

Towards Quantum-Enabled 6G Slicing

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I. EXTENDED ABSTRACT

The quantum machine learning (QML) paradigms and their synergies with network slicing can be envisioned to be a disruptive technology on the cusp of entering to era of sixth-generation (6G), where the mobile communication systems are underpinned in the form of advanced tenancy-based digital use-cases to meet different service requirements [1], [2], [3], [4], [5]. To overcome the challenges of massive slices such as handling the increased dynamism, heterogeneity, amount of data, extended training time, and variety of security levels for slice instances, the power of quantum computing pursuing a distributed computation and learning can be deemed as a promising prerequisite. In this intent, we propose a cloud-native federated learning framework based on quantum deep reinforcement learning (QDRL) where distributed decision agents deployed as micro-services at the edge and cloud through Kubernetes infrastructure then are connected dynamically to the radio access network (RAN). Specifically, the decision agents leverage the remold of classical deep reinforcement learning (DRL) algorithm into variational/parametrized quantum circuits (VQCs or PQCs) to obtain the optimal cooperative control on slice resources. In this context, temporal variations of the traffic demand deeply complicate resource planning and allocation tasks, especially in the RAN domain. Hence, the complexity of automated management and orchestration (MANO) [5] operations such as resource allocation arises dramatically concerning these progressive developments. Indeed, developing new DRL approaches to tackle these challenging multi-tasks can be considered a necessity in multi-domain 6G. A trend is emerging to combine DRL with quantum computing in the form of QDRL that has significantly fewer parameters by leveraging the power of quantum neural network (QNN) and utilizing the qubit properties such as superposition and entanglement. Considering the privacy concerns associated with large-scale and distributed 6G infrastructures and the limited quantum capabilities of different quantum machines in the noisy intermediate-scale quantum (NISQ) [6] era, we propose a federated learning scheme to provide a distributed computing pursuing a secure QML training while enriching the capabilities of the QDRL decision agents through learning more trajectory of experiences and model generalization. The suitability of utilizing VQCs for function approximation in RL is still an open question [7]. As shown in Fig. 1, we implement decision agents based on a VQC in TensorFlow quantum (TFQ) [8], where the Q-function

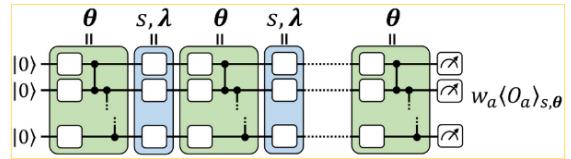


Figure 1: The generic layout of PQC with data re-uploading. State s , action a , observable weights w , input scaling parameters λ , and function approximator $\langle O_a \rangle_{s,\theta}$ [7].

approximator trained with deep Q-network (DQN). To obtain better expressive power [9], we leverage re-uploadings [10] for single-qubit encodings.

In our proposed framework, quantum DQN (QDQN) [11], [12], [13] agents optimally allocate radio resources to each slice, while a federation layer enables a periodical exchange of the QDQN's parameter values to improve the learning process across multiple agents of the same slice. We analyze the performance of proposed framework based on both simulation and testbed environment. As depicted in Fig. 2, we implement our framework based on Python programming and exploiting OpenAI Gym library [14] interfacing QDRL agents with a custom base station (BS) simulator environment. We highlight the O-RAN [15] synergies with respect to our proposed approach which includes virtual transmission queues and main PHY/MAC/RLC functionalities, together with O-RAN E2 interface to allow gathering the slice networking statistics from each distributed unit (O-DU). The QDRL agents

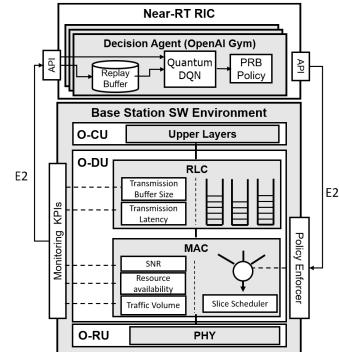


Figure 2: The software protocol stack overview with O-RAN compliance for gNodeB.

enforce physical resource blocks (PRBs) policy decisions in the BS slice scheduler and finally a federation layer connects the QDRL agents of the i -th slice to enable inter-agent information exchange and expedite the overall learning procedure. Fig. 3

demonstrates our testbed structure where three Amarisoft¹ gNodeBs jointly with a single Open5Gs² core provide 5G segments and connectivity. In this 5G segment, Open5Gs core can be containerized in Kubernetes infrastructure or can be deployed in virtual machines (VMs). We also have Amarisoft user emulators (UEs) that can generate 5G users. As shown in Fig. 3, our 5G segment as a shared network slice sub-instance (NSSI-1) connected with our designed platform as a service (PaaS) Kubernetes infrastructure (according to ETSI-029 [16]) with scalable network sub instances (NSSI-2). PaaS Kubernetes infrastructure can be scaled in/out NSSIs for the sake of resource management. The decision agents are deployed in edge nodes while federation layers at the cloud node in our Kubernetes infrastructure connected to 5G segments.

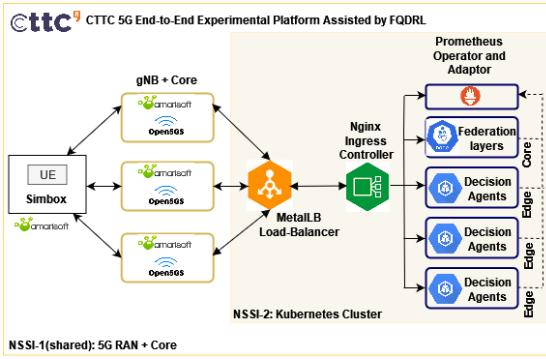


Figure 3: The proposed testbed framework with QDRL-based decision agents.

We perform simulations to compare the initial results of federated classical DRL (FDRL) and FQDRL to demonstrate the potential of FQDRL based on a standard RL benchmark from OpenAI Gym [14]. We use a continuous state space while the action space is discrete and run our experiments on a dedicated server, equipped with two Intel(R) Xeon(R) Gold 5218 CPUs @ 2.30GHz and two NVIDIA GeForce RTX 2080 Ti GPUs. Moreover, the deep neural networks (DNNs) are implemented based on TensorFlow-gpu and utilize TensorFlow Quantum [8] and Cirq³. Fig. 4 shows the architecture of a single FQDRL agent with 5 layers in the PQC. Fig. 5 provides a

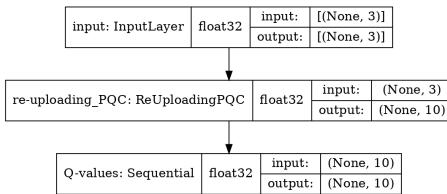


Figure 4: The architecture of local agent model with 3 qubits.

comparison of learning performance in terms of average reward over 15 BS (gNBs).

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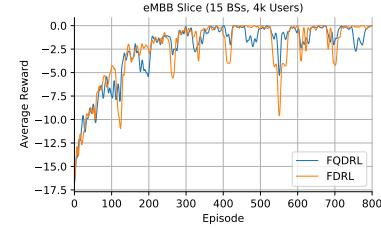


Figure 5: Comparison of global performances for different federation approaches.

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