AI-Enabled Network-Functions Virtualization and Software-Defined Architectures for Customized Statistical QoS Over 6G Massive MIMO Mobile Wireless Networks

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Abstract

With the rapid deployments of the fifth generation (5G) mobile wireless networks, the shift from the 5G to the sixth generation (6G) mobile wireless networks has attracted tremendous research attention around the world. Featuring with the explosively increasing multimedia-traffics with very diverse services requirements, the 6G mobile wireless networks need to provide the customized services with heterogeneous types of quality of service (QoS) guarantees. However, how to efficiently support these customized services with heterogeneous QoS provisioning for 6G wireless networks has imposed many new challenges not encountered before. To conquer these difficulties, in this article we propose the artificial intelligence (AI)-enabled integration of massive multiple-input-multiple-output (massive-MIMO) techniques with network functions virtualization (NFV) and software-defined network (SDN) architectures to support the customized services over the 6G mobile wireless networks. Specifically, we develop the AI-enabled network architectural schemes which efficiently integrate three 6G-candidate techniques — massive-MIMO, NFV, and SDN — to significantly improve key performances of heterogeneous statistical QoS provisioning in terms of effective capacity. We apply the massive MIMO transmission to substantially improve the channel throughput. Our NFV-based schemes abstract and slice the physical infrastructure and wireless resources in network data plane into several virtualized networks and obtain the optimal service delivery path with the maximum effective capacity among virtualized networks. Also, we develop a set of AI-enabled techniques including multi-agent AI-plane architectures, edge-AI frameworks, and federated learning mechanisms for efficiently implementing our developed massive-MIMO-NFV-SDN integrated schemes. Collaborating with our developed platform and techniques, our multi-agent AI-plane based SDN controller coordinates the network nodes and resources allocations for each virtualized network. Our conducted extensive simulations validate and evaluate our developed massive-MIMO-NFV-SDN integrated architectures using AI-techniques, showing that they can efficiently support the customized statistical delay-bounded QoS provisioning over 6G mobile wireless networks.

Introduction

Although the fifth generation (5G) mobile communication networks have been implemented around the world, there are a number of emerging applications that cannot be adequately served by 5G wireless networks as the new applications' needs continue to evolve. Therefore, the wireless network researches have been moved forward to the sixth generation (6G) mobile wireless communication networks. To satisfy clients' disparate applications and requirements, the 6G wireless networks are expected to provide the multipurpose platforms and accommodate diverse *customized services* including: massive ultra-reliable low-latency communications (mURLLC), enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), uplink centric broadband communication (UCBC), real-time broadband communication (RTBC), and harmonized communication and sensing (HCS), and so on, which require different latencies, data rates, error rates, device densities, and so on [1–4]. The mURLLC demands the stringent guarantees on transmission delay and error rate for mission critical wireless communications under mobile users' massive access, such as motion control and e-health. The services of eMBB require high data rates across a wide coverage area, such as interactive virtual reality and augmented reality. The services of mMTC provide the massive access for a large number of devices in a small area, such as smart traffic and environmental monitoring. The techniques of UCBC accelerate the mobile user's uploading speed. The communications of RTBC deliver a large bandwidth with a given latency and a certain level of reliability, such as video streaming. HCS services support high-accuracy localization and high-resolution sensing, enabling the navigation and monitoring for autonomous vehicles.

In contrast to 5G wireless networks that can only guarantee the average performance of nearby mobile users (MUs), the 6G wireless networks aim at supporting customized statistical QoS, which guarantee each MU's diverse and time-varying quality-of-service (QoS) [4]. One of the major challenges for 6G wireless networks is how to simultaneously support the *heterogeneous QoS* [5, 6] for multi-types of traffics imposed by these customized services and applications with

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different requirements under the constrained network resources and dynamic network conditions. Toward the above end, the statistical QoS provisioning theory has been applied for *feasibly guaranteeing* the given *stochastic-bound* of QoS requirements with the controlled violation probabilities over the time-varying wireless fading channels, and thus, has been recognized as a powerful tool to support the customized applications over the 6G wireless networks. Moreover, the following three advanced wireless-network *techniques and architectures* have been proposed to efficiently support the heterogeneous statistical QoS provisioning over the imminent 6G mobile wireless networks, which include:

- **Massive multiple-input-multiple-output (MIMO) techniques** [7–9], including multiple-input-single-output (MISO), MIMO, massive MIMO, and cell-free massive MIMO (CF-M-MIMO), to point the main beam of signal waves toward the targeted MUs, serving more users through spatial multiplexing, and mitigating the mutlipath effect via different antenna's spatial diversity.
- **Network-functions virtualization (NFV) architectures** [10], where the PHY-layer network elements and wireless power/spectrum resources are split and deployed as reusable software instances modules, enabling the coexistence of multiple and dynamically-/adaptively-reconfigurable virtual-networks slices.
- **Software defined networking (SDN) architectures** [11, 12], where the network controller is logically decoupled from the underlaying PHY-layer to adaptively dictate PHY-layer infrastructures' allocations for flexible implementations of diverse networks architectures and functions, through programming-interfaces between the control plane and data plane.

However, how to efficiently integrate the massive MIMO techniques and NFV and SDN network architectures to sufficiently satisfy heterogeneous statistical QoS requirements of MUs over 6G wireless networks remains a challenging open problem. To overcome the above challenges, we propose to develop AI-enabled network-functions virtualization and software-defined architectures for customized statistical QoS over 6G massive MIMO mobile wireless networks. First, to leverage the beamforming gain and spatial multiplexing, we propose to deploy multiple antennas on WiFi access points (AP) and massive MIMO antennas on base stations (BSs) to cooperatively serve multiple MUs in the same time-frequency resource through space-division duplex operation. Second, to deliver the requested services to MUs with distinct QoS requirements, we use NFV techniques to abstract and slice the wireless network physical infrastructure and resources of the network data plane into several virtualized networks. Each virtual network, consisting of the optimal network components, yields the optimal data delivery path to independently support the data content transmissions for each type of service. We characterize the performance of data transmissions by the effective capacity, and conduct the case study in searching for the optimal data delivery path, which is either a direct transmission or going

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through relay nodes to maximize the effective capacity among all virtualized networks. Third, we employ the SDN architecture to dictate the network slicing and to allocate the physical wireless resources for each virtualized network. This software-defined control architecture aims at optimizing the overall performances for the 6G wireless networks.

On the other hand, since MUs for 6G wireless networks have the distinct requirements for their customized services demands, SDN mechanisms need to support the comprehensive wireless resource schedulings. These wireless resource schedulings and service predictions require the efficient and powerful QoS-supporting systems. In addition, due to 6G MUs' heterogeneity in service types, mobility in trajectories, and stringency in QoS requirements, the SDN's dynamically programming control and real-time decision makings all significantly increase wireless-resources costs and implementing complexities. To remedy these difficulties and offload the computational burdens of SDN control plane, we propose to develop artificial intelligence (AI)-enabled mechanisms and techniques including multi-agent AI-plane architectures, edge-AI frameworks, and federated learnings, which can efficiently implement the dynamic programming and real-time decision-making in our developed massive-MIMO-NFV-SDN integrated network architectures. Specifically, in our proposed SDN architecture we develop and embed a multi-agent AI-plane between data-plane and control-plane. The AI-plane receives, analyzes, and processes 6G traffics' diverse statistical QoS requests from the multiple-agents, including MUs, BSs, and APs agents, by making the best use of the pre-trained models, and then forwards its calculated/derived results (including the optimal hardware and software allocations strategies/decisions) to SDN's control plane, which then proceeds with these pre-calculated/-trained results to dictate and monitor the allocations for PHY-layer-infrastructures and wireless resources in SDN's data plane.

The System Models

Figure 1 shows the system models of our proposed AI-based network-functions virtualization and software-defined architectures for the customized statistical QoS provisioning over 6G massive MIMO mobile wireless networks, which consist of the following three core AI-enabled promising 6G-candidate architectural techniques as elaborated on, respectively, as follows.

AI-Enabled Massive-MIMO Techniques Over 6G Mobile Wireless Networks

Figure 1 shows our massive-MIMO based 6G wireless networks architecture, which merges MISO, MIMO, massive MIMO, and CF-M-MIMO communications techniques. To serve massive MUs in a small area to support mMTC, massive MIMO has been recognized as the enabling tech-

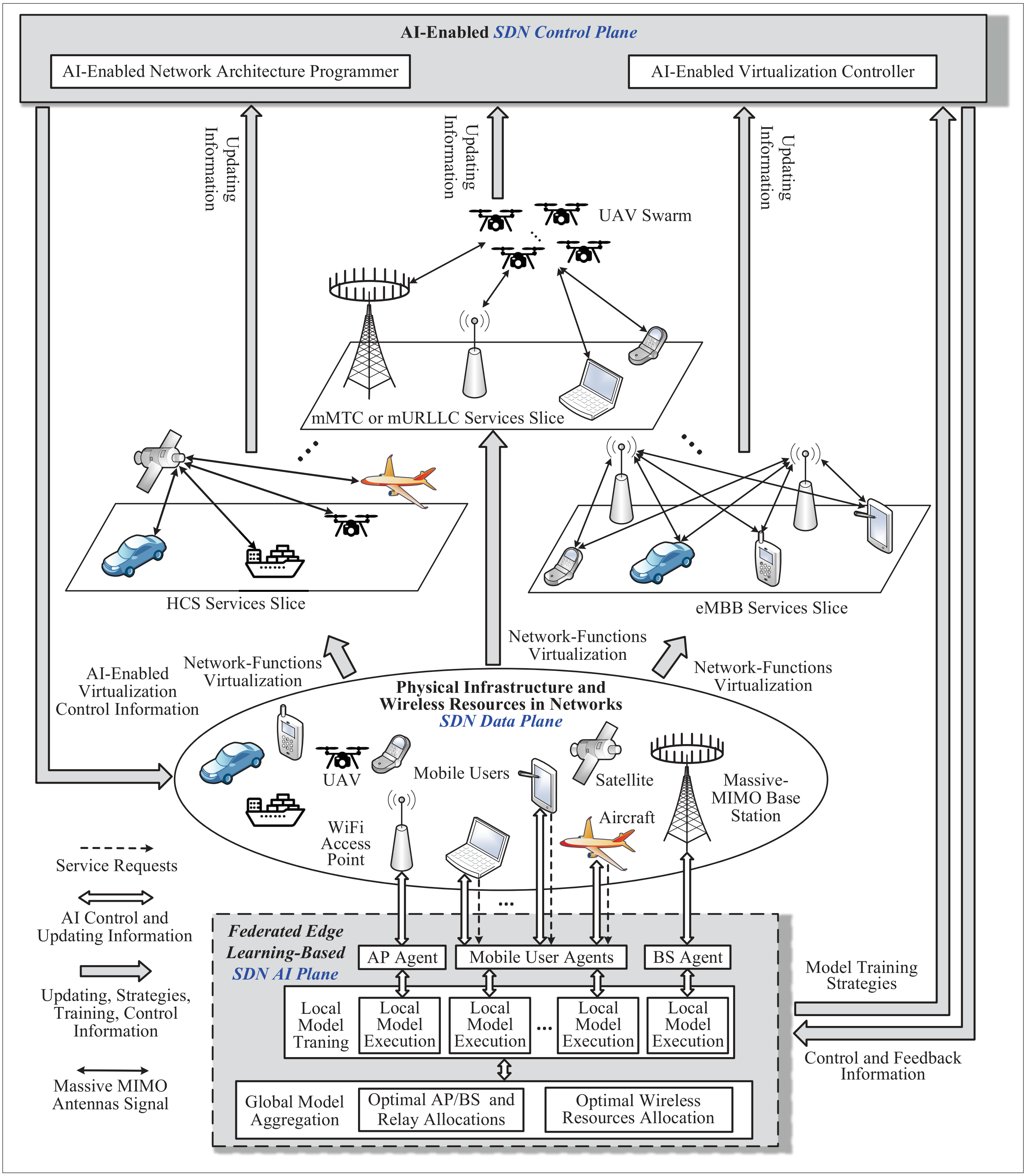

FIGURE 1. The system models of our proposed AI-based network-functions virtualization and software-defined architectures for the customized statistical QoS provisioning over 6G massive MIMO mobile wireless networks.

nique thanks to its advantages in the beamforming gain and spatial multiplexing, and so on. As one of the key promising candidate techniques for 6G wireless networks, CF-M-MIMO comprises massive distributed APs to jointly and simultaneously serve a group of MUs using the same time-frequency resources over a wide area, which is a typical communication enabler for eMBB. The unmanned aerial vehicle (UAV) swarm is applied in mURLLC services because of its mobility, which enables a flexible network architecture at the air interface and converts the non-line-of-sight scenario into line-of-sight scenario. The signal's multiple input from the UAV swarm and single output to the MU equipped with a single antenna form the MISO communications. The data exchanging between a multiple antennas sender and multiple antennas receiver constitutes the MIMO communications.

AI-Driven NFV Architectures Over 6G Mobile Wireless Networks

NFV architectures split the physical network infrastructures and wireless resources into several virtual slices, enabling the sharing of all wireless network functionalities among multiple service providers and supporting different applications under diverse requirements and logical architectures through the same infrastructure [13]. Deploying the AI-driven data plane mechanism in NFV, this network-functions virtualization operation breaks down the heterogeneous QoS provisioning problem of the entire network into a number of homogeneous QoS provisioning problems, each of which takes the responsibility of one type of data content transmission on one virtual network while statistically satisfying its QoS requirements. Using NFV techniques, each statistical QoS provisioning service can be easily embedded in the physical networks without considering the complicated interfaces and characteristics of the physical infrastructures. Virtual networks cooperate with each other to efficiently share these resources for the better service performances, which thus significantly improves the entire network efficiency and utilization. Since the 6G wireless networks need to accommodate customized services, we propose to develop the flexible AI-driven data plane over the NFV architecture to satisfy the heterogenous statistical QoS requirements for different types of MUs and their applications. In Fig. 1, we use the typical 6G services such as HCS, eMBB, mMTC, and mURLLC as examples to represent different MUs' statistical QoS service requirements. The NFV-based architecture dynamically allocates the edge resources (i.e., bandwidth, transmit power, etc.) to different network slices to achieve the overall networks performance metrics maximization.

AI-Plane Based SDN Architectures Over 6G Mobile Wireless Networks

SDN is a paradigm where a central software program, called control plane, dictates the overall dynamics behavior of the physical substrate wireless network, called data plane, which consists of all physical infrastructures, devices, and nodes (such as MUs, BSs, routers, gateways, etc.) constituting data-packet forwarding devices. To offload and reduce the SDN control-plane's computational complexities and work loads and make it timely respond to MU's service requests, we develop and deploy a multi-agent AI-plane between data plane and control plane, see Fig. 1, for optimizing the network nodes mapping and wireless resource allocations scheduling. Our developed multi-agent AI-plane mainly consists of two types of agents:

- **The MU agent** is responsible for collecting MUs' historical behaviors, current service requests, and moving directions and speeds, and so on, for predicting their future behaviors.
- **The AP/BS agent** is used to integrate traffic requests with service type request for allocating the optimal wireless resources.

To offload and reduce the SDN control-plane's computational complexities and work loads and make it timely respond to MU's service requests, we develop and deploy a multi-agent AI-plane between data plane and control plane for optimizing the network nodes mapping and wireless resource allocations scheduling.

Instead of directly sending data requests to the SDN control plane, MUs send these requests with QoS requirements to the MU agent in AI-plane, who will then contact the AP/BS agents to derive the optimal wireless resources allocations. Under the assistance of AP/BS agents, SDN control plane selects the optimal massive-MIMO techniques form MISO, MIMO, massive-MIMO, and CF-M-MIMO, and then, maps the corresponding AP/BS, MU, and necessary network components to virtual network slices with an *optimal service delivery path*. The SDN control plane makes these mapping decisions based on the information about the network traffic condition and the predictions for MUs' behaviors provided by AP/BS/MU agents.

AI-Enabled Massive-MIMO Communications Techniques for 6G Mobile Wireless Networks

Achievable Coding Rates for MUs

Assume that each MU can be equipped with a single antenna or multiple antennas. Denoted by $x(t)$ the total number of MU at time t in a service coverage area. The effect of small-scale fading between the AP/BS and the ith MU is given by h_i, where i is the index of MU and $i \in \{1, 2, ..., x(t)\}$. Let P_i be the transmit power allocation of the ith MU, and let $\boldsymbol{d}_i$ be the ith MU's geographic position vector in the wireless network. Denote by R_i the achievable coding rate for the ith MU, and denote by B_i the bandwidth allocation for the ith MU. The R_i can be written as:

$$R_i = B_i \, \mathbb{E}_{h_i}[\log_2(1 + \gamma_i (h_i, P_i, \boldsymbol{d}_i))] \quad (1)$$

where $\mathbb{E}_{h_i}[\cdot]$ is taking the expectation operation with respect to h_i, $\gamma_i (h_i, P_i, \boldsymbol{d}_i)$ is the signal to interference and noise ratio (SINR) of the ith MU, which is a function of h_i, P_i, and $\boldsymbol{d}_i$. When the ith MU is served through MISO, MIMO, massive-MIMO, and CF-M-MIMO communications, respectively, the SINR $\gamma_i (h_i, P_i, \boldsymbol{d}_i)$ needs to be derived correspondingly.

According to Eq. 1, we observe that R_i is an increasing function of SINR, and thus, to improve the channel throughput, we need to significantly increase the value of SINR, which can be achieved by applying massive-MIMO techniques. The communications process through massive-MIMO can be summarized in the following three phases:

- **Uplink training** to estimate the channel gain information
- **Linear precoding** for beamforming
- **Downlink payload data transmission** to transmit the service data.

Uplink Training: Each antenna of the MU sends the uplink pilot signal, which is an orthog-

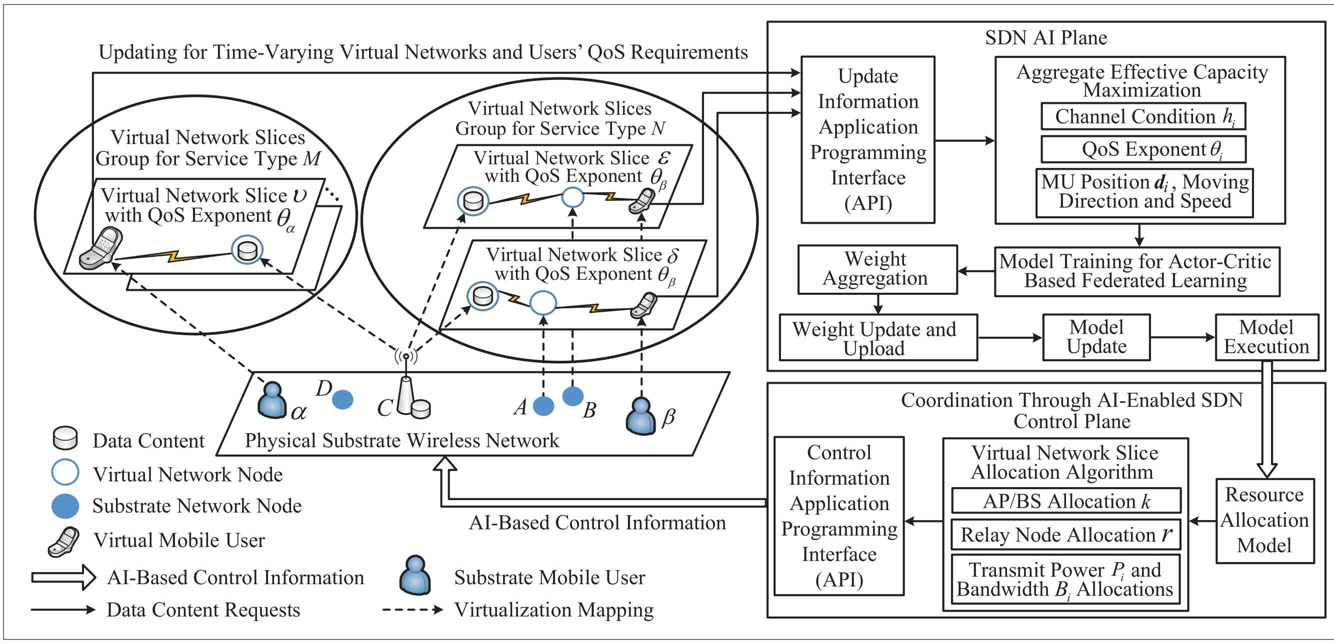

FIGURE 2. A case study architecture of wireless network functions virtualization (NFV) using virtual network slicing and wireless resources allocation control architectures via the AI-enabled SDN control plane, where $i \in \{1, 2, ..., x(t)\}$ is the index of MUs.

onal training sequence known by both MUs and AP/BS, to the AP/BS. After receiving the pilot signal, AP/BS applies signal processing schemes to the received pilot signal by correlating its received pilot signal with its known pilot signal. Then, by using the channel estimation schemes, for example, minimum mean-square error (MMSE) estimation, AP/BS is able to estimate the channel gain.

Linear Precoding: Before the AP/BS sends the data to MUs, it generates a precoder matrix, which controls the transmitted signal's power and direction. Multiplying the precoder by the transmitted signal, AP/BS can achieve spatial multiplexing by focusing the transmit power into specific directions (i.e., beamforming), so that it serves multiple MUs simultaneously while mitigating the interference.

Downlink Payload Data Transmission: The AP/BS sends the service data to MUs through the downlink channel, by treating the channel gain estimation as the true channel. Moreover, each antenna of the AP/BS individually sends the same signal to MUs, weakening the multipath effect and reducing the outage probability of the wireless channel.

Heterogeneous Statistical QoS Provisioning Theory and the Effective Capacity

We apply the *effective capacity* [5, 6, 14] in statistical QoS theory to characterize the performance of data transmission under a given statistical delay-bounded QoS requirement. The *effective capacity* is defined as the maximum constant arrival rate that a wireless channel can support while guaranteeing the QoS requirement, for each data-content streaming transmission. The effective capacity, denoted by $EC(\theta_i)$, is given by [14, Eq. 3]

$$EC(\theta_i) = -\frac{1}{\theta_i}\log\left(\mathbb{E}\left[e^{-\theta_i R_i}\right]\right), \qquad \theta_i > 0 \tag{2}$$

where $\mathbb{E}[\cdot]$ is the expectation operation, R_i is given by Eq. 1, and θ_i is the *QoS exponent* for the *i*th MU's services that measures the stringency of the statistical delay-bounded QoS requirement for its service. Note that the QoS exponent varies for not only different types of services, but also different data-content demands within the same type of service. Then, we also define the *aggregate effective capacity* as the sum of all MUs connecting to the same AP/BS, which can be written by $\sum_i EC(\theta_i)$.

NFV-Based Optimal Service Delivery Path for AI-Enabled Heterogeneous Statistical QoS Provisioning

The 6G wireless network architectures select the corresponding optimal paths to deliver services to the targeted MUs, which have different statistical delay-bounded QoS requirements. Applying NFV architectures, we virtualize physical substrate network infrastructures and resources into several optimal virtual networks corresponding to different MUs' diverse statistical QoS requirements, and the SDN architectures dictate these virtualizations.

In Fig. 2, we conduct a case study of NFV model where MUs with diverse statistical QoS requirements demand the same data content. The AP/BS can transmit a requested data to the MU over a direct wireless link (i.e., direct transmission method), or employing one neighbor node as a relay to set up a single-relay transmission (i.e., relay transmission method). The AP/BS, denoted by *C*, sends a data content requested by both MU α and MU β. The required QoS exponents of MUs α and β are denoted by θ_α and θ_β, respectively, constituting a heterogeneous QoS provisioning network [12]. The AI-enabled control plane obtains the information that this data is located at AP/BS *C*, and then, maps the optimal delivery path (direct transmission path or relay transmission path with an optimal relay) for MUs α and β to the corresponding virtual networks, respectively. Since the wireless fading conditions are different, we establish distinct virtual slices for different fadings. For example, if the relay transmission through the relay node *B* can achieve the maximum effective capacity, we configure virtual network slice ε to be the optimal network slice. When the relay transmission through node A can achieve the maximum effective capacity, we establish the network slice δ by using the node *A* to forward the data to the MU β. Alternatively, if the direct transmission from node C to MU α can realize the maximum effective capacity, we employ the network slice ν as the optimal virtual network slice.

To select the optimal data-delivery-path for each MU, we derive the effective capacity of direct transmission, denoted by $EC_d(\theta_i)$, and the effective capacity of relay transmission, denoted by $EC_r(\theta_i)$, with employing the relay node *r*, where $\forall r \in \{A, B\}$, $\forall i \in \{\alpha, \beta\}$, respectively. We formulate the Lagrange functions, denoted by J_1 and J_2, for direct and relay transmissions, respectively, as follows:

$$\begin{cases} J_1 = \mathbb{E}\{EC_d(\theta_i)\} - \xi_1 \mathbb{E}\{P_i - \bar{P}\}, \\ J_2 = \mathbb{E}\{EC_r(\theta_i)\} - \xi_2 \mathbb{E}\{P_c + P_r - \bar{P}\}, \end{cases} \tag{3}$$

$\forall r \in \{A, B\}$, $\forall i \in \{\alpha, \beta\}$, where ξ_1 and ξ_2 are the Lagrange multipliers, P_c and P_r are transmit power allocations for node *C* and relay node r for relay transmission, respectively, such that $P_c + P_r = P_i$, and $\overline{P}$ is the total transmit power consuming constraint. Solving Eq. 3, we obtain optimal powers: P_i, P_c, and P_r and also obtain the effective capacities for direct transmission and relay transmission, respectively. After obtaining $EC_d(\theta_i)$, $EC_A(\theta_i)$, and $EC_B(\theta_i)$, we select the path that achieves the maximum effective capacity as the *optimal data delivery path*.

The AI-Plane and Federated Learning Based SDN Control Architectures

We develop the mapping algorithm in the SDN control-plane to assign the optimal AP or BS into a virtual network slice and allocate the optimal MUs according to their requested service types, locations, moving trajectories, and so on, to each network slice. Then, we propose a federated learning based mechanism in SDN AI-plane to assist the control-plane for decision making about the MUs' wireless resources allocations.

Optimal Virtual Network Slicing and MUs Allocation Schemes Managed by SDN Control Plane

We partition the SDN data plane into multiple virtual network slices according to different service types. Each virtual network slice dedicatedly provides one type of service and there also exist multiple slices to provide different statistical QoS requirements for each type of service. Therefore, we are able to develop the SDN architecture based network management algorithm, which can be summarized by Algorithm 1. In Algorithm 1, the maximization of aggregate effective capacity in a network slice can be achieved by the calculation of SDN AI-plane for offloading the computational burden in SDN control-plane.

Figure 2 shows a case study of the virtual network slicing and data delivery path selections schemes via the AI-enabled SDN control plane architecture, which is assisted by the federated edge learning in the SDN AI-plane. The control plane receives the virtual network updated status from the application programming interface (API). After getting the coordination decisions from the AI-plane, the resources allocation model in control plane converts these decisions to AP/BS and relay nodes allocations, as well as transmit power and spectrum bandwidth allocations, respectively. Finally, the data-plane applies the control information through the control information API, finalizing the virtual network slicing and wireless resources allocation controls.

```
Input: AP/BS set and MU set; each MU's service type, QoS exponent θ_i, position d_i, moving direction, and speed.
for Each MU that requests services from the 6G wireless networks do
    Assign the MU to the virtual network slices group corresponding to its service type.
    for Each AP/BS in this virtual network slices group do
        Determine the channel condition h_i for this MU, according to its position d_i, moving direction, and speed.
        Using the θ_i for the MU and by solving Eq. 3, obtain the optimal data delivery path (relay or direct transmission), which
        maximizes its effective capacity, between the MU and this AP/BS.
    end for
    Select the optimal AP/BS which provides the maximum effective capacity for this MU.
    Assign the selected AP/BS and the MU into a network slice in this virtual network slices group.
end for
Output: Optimal edge network slicing and optimal data delivery path selection.
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ALGORITHM 1. SDN architecture for optimal virtual network slicing and data delivery path selection.

The Actor-Critic Algorithm Based Multi-Agent Federated Edge Learning Mechanism for Implementing AI-Plane in SDN

We apply the edge learning mechanism in the SDN AI-plane to assist the maximization of aggregate effective capacity in Algorithm 1. We develop a federated edge learning model to achieve this goal through integrating the traditional federated learning with edge computings at each AP/BS agent, which consists of four major steps as shown in the following algorithm.

Step 1: Local Training: Each agent k trains a local model to minimize a local loss function F_k. The local models focus on solving Eq. 3. During this local training, each agent *k* obtains the weight of its local model w_k and the gradient of the local loss function ∇F_k.

Step 2: Global Aggregation: Each agent *k* uploads its obtained weight w_k and gradient ∇F_k to a central server. The central server aggregates weights and gradients from all agents, and derives the average weight $\overline{w}$ and average gradient $\nabla \overline{F}$.

Step 3: Model Updating: The global model uses the average weight $\overline{w}$ and average gradient $\nabla \overline{F}$ to update parameters for the global model to improve the accuracy of the global model. The updated global model with these updated parameters are then sent back to all agents for updating their local models.

Step 4: Control and Feedback: Each agent periodically communicates with the global model to upload and update the parameters of its local model. The global model sends the control and feedback information, for example, new learning rate schedules and regularization parameters, to all agents, so that each agent is able to improve

Initialize: Actor parameter τ, critic parameter q, $x(0)$, learning rates ϕ_τ and ϕ_q.
for time slot t in 1, 2, ... **do**
  Each AP/BS agent k selects an action $\mathbf{a}(t)$ from action space $\mathcal{A}$ according to policy $\pi_k(x(t), \tau)$.
  Use the current state to obtain reward $r_t = \sum_i EC(\theta_i)$ by solving Eq. 3.
  Obtain the next state $x(t+1)$ and the next action $\mathbf{a}(t+1)$.
  Update the policy parameter $\tau \leftarrow \tau + \phi_\tau Q_q(x(t), \mathbf{a}(t)) \nabla_\tau \log \pi_k(x(t), \tau)$
  Compute the correction for action values $\in \triangleq r_t + \eta Q_q(x(t+1), \mathbf{a}(t+1)) - Q_q(x(t), \mathbf{a}(t))$.
  Use $\in$ to update the parameter of value function $q \leftarrow q + \phi_q \in \nabla_q Q_q(x(t), \mathbf{a}(t))$.
end for
Output: optimal transmit power and bandwidth allocations and optimal service delivery path for each MU.

ALGORITHM 2. Training algorithm of "Actor-Critic Based Federated Edge Learning" for optimal relays and wireless resources allocations.

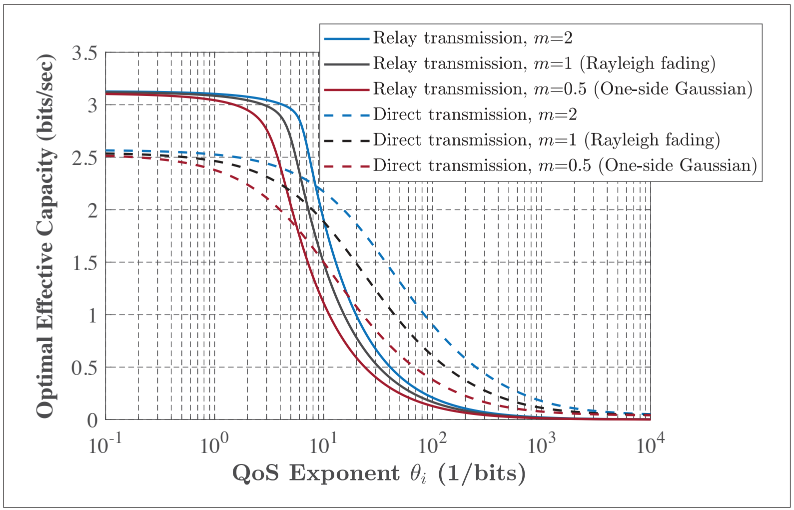

FIGURE 3. Optimal effective capacity for direct transmission $EC_d(\theta_i)$ and relay transmission $EC_r(\theta_i)$ versus QoS exponent θ_i under different values of the Nakagami-m fading parameter m.

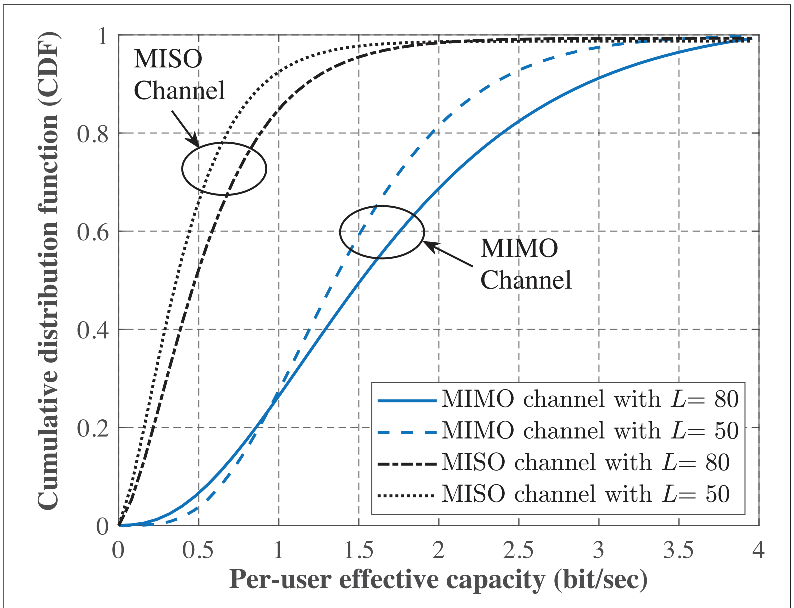

FIGURE 4. Comparison of the CDF (probability) of per-user effective capacity for MISO and MIMO channel with different number of BS antennas.

its local model and obtain the latest hardware and wireless resources allocation schemes.

We then show the detailed local training model in the above Step 1 through *actor-critic* algorithm [15], which integrates the actor-only method with critic-only method of machine learning. We use the learning procedure for the optimal solution of Eq. 3 as an example to show the actor-critic algorithm. In actor-critic algorithm, the actor decides which action optimizes the objective function given by Eq. 3 according to the current state. The critic evaluates this action through a value function, and then, informs the actor how good the action is and how to improve the action.

Each AP/BS agent k uses the Markov decision process (MDP) to solve Eq. 3, and each AP/BS shares the same index with its agent since we assume that each AP/BS is equipped with its own agent. We define the finite state space, denoted by $\mathcal{X}$, to characterize the MDP's *states* describing the total numbers of MUs in a service coverage area at time t. We have $x(t) \in \mathcal{X}$ due to the definitions above. Define $\mathbf{a}(t) \triangleq [a_1(t), a_2(t), ..., a_{x(t)}(t)] \in \mathcal{A}$, where $\mathcal{A}$ is the *action* set of this MDP for all MUs, and $a_i(t)$ with $i \in \{1,2, ..., x(t)\}$ denotes the transmit power allocations P_i or (P_c, P_r) and bandwidth allocation B_i for the ith MU at time t. If $P_i = P_c = P_r = 0$, or $B_i = 0$, the ith MU will not be served by the kth AP/BS. We also denote the actor parameter by τ over the parameter space $\mathcal{T}$, and denote the critic parameter by q. We then define the *policy* π_k of the AP/BS agent k as a mapping π_k: $\mathcal{X} \times \mathcal{T} \rightarrow \mathcal{A}$ that assigns each state-parameter pair $(x(t), \tau) \in \mathcal{X} \times \mathcal{T}$ to the transmit power and bandwidth allocation schemes $\mathbf{a}(t) \in \mathcal{A}$. Define the *reward* r_t of the actor-critic algorithm at time t as the gain of the *aggregate effective capacity* $\sum_i EC(\theta_i)$, where $EC(\theta_i)$ is calculated by solving Eq. 3. We also define the *value* of the current policy under the critic parameter ϕ_q as $\phi_q(x(t), \mathbf{a}(t))$. This actor-critic algorithm is summarized in Algorithm 2, where η represents the importance of future rewards, and ϕ_τ and ϕ_q measure how quickly the local model learns for the actor and the critic, respectively.

Performance Evaluations

Figure 3 evaluates our proposed direct and relay transmission schemes under the Nakagami-m fading channel model where m is the fading parameter. We set average SNR as 5dB. We observe from Fig. 3 that effective capacity is an increasing function of the parameter m. A larger m represents the milder fading, and thus provides a larger effective capacity given the same θ_i. Figure 3 also shows that the effective capacity monotonically decreases as θ_i increases. From Fig. 3, we discover that for loose delay-bounded QoS requirements (small θ_i's), the relay transmission outperforms the direct transmission, suggesting us to choose the relay transmission as the optimal delivery path. For stringent delay-bounded QoS requirements (large θ_i's), the direct transmission outperforms the relay transmission, thus suggesting us to choose the direct transmission as the optimal delivery path.

Figure 4 plots the cumulative distribution function (CDF) of per-user effective capacity for MISO and MIMO channels with the different numbers of BS antennas L = 80 and L = 50, respectively. Figure 4 shows that the effective capacity performance increases as the number of BS antennas increases, and in general MIMO-based scheme outperforms (MIMO's plots are at right side of

MISO's plots) the MISO-based scheme regardless of the number of BS antennas L used. We can also observe from Fig. 4 that when effective capacity is small (i.e., effective capacity is less than 5 bits/sec), the channel performance of $L = 50$ is better than $L = 80$. This is because the large number of antennas in BS results in more interference to mobile users when the number of mobile users is large.

Conclusions

Applying the AI-enabled techniques, we developed the massive-MIMO-NFV-SDN integrated architectures to provide heterogeneous statistical QoS provisioning for customized services over 6G mobile wireless networks. The massive-MIMO techniques are implemented through deploying massive MIMO antennas on APs, BSs, and MUs to increase the channel quality. We applied the NFV techniques to construct the optimal data delivery paths for different requirements of services, respectively. Collaborating with our developed AI-enabled architectures and AI-plane, the SDN control plane intelligently coordinates the network nodes and resources allocations for each virtual network slice. We conducted extensive simulations and numerical analyses to verify and evaluate our developed massive-MIMO-NFV-SDN integrated architectures using AI-techniques, showing that they can support the AI-enabled statistical delay-bounded QoS provisioning over 6G mobile wireless networks.

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