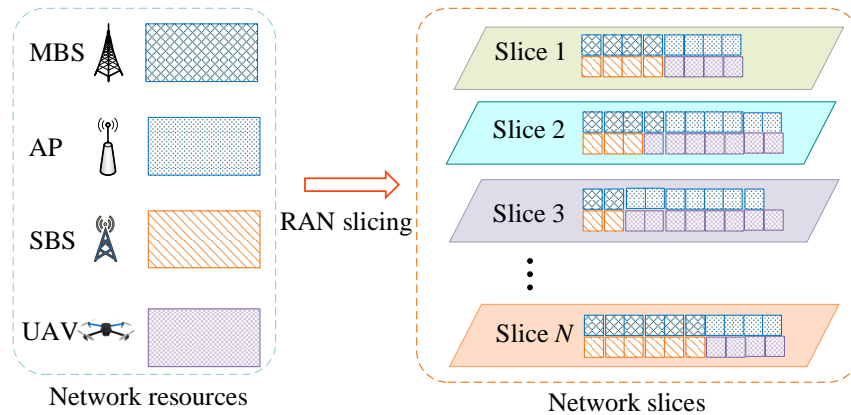


Fig. 5: The network resources of the shared network infrastructure are allocated to each slice via RAN slicing.

including cellular BSs, drone BS, WiFi access points (APs), etc., as shown in Fig. 4. The densely deployed network infrastructures have overlapped coverage, and hence users can associate with multiple networks, thereby rendering a complex network topology; 2) Computing/caching-aided network infrastructure - In addition to communication functionality, network infrastructures are endowed with computing and caching functionalities. To support emerging real-time mobile services, such as virtual reality (VR), augmented reality (AR), and autonomous driving, mobile edge computing (MEC) extends the computing functionality from cloud to edge networks and reduces task processing latency. Network infrastructures, such as cellular BSs, are equipped with MEC servers to provide computing services for resource-limited mobile users. Similarly, widely deployed caching servers in edge network can store popular contents and facilitate low-latency service; and 3) Differentiated QoS requirements - Due to user diversity and service heterogeneity, differentiated QoS requirements should be satisfied for various services. Typically, services can be divided into three categories based on the QoS requirements: i) URLLC services which desire high reliability and low latency, such as mission critical environmental sensing for autonomous driving and tactile applications with millisecond latency requirement; ii) eMBB services which aim to have a high throughput for a large amount of data, such as video streaming and VR/AR gaming; and iii) mMTC services which target to connect massive devices with low throughput requirements, such as Internet of things (IoT) sensor monitoring.

The goal of RAN slicing is to provide customized services for mobile users with differentiated QoS requirements in the above heterogeneous networks. Hence, the key issue of RAN slicing

TABLE II: Summary of Literature on RAN Slicing

Topic	Related Work	Contribution	Approach
Resource Allocation	[20]	Maximize the proportional sum rate of all the users via spectrum slicing in two-tier cellular networks	Optimization
	[51]	Maximize the network utility via spectrum slicing and transmit power allocation in vehicular networks	Optimization
	[25]	Maximize network revenue for URLLC and eMBB services in cellular networks	Optimization
	[52]	Maximize the network revenue by intelligently admitting network slice requests	RL
	[53]	Maximize the network revenue via dynamically slicing time-varying spectrum resource in indoor neural-host small cells	DDPG
	[54]	Minimize service latency in a sliced RAN by computing resource allocation and task transmission scheduling	Deep learning
	[55]	Maximize the long-term utility of the service provider via channel allocation in a sliced RAN	Multi-agent stochastic learning
	[56]	Maximize the utility of individual service provider by joint slicing computing and communication resources	Multi-agent double deep Q learning
Traffic Prediction	[57]	Predict the average service traffic in a LTE testbed	LSTM
	[58]	Predict the maximum service-specific traffic for each slice based on real-world 5G network data	Deep learning
	[52]	Predict the service-specific traffic per slice based on customized user mobility pattern	Unsupervised learning

is how to efficiently allocate network resources while meeting the user QoS requirements, as shown in Fig. 5. Since emerging services may consume multiple network resources, RAN slicing needs to jointly allocate the abstracted communication, computing, and caching resources from distributed network infrastructures. Specifically, based on *a priori* service-specific traffic statistics, the communication resources can be sliced in terms of radio spectrum bandwidth, the computing resources can be sliced in terms of CPU power, and the caching resources can be sliced in terms of storage unit for each slice. Hence, RAN slicing should jointly allocate these multiple network resources (e.g., communication, computing, and caching) to optimize the network utility while satisfying the differentiated QoS requirements of customized services. Due to the heterogeneous network architectures and differentiated QoS requirements, RAN slicing faces the following unique challenges.

- Resource interplay - Since a service may consume multiple network resources, there exists an inherent tradeoff among multiple network resources. For example, in computing offloading services, the service latency consists of two elements: task transmission latency and task processing latency. If a user associates with a remote MEC server having

abundant computing resources for task processing, a high task transmission latency will be incurred. On the other hand, if a user associates with a nearby MEC server having insufficient computing resources, it takes a longer time for task processing. In such manner, the allocation of computing and communication resources is coupled with each other in the exemplary computing offloading services. Similarly, the allocation of multiple network resources is intertwined, which complicates the RAN slicing. A joint multiple network resource allocation scheme should be judiciously designed to maximize network welfare;

- **Strict QoS requirements** - Compared with traditional 4G networks, 5G networks and beyond have stricter QoS requirements, including a higher throughput and a lower latency. Especially, the typical URLLC service in 5G requires an ultra-high reliability (e.g., 99.999%), which is much stricter than that of other services. In addition, the payload of data packets in URLLC services is usually small, such as around 32 bytes [59]. The transmission performance of short-length packets cannot be characterized by the traditional Shannon theory which is suitable for long-length packet transmission due to a large transmission overhead. Instead, the finite block length channel coding theory should be applied to characterize the achievable rate for short-length packets [60]. Traditional QoS provisioning is unsuitable for short-length packet URLLC services with ultra-high reliability. Thus, an accurate QoS provisioning for URLLC services is desired in the RAN slicing framework;
- **User mobility** - Due to the high network density, users may frequently move out the coverage of its associated network infrastructure, which results in dynamic network topology. For example, high-mobility vehicle users can trigger handover frequently. The dynamic network topology changes the service traffic distribution, rendering previously optimal slice allocation suboptimal over time, degrading network performance, and may even violating users' QoS requirements. When the network performance degrades to a threshold, adjusting existing slices or creating new slices will be triggered, which incurs slice reconfiguration overhead. Thus, dynamic yet efficient RAN slicing to accommodate user mobility remains a challenging issue.

B. Existing Approaches

Due to the advantages in reducing network operation cost and improving resource utilization, extensive research efforts have been devoted to RAN slicing in different contexts. Based on the known service-specific traffic statistics, a communication resource slicing strategy was proposed

to support both machine-type users and mobile users, by allocating the spectrum in heterogeneous networks [20], in which bandwidth resource and user association are jointly allocated to maximize network utility. The results show that the proposed slicing strategy can effectively boost the network utility compared with benchmark schemes. An extended work developed a communication resource slicing strategy to provide customized services in the context of vehicular networks [51]. These works mainly formulate a RAN slicing problem as an optimization problem with the objective of maximizing network utility, while satisfying the QoS constraints of admitted slices. By resorting to optimization theory, these complicated optimization problems can be solved by classic iterative optimization algorithms. Another line of work focuses on the communication resource slicing from the perspective of a network operator with an objective of maximizing the operator's revenue in different scenarios, such as in cellular networks [25] and indoor neutral-host small cell networks [53]. In the latter two works, sub-optimal algorithms are applied to solve these complicated slicing problems. The above works [51] [20] [25] focused on addressing the communication resource slicing from different perspectives. Since emerging services consume multiple resources, further investigation is needed for RAN slicing that incorporates multiple network resources. However, a multiple-resource slicing problem is much more complex than an individual resource slicing problem. In addition, existing works mainly deal with services attached to relatively loose QoS requirements, and hence developing RAN slicing to support strict URLLC services requires further investigation. In summary, optimization-based methods are widely applied to solve RAN slicing problems, which can effectively manage resources in a small-scale network.

However, existing optimization-based methods suffer from two limitations: i) the prerequisite of *a priori* accurate traffic model - Service demand statistics are usually assumed to be known in advance and accurate in most of the existing works. For example, [20] assumes a known Poisson process to model service traffic of mobile users. However, these assumptions do not hold in practical time-variant wireless networks, especially in highly-mobility scenarios; and ii) high computational complexity - With the dense deployment of wireless networks, efficient RAN slicing for a large-scale network (e.g., tens to hundreds of BSs) is required. Applying existing iterative optimization-based methods may be unsuitable for a large-scale RAN slicing problem since the computational complexity greatly increases with the network scale, such that slicing algorithms may take a long time to converge. These limitations may undermine the practicality of the existing optimization-based methods. Hence, an efficient RAN slicing strategy for large-scale

networks without accurate *a priori* traffic model, is of paramount importance.

C. AI-based RAN Slicing

As aforementioned, existing optimization-based methods for RAN slicing problems face two fundamental challenges: *a priori* accurate traffic modeling and high computational complexity. With the development of advanced AI techniques, model-free AI-based methods become promising techniques to provide potential benefits to address these challenges. In the following, the potential benefits and challenges of AI-based RAN slicing are discussed in detail.

1) *Potential Benefits:* AI-based methods can provide two potential benefits for RAN slicing. On the one hand, AI-based methods may provide accurate service-specific traffic prediction. Only with the accurately predicted service-specific traffic, RAN slicing can effectively allocate network resources to accommodate future service demands. An overestimation result (i.e. allocating network resources exceeding service demands) wastes cherished resource and reduces network welfare, while an underestimation result (i.e., allocating network resources less than required) renders SLA violations. Recently, advanced AI-based methods, e.g., deep neural network (DNN), long short-term memory (LSTM), etc., are capable of accurately forecasting service-specific traffic. A recent work applied a DNN to predict aggregated data traffic in cellular networks based on historical service requests [61]. For fine-grained service-specific traffic, the authors in [57] developed a prediction model based on a modified LSTM network, which can accurately predict the average traffic, thereby greatly reducing over-provisioning and SLA violations. Unlike [57], which focused on predicting the average traffic, another work designed a deep learning framework for the maximum service traffic prediction [58]. Based on historical user service requests and a known user mobility model, Sciancalepore *et al.* developed an unsupervised learning based forecasting module to predict service traffic [52]. While the prediction accuracy highly depends on the accuracy of the user mobility model which is difficult to be guaranteed in practical high-mobility scenarios. The above research efforts illustrated that the AI-based prediction method can accurately predict and capture service traffic pattern. Hence, with accurate online service-specific traffic prediction, complicated service-specific traffic models may no longer be requisites for RAN slicing problems.

AI-based methods can also facilitate efficient resource allocation for RAN slicing. AI-based methods can make online resource allocation decisions with a low complexity once the neural network is well-established in the (offline) training procedure, which can conquer the high

computational complexity challenge. Recently, extensive research works have shown that AI-based methods can be widely applied in solving complicated resource management problems in wireless networks, such as power allocation for the interference management [62], resource block allocation in cloud radio access networks (CRANs) [63], SBS on/off scheduling in cellular networks [61], computing task offloading in space-air integrated networks [64], etc. These works mainly formulate the targeted resource allocation problem as a Markov decision process (MDP) problem, and then resort to the celebrated RL framework to address the MDP problem and make online decisions. Note that the essence of RAN slicing is an optimization problem with the objective of maximizing network performance and constraints of satisfying QoS requirements, which can also be addressed by RL-based methods. Hence, RL-based methods are widely applied in solving the resource allocation problem in RAN slicing framework. A pioneering work in [52] developed an RL algorithm to determine the optimal set of admitted slices with the objective of maximizing the welfare of the infrastructure provider (e.g., 5G broker). However, traditional RL methods, such as Q-learning, suffer from the curse of dimensionality, which are only suitable for RAN slicing problems in small-scale networks. Recent advanced deep RL methods that incorporate the deep learning network in RL framework, can effectively address the RAN slicing problem in large-scale networks. Chen *et al.* designed a deep RL learning based scheduling strategy to minimize service latency in a sliced RAN [54], in which a modified deep RL method is leveraged for computing power allocation and task transmission scheduling. An enhanced RL method, deep deterministic policy gradient (DDPG), was adopted to dynamically slice the shared time-varying spectrum resource in indoor small cell networks [53]. The above works [52]–[54] focused on managing network resources for RAN slicing in a centralized manner. Apart from learning in a centralized manner, AI-based methods can also be applied in a decentralized manner for RAN slicing, namely, a multi-tenant RAN slicing problem, in which multiple tenants (i.e., slice owners) contend for the network resource from an infrastructure provider. The multi-agent RAN slicing problem aims at bidding and allocating network resources to maximize the revenue of each tenant. The authors in [55] first modeled multi-tenant RAN slicing problem as a non-cooperative stochastic game and then proposed a stochastic learning algorithm for communication resource allocation. An extended work further developed a deep learning approach based on a double deep Q network for jointly allocating communication and computing resources to maximize the welfare of each tenant [56]. The results in above research works [52]–[56] showed that the AI-based methods hold the potential to efficiently

boost the performance of the RAN slicing with a low complexity as compared with conventional optimization-based methods. Existing works reviewed above indicated AI-based methods may be applied to address the RAN slicing problem in various contexts. In summary, through tracking the accurate service-specific traffic, AI-based methods may become promising candidates to automatically manage network resources in complicated RAN slicing problems.

2) *Challenges*: However, AI-based RAN slicing faces a unique challenge: strict QoS guarantee within the RL framework. Essentially, the RAN slicing problem is an optimization problem with strict constraints. How to satisfy these constraints in the RL framework is a challenging issue. Due to the limitation of the Q-value based mathematical modeling of RL, the QoS requirements are usually integrated into the reward function by some predefined weights such as [61]. In such a manner, strict QoS requirements cannot be guaranteed unless appropriate weights for the QoS requirements is determined, especially when the QoS requirements are multi-dimensional. For example, the existing work [53] can only satisfy soft QoS requirements. Thus, developing an efficient RL-based RAN slicing algorithm while satisfying strict QoS constraints requires further investigation.

IV. AUTOMATED RAT SELECTION/USER ASSOCIATION

In next-generation heterogeneous wireless networks, multiple types of RAT will coexist, and thus users could face the problem of RAT selection. RAT selection is closely related to user association, which associates users with specific APs.¹ In this section, we use “RAT selection” as a synonym of “user association” in the case of multiple coexisting RATs.

User association has been widely studied under different network scenarios, especially in the case of a single RAT. Some studies focused on user association in a multi-tier cellular network [65], [66]. Others investigated user association under particular physical-layer settings (such as MIMO [67], mmWave [68], energy harvesting [69]) or network environments (such as self-organizing networks [70], D2D communications [71], and UAV-to-ground communications [72]). In addition, various metrics, including spectrum efficiency, energy efficiency, and energy consumption, have been adopted in the study of user association [73].

¹In a simple scenario with several APs each using a different RAT, RAT selection is equivalent to user association. In more general scenarios where each RAT is used by one or more APs, associating a user to an AP requires both the selection of an RAT and the selection of a specific AP given the chosen RAT.

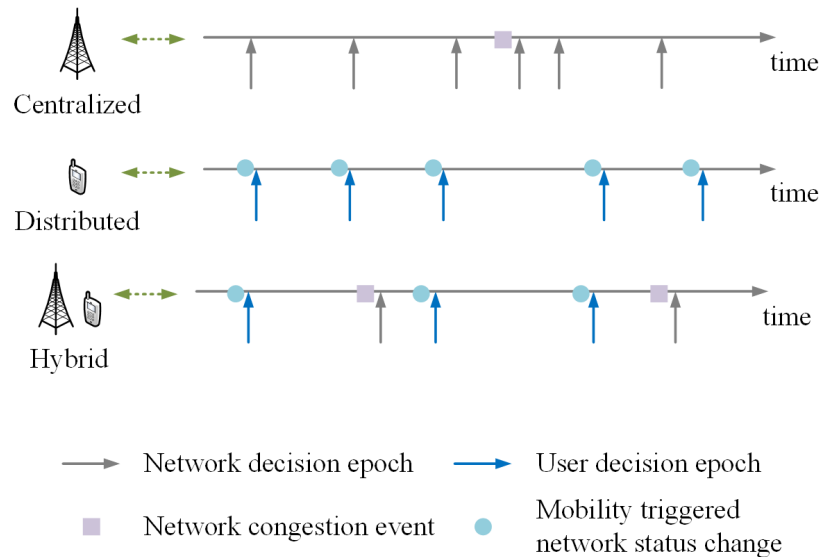


Fig. 6: The classification of RAT selection based on the control paradigm: centralized, distributed, and hybrid. For distributed user association, the case of mobility triggered network selection is illustrated here as an example.

In the rest of the section, we focus on RAT selection in the slicing-based next-generation wireless networks. Firstly, we give an overview of conventional user association schemes. Then, we introduce RAT selection in network-slicing based next-generation wireless networks. After that, we review and discuss AI-assisted RAT selection.

A. Conventional User Association Approaches

As shown in Fig. 6, conventional user association can be divided into three categories: centralized, distributed and hybrid based on control paradigm [74].² A global controller is assumed in the case of a centralized control to collect network-related information. The centralized method usually finds the network association strategy by formulating the problem based on a Markov model or through a centralized optimization. Using a Markov model, the network selection is usually formulated as a joint user association and mobile traffic offloading problem. The target is to obtain a desirable admission and offloading policy to optimize certain system-level metrics such as service blocking probability [75]–[77]. In the centralized optimization approach [20],

²Similarly, user association can also be classified as network controlled, user controlled, and network assisted according to the control entity.

[66], a selection algorithm is executed each time when association decisions need to be made. The target is to optimize system-level performance such as energy efficiency, spectrum efficiency, load balancing or system aggregated utility subject to network resource availability and user association constraints. However, both Markov model based and optimization based centralized user association have limitations. In the Markov-based approach, user mobility and handoff are generally ignored (i.e., the users are assumed to associate with the same AP until the end of a service session). Moreover, users are treated without any differentiation i.e., user preference and service priorities are ignored in general. Meanwhile, the centralized optimization method suffers from scalability and efficiency issues. In addition, the optimality is usually achieved at the cost of signaling overheads in the information gathering and the policy enforcement stages.

Distributed user association has been studied using various models, including multiple attribute decision making (MADM) [78], [79], MDP [80], fuzzy-logic [81], game theory (e.g. cooperative game [82], and non-cooperative game [67]), etc. Under the distributed setting, network attributes are collected or estimated at the user side. The user then chooses the AP with the best performance. Compared to the centralized method, a distributed selection scheme can usually be implemented with less complexity. Besides, a decentralized approach can reduce the signaling overhead at the cost of suboptimal performance. The distributed selection schemes also have some limitations, including: i) Non-cooperative user association can lead to network load oscillation when multiple devices try to associate and disassociate with the same AP concurrently; and ii) The design of effective information exchange is necessary for distributed cooperative user association but can be very challenging.

For the hybrid selection, a tradeoff between network performance and signaling overhead can be achieved. The hybrid approach can be implemented as a mixture of centralized and distributed control. In [83], Elayoubi *et al.* solved the user association problem using a Bayesian game. Two types of players are involved, which are the different networks and the users. Each user selfishly maximizes their own utility without any cooperation while each network cooperates with users within its coverage, broadcasting its current status (such as the load) to maximize the total utility of the users associated with it. Such a design may result in multiple Nash equilibria. Therefore, the information that the network needs to broadcast should be carefully designed so that an equilibrium with a relatively high efficiency can be achieved.

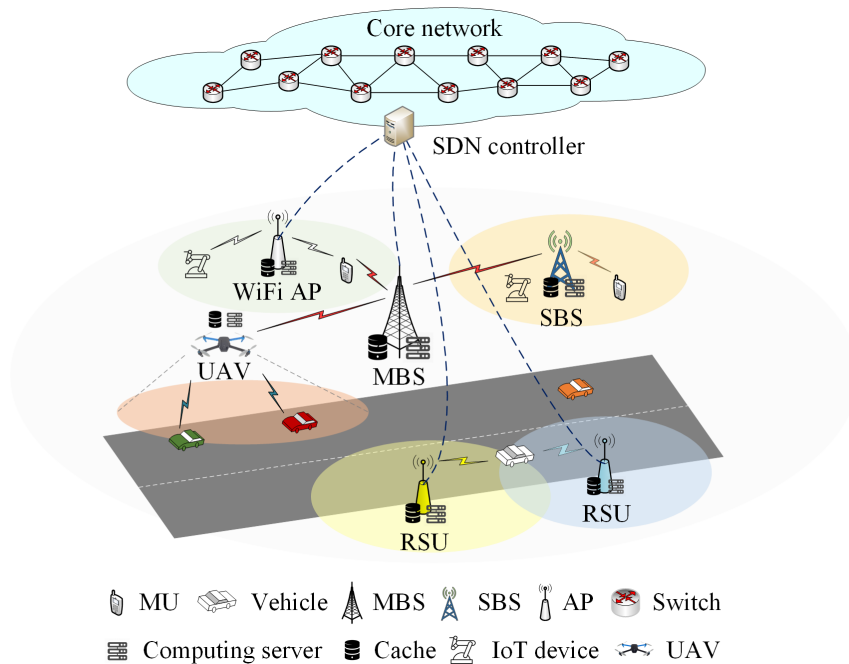


Fig. 7: The RAT selection in next-generation wireless networks with multiple services and multiple available RATs.

B. RAT Selection in Slicing-based Heterogeneous Networks

Figure 7 shows an envisioned scenario of next-generation heterogeneous wireless networks. In such networks, multiple types of RATs, multiple types of APs, multiple types of UEs with various service requirements, and multiple types of resources jointly contribute to an unprecedented level of heterogeneity. In the rest of this section, we present the main differences of RAT selection under the slicing-based next-generation wireless networks compared to conventional user association.

Firstly, from the control perspective, the capacity of the SDN controller for information collection and centralized control should be leveraged in the RAT selection. It can be seen from Fig. 7 that a global view of the network is enabled through the deployment of the SDN controller. Network status information such as current network loads, user service demands, and user distribution, as well as user status information such as user location, speed, and moving direction can be obtained by the SDN controller for centralized decision making. However, the above centralized control is not scalable and can yield significant signaling overhead. Therefore, a hybrid control architecture is preferred in the next-generation wireless networks, in which users

make distributed RAT selection decisions at a small timescale while the centralized control is triggered at a large timescale.

Secondly, given the SDN/NFV enabled network slicing architecture [23], each slice is assigned with only a portion of physical resources based on its target type of service. Therefore, the resource availability and resource utilization level of each slice become a concern and need to be accounted for properly via the RAT selection. Besides, considering network slicing, it is possible that a user is involved in multiple network slices [84]. The RAT selection/user association in such case requires further investigation.

Finally, new types of network resources are emerging, which can affect the RAT selection. Traditional network infrastructures (e.g., cellular BSs and WiFi APs) only have the communication functionality. As the network continues to evolve, these infrastructures are supporting caching and computing services. Such improvement leads to diverse network resources compared to that in previous generations. In addition, an unprecedented level of heterogeneity will be expected as next-generation wireless networks continue to evolve. Consequently, it is foreseen that the complexity in solving RAT selection problem will increase in the next generation communication networks.

C. Research Challenges

Based on the preceding discussion, several research challenges related to RAT selection in the next-generation wireless networks are listed as follows.

1) Service modeling: The dependence between service requirements and the corresponding demands for multi-dimension resources has not been modeled explicitly in conventional user associations. In the literature, users can either select the network based on a radio link quality, i.e., the “always-best-connected” (ABC) [85], or associate with a nearby AP that has the content of their interest in its cache [86] or a nearby AP that has high computing capacity [87]. However, the network selection in next-generation wireless networks should be determined based on multi-dimensional resource availability for communication, caching, and computing, considering that different services can have totally different requirements on the three types of resources. For example, video streaming services pay most attention to the communication resources (i.e., the link quality, the available bandwidth and so on); vehicles downloading high-definition maps prefer to connect to an AP which caches contents of their interest; for VR applications [88]

(e.g., Pokémon GO), computing resources are of the foremost concern. As a result, the demand for different resources will impact on the RAT selection.

Some recent works provided ideas on how to model tasks of different services. Mao *et al.* modeled a computing task using three parameters: offloaded task size (in bits), computation intensity (in CPU cycles per bit), and completion deadline [89]. A VR related task modeling with three-dimension resources was proposed in [90], [91], in which cached contents are used as inputs of the computing stage. However, a general model to describe the dependence between service requirements and multi-dimensional resources is not available yet. The complexity in developing such a service model comes from the variety of services and their diversified requirements.

2) Resource slicing: Different RATs may adopt different resources allocation schemes and yield different resource utilization. Therefore, resource allocation and RAT selection are mutually dependent, and joint network resource allocation and user association should be considered. Existing works on joint computing resources allocation and user association [92], [93], joint caching resources allocation and user association [94], or a joint allocation of the communication, computing and caching resources and user association [95], [96] do not consider network slicing. Meanwhile, current works on network slicing consider only one type of RAT and/or only the communication resources [20], [97], which limits their applications in next-generation wireless networks with multiple RATs and multiple resources.

After RAN slicing in the planning stage, multiple slices are established. Within each network slice, RAT selection adjustments may be required in the scheduling stage due to user mobility, network load distribution, scheduled power-off of APs [61] and so on. For such adjustments of RAT selection conducted within a slice, it may be possible to extend some existing works that study user association without considering network slicing to solve the RAT selection adjustment problem.

3) User mobility: Mobility is an essential issue in the RAT selection. A properly designed association algorithm should avoid unnecessary handoffs since a re-association procedure incurs extra signaling and excessive execution latency. To reduce unnecessary handoffs, RAT selection can be based on predicted user mobility. Many state-of-the-art prediction algorithms has been proposed to estimate user trajectory, cell dwelling time, and other mobility-related information such as data-based [98] and model-based [99] mobility prediction methods. With the prediction of user mobility, a proactive network resource adjustment can be designed to achieve a timely and smooth handoff. For instance, the network can adaptively or proactively adjust their resource

allocation, using mobility-aware computing strategy [100] and/or caching strategy [101]. However, these mobility-aware resource allocation strategies assume that the user association policy is known and fixed, which is inappropriate in the next-generation wireless networks. In order to more efficiently utilize network resources, user association should be considered jointly with mobility-aware network resource allocation. For example, a joint user association and content placement in edge caching scenario considering user mobility was studied [102]. When mobility and resource allocation are both taken into account, the resulting RAT selection problem would be much more complex than the conventional one.

Moreover, due to user mobility, a communication or computing task may not finish while a user is temporally connected to an AP. As a result, a task handover from the original AP is necessary. For example, when a user is moving out of the coverage of an AP and thus cannot finish downloading a content, it would prefer to connect to another AP that caches the same content to continue the downloading task. Similarly, in order to preserve service continuity in a computation task, the original task can be decomposed into several subtasks. Each subtask is offloaded to an AP with computing capacity so that it can be finished before the user moves out of the coverage of the current AP. Therefore, the current user task completion status should be incorporated in the RAT selection in the scheduling stage.

4) Multi-connectivity: In addition to the multi-mode capacity which allows only one RAT connection at any time, multi-connectivity/multi-homing terminals have the ability to support multiple RAT connections simultaneously [110], [111]. Using concurrent connections for a single service has the benefit of improving the service reliability [112]. The multi-homing related RAT selection has been investigated from different perspectives. From the perspective of network, the network operator aims to optimally allocate downlink (DL) bandwidth among multiple radio connections to support users with different services in a multi-RAT environment [110]. In contrast, from the perspective of a single user, the user aims to achieve a better QoS by optimally distributing packets among multiple radio interfaces during an uplink (UL) transmission [111]. In general, an RAT selection problem considering multi-homing terminals is much more complicated than a problem that only considers multi-mode, since we need to determine how many connections to establish and which set of the available radio networks to connect for the user. Initial work on multi-homing connection can be found in [113], which did not consider network slicing and only focused on the communication resource.

TABLE III: Summary of Literature on User Association in Heterogeneous Networks

User Mode	Work	Control Paradigm	Objective	Scenario	Link	User Mobility	Resource
Multi-Mode	[20]	Centralized	Fairness	Two-tier network	DL	No	Bandwidth
	[72]	Centralized	Average drone-to-user pathloss minimization	UAV-assisted RAN	DL	Yes	Time slots
	[74]	Centralized	Load balancing	Vehicular network	DL	Yes	Scheduled time fraction
	[87]	Distributed	Energy efficiency maximization	MEC	UL	Yes	CPU-cycle frequency
	[94]	Distributed	Profit related utility maximization	Information-centric network	DL	No	Virtual resources & caching resources
	[95]	Centralized	Computational overhead minimization	MEC	UL&DL	No	Communication, computing & caching resources
	[96]	Centralized	Average service latency minimization	Fog-computing IoT network	UL&DL	No	Communication, computing & caching resources
	[103]	Centralized	Profits maximization	CRAN	DL	No	Cache & resource blocks
	[104]	Centralized	Load balancing	CRAN	DL	No	Transmission power
	[105]	Centralized	Load balancing	Cellular network	DL	No	Transmission power
	[106]	Centralized	Load balancing & energy efficiency maximization	mmWave communications	DL	No	Transmission power
[107]	Centralized	Service capacity maximization	mmWave communications	DL	No	Communication, computing & caching resources	
Multi-Connectivity	[68]	Centralized	Service capacity maximization	mmWave communications	DL	No	RF chains
	[108]	Centralized	Energy efficiency maximization	Multi-tier network	DL	No	Transmission power
	[109]	Centralized	Power consumption minimization	MIMO cellular network	DL	No	Transmission power

D. AI-based RAT Selection

In Table III, we summarize a few related works on user association in heterogeneous networks. Some of these works adopt optimization techniques, while others use learning-based approaches.³ In this section, we first review optimization-based solutions, and then the learning-based solutions, followed by discussions regarding the challenges of applying AI in RAT selection.

Optimization-based approaches for solving user association problems can be categorized into two classes: deterministic optimization-based approach [66], [68], [106] and stochastic optimization-based approach [90]. Both classes have the following limitations. Firstly, user association related problems are usually formulated as combinatorial optimizations, which is non-convex and usually

³Markov chain-based approach is considered as a special case of optimization where the objective is to optimize a network's steady-state performance.

NP-hard. Therefore, applying optimization-based methods may result in significant computation latency and overhead [89]. Even if the optimal solution can be found, the complexity of finding the solution can be prohibitive as the network size or the set of service types grows due to “the curse of dimensionality”. Secondly, optimization-based approaches rely on the prior knowledge of the network (e.g., network topology, user density, mobility, channel statistics, and service requirements) and/or the assumptions made for mathematical tractability (e.g., Poisson arrivals, exponential service time, uniform user distribution, and so on). When network dynamics vary, established theoretical models may no longer be applicable and the performance of a previously obtained association solution can degrade significantly.

Unlike optimization-based approaches, model-free RL provides an alternative approach for finding the optimal solution of a problem through “trial and error” in the interactions with the environment. According to the learning agent, RL-based RAT selection can be classified into two classes. A class of such works choose individual users as the learning agents. In [114], a distributed Q-learning-based handoff was adopted to optimize the long-term discounted rewards of users. RL can also be combined with traditional RAT selection algorithm for performance improvement. In [115], RL was adopted by users to learn the optimal cell range extension bias with the global objective of minimizing the total number of devices in outage. In the scenario of edge computing, RL was adopted to make user association decisions to improve computing energy efficiency [87]. The second class of RL-related works assume the APs as the learning agents. For example, load balancing through RAT association in a vehicular network where the BS is the learning agent was studied in [74].

However, there are also several challenges in developing ML-based approaches for solving the RAT selection problem: i) The underlying MDP model may not always capture the RAT automation problem accurately. It is possible that only partial information is available or observation errors exist. In such cases, a generalized partially observable MDP (POMDP) can be adopted [116]; and ii) Deriving models and metrics to characterize the performance, or even a performance bound, of the learning algorithm is also a major challenge. Most learning algorithms are only evaluated numerically. Sun *et al.* presented a proof on the performance bounds for their proposed learning algorithm in [87]. However, a unified framework on the convergence and performance analysis of RL is not available.

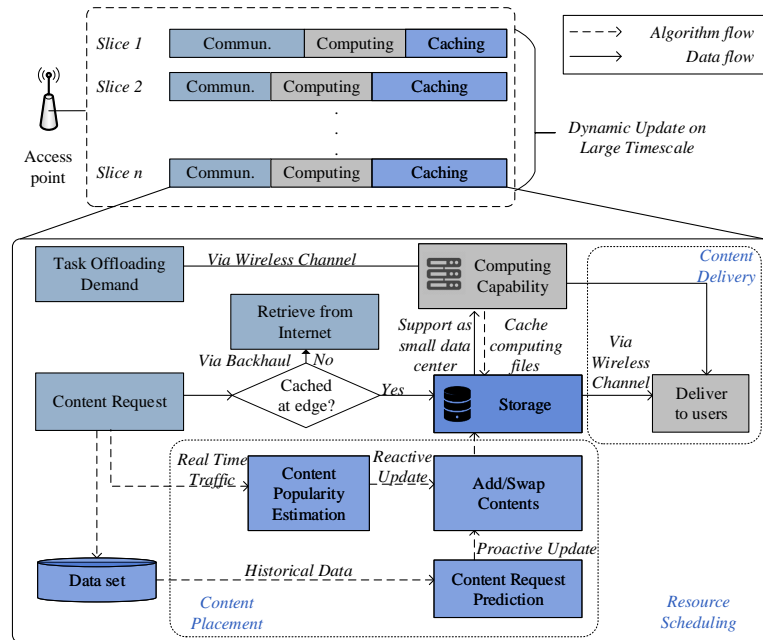


Fig. 8: Overview of caching-centric resource management in a network-slicing based architecture.

V. MOBILE EDGE CACHING AND CONTENT DELIVERY

As mentioned previously, resources in next-generation wireless networks will extend beyond communication resources and include caching resources. Mobile edge caching leverages storage spaces at the network edge to cache popular contents within the RAN. As a result, mobile edge caching may reduce content retrieval time for users and alleviate backhaul congestion for the network [117]. Meanwhile, mobile edge caching is usually limited by the cache size, which necessitates optimized caching strategies that can maximize caching resource utilization. In this section, we present research challenges of mobile edge caching in conventional and network-slicing based wireless networks, respectively. The related research works are reviewed, and future research directions on AI-based mobile edge caching are discussed.

A. Research Challenges

There are two main research issues in mobile edge caching, i.e., content placement and content delivery. Content placement determines which contents to be cached at the edge, while content delivery determines how to deliver cached contents to users [118]. The first major challenge in content placement roots from time-variant content popularity and/or an evolving content

catalogue. If the content popularity can be accurately estimated, the problem of maximizing cache hit rate would be simple. However, it can be very difficult to predict the content popularity, especially when the popularity demonstrates spatial-temporal variations [119]. The second challenge in content placement is due to the multi-tier cache system with overlapped spatial coverage in heterogeneous wireless networks [120]. When content delivery is also considered, the joint optimization of communication and caching strategy, which corresponds to a complex decision making problem, becomes another major challenge.

The next-generation wireless networks demonstrate heterogeneity in both resources and service types. In the network-slicing based architecture, the resources in RAN, including communication, caching, and computing resources, are orchestrated and sliced to support the corresponding virtual networks with QoS guarantee [121], [122]. An overview of caching-centric resource management in a network-slicing based architecture is illustrated in Fig. 8. After slicing the resources in the planning stage, the resources will be further scheduled in each slice to improve user service experience. In resource scheduling, in addition to content placement and content delivery, joint caching and communication resource management should also be taken into account. Under this network-slicing based architecture, new challenges in content placement and content delivery are summarized as follows.

- 1) Heterogeneity among different slices: The physical cache for an edge entity can be sliced into several logical caches for serving different applications with heterogeneous QoS requirements. Different from the conventional caching, content requests are accommodated into different slices in next-generation wireless networks. User access patterns and popular contents in different virtual networks can have distinct characteristics. For example, in IoT applications, users usually fetch contents from a static content catalogue periodically, while, in mobile applications, users typically request contents from an evolving catalogue. Hence, designing a customized content placement policy to support diversified virtual networks is challenging and requires further investigation;
- 2) Dynamic cache size: By resource virtualization, the cache size for a slice can be modified as a result of dynamic slicing on a large timescale. The cache placement policy should be updated dynamically to adapt to the variable cache size. When the cache size allocated to a slice is sufficient, contents with a large size can be cached to reduce the backhaul usage. Otherwise, popular contents with a small size should be cached to improve the cache hit rate. Thus, besides time-variant content popularity and evolving content catalogue, new

TABLE IV: Summary of Literature on Caching Resource Management

Topic	Related Work	Contribution	Approach
Content Placement	[123]	Reduce content popularity estimation interval by utilizing knowledge obtained from user's interactions with a social community.	Transfer learning
	[124]	Increase cache hit rate by cooperative content popularity estimation among multiple servers.	Transfer learning
	[125]	Prefetch contents according to the mobility of user and demonstrate performance improvement on content prefetching.	Markov chain
	[126]	Track and predict time-variant content requests from users.	Neural network
	[127]	Reduce cost of downloading contents from the Internet by adding or swapping contents according their lifetime.	Reinforcement learning
Content Delivery	[128]	Analyze the coupled relation between content placement and communication resource allocation to reduce backhaul traffic.	Heuristic
	[129]	Maximize the quantity of contents delivered by a cache-enabled UAV.	Optimization
	[130]	Allocate caching and communication resources to maximize the revenue by serving end users.	Distributed optimization
	[95]	Minimize overall content access time and energy overhead by selecting the optimal spectrum for content delivery.	Hopfield neural network
	[96]	Minimize content delivery and computing latency by jointly optimize caching, computing, and communication resource.	Reinforcement learning
	[122], [131]	Determine caching and computing offloading decisions to reduce operational cost on edge server, where the interference from other edge servers is evaluated.	Deep Q learning

uncertainty is introduced due to the variable cache size, which may make the content placement problem intractable;

- 3) Multi-resource allocation: MEC is expected to be a basic element in next-generation wireless networks. The contents cached by an edge will not only include popular contents such as videos, but also include the essential files for implementing computing functions. To improve the computing service performance, computing, caching, and communication resources should be jointly optimized in terms of content delivery. However, the multi-resource allocation problem can be too complicated to solve in real-time using model-based approaches.

B. State-of-the-art

This section reviews related works on content placement and content delivery. For content placement, we summarize research efforts on content updating strategies at a single caching server. For content delivery, we focus on research works that study joint caching and communication resource management. A summary of the literature is provided in Table IV.

1) *Content Placement*: Content popularity is time-varying in general, and hence the cached contents stored at a server need to be updated dynamically. The main goal of content placement is to maximize the cache hit probability. As illustrated in Fig. 8, there are two types of caching policies to update the contents in a cache, namely the reactive caching policy and the proactive caching policy.

In the reactive caching policy, the edge node determines whether or not to cache a content after a request for that content arrives [132]. A common assumption is that the content popularity follows a stochastic distribution, such as Zipf distribution [129], [133]. However, the popularity of contents varies over time, and different types of contents can exhibit a variety of popularity evolution patterns. To adapt to non-stationary traffic and content popularity, content updating policies have been proposed. For example, the least recently used (LRU) policy replaces the least recently requested content in the cache when the cache is full. To improve the cache hit rate, the work [123] estimated the content popularity according to the content request during a period of time. However, in practice, the reactive caching policies adapt slowly to the change in content popularity [118], [134].

Proactive caching policies aim to prefetch popular contents that are likely to be requested by users ahead of time. Therefore, proactive caching can mitigate backhaul usage if prefetching is scheduled during off-peak hours. Proactive caching is illustrated in the bottom part of Fig. 8, where historical content requests used for predicting popular contents are added into a data set as records. Future content requests can be predicted by exploiting the spatio-temporal association among the records in the data set, such that the edge server can proactively cache contents for improving the cache hit rate [126]. Another category of literature does not directly predict requests, but formulates an MDP problem to find an optimal content placement policy which maximizes the cache hit rate in the long term [96], [122], [127], [131]. Since the content placement problem has large state-action space and unknown state transition probabilities caused by a dynamic network environment, it is difficult to solve the MDP problem by the conventional dynamic programming method. RL can be utilized to solve the MDP problem according to the reward feedback from the network environment. However, RL has some limitations in solving the content placement problem. The first limitation is the Markov property of the underlying MDP, which is assumed when RL is applied. As a result, it is difficult for RL to explore the temporal correlation in a sequence of historical user requests. Second, most works using RL for optimizing caching strategies assume that the catalogue of contents is known in advance, which can be

unrealistic for the scenario in which the content catalogue is changing dynamically. Therefore, in the case when new contents dynamically emerge, the RL based approaches in most works, such as [96], [122], [131], cannot be applied since they cannot predict the popularity of the new contents. One potential solution to handle a changing content catalogue is adding or removing contents based on their lifetime, as proposed in [127], so that caching decisions can be made for an evolving catalogue of contents. However, such an approach yields another challenge, i.e., estimating the lifetime of contents. Besides, existing works predict content requests according to all content requests received at the server, without considering the type of services or applications. However, such granularity is not fine enough in a network-slicing based network architecture as different slices may have different traffic and content popularity patterns.

In summary, both reactive and proactive content placement aim to improve the cache hit rate. A reactive caching policy can handle a varying content catalogue or evolving content popularity via an online content update, while a proactive caching policy exploits historical user requests and predicts the content popularity offline. Since the pattern of the evolving content popularity might become more evident after the network resources are sliced based on service types, proactive caching can be a potential approach to find customized content placement policies for virtual networks. Besides the spatio-temporal features of user requests, other features can be excavated to further improve the performance of service-specific content request prediction, such as the QoS requirements and the application types for the corresponding virtual network. In addition, existing works generally assume that all contents have an identical size, which is not practical. The content size can substantially affect caching performance due to the dynamic slicing of the physical cache. Therefore, the tradeoff between the backhaul usage decrease and cache hit rate improvement needs to be studied in the case of dynamic slicing of the physical cache.

2) *Content Delivery*: The main goal of content delivery is to reduce content transmission time. In order to achieve this objective, not only should the popular contents be cached in the edge server to reduce the time in backhaul transmission, the average communication delay between users and the edge server should also be minimized. A tradeoff between the transmission delay and caching service coverage was discussed in [129], where a cache-enabled UAV is deployed as an edge server. When the UAV is deployed at a high altitude, it can cover a large number of users and reduce content delivery time for these served users. However, the data rate of content delivery from the UAV to the users can be low due to the high altitude of the UAV. By contrast, when the UAV is deployed at a low altitude, the data rate can be improved, but fewer users can

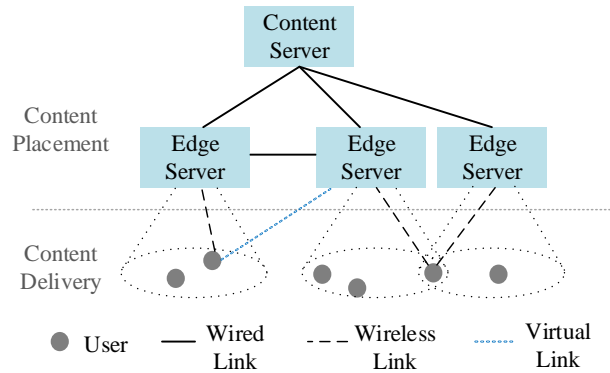


Fig. 9: Decisions in Caching Placement and Delivery.

benefit from the cached contents due to the reduced coverage of the UAV.

In more general scenarios, e.g., when there are multiple edge servers connected with each other, a coupling relation between cache and communication resources can emerge across the servers [128]. As shown in Fig. 9, besides determining which content to be cached, the cooperation among edge servers and the network topology should be considered in the content placement and delivery problem. The edge servers can cooperate with each other in content placement and delivery in order to improve the overall cache hit rate and, as a result, reduce the backhaul congestion. The user can access contents from both its own server and, via the relay of its server, other edge servers (shown as the virtual link in Fig. 9). The joint problem of content placement and routing among the servers can be formulated as a mixed-integer problem, which generally has high complexity. The work [95] utilized a Hopfield neural network (HNN) network to solve the problem of routing without considering resource allocation in cooperative caching. However, solving the joint resource allocation and routing problem in a scalable manner for cooperative caching with multiple edge servers remains an open research problem. As the network topology becomes more complex in next-generation wireless network, the association between users and edge devices should be considered while deciding content placement in order to minimize the content delivery delay. In this case, a user can connect with multiple edge servers which cache popular contents. The trade-off between caching diversity and spectrum efficiency was investigated in [135]. Cooperative caching and transmission were also considered in [136] in the context of coordinated multi-point transmission. In addition, with different network topology, the optimal content placement and delivery decision can vary significantly [137]. The network connectivity graph was analyzed in [120] for allocating content to multiple edge servers given the

network topology and the content popularity. When the number of users increases, the optimal content placement policy becomes intractable.

With the emergence of MEC in 5G, contents stored in the cache include the files and data for implementing the computing functions. To satisfy QoS requirements of MEC, the resources (including communication, caching, and computing resources) should be jointly optimized [138]. As mentioned, RL is a known technique for solving complex decision-making problems. RL has been adopted in many works to jointly allocate caching, computing, and communication resources [96], [122], [131]. While the resulting caching strategies obtained using RL can achieve a near-optimal performance, they cannot handle an evolving content catalogue in general. Moreover, existing works assume that computing and caching resources can be allocated independently, while computing tasks can only be executed when the corresponding files and data are stored at the edge. Such dependency can further complicate the content placement and computing offloading decision.

In summary, the essence of content delivery is a multi-dimensional resource management problem. In the conventional caching scenario, communication and caching resources are jointly optimized to balance the content delivery time and the cache hit rate. In the network-slicing based architecture, computing resource at the edge is utilized to perform latency-critical tasks in virtual networks. Thus, the concept of content delivery is extended to computing offloading and execution. The multi-resource allocation problem incurs high complexity in problem solving. A tractable optimization method is required to make real-time caching and offloading decisions. Moreover, the dependency among caching, computation, and communication resources needs to be further investigated. The caching performance is not only restricted by the sliced caching resource (i.e., the size of logical caches) but also constrained by sliced computing and communication resources. Last, users with high mobility may fail to download the content from or offload their tasks to the edge due to intermittent connections [121]. Thus, user mobility prediction should be incorporated to improve the performance of content delivery.

C. Future Research Directions in AI-based Caching

Given the aforementioned challenges, next, we discuss the potential applications of ML for caching from three aspects: content popularity prediction in proactive content placement, dynamic content placement policy adjustment, and multi-resource allocation in content delivery.

For content popularity prediction, ML based approaches, e.g., DNN, can extract features from recorded content request data to facilitate the content popularity prediction. In the network-slicing based architecture, a local SDN controller can be deployed to monitor content requests and associate the requests with user IDs, request time instants, and locations [139]. Given a sufficiently large dataset of request records collected by the controller, DNN can utilize the records for predicting the content requests in future. Compared with conventional statistical methods, such as regression or Kalman filter, DNN has the advantage of exploiting a large data set to make more accurate predictions. However, the performance of content popularity prediction can be degraded by many factors, such as an evolving content catalogue or time-variant content popularity. As a variant of DNN, recurrent neural network (RNN) has been widely adopted for prediction from historical data due to its ability to track time-variant patterns [140], [141]. Compared to the conventional neural networks, RNN applies internal memory to capture temporal correlations in the input data. Therefore, RNN has been adopted to track time-variant content popularity in the literature [126]. In addition to the temporal correlation in the content requests, ML based approaches can also be used to capture the spatial correlation in the requests. Convolution neural network (CNN) can be a potential tool for capturing such spatial correlations. Despite the above advantages, several issues need to be addressed while developing ML based approaches for caching in future communication networks. Firstly, while DNN and RNN have the potential to predict future content requests with a high accuracy based on spatio-temporal features, deploying dedicated CNN/RNN based prediction modules for content placement can lead to a high computation load. This, in turn, requires a characterization of the improvement in caching performance versus the resulting computation load. As a result, a trade-off between computation and caching performance needs to be investigated. Secondly, in the network-slicing based architecture, content requests are distributed into different virtual networks. Consequently, deploying one neural network as an open module that all slices can use is preferred in terms of complexity, but may not adapt to the specific characteristics of individual slices. By contrast, deploying one neural network for each slice allows a customized prediction module for each service or application, but the resulting complexity can be prohibitive.

For caching policy adjustment, RL is a potential approach to adjust the content placement policy in a dynamic environment with flexible cache size for each slice and time-variant content request pattern. The instantaneous cache size, cached contents, requested content, etc., can be modeled as states, and the content update process can be modeled as actions. The resulting model

will be based on an MDP with unknown state transition probabilities, and RL can be applied to find an efficient content updating policy [142]. However, the assumption of an underlying MDP model, and the resulting Markov property in state transitions, can be impractical. The resulting RL based approach may not fully capture the correlations of content requests over the time domain. In addition, as mentioned in Section V.B, the ML algorithm should be able to handle an evolving content catalogue while updating the caching policy. Devising such an ML algorithm without incurring significant complexity, e.g., having to deploy an additional prediction module for predicting the life time of all contents, remains an open and challenging problem.

For content delivery, deep RL is expected to provide a tractable approach to coordinate and allocate multiple types of resources, including communication, computation, and caching. While the state-action space of multi-dimensional decision making in joint caching, computing, and communication resource allocation, can be too large for conventional RL, deep RL adopts the deep learning technique to estimate policy and value function, and thus can handle the large state-action space from the joint allocation of multiple resources for content delivery. However, classic deep RL has limitations when dealing with constrained decision-making problems, in which the dependency among the resources exists and introduces constraints in resource allocation. For example, a user with a computing task to offload prefers an edge server that caches the data and files for this computing task. In such a case, the content placement at the edge server yields a constraint on the task offloading decision of the user. Constrained MDP can be a possible model for incorporating the above-mentioned constraints [143], while how to design a deep RL based approach to solve the constrained MDP problem needs further investigation.

VI. CONCLUSIONS

In this paper, we have illustrated the network-slicing based architecture, focusing particularly on the RAN, and elaborated how AI can potentially empower this architecture for next-generation heterogeneous wireless networks. Through the investigation of three research problems, i.e., RAN slicing, automated RAT selection/user association, and content placement and delivery, we have demonstrated new challenges, as a result of the heterogeneity, dynamic environment, and/or strict and diversified service requirements, in network management and resource orchestration under the network-slicing based architecture. Most of these challenges cannot be addressed by directly extending existing research. Therefore, it is necessary to develop novel models, technique tools, and/or problem-solving approaches. Summarizing related research efforts, we

have demonstrated the potential approaches and benefits in the application of ML for solving the three problems. Meanwhile, we have also noted the challenges of applying ML-based approaches, e.g., handling non-stationary network environment. Through the three considered problems, this paper takes an initial step towards understanding the development of models and algorithms for intelligent network management and resource orchestration in network-slicing based next-generation wireless networks.

REFERENCES

- [1] ITU-R, "Minimum requirements related to technical performance for IMT2020 radio interface(s)," Tech. Rep. ITU-R M.2410-0, Nov. 2017.
- [2] Z. Zhang, Y. Xiao, Z. Ma, M. Xiao, Z. Ding, X. Lei, G. K. Karagiannidis, and P. Fan, "6G wireless networks: Vision, requirements, architecture, and key technologies," *IEEE Veh. Technol. Mag.*, 2019, early access.
- [3] L. Hobert, A. Festag, I. Llatser, L. Altomare, F. Visintainer, and A. Kovacs, "Enhancements of V2X communication in support of cooperative autonomous driving," *IEEE Commun. Mag.*, vol. 53, no. 12, pp. 64–70, Dec. 2015.
- [4] S. Jeong, W. Na, J. Kim, and S. Cho, "Internet of things for smart manufacturing system: Trust issues in resource allocation," *IEEE Internet Things J.*, vol. 5, no. 6, pp. 4418–4427, Dec. 2018.
- [5] H. Beyranvand, M. Lévesque, M. Maier, J. A. Salehi, C. Verikoukis, and D. Tipper, "Toward 5G: FiWi enhanced LTE-A HetNets with reliable low-latency fiber backhaul sharing and WiFi offloading," *IEEE/ACM Trans. Netw.*, vol. 25, no. 2, pp. 690–707, Apr. 2017.
- [6] D. López-Pérez, M. Ding, H. Claussen, and A. H. Jafari, "Towards 1 Gbps/UE in cellular systems: Understanding ultra-dense small cell deployments," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2078–2101, Fourthquarter 2015.
- [7] X. Zhu, C. Jiang, L. Yin, L. Kuang, N. Ge, and J. Lu, "Cooperative multigroup multicast transmission in integrated terrestrial-satellite networks," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 5, pp. 981–992, May 2018.
- [8] M. Peng, S. Yan, K. Zhang, and C. Wang, "Fog-computing-based radio access networks: Issues and challenges," *IEEE Netw.*, vol. 30, no. 4, pp. 46–53, Jul. 2016.
- [9] M. Sharma and A. Sahoo, "Stochastic model based opportunistic channel access in dynamic spectrum access networks," *IEEE Trans. Mobile Comput.*, vol. 13, no. 7, pp. 1625–1639, Jul. 2014.
- [10] J. Zheng, Y. Cai, N. Lu, Y. Xu, and X. Shen, "Stochastic game-theoretic spectrum access in distributed and dynamic environment," *IEEE Trans. Veh. Technol.*, vol. 64, no. 10, pp. 4807–4820, Oct. 2015.
- [11] Q. Li, L. Zhao, J. Gao, H. Liang, L. Zhao, and X. Tang, "SMDP-based coordinated virtual machine allocations in cloud-fog computing systems," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 1977–1988, Jun. 2018.
- [12] B. Zong, C. Fan, X. Wang, X. Duan, B. Wang, and J. Wang, "6G technologies: Key drivers, core requirements, system architectures, and enabling technologies," *IEEE Veh. Technol. Mag.*, 2019, early access.
- [13] Q. Ye, J. Li, K. Qu, W. Zhuang, X. Shen, and X. Li, "End-to-end quality of service in 5G networks: Examining the effectiveness of a network slicing framework," *IEEE Veh. Tech. Mag.*, vol. 13, no. 2, pp. 65–74, Jun. 2018.
- [14] S. Yan, P. Yang, Q. Ye, W. Zhuang, X. Shen, X. Li, and J. Rao, "Transmission protocol customization for network slicing: A case study of video streaming," *IEEE Veh. Tech. Mag.*, to appear.
- [15] X. Foukas, G. Patounas, A. Elmokashfi, and M. K. Marina, "Network slicing in 5G: Survey and challenges," *IEEE Commun. Mag.*, vol. 55, no. 5, pp. 94–100, May 2017.

- [16] K. Samdanis, X. Costa-Perez, and V. Sciancalepore, "From network sharing to multi-tenancy: The 5G network slice broker," *IEEE Commun. Mag.*, vol. 54, no. 7, pp. 32–39, Jul. 2016.
- [17] T. Guo and A. Suárez, "Enabling 5G RAN slicing with EDF slice scheduling," *IEEE Trans. Veh. Technol.*, vol. 68, no. 3, pp. 2865–2877, Mar. 2019.
- [18] F. Z. Yousaf, M. Bredel, S. Schaller, and F. Schneider, "NFV and SDN - Key technology enablers for 5G networks," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 11, pp. 2468–2478, Nov. 2017.
- [19] ONF, "Applying SDN architecture to 5G slicing," Tech. Rep. TR-526, Apr. 2016.
- [20] Q. Ye, W. Zhuang, S. Zhang, A. Jin, X. Shen, and X. Li, "Dynamic radio resource slicing for a two-tier heterogeneous wireless network," *IEEE Trans. Veh. Technol.*, vol. 67, no. 10, pp. 9896–9910, Oct. 2018.
- [21] W. Zhuang, Q. Ye, F. Lyu, N. Cheng, and J. Ren, "SDN/NFV empowered future IoV with enhanced communication, computing, and caching," Submitted to *Proc. IEEE*, 2019.
- [22] 3GPP, "Network Functions Virtualisation (NFV) Release 3; Evolution and Ecosystem; Report on Network Slicing Support with ETSI NFV Architecture Framework," Tech. Rep. ETSI GR NFV-EVE 012 V3.1.1, Dec. 2017.
- [23] J. Ordóñez-Lucena, P. Ameigeiras, D. Lopez, J. J. Ramos-Munoz, J. Lorca, and J. Folgueira, "Network slicing for 5G with SDN/NFV: Concepts, architectures, and challenges," *IEEE Commun. Mag.*, vol. 55, no. 5, pp. 80–87, May 2017.
- [24] S. E. Elayoubi, S. B. Jemaa, Z. Altman, and A. Galindo-Serrano, "5G RAN slicing for verticals: Enablers and challenges," *IEEE Commun. Mag.*, vol. 57, no. 1, pp. 28–34, Jan. 2019.
- [25] J. Tang, B. Shim, and T. Q. S. Quek, "Service multiplexing and revenue maximization in sliced C-RAN incorporated with URLLC and multicast eMBB," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 4, pp. 881–895, Apr. 2019.
- [26] F. D. Calabrese, L. Wang, E. Ghadimi, G. Peters, L. Hanzo, and P. Soldati, "Learning radio resource management in RANs: Framework, opportunities, and challenges," *IEEE Commun. Mag.*, vol. 56, no. 9, pp. 138–145, Sep. 2018.
- [27] Z. Chen, J. Wen, and Y. Geng, "Predicting future traffic using hidden markov models," in *Proc. IEEE ICNP '16*, Nov. 2016.
- [28] Z. Fan and R. Liu, "Investigation of machine learning based network traffic classification," in *Proc. ISWCS '17*, Aug. 2017.
- [29] B. Cao, L. Zhang, Y. Li, D. Feng, and W. Cao, "Intelligent offloading in multi-access edge computing: A state-of-the-art review and framework," *IEEE Commun. Mag.*, vol. 57, no. 3, pp. 56–62, Mar. 2019.
- [30] F. B. Mismar and B. L. Evans, "Partially blind handovers for mmWave new radio aided by sub-6 GHz LTE signaling," in *Proc. IEEE ICC Wkshps '18*, May 2018.
- [31] W. Wu, N. Cheng, N. Zhang, P. Yang, W. Zhuang, and X. Shen, "Fast mmWave beam alignment via correlated bandit learning," *IEEE Trans. Wireless Commun.*, to appear.
- [32] H. Nguyen, G. Zheng, R. Zheng, and Z. Han, "Binary inference for primary user separation in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 4, pp. 1532–1542, Apr. 2013.
- [33] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Commun. Surveys Tuts.*, 2019, early access.
- [34] Y. Yu, T. Wang, and S. C. Liew, "Deep-reinforcement learning multiple access for heterogeneous wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 6, pp. 1277–1290, Jun. 2019.
- [35] Y. Wei, F. R. Yu, M. Song, and Z. Han, "User scheduling and resource allocation in hetnets with hybrid energy supply: An actor-critic reinforcement learning approach," *IEEE Trans. Wireless Commun.*, vol. 17, no. 1, pp. 680–692, Jan. 2018.
- [36] L. Pierucci and D. Micheli, "A neural network for quality of experience estimation in mobile communications," *IEEE Multimedia*, vol. 23, no. 4, pp. 42–49, Oct. 2016.

- [37] C. Yang, M. Sun, W. X. Zhao, Z. Liu, and E. Y. Chang, "A neural network approach to jointly modeling social networks and mobile trajectories," *ACM Trans. Inf. Syst.*, vol. 35, no. 4, pp. 36:1–36:28, Aug. 2017.
- [38] Y. He, N. Zhao, and H. Yin, "Integrated networking, caching, and computing for connected vehicles: A deep reinforcement learning approach," *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 44–55, Jan. 2018.
- [39] S. O. Somuyiwa, A. György, and D. Gündüz, "A reinforcement-learning approach to proactive caching in wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 6, pp. 1331–1344, Jun. 2018.
- [40] H. Zhang, "Future wireless network: MyNET platform and end-to-end network slicing," *arXiv Preprint arXiv:1611.07601*, 2016, [Online]. Available: <https://arxiv.org/abs/1611.07601>.
- [41] V. Quintana Rodriguez and F. Guillemin, "Cloud-RAN modeling based on parallel processing," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 3, pp. 457–468, Mar. 2018.
- [42] P. Rost, I. Berberana, A. Maeder, H. Paul, V. Suryaprakash, M. Valenti, D. Wübben, A. Dekorsy, and G. Fettweis, "Benefits and challenges of virtualization in 5G radio access networks," *IEEE Commun. Mag.*, vol. 53, no. 12, pp. 75–82, Dec. 2015.
- [43] H. Zhang, S. Vrzic, G. Senarath, N.-D. Dao, H. Farmanbar, J. Rao, C. Peng, and H. Zhuang, "5G wireless network: MyNET and SONAC," *IEEE Netw.*, vol. 29, no. 4, pp. 14–23, Jul. 2015.
- [44] Fierce Wireless, "Active RAN sharing could save operators US 60bn," 2019.
- [45] ITU, "Framework of the IMT-2020 network," Tech. Rep. Rec. ITU-T Y.3102, May 2018.
- [46] 3GPP, "Study on radio access network (RAN) sharing enhancements," Tech. Rep. Rel. 13, 3GPP TR 22.852, Sep. 2014.
- [47] —, "Telecommunication management; network sharing; concepts and requirements," Tech. Rep. Rel. 15, 3GPP TS 32.130, Jun. 2018.
- [48] X. Foukas, M. K. Marina, and K. Kontovasilis, "Orion: RAN slicing for a flexible and cost-effective multi-service mobile network architecture," in *Proc. ACM Mobicom '17*, 2017, pp. 127–140.
- [49] C. Marquez, M. Gramaglia, M. Fiore, A. Banchs, and X. Costa-Perez, "How should I slice my network?: A multi-service empirical evaluation of resource sharing efficiency," in *Proc. ACM MobiCom '18*, 2018, pp. 191–206.
- [50] I. Afolabi, T. Taleb, K. Samdanis, A. Ksentini, and H. Flinck, "Network slicing and softwarization: A survey on principles, enabling technologies, and solutions," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 3, pp. 2429–2453, 2018.
- [51] H. Peng, Q. Ye, and X. Shen, "Spectrum management for multi-access edge computing in autonomous vehicular networks," *IEEE Trans. Intell. Transp. Syst.*, 2019, early access.
- [52] V. Sciancalepore, X. Costa-Perez, and A. Banchs, "RL-NSB: Reinforcement learning-based 5G network slice broker," *IEEE/ACM Trans. Netw.*, vol. 27, no. 4, pp. 1543–1557, Aug. 2019.
- [53] X. Foukas, M. K. Marina, and K. Kontovasilis, "Iris: Deep reinforcement learning driven shared spectrum access architecture for indoor neutral-host small cells," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 8, pp. 1820–1837, Aug. 2019.
- [54] X. Chen, H. Zhang, C. Wu, S. Mao, Y. Ji, and M. Bennis, "Optimized computation offloading performance in virtual edge computing systems via deep reinforcement learning," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4005–4018, Jun. 2018.
- [55] X. Chen, Z. Han, H. Zhang, G. Xue, Y. Xiao, and M. Bennis, "Wireless resource scheduling in virtualized radio access networks using stochastic learning," *IEEE Trans. Mobile Comput.*, vol. 17, no. 4, pp. 961–974, Apr. 2018.
- [56] X. Chen, Z. Zhao, C. Wu, M. Bennis, H. Liu, Y. Ji, and H. Zhang, "Multi-tenant cross-slice resource orchestration: A deep reinforcement learning approach," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 10, pp. 2377–2392, Oct. 2019.
- [57] C. Gutterman, E. Grinshpun, S. Sharma, and G. Zussman, "RAN resource usage prediction for a 5G slice broker," in *Proc. ACM MobiHoc '19*, 2019, pp. 231–240.

- [58] D. Bega, M. Gramaglia, M. Fiore, A. Banchs, and X. Costa-Perez, "DeepCog: Cognitive Network Management in Sliced 5G Networks with Deep Learning," in *Proc. of IEEE INFOCOM '19*, 2019, pp. 280–288.
- [59] R. Dong, C. She, W. Hardjawana, Y. Li, and B. Vucetic, "Deep learning for hybrid 5G services in mobile edge computing systems: Learn from a digital twin," *IEEE Trans. Wireless Commun.*, 2019, early access.
- [60] Y. Polyanskiy, H. V. Poor, and S. Verdú, "Channel coding rate in the finite blocklength regime," *IEEE Trans. Inf. Theory*, vol. 56, no. 5, pp. 2307–2359, May 2010.
- [61] J. Ye and Y. Zhang, "DRAG: Deep reinforcement learning based base station activation in heterogeneous networks," *IEEE Trans. Mobile Comput.*, 2019, early access.
- [62] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiropoulos, "Learning to optimize: Training deep neural networks for interference management," *IEEE Trans. Signal Process.*, vol. 66, no. 20, pp. 5438–5453, Oct. 2018.
- [63] I. Alqerm and B. Shihada, "Sophisticated online learning scheme for green resource allocation in 5G heterogeneous cloud radio access networks," *IEEE Trans. Mobile Comput.*, vol. 17, no. 10, pp. 2423–2437, Oct. 2018.
- [64] N. Cheng, F. Lyu, W. Quan, C. Zhou, H. He, W. Shi, and X. Shen, "Space/aerial-assisted computing offloading for IoT applications: A learning-based approach," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 5, pp. 1117–1129, May 2019.
- [65] S. Corroy, L. Falconetti, and R. Mathar, "Dynamic cell association for downlink sum rate maximization in multi-cell heterogeneous networks," in *Proc. IEEE ICC '12*, Jun. 2012, pp. 2457–2461.
- [66] Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis, and J. G. Andrews, "User association for load balancing in heterogeneous cellular networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 6, pp. 2706–2716, Jun. 2013.
- [67] M. Hong and Z. Luo, "Distributed linear precoder optimization and base station selection for an uplink heterogeneous network," *IEEE Trans. Signal Process.*, vol. 61, no. 12, pp. 3214–3228, Jun. 2013.
- [68] V. Boljanovic, F. Yaghoubi, and D. Cabric, "User association in dense mmWave networks based on rate requirements," *arXiv preprint arXiv:1905.04395*, 2019.
- [69] H. S. Dhillon, Y. Li, P. Nuggehalli, Z. Pi, and J. G. Andrews, "Fundamentals of heterogeneous cellular networks with energy harvesting," *IEEE Trans. Wireless Commun.*, vol. 13, no. 5, pp. 2782–2797, May 2014.
- [70] H. Hu, J. Zhang, X. Zheng, Y. Yang, and P. Wu, "Self-configuration and self-optimization for LTE networks," *IEEE Commun. Mag.*, vol. 48, no. 2, pp. 94–100, Feb. 2010.
- [71] C. Vlachos and V. Friderikos, "Optimal device-to-device cell association and load balancing," in *Proc. IEEE ICC '15*, Jun. 2015, pp. 5441–5447.
- [72] W. Shi, J. Li, N. Cheng, F. Lyu, S. Zhang, H. Zhou, and X. Shen, "Multi-drone 3-D trajectory planning and scheduling in drone-assisted radio access networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 8145–8158, Aug. 2019.
- [73] D. Liu, L. Wang, Y. Chen, M. ElKashlan, K. Wong, R. Schober, and L. Hanzo, "User association in 5G networks: A survey and an outlook," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1018–1044, Secondquarter 2016.
- [74] Z. Li, C. Wang, and C. Jiang, "User association for load balancing in vehicular networks: An online reinforcement learning approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 8, pp. 2217–2228, Aug. 2017.
- [75] X. Gelabert, J. Pérez-Romero, O. Sallent, and R. Agustí, "A Markovian approach to radio access technology selection in heterogeneous multiaccess/multiservice wireless networks," *IEEE Trans. Mobile Comput.*, vol. 7, no. 10, pp. 1257–1270, 2008.
- [76] O. Galinina, S. Andreev, M. Gerasimenko, Y. Koucheryavy, N. Himayat, S. Yeh, and S. Talwar, "Capturing spatial randomness of heterogeneous Cellular/WLAN deployments with dynamic traffic," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1083–1099, Jun. 2014.
- [77] A. Roy, P. Chaporkar, and A. Karandikar, "Optimal radio access technology selection algorithm for LTE-WiFi network," *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 6446–6460, Jul. 2018.

- [78] F. Bari and V. Leung, "Multi-attribute network selection by iterative TOPSIS for heterogeneous wireless access," in *Proc. IEEE CCNC '07*, 2007, pp. 808–812.
- [79] S. Barmponakis, A. Kalokylos, P. Spapis, and N. Alonistioti, "Context-aware, user-driven, network-controlled RAT selection for 5G networks," *Comput. Netw.*, vol. 113, pp. 124–147, 2017.
- [80] E. Stevens-Navarro, Y. Lin, and V. W. Wong, "An MDP-based vertical handoff decision algorithm for heterogeneous wireless networks," *IEEE Trans. Veh. Technol.*, vol. 57, no. 2, pp. 1243–1254, 2008.
- [81] J. Hou and D. C. O'Brien, "Vertical handover-decision-making algorithm using fuzzy logic for the integrated radio-and-ow system," *IEEE Trans. Wireless Commun.*, vol. 5, no. 1, pp. 176–185, 2006.
- [82] D. Liu, Y. Chen, K. K. Chai, T. Zhang, and M. Elkashlan, "Opportunistic user association for multi-service HetNets using Nash bargaining solution," *IEEE Commun. Lett.*, vol. 18, no. 3, pp. 463–466, Mar. 2014.
- [83] S. E. Elayoubi, E. Altman, M. Haddad, and Z. Altman, "A hybrid decision approach for the association problem in heterogeneous networks," in *Proc. IEEE INFOCOM '10*, 2010, pp. 1–5.
- [84] M. Richart, J. Baliosian, J. Serrat, and J. Gorricho, "Resource slicing in virtual wireless networks: A survey," *IEEE Trans. Netw. Service Manag.*, vol. 13, no. 3, pp. 462–476, Sep. 2016.
- [85] E. Gustafsson and A. Jonsson, "Always best connected," *IEEE Wireless Commun.*, vol. 10, no. 1, pp. 49–55, Feb. 2003.
- [86] Y. Wang, X. Tao, X. Zhang, and G. Mao, "Joint caching placement and user association for minimizing user download delay," *IEEE Access*, vol. 4, pp. 8625–8633, 2016.
- [87] Y. Sun, S. Zhou, and J. Xu, "EMM: Energy-aware mobility management for mobile edge computing in ultra dense networks," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 11, pp. 2637–2646, Nov. 2017.
- [88] E. Bastug, M. Bennis, M. Medard, and M. Debbah, "Toward interconnected virtual reality: Opportunities, challenges, and enablers," *IEEE Commun. Mag.*, vol. 55, no. 6, pp. 110–117, Jun. 2017.
- [89] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2322–2358, Fourthquarter 2017.
- [90] X. Yang, Z. Chen, K. Li, Y. Sun, N. Liu, W. Xie, and Y. Zhao, "Communication-constrained mobile edge computing systems for wireless virtual reality: Scheduling and tradeoff," *IEEE Access*, vol. 6, pp. 16 665–16 677, 2018.
- [91] T. Dang and M. Peng, "Joint radio communication, caching, and computing design for mobile virtual reality delivery in fog radio access networks," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 7, pp. 1594–1607, Jul. 2019.
- [92] S. Barbarossa, S. Sardellitti, and P. Di Lorenzo, "Joint allocation of computation and communication resources in multiuser mobile cloud computing," in *Proc. IEEE SPAWC Wkshps '13*, Jun. 2013, pp. 26–30.
- [93] C. You, K. Huang, H. Chae, and B. Kim, "Energy-efficient resource allocation for mobile-edge computation offloading," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1397–1411, Mar. 2017.
- [94] C. Liang, F. R. Yu, H. Yao, and Z. Han, "Virtual resource allocation in information-centric wireless networks with virtualization," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 9902–9914, Dec. 2016.
- [95] A. Asheralieva, "Optimal computational offloading and content caching in wireless heterogeneous mobile edge computing systems with Hopfield neural networks," *IEEE Trans. Emerg. Topics Comput. Intell.*, 2019, early access.
- [96] Y. Wei, F. R. Yu, M. Song, and Z. Han, "Joint optimization of caching, computing, and radio resources for fog-enabled IoT using natural actor-critic deep reinforcement learning," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2061–2073, Apr. 2019.
- [97] A. A. Gebremariam, M. Chowdhury, A. Goldsmith, and F. Granelli, "Resource pooling via dynamic spectrum-level slicing across heterogeneous networks," in *Proc. IEEE CCNC '17*, 2017, pp. 818–823.
- [98] K. Lee and I. Shin, "User mobility model based computation offloading decision for mobile cloud," *J. Comput. Inf. Sci. Eng.*, vol. 9, no. 3, pp. 155–162, Sep. 2015.

- [99] Tong Liu, P. Bahl, and I. Chlamtac, "Mobility modeling, location tracking, and trajectory prediction in wireless ATM networks," *IEEE J. Sel. Areas Commun.*, vol. 16, no. 6, pp. 922–936, Aug. 1998.
- [100] M. R. Rahimi, N. Venkatasubramanian, and A. V. Vasilakos, "MuSIC: Mobility-aware optimal service allocation in mobile cloud computing," in *Proc. IEEE CLOUD '13*, 2013, pp. 75–82.
- [101] R. Wang, X. Peng, J. Zhang, and K. B. Letaief, "Mobility-aware caching for content-centric wireless networks: Modeling and methodology," *IEEE Commun. Mag.*, vol. 54, no. 8, pp. 77–83, Aug. 2016.
- [102] F. Pantisano, M. Bennis, W. Saad, and M. Debbah, "Cache-aware user association in backhaul-constrained small cell networks," in *Proc. IEEE WiOpt '14*, May 2014, pp. 37–42.
- [103] L. Liu, Y. Zhou, J. Yuan, W. Zhuang, and Y. Wang, "Economically optimal MS association for multimedia content delivery in cache-enabled heterogeneous cloud radio access networks," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 7, pp. 1584–1593, Jul. 2019.
- [104] M. Z. Hassan, M. J. Hossain, J. Cheng, and V. C. M. Leung, "Joint FSO fronthaul and millimeter-wave access link optimization in cloud small cell networks: A statistical-QoS aware approach," *IEEE Trans. Commun.*, vol. 67, no. 6, pp. 4208–4226, Jun. 2019.
- [105] T. Zhou, Z. Liu, J. Zhao, C. Li, and L. Yang, "Joint user association and power control for load balancing in downlink heterogeneous cellular networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 3, pp. 2582–2593, Mar. 2018.
- [106] H. Zhang, S. Huang, C. Jiang, K. Long, V. C. M. Leung, and H. V. Poor, "Energy efficient user association and power allocation in millimeter-wave-based ultra dense networks with energy harvesting base stations," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 9, pp. 1936–1947, Sep. 2017.
- [107] M. S. Elbamby, C. Perfecto, M. Bennis, and K. Doppler, "Edge computing meets millimeter-wave enabled VR: Paving the way to cutting the cord," in *Proc. IEEE WCNC '18*, Apr. 2018, pp. 1–6.
- [108] J. Li, E. Björnson, T. Svensson, T. Eriksson, and M. Debbah, "Joint precoding and load balancing optimization for energy-efficient heterogeneous networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 10, pp. 5810–5822, Oct. 2015.
- [109] T. Van Chien, E. Björnson, and E. G. Larsson, "Downlink power control for massive MIMO cellular systems with optimal user association," in *Proc. IEEE ICC '16*, May 2016, pp. 1–6.
- [110] M. Ismail and W. Zhuang, "A distributed multi-service resource allocation algorithm in heterogeneous wireless access medium," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 2, pp. 425–432, Feb. 2012.
- [111] —, "Mobile terminal energy management for sustainable multi-homing video transmission," *IEEE Trans. Wireless Commun.*, vol. 13, no. 8, pp. 4616–4627, Aug. 2014.
- [112] J. J. Nielsen and P. Popovski, "Latency analysis of systems with multiple interfaces for ultra-reliable M2M communication," in *Proc. IEEE SPAWC Wkshps '16*, Jul. 2016, pp. 1–6.
- [113] Y. Wang, Q. Chen, and G. Yu, "Multi-homing in unlicensed LTE networks," in *Proc. IEEE ICC '18*, 2018, pp. 1–6.
- [114] C. Dhahri and T. Ohtsuki, "Q-learning cell selection for femtocell networks: Single- and multi-user case," in *Proc. IEEE GLOBECOM '12*, Dec. 2012, pp. 4975–4980.
- [115] T. Kudo and T. Ohtsuki, "Cell range expansion using distributed Q-learning in heterogeneous networks," in *Proc. IEEE VTC Fall '13*, Sep. 2013, pp. 1–5.
- [116] M. Li, F. R. Yu, P. Si, E. Sun, Y. Zhang, and H. Yao, "Random access and virtual resource allocation in software-defined cellular networks with machine-to-machine communications," *IEEE Trans. Veh. Technol.*, vol. 66, no. 7, pp. 6399–6414, Jul. 2017.
- [117] H. Zhu, Y. Cao, W. Wang, T. Jiang, and S. Jin, "Deep reinforcement learning for mobile edge caching: Review, new features, and open issues," *IEEE Netw.*, vol. 32, no. 6, pp. 50–57, Nov. 2018.

- [118] G. S. Paschos, G. Iosifidis, M. Tao, D. Towsley, and G. Caire, "The role of caching in future communication systems and networks," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 6, pp. 1111–1125, Jun. 2018.
- [119] P. Yang, N. Zhang, S. Zhang, L. Yu, J. Zhang, and X. Shen, "Content popularity prediction towards location-aware mobile edge caching," *IEEE Trans. Multimedia*, vol. 21, no. 4, pp. 915–929, Apr. 2019.
- [120] K. Shanmugam, N. Golrezaei, A. G. Dimakis, A. F. Molisch, and G. Caire, "FemtoCaching: Wireless content delivery through distributed caching helpers," *IEEE Trans. Inf. Theory*, vol. 59, no. 12, pp. 8402–8413, Dec. 2013.
- [121] S. Zhang, W. Quan, J. Li, W. Shi, P. Yang, and X. Shen, "Air-ground integrated vehicular network slicing with content pushing and caching," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 9, pp. 2114–2127, Sep. 2018.
- [122] Y. He, F. R. Yu, N. Zhao, V. C. M. Leung, and H. Yin, "Software-defined networks with mobile edge computing and caching for smart cities: A big data deep reinforcement learning approach," *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 31–37, Dec. 2017.
- [123] B. N. Bharath, K. G. Nagananda, and H. V. Poor, "A learning-based approach to caching in heterogenous small cell networks," *IEEE Trans. Commun.*, vol. 64, no. 4, pp. 1674–1686, Apr. 2016.
- [124] T. Hou, G. Feng, S. Qin, and W. Jiang, "Proactive content caching by exploiting transfer learning for mobile edge computing," in *Proc. IEEE GLOBECOM '17*, 2017.
- [125] Z. Zhao, L. Guardalben, M. Karimzadeh, J. Silva, T. Braun, and S. Sargento, "Mobility prediction-assisted over-the-top edge prefetching for hierarchical VANETs," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 8, pp. 1786–1801, Aug. 2018.
- [126] L. Ale, N. Zhang, H. Wu, D. Chen, and T. Han, "Online proactive caching in mobile edge computing using bidirectional deep recurrent neural network," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 5520–5530, Jun. 2019.
- [127] S. O. Somuyiwa, A. György, and D. Gündüz, "A reinforcement-learning approach to proactive caching in wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 6, pp. 1331–1344, Jun. 2018.
- [128] G. S. Park and H. Song, "Cooperative base station caching and X2 link traffic offloading system for video streaming over SDN-enabled 5G networks," *IEEE Trans. Mobile Comput.*, vol. 18, no. 9, pp. 2005–2019, Sep. 2019.
- [129] B. Jiang, J. Yang, H. Xu, H. Song, and G. Zheng, "Multimedia data throughput maximization in Internet-of-Things system based on optimization of cache-enabled UAV," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 3525–3532, Apr. 2019.
- [130] C. Liang, F. R. Yu, H. Yao, and Z. Han, "Virtual resource allocation in information-centric wireless networks with virtualization," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 9902–9914, Dec. 2016.
- [131] Y. He, N. Zhao, and H. Yin, "Integrated networking, caching, and computing for connected vehicles: A deep reinforcement learning approach," *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 44–55, Jan. 2018.
- [132] S. Ullah, K. Thar, and C. S. Hong, "Management of scalable video streaming in information centric networking," *Multimed. Tools Appl.*, Oct. 2017.
- [133] X. Wang, M. Chen, T. Taleb, A. Ksentini, and V. C. M. Leung, "Cache in the air: Exploiting content caching and delivery techniques for 5G systems," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 131–139, Feb. 2014.
- [134] J. Tadrous and A. Eryilmaz, "On optimal proactive caching for mobile networks with demand uncertainties," *IEEE/ACM Trans. Netw.*, vol. 24, no. 5, pp. 2715–2727, Oct. 2016.
- [135] S. Zhang, P. He, K. Suto, P. Yang, L. Zhao, and X. Shen, "Cooperative edge caching in user-centric clustered mobile networks," *IEEE Trans. Mobile Comput.*, vol. 17, no. 8, pp. 1791–1805, Aug. 2018.
- [136] H. Wu, X. Tao, N. Zhang, D. Wang, S. Zhang, and X. Shen, "On base station coordination in cache- and energy harvesting-enabled HetNets: A stochastic geometry study," *IEEE Trans. Commun.*, vol. 66, no. 7, pp. 3079–3091, July 2018.
- [137] W. Wu, N. Zhang, N. Cheng, Y. Tang, K. Aldubaikhy, and X. Shen, "Beef up mmWave dense cellular networks with D2D-assisted cooperative edge caching," *IEEE Trans. Veh. Technol.*, vol. 68, no. 4, pp. 3890–3904, Apr. 2019.

- [138] R. Huo, F. R. Yu, T. Huang, R. Xie, J. Liu, V. C. M. Leung, and Y. Liu, "Software defined networking, caching, and computing for green wireless networks," *IEEE Commun. Mag.*, vol. 54, no. 11, pp. 185–193, Nov. 2016.
- [139] P. Ameigeiras, J. J. Ramos-munoz, L. Schumacher, J. Prados-Garzon, J. Navarro-Ortiz, and J. M. Lopez-soler, "Link-level access cloud architecture design based on SDN for 5G networks," *IEEE Netw.*, vol. 29, no. 2, pp. 24–31, Mar. 2015.
- [140] M. Lopez-Martin, B. Carro, A. Sanchez-Esguevillas, and J. Lloret, "Network traffic classifier with convolutional and recurrent neural networks for Internet of Things," *IEEE Access*, vol. 5, pp. 18 042–18 050, Sep. 2017.
- [141] J. Wang, J. Tang, Z. Xu, Y. Wang, G. Xue, X. Zhang, and D. Yang, "Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach," in *Proc. IEEE INFOCOM '17*, 2017.
- [142] Z. M. Fadlullah, F. Tang, B. Mao, N. Kato, O. Akashi, T. Inoue, and K. Mizutani, "State-of-the-art deep learning: Evolving machine intelligence toward tomorrow's intelligent network traffic control systems," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2432–2455, Fourthquarter 2017.
- [143] V. Borkar, "An actor-critic algorithm for constrained Markov decision processes," *Syst. Control Lett.*, vol. 54, no. 3, pp. 207 –213, Mar. 2005.