Network Intelligence with Quantum Computing in 6G and B6G: Design Principles and Future Directions

Francesco Vista[1,2], Vittoria Musa[1,2], Giuseppe Piro[1,2], Luigi Alfredo Grieco[1,2], and Gennaro Boggia[1,2]
[1]*Dept. of Electrical and Information Engineering, Politecnico di Bari*, Italy
[2]*CNIT, Consorzio Nazionale Interuniversitario per le Telecomunicazioni*, Italy
email: {francesco.vista, vittoria.musa, giuseppe.piro, alfredo.grieco, gennaro.boggia}@poliba.it

***Abstract*—Network intelligence in 6G systems and beyond may require computing power and computation time hard to reach in current deployments. While the employment of quantum computers for supporting Quantum Machine Learning emerged as a viable solution to overcome this issue, their integration within a network architecture still represents an uncovered research topic. To bridge this gap, this paper proposes design principles for centralized and distributed architectures, where quantum computers are deployed in the remote cloud or geographically distributed at the edge, respectively. The advantages and disadvantages of resulting network architectures are investigated to point out open issues and future research directions.**

***Index Terms*—6G, B6G, Quantum Computing, Quantum Machine Learning.**

I. Introduction

Mobile radio networks continuously evolve over the years. Today, while the standardization process for the 5-th generation (5G) of mobile systems is ending with the 3GPP Release 16, the scientific community already started investigating the next frontier of wireless communication systems, including 6-th generation (6G) and Beyond 6G (B6G) [1].

In this context, the challenging Key Performance Indicators (KPIs) characterizing the emerging services and applications will require the strengthening of some methodologies already born with the 5G, as well as the introduction of novel enabling technologies [1]–[3]. For instance, Software-Defined Networking (SDN) and Network Function Virtualization (NFV) paradigms will still sustain network management tasks. The pervasive monitoring of network equipment and users' behaviour is fundamental for dynamically configuring virtualized network functionalities and isolating resources and services within specific portions of the network, namely network slices [1]. Differently, new communication schemes, like Terahertz (THz), Visible Light Communications (VLCs), Intelligent Reflective Surfaces (IRSs) and cell-free massive Multiple-Input/Multiple-Output (MIMO), are gaining momentum for providing very high data rates in scenarios with reduced or controllable noise and propagation phenomena [2], [3]. Nevertheless, excepting these valuable network management and communication technologies, network intelligence will significantly boost the evolution of 6G and B6G. According to the scientific literature, in fact, Machine Learning (ML) algorithms can be used at different network levels to retrieve technical details through data mining, investigate and predict the system behaviour, and optimally configure communication protocols, resources, and services, also at large scale [1].

Unfortunately, ML algorithms require a heavy (and sometimes recursive) learning phase, asking for huge computing capabilities [4], [5]. Therefore, the expected massive amount of data to be processed in 6G and B6G use cases would need computing power and computation time capabilities hard to reach in today architectures [6]. In this case, the absence of plentiful computing capabilities across the network may even wipe out the benefits arising from the joint integration of aforementioned key enabling technologies.

Quantum Computing (QC) can be considered a possible way to counteract this issue [6]. Specifically, QC leverages quantum mechanics principles to develop new type of algorithms able to solve complex problems in a very faster manner than classical approaches. In this sense, QC may speed up ML techniques and make them suitable also for computationally heavy and real-time applications. The resulting approach is known as Quantum Machine Learning (QML) [7]. While most of the scientific contributions on QML focus on the design and implementation of specific algorithms (see for example [8]–[11]), very few works introduce QML as an essential building block for 6G and B6G [6], [12], [13]. Unfortunately, the integration of quantum computers in 6G and B6G systems, the investigation of the resulting network architectures, and the analysis of design implications derived from the deployment of pervasive network intelligence schemes still represent an unexplored research topic.

To provide initial answers in this direction, this work presents design principles for a QC-aided network intelligence and illustrates the related emerging research challenges. The study considers both centralized and distributed network architectures, properly extending well-known 5G and beyond architectures with specific nodes to support QC functionalities. The former is supposed to sustain QML by means of quantum computers developed by Tech Giants in their clouds. Considering that IBM, Google, and Microsoft already have quantum computers with up to a hundred qubits [7] (and further improvements are expected in the next years), the centralized architecture could be an initial reasonable approach in 6G networks. At the same time, the growing scientific interest and the technological advancements in quantum computing systems is expected to enable, in a very far future, the interconnection among geographically distributed quantum devices by means of quantum Internet (as explicitly stated in [14]). This approach may lead towards the design of a distributed architecture, especially suitable for B6G systems, where simpler quantum computers are deployed at the edge of the network. The pros and cons of both architectures are deeply investigated by considering communication latency, network congestion, load balancing, security, and implementation facets. Finally, the discussion highlights future research directions to be undertaken by the scientific community to move from myth to reality.

II. How to achieve network intelligence

Thanks to their ability to extract fine-grained analytics from available data, ML and QML are key instruments to achieve network intelligence.

A. Machine Learning

ML techniques include supervised, unsupervised, and reinforcement learning [4]. Supervised learning trains models over time by exploiting a training dataset composed of input-output pairs. The related algorithms minimize the loss function by adjusting at each iteration the control parameters. On the contrary, unsupervised learning investigates unspecified patterns directly from the training dataset composed of unlabelled data. In this case, the goal is to discover the dataset structure in order to retrieve new useful data. Finally, with reinforcement learning, models learn by choosing the sequence of actions that maximize the cumulative reward given by the environment feedback at each iteration. Besides the aforementioned ML techniques, in the last years, federated learning is arising as a new distributed learning approach. Indeed, collaborative remote devices train a shared model using their local data, strongly reducing latency and power consumption.

Different ML-based methodologies emerged for various purposes. Few valuable examples are reported below.

- At the physical layer, deep and convolutional neural networks are used for optimizing Orthogonal Frequency-Division Multiplexing receivers, signal classification, channel decoding, and signal detection [4]. ML is also employed for channel estimation to optimally choose the communication frequency and control the IRSs reflection angle, thus reducing attenuation effects of high-frequency communications [1].
- At the data-link layer, ML algorithms optimize the packet retransmissions process and the dynamic allocation of network resources, while reducing network overhead and latency also in heterogeneous scenarios [12].
- At the network layer, ML techniques predict data contents to be cached in specific places of the network, choose serving and target cells during handover, and efficiently balance the network load with traffic classification [4]. The prediction of users' mobility sustains NFV/SDN paradigms to optimally configure the network and allocate communication and computing resources.
- At the application layer, ML studies packet features (e.g., packet sizes and inter-arrival times) and classifies the application type of data stream in order to optimize the resource allocation [4].

Pervasive network intelligence is a cornerstone enabling factor also for many 6G and B6G use cases, grouped in the following application areas: 1) Mobile Broadband Reliable Low Latency Communications (MBRLLC) combining data rate, latency and reliability requirements, e.g., Virtual Reality (VR), Augmented Reality (AR), and unmanned vehicles; 2) massive Ultra Low Latency Communications (mURLLC) including massive communications with low latency and high reliability, e.g., Massive Internet of Things (M-IoT), Robotics, and Industry 4.0; and 3) Human-Centric Services (HCS) supporting novel applications in the medical field, e.g, E-Health, haptic communication, and telesurgery [2]. Table I summarizes the main KPIs and the involved communication technologies for these use cases, and highlights the main role covered by ML techniques.

Now, despite its unquestionable benefits, the learning process often requires long computation times and high computing power [4], [5]. Concerning 6G and B6G applications, the amount of time needed to complete a single task may be conflicting with the expected QoS constraints (specifically, the communication latency). At the same time, the aggregated computing demand requested by high connectivity density and fully intelligent 6G and B6G systems may be hard to reach in current deployments [6].

B. Quantum Computing

Thanks to quantum mechanics principles (i.e., quantum superposition, quantum decoherence, no-cloning theorem, and quantum entanglement), QC is gaining momentum as a new technology able to solve complex problems that would otherwise be impossible with classical computers [14]. First of all, quantum information is encoded in terms of quantum bits (namely qubits), which can be 0, 1, or a superposition of both: n qubits encode 2^n states simultaneously. Accordingly, the power of QC exponentially increases with the number of qubits.

The number of operating qubits and, in turn, the power of QC can be increased by distributing the ML algorithms on multiple connected quantum computers, where the distributed computing resources are managed by a control system [15]. However, differently from classical data, quantum information cannot be copied due to the no-cloning theorem, forbidding traditional error correction mechanisms and limiting the communication distance. Quantum states, however, can be transferred through quantum communications (i.e., quantum entanglement and teleportation). With the quantum entanglement, two particles share a quantum state and the measurement of one particle determines the outcome of the measurement of the entangled one. The teleportation, instead, allows retrieving a quantum state by exploiting entangled particles previously

TABLE I

COMMUNICATION FEATURES AND NETWORK INTELLIGENCE USAGE IN MAIN 6G AND B6G USE CASES.

Application Area	Use cases	Main KPI	Communication Technologies				How is ML used?
			THz	VLC	IRS	Cell-free	
MBRLLC	VR/AR	Peak data rate: > 1 Tbps Traffic capacity: 1 Gbps/m^2 Spectrum efficiency: $2-10$x Latency: < 1 ms	✓			✓	- predict users' mobility; - estimate channel conditions; - allocate network resources; - reduce network traffic by reproducing the interested image portion.
	Unmanned vehicles	Peak data rate: > 1 Tbps Connectivity density: 10^7 d/km^2 Mobility: 1000 km/h Reliability: 99.9999999% Latency: < 1 ms	✓	✓	✓	✓	- optimize the vehicles path; - predict vehicles mobility; - recognize obstacles; - optimize the resource allocation.
mURLLC	M-IoT	Connectivity density: 10^7 d/km^2 Energy efficiency: $10-100$x	✓	✓		✓	- identify patterns; - classify the collected data; - adapt communication features based on environment conditions; - predict users' mobility.
	Robotics and Industry 4.0	Peak data rate: > 1 Tbps Jitter: 1 μs Spectrum efficiency: $2-10$x Latency: < 1 ms	✓		✓		- optimize data processing; - robot localization; - improve the human-robot interaction.
HCS	E-Health	Peak data rate: > 1 Tbps Connectivity density: 10^7 d/km^2 Energy efficiency: $10-100$x Reliability: 99.9999999% Mobility: 1000 km/h	✓	✓		✓	- detect medical diseases; - drive real-time decisions of devices; - support the doctor in treatments prescription.
	Haptic and telesurgery	Peak data rate: > 1 Tbps Traffic capacity: 1 Gbps/m^2 Spectrum efficiency: $2-10$x Reliability: 99.9999999% Latency: < 1 ms	✓	✓		✓	- predict and reproduce doctor's movements in case of packets loss; - network traffic reduction by reproducing the interested image portion.

distributed by a third party through quantum channels. Specifically, the sender performs a Bell measurement of the state that it wants to send and its entangled particle. Then, the outcome is sent through traditional channel to the receiver, which reconstructs the state with local operations. As a result, quantum communication can be exploited to increase QC capabilities creating a network of distributed quantum computers sharing a higher number of qubits through the quantum Internet [14].

On the other hand, due to the decoherence principle, quantum states can be easily altered by the interaction with the environment. Nowadays, only very large and bulked equipment keeping the temperature under the absolute zero are used to reduce the decoherence principle effects [7]. Accordingly, the overall cost of the quantum infrastructure may be excessive in the near future, thus strongly limiting the number of available quantum computers to exploit in initial deployments.

C. Quantum Machine Learning

QML emerged as a combination of QC and ML [7]. It studies how to translate classical algorithms in quantum-compliant language to exploit quantum principles for learning and inference operations [9], [10]. Accordingly, traditional ML methods can be revised in the context of QML, leading to the definition of quantum supervised, unsupervised, and reinforcement learning algorithms [8]. The adoption of these techniques requires pre-processing operations to convert the data collected from the environment into feasible input-data for quantum computers. Nowadays, the scientific literature proposes several encoding methods, such as basis encoding, amplitude encoding, Qsample encoding, dynamic encoding, and Hamiltonian encoding [9], [11].

QML can easily outperforms classical ML algorithms by providing an exponential speed-up and reducing the computational complexity of heavy operations and learning processes [6], [12]. Accordingly, QML appears as a suitable solution for typical real-time and computationally heavy 6G and beyond application scenarios, such as M-IoT, unmanned vehicles and robotics [6]. QC is also proposed to preserve the data privacy in distributed ML and QML scenarios, thus improving security functionalities in 6G and B6G networks [12], [13].

III. DESIGN PRINCIPLES FOR QC-AIDED NETWORK INTELLIGENCE

The introduction of QML methodologies in 6G and B6G systems requires the definition of novel network architectures, with new logical entities and functionalities. Unfortunately, at the time of this writing and to the best of authors' knowledge, there are no contributions investigating nor the design of network architectures for the effective implementation of QC-aided ML techniques in 6G and B6G systems, neither the main research challenges to be faced by the scientific community in the near and far future. Based on these premises, this Section presents design principles that characterize centralized and distributed deployments.

A. Centralized Architecture

The centralized architecture, depicted in Fig. 1, is described across four general tiers: access network, edge network, core network, and remote cloud. The access network hosts heterogeneous network attachment points, which offer mobile connectivity through different wireless communication technologies (i.e., mmWaves, THz communications, VLC, IRS, and so on). The edge network provides a flexible interface between access and core networks, while managing virtualized network functionalities and implementing advanced services and applications very close to the end-users. The core network forwards traffic flows across geographically distributed nodes. Its features are dynamically monitored and configured by SDN controllers. Finally, the remote cloud makes available network and service management functionalities through the Network Function Virtualization Orchestrator (NFVO).

All the resources that an infrastructure provider deploys across the four tiers can be exploited by various service providers for offering vertical services. Without loss of generality, the discussion below assumes that a single service provider has data available in its network. But, the whole protocol architecture can be easily extended by considering the possibility to perform data mining and big data analytics on information shared across organizations and boundaries.

As for the current 5G deployments, a service provider can still use nodes at the network edge with their local computing capabilities for executing very simple ML tasks. At the same time, the centralized architecture takes advantage of quantum computers in the cloud for carrying out QML techniques. In this context, a service provider could exploit computing capabilities deployed by third-party Tech Giants, such as IBM, Google, and Microsoft, for running complex tasks based on QML algorithms. As expected, this opportunity shall be regulated by specific subscription fees. The service provider has a perfect knowledge of computing resources available at both network edge (for simple ML tasks) and in the cloud (for complex QML tasks). The allocation of computing resources among ML and QML tasks is done by a centralized Intelligence Orchestrator, deployed in the remote cloud.

Specifically, the centralized architecture works as follows.

- End-users and network equipment continuously generate data. Those provided by the end-users are strictly related to both communication technologies and reference use cases (e.g., channel quality indicators, performance levels of high-level applications). Network equipment, instead, provides details about their functioning (e.g., bandwidth and energy consumption).
- Data Aggregators, placed at the edge and core network, collect these data through REST or RESTful communication protocols recommended by the scientific literature. Then, they create (and, if needed, partially overlapped) datasets to be used for specific purposes, ranging from service management to network optimization.
- Data Aggregators periodically send high-level descriptions of the available datasets to the remote Intelligence Orchestrator. The generic data descriptor message contains information about data (e.g., format and size).
- Based on the complexity of the data mining procedure and big data analytics and the status of computing resources, the Intelligence Orchestrator distributes computing tasks to nodes implementing simple ML mechanisms and quantum computers implementing QML schemes.
- In case the QML approach is selected, the Quantum Interface (QI) logical entity is contacted for converting classical data into quantum data, and vice-versa.
- Finally, ML and QML outcomes (e.g., the hyperparameters of the model in case of learning procedures; classification, prediction, or specific actions in other cases) can be transmitted to: 1) NFVO for optimally managing upper layer services and allocating virtual resources among active applications; 2) SDN controllers to dynamically configure network functionalities (e.g., flow forwarding and load balancing) and solve complex routing problems based on users' mobility and traffic dynamics; 3) edge nodes to update ML models; 4) base stations for resource scheduling and allocation.

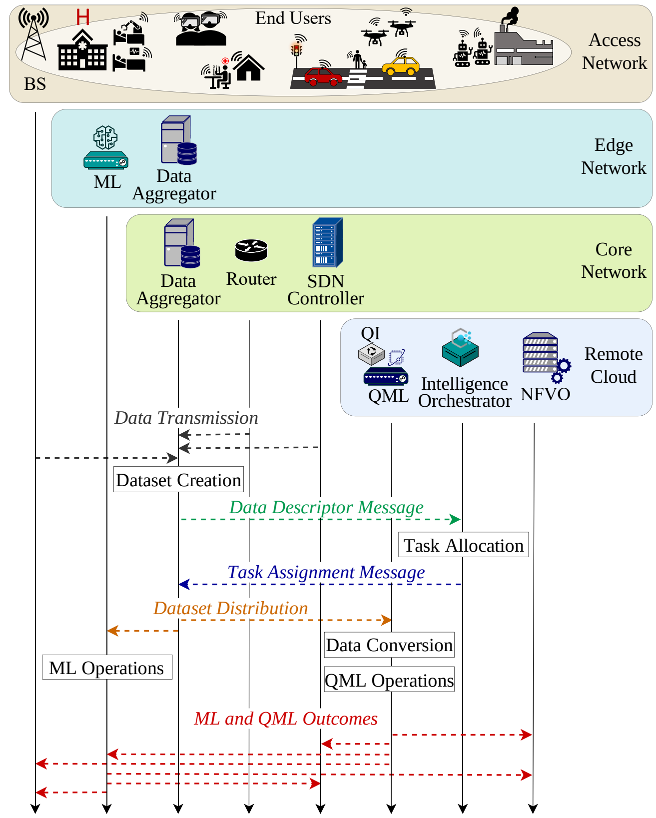

Fig. 1. QC-aided network intelligence: centralized deployment.

B. Distributed Architecture

Today, the number of available quantum computers and qubits is strongly limited by physical and economical constraints. Indeed, the centralized approach emerges as the first feasible strategy to achieve QC-aided network intelligence. Nevertheless, in a long-term vision, the scientific community envisages the deployment of geographically distributed quantum computers interconnected through the quantum Internet [14]. In this scenario, it is reasonable to consider a distributed architecture, where complex QML algorithms can be executed directly at the network edge. In this case, the service provider could plan the deployment of its own quantum computers, equipped with few qubits to mitigate the deployment cost.

More specifically, the distributed architecture, shown in Fig. 2, works as in what follows.

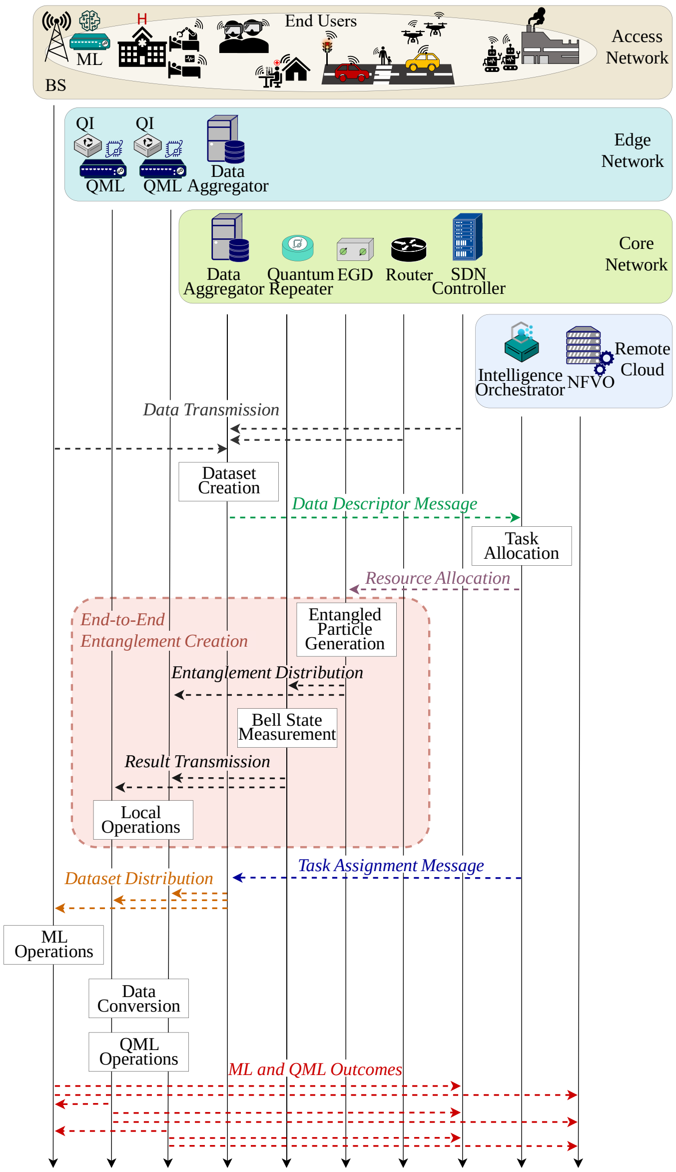

Fig. 2. QC-aided network intelligence: distributed deployment.

- Similarly to the centralized architecture, also in this case Data Aggregators collect data generated by end-users and network equipment, create specific datasets, and deliver their high-level descriptions to the Intelligence Orchestrator available in the cloud.
- The novelty introduced with the distributed architecture is that data mining tasks and big data analytics must be implemented by quantum nodes deployed at the network edge. To scale up the number of qubits and solve complex ML tasks, the Intelligence Orchestrator is responsible for creating networks of quantum nodes, namely quantum clusters, based on the required computational complexity.
- Since quantum computers involved in the same cluster must be able to transmit quantum information through teleportation protocol, they share entangled particles previously distributed by a third node, named Entanglement Generator and Distributor (EGD).
- Usually, EGD transmits entangled particles by using fiber-based or ground-satellite communications to strongly reduce attenuation effects. However, the entanglement distribution can be impaired as well as the distance between quantum computers increases, thus requiring the adoption of quantum repeaters [14]. They are able to establish a longer-distance end-to-end entanglement through the entanglement swapping. For example, considering two distant quantum computers and a quantum repeater, the entanglement swapping procedure mainly consists of four phases: (i) the EGD transmits a pair of entangled particles to the first quantum computer and the quantum repeater, (ii) the quantum repeater performs a Bell-state measurement on entangled particles shared with the two quantum computers causing the collapse of the corresponding particles, (iii) the obtained results are sent to quantum computers through classical channels, and (iv) quantum computers execute local operations to retrieve the entanglement state. Without loss of generality, this procedure can be extended for multiple quantum repeaters scenarios.
- Quantum computers receive the dataset from the Data Aggregator and convert it through QI devices before executing QML algorithms.
- The processing outcomes can be sent to different network layers to optimize the routing in the core network through SDN controllers, allocate virtual network resources through the NFVO, and optimize the resource scheduling at the base stations, as already discussed in the centralized architecture.

IV. Challenges and Future Research Directions

Both centralized and distributed architectures present advantages and disadvantages.

In the centralized architecture, the Intelligence Orchestrator has direct control of computing resources exposed by few quantum computers. Therefore, the management of these resources is simplified, and many state-of-the-art methodologies can be adopted for properly scheduling task execution. Nevertheless, the sharing of a huge amount of data from end users to the remote cloud produces very high bandwidth (and energy) consumption across the whole network. Together with possible congestion episodes, the centralized architecture also introduces higher communication latency, which should be avoided for applications with very strict deadline constraints.

The proposed distributed approach allows overcoming some issues highlighted in the centralized architecture. The number of quantum computers distributed at the network edge alleviates network congestion problems, improves scalability, and reduces communication latency. On the other hand, the distributed architecture introduces three main challenges. First, its physical implementation has to face problems related to the quantum Internet, like entanglement distribution and heterogeneity of qubits [14]. In fact, initially, the quantum

Internet will be only used to transmit quantum information in the same data center, with limited communication distance and homogeneous qubits. The proposed distributed architecture, instead, may be feasible only with very far future quantum communications supporting heterogeneous qubits and geographically distributed entanglement creation. Second, given that quantum computers involved in the distributed approach are simpler, complex ML tasks require a high cluster size. Nevertheless, it is preferred to use small clusters due to the delays and error rates introduced by the connection among remote quantum computers. Third, the whole network architecture is more complex than the centralized approach, requiring more effort from the Intelligence Orchestrator for the load balancing of computing services among clusters of quantum computers.

Looking at latency and scalability aspects, the centralized architecture is very suitable for long-running tasks, where a non-real-time learning process is allowed, and for low connectivity density applications, such as VR, AR, and robotics and Industry 4.0. The distributed architecture, instead, would be helpful to prevent problems caused by the huge amount of requests and real-time applications, becoming essential for applications such as unmanned vehicles, M-IoT, E-Health, haptic communications, and telesurgery.

On the other hand, the open issues just discussed introduce the following new research directions for the scientific community. First, the dissemination of data from Data Aggregators and Quantum Interfaces requires an optimized and energy-aware routing strategy, willing to better exploit the communication bandwidth in the core network. This goal is particularly important for the centralized architecture, where quantum computers in the remote cloud will collect all the data before executing QML algorithms. Second, to improve scalability, the number and the position of Data Aggregators can be dynamically defined through new optimization methodologies, while taking into account services details and users' statistics. Third, it is necessary to design innovative encoding techniques for a more efficient and faster transformation of classical data into quantum data, and vice-versa. Fourth, in the distributed architecture, it is important to conceive an optimal allocation scheme for distributing quantum algorithms among quantum computers, to jointly minimize the cluster size (and, in turn, the number of teleportation) and the latency due to the user-quantum computer distance. The deployment of more quantum computers should be addressed where a higher number of demands for computational tasks is expected. Fifth, fast prediction of problem complexity and fine-grained management of the computing resources can be used to optimize the load balancing between quantum and traditional computers. Sixth, it is fundamental the introduction of new security mechanisms exploiting quantum principles to protect the data integrity and confidentiality of exchanged information and guarantee fast access control. Last but not least, it is important to quantify the performance gain (and the margins of improvement of available solutions) offered by centralized QML and distributed QML with respect to classical ML approaches, by using both simulation and physical implementations.

V. Conclusions

This paper investigated the integration of Quantum Machine Learning in 6G and Beyond systems for boosting network intelligence. Design principles for centralized and distributed architecture were presented, alongside the description of logical nodes, interactions, and offered functionalities. Pros and cons of the conceived network architectures were illustrated as well to highlight future research directions to be undertaken by the scientific community to move from myth to reality.

VI. Acknowledgments

This work was supported by the PRIN project no. 2017NS9FEY entitled "Realtime Control of 5G Wireless Networks: Taming the Complexity of Future Transmission and Computation Challenges" funded by the Italian MIUR. It has been also partially supported by the Italian MIUR PON projects Pico&Pro (ARS01_01061), AGREED (ARS01_00254), FURTHER (ARS01_01283), RAFAEL (ARS01_00305).

References

[1] I. F. Akyildiz, A. Kak, and S. Nie, "6G and Beyond: The Future of Wireless Communications Systems," *IEEE Access*, vol. 8, pp. 133 995–134 030, 2020.

[2] W. Saad, M. Bennis, and M. Chen, "A Vision of 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems," *IEEE Netw.*, vol. 34, no. 3, pp. 134–142, 2020.

[3] M. Giordani, M. Polese, M. Mezzavilla, S. Rangan, and M. Zorzi, "Toward 6G Networks: Use Cases and Technologies," *IEEE Commun. Mag.*, vol. 58, no. 3, pp. 55–61, 2020.

[4] C. Zhang, P. Patras, and H. Haddadi, "Deep Learning in Mobile and Wireless Networking: A Survey," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2224–2287, 2019.

[5] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 4, pp. 3039–3071, 2019.

[6] S. J. Nawaz, S. K. Sharma, S. Wyne, M. N. Patwary, and M. Asaduzzaman, "Quantum Machine Learning for 6G Communication Networks: State-of-the-Art and Vision for the Future," *IEEE Access*, vol. 7, pp. 46 317–46 350, 2019.

[7] W. O'Quinn and S. Mao, "Quantum Machine Learning: Recent Advances and Outlook," *IEEE Wireless Commun.*, vol. 27, no. 3, pp. 126–131, 2020.

[8] T. M. Khan and A. Robles-Kelly, "Machine learning: Quantum vs classical," *IEEE Access*, vol. 8, pp. 219 275–219 294, 2020.

[9] G. Sergioli, "Quantum and Quantum-Like Machine Learning: A Note on Differences and Similarities," *Soft Computing*, vol. 24, no. 14, pp. 10 247–10 255, 2020.

[10] Y. Li, M. Tian, G. Liu, C. Peng, and L. Jiao, "Quantum Optimization and Quantum Learning: A Survey," *IEEE Access*, vol. 8, pp. 23 568–23 593, 2020.

[11] D. Sierra-Sosa, M. Telahun, and A. Elmaghraby, "TensorFlow Quantum: Impacts of Quantum State Preparation on Quantum Machine Learning Performance," *IEEE Access*, vol. 8, pp. 215 246–215 255, 2020.

[12] J. R. Bhat and S. A. AlQahtani, "6G Ecosystem: Current Status and Future Perspective," *IEEE Access*, 2021.

[13] J. F. Monserrat, D. Martin-Sacristan, F. Bouchmal, O. Carrasco, J. Flores de Valgas, and N. Cardona, "Key Technologies for the Advent of the 6G," in *2020 IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*, 2020, pp. 1–6.

[14] M. Caleffi, D. Chandra, D. Cuomo, S. Hassanpour, and A. S. Cacciapuoti, "The Rise of the Quantum Internet," *Computer*, vol. 53, no. 6, pp. 67–72, 2020.

[15] S. DiAdamo, M. Ghibaudi, and J. Cruise, "Distributed Quantum Computing and Network Control for Accelerated VQE," *IEEE Trans. on Quantum Eng.*, vol. 2, pp. 1–21, 2021.