Distributed Quantum Multi-Agent Deep Reinforcement Learning for 6G Wireless Systems

Background The sixth-generation (6G) wireless systems will be an *artificial intelligence (AI)-native network*, as envisioned by industry, academia, and standardization bodies [1]. Deep reinforcement learning (DRL) with decentralized architecture has been proposed to address various 6G problems ranging from transceiver design to radio resource management and intelligent spectrum access. Inter alia, distributed multi-agent DRL (MADRL) [2] has been envisaged as an indispensable part of AI-native 6G networks because: 1) MADRL enables implementing distributed wireless protocols at the edge; 2) MADRL agents can share experiences so that less-trained agents can learn from their better-skilled partners; and 3) MADRL can accommodate heterogeneous agents with various learning goals and device capabilities. However, existing MADRL frameworks are limited in many ways: 1) *non-stationarity*: state transition and each agent's reward function are affected by joint actions so that non-stationarity holds; 2) *instability and scalability*: as the number of agents increases (e.g., systems with thousands of wireless devices), the complexity and action spaces increase exponentially; 3) *partial observability*: full observability of states from the environment does not hold in sophisticated multi-agent cases; and 4) *high training burden*: the need for updating large number of deep neural network (DNN) parameters makes MADRL computation-hungry and time-inefficient.

Motivation To overcome these limitations, we propose a *novel framework of quantum MADRL (QMADRL)* that combines the benefits of quantum mechanics with those of distributed MADRL, and that will be *designed and deployed to address major 6G wireless challenges*. Recent works on quantum machine learning (QML) showed that quantum mechanics are beneficial for improving efficiency [3] and enhancing generalization [4] for machine learning systems. Moreover, several works illustrated that quantum mechanics can enhance learning efficiency and robustness for DRL. For example, comparable or better learning performance with much lighter parameter updating of quantum DRL algorithm has been reported in [5], compared to conventional DNN-based DRL. *A fundamental question* here is whether one can build a novel QMADRL framework that can be used to design AI-native 6G wireless systems, with low latency and high reliability. Although there exist some recent works on quantum DRL, e.g., [5-7], they cannot be used to address 6G wireless problems because they mostly rely on a single agent or they make impractical assumptions for 6G systems, e.g., quantum errors were not considered and full observability of environment was naively adopted.

Aim and Methodology The *aim of this project* is thus to lay the theoretical foundations of *distributed* QMADRL for the design, analysis, and optimization of AI-native 6G wireless systems and protocols. 1) A first key goal is to develop new distributed QMADRL algorithms tailored towards solving optimization problems in 6G networks with distributed wireless data, in terms of radio resource coordination, e.g., beamforming design, spectrum access, resource (power, bandwidth) allocation, and energy efficiency. Decentralized actors will be redesigned with variational quantum circuit (VQC) including state encoding as well as parametric quantum circuit (PQC) and quantum measurements, while VQC-based critic would remain centralized for dealing with non-stationarity. Here, we will investigate the impact of various existing PQC ansatzes, and then design novel ansatzes that can better adapt to 6G transmission scenarios. 2) For QMADRL, we will investigate the signalling overhead and information sharing among distributed agents, 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. Our designs will incorporate practical considerations on partial observability of complex 6G wireless environments. The application of VQC-aided training architecture for QMADRL can significantly reduce the number of training parameters, which thus can potentially help overcome the scalability and latency challenges of conventional DNN-based MADRL frameworks. Next, we will leverage promising techniques such as space compression, meta-learning and transfer learning to enhance the robustness and scalability of the proposed QMADRL for large-scale and heterogeneous 6G networks. 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 QMADRL* solutions, and we will propose efficient strategies to counter this shortcoming, including hybrid optimization, ensemble learning, and use of kernel matrices.

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 QMADRL applied to 6G wireless systems. Dr. Li plans 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., GLOBECOM, 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.

Difference from Previous Research Dr. Li's previous research experience includes proposing and analysing wireless protocols, and designing classical DRL or innovating quantum-inspired DRL algorithms for optimizing wireless communications, where 6G networks, distributed learning, signalling overhead among AI agents, robustness and scalability of decentralised learning algorithms, VQC-aided actor/critic, and quantum noise were not considered. This project will holistically and rigorously focus on initiating robust and scalable distributed multi-agent AI frameworks together with practical quantum aids to help design, analyze and optimize intelligent 6G wireless systems, and thus pioneering this first-of-its-kind interdisciplinary research area.

Research Reasons for Selected Institution [redacted] has posed priority on quantum and its applications, where several quantum initiatives have been launched to pioneer this highly promising technology, e.g., [redacted] and [redacted]. Dr. Li will work with colleagues in the [redacted], where the host mentor Prof [redacted]'s world-class expertise in AI-native wireless systems will provide an ideal platform for Dr. Li to pioneer this emerging research area of distributed QML for AI-native 6G networks, by tightly collaborating with [redacted]'s quantum initiatives.

Contribution to Fellow Career Goals Dr. Li's career goal is to become a world-leading researcher in the emerging area of distributed QML for 6G systems. This fellowship can provide an optimal path for boosting his chances of achieving his long-term aspiration, by offering him invaluable real-world expertise in leading research projects independently, and helping him expand his scholarship, track record and academic visibility.

References **[1]** Talwar, Shilpa, et al. "6G: Connectivity in the era of distributed intelligence." IEEE Communications Magazine 59.11 (2021): 45-50. **[2]** Zhang, Kaiqing, et al. "Multi-agent reinforcement learning: A selective overview of theories and algorithms." Handbook of Reinforcement Learning and Control (2021): 321-384. **[3]** Liu, Yunchao, et al. "A rigorous and robust quantum speed-up in supervised machine learning." Nature Physics 17.9 (2021): 1013-1017. **[4]** Caro, Matthias C., et al. "Generalization in quantum machine learning from few training data." Nature Communications 13.1 (2022): 1-11. **[5]** Chen, Samuel Yen-Chi, et al. "Variational quantum circuits for deep reinforcement learning." IEEE Access 8 (2020): 141007-141024. **[6]** Saggio, Valeria, et al. "Experimental quantum speed-up in reinforcement learning agents." Nature 591.7849 (2021): 229-233. **[7]** Li, Ji-An, et al. "Quantum reinforcement learning during human decision-making." Nature Human Behaviour 4.3 (2020): 294-307. **[8]** Li, Yuanjian, et al. "Path planning for cellular-connected UAV: A DRL solution with quantum-inspired experience replay." IEEE Transactions on Wireless Communications (2022).