Quantum Federated Reinforcement Learning for 6G Wireless Systems

Background The sixth-generation (6G) wireless systems, inter alia, cell-free distributed multiple-input multiple-output (MIMO) networks, internet of everything (IoE), digital twin, e-finance and e-health, have been envisioned to be *artificial intelligence (AI)-native networks*, by industry, academia, and standardization bodies [1]. An AI-native wireless network is one in which the entire protocol stack, from the physical layer to the application layer, is designed using data-driven machine learning (ML) techniques. Radio resource management is one of the major building blocks for realizing agile and robust 6G networks, which would be designed using data-driven ML approaches. Deep reinforcement learning (DRL) is one well-known type of ML frameworks, which is the backbone enabling the mind-blowing AlphaGo and ChatGPT. Thanks to its adaptive and flexible decision-making ability via learning unknown environments in a model-free and trial-and-error manner [2], DRL is believed to be a competitive candidate to realize efficient and intelligent radio resource coordination for intelligent 6G systems. To enable the practically real-time application of AI-enabled solutions within extreme-large-scale and highly heterogeneous future 6G wireless systems, existing ML frameworks that are inherently based on centralized training inevitably suffer from inefficiency of scaling, e.g., significant latency and overhead for coordinating massive networks, not to mention that data privacy and security amid wireless transmissions among 6G transceivers fundamentally require to be taken more serious care of, e.g., genetic/biometric data, trade secret and marketing strategies. Among other ML techniques, federated learning (FL) is standing out to help deal with the key constraints of model scalability and data privacy, blessed by FL's nature of decentralized learning where distributed clients train their provincial models from locally collected data while the server trains the global model via aggregating model parameters extracted from distributed clients, rather than raw privacy-sensitive data. Recent advancements in quantum computing devices, e.g., quantum supremacy reported by IBM and Google, and the latest Nobel prize in Physics for ground-breaking experiments with quantum entangled particles, further reveal the promise and importance of quantum computing for leading the next industrial revolution. Besides, recent works on quantum machine learning (QML) showed that quantum computing is beneficial for improving efficiency [3] and enhancing generalization [4] for ML systems, e.g., comparable or better learning performance with much lighter parameter updating of quantum DRL algorithm has been reported in [5], compared to the conventional deep neural network (DNN)-based DRL. To leverage quantum advantages into decentralized privacy-preservative ML regime, a handful of related works in the interdisciplinary area of quantum FL (QFL) has emerged in recent years, e.g., FL-inspired variational quantum algorithm (VQA) with distributed data [6] and ML framework with federated training on hybrid quantum-classical learning models [7]. These works reported that QFL can help achieve favourable scalability and meanwhile safeguard privacy/security-sensitive data.

Motivation Unfortunately, there remains a research blank where quantum computing together with decentralized privacy-preservative ML and DRL is invoked to support 6G wireless systems. To fill this gap and thus pioneer this infant yet promising research direction, this project proposes *a novel interdisciplinary framework of QFL-aided DRL (QFRL) for intelligently allocating radio resources for future 6G wireless systems*, where distributed training, model scalability and data privacy/security will be achieved. *A fundamental question* here is whether one can build a novel QFRL framework that can be used to design AI-native 6G wireless systems, to achieve practical scalability and preserve data privacy with low latency and high reliability. *Another inherent challenge* is how to leverage quantum advantages to help deal with drawbacks or shortcomings of existing ML frameworks with federated training.

Aim and Methodology The *aim of this project* is thus to lay the theoretical foundations of *distributed privacy-preservative* QFRL for optimizing transmission performance of AI-native 6G wireless systems and protocols. 1) A first key goal is to develop new QFRL algorithms tailored towards solving optimization problems in 6G networks with distributed wireless transceivers, in terms of radio resource coordination, e.g., beamforming design, spectrum access, resource (power, bandwidth) allocation, and energy efficiency. Hereby, QFRL solutions will be designed and developed. Specifically, decentralized RL clients will be redesigned with variational quantum circuit (VQC) including state encoding as well as parametric quantum circuit (PQC) and quantum measurements, while VQC-based server aggregates model parameters reported from clients to formulate the global model. Here, we will investigate the impact of various existing PQC ansatzes, and then design novel ansatzes that can better adapt to 6G transmission scenarios. Furthermore, we will investigate the signalling overhead and information sharing among distributed clients, and we will theoretically and empirically show how and when quantum designs can reduce such overhead, while identifying its impact on the learning in impactful use cases within 6G networks. Moreover, our designs will incorporate practical considerations on partial observability of complex 6G wireless environments. The application of VQC-aided training architecture for QFRL can significantly reduce the number of training parameters, which thus can potentially help overcome the scalability and latency challenges. Next, we will leverage promising techniques such as space compression, meta-learning and transfer learning to enhance the robustness and scalability of the proposed QFRL framework for large-scale and heterogeneous 6G networks. 2) Within practical 6G wireless systems, heterogenous and/or multi-modal clients' training data would not anymore be independent and identically distributed (non-i.i.d.), which could significantly deteriorate the learning performance of variants of classical FL. Therefore, we will investigate how skewed non-i.i.d. data affect the proposed QFRL framework, in terms of, e.g., learning efficiency and robustness, via both theoretical and numerical analyses. Then, we will focus to propose solutions to improve the proposed QFRL framework's trainability over non-i.i.d. wireless data, e.g., *data augmentation* via enabling clients to collectively train a generative model and then augment their local data towards achieving i.i.d. dataset, *multi-task learning* and *knowledge distillation*. 3) In the current noise intermediate-scale quantum (NISQ) era, quantum errors caused by quantum decoherence and imprecision of quantum gates will inevitably jeopardize the learning performance of VQC-based schemes. Hence, we will explicitly investigate the *fundamental effects of quantum noise on our QFRL* solutions, and we will propose efficient strategies to counter this shortcoming, including hybrid optimization, ensemble learning, and use of kernel matrices. 4) To make the proposed QFRL solution more communication-efficient when coping with time-varying 6G wireless channels, we will study the depth-manageable architecture of VQC over its depth-fixed counterpart. Inspired by the slimmable FL (SFL) technique, we aim to initiate entangled slimmable PQC with multiple depths to rebuild the proposed QFRL framework as entangled silimmable QFRL. Herein, the clients of entangled silimmable QFRL will communicate superposition-coded parameters to realize federated training. Then, we will aim to develop an optimal power allocation strategy for superposition coding which is used to encode clients' model parameters. However, entangled slimmable PQC may lead entangled silimmable QFRL to be less trainable, as significant entanglement entropy and inter-depth interference would be inevitably introduced. We will thus try to tackle this challenge by adopting advanced techniques from quantum computing, e.g., entanglement controlled universal gates and in-place fidelity distillation regularizer.

Outcomes The proposed research will *contribute simultaneously to AI, machine learning, quantum computing, and 6G wireless systems* thus providing scientific foundations for pioneering the emerging yet promising interdisciplinary area of QFRL applied to 6G wireless systems. We plan to submit high-impact papers to leading communications (e.g., IEEE Transactions on Wireless Communications), AI (e.g., IEEE Transactions on Pattern Analysis and Machine Intelligence), and quantum (e.g., Quantum Information Processing) venues, while regularly publishing in top-tier international conferences, e.g., IEEE GLOBECOM, IEEE ICC, NeurIPS and ICML. Besides, this project's scientific outcomes can potentially contribute to the development of future 6G standards, by introducing quantum to aid the AI-native nature of 6G networks.

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