Quantum Graph Learning for Fluid Antenna Systems: Enabling Hyper-Reliable Low-Latency Communication

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***Abstract*—Fluid antenna systems (FAS) unlock enhanced spatial adaptability by dynamically adjusting the position of their radiating ports within a compact footprint, supporting capabilities beyond the reach of conventional fixed antennas. However, this flexibility may impose real-time challenges, particularly when underlying algorithms are unable to track rapid spatial and temporal variations in adjusting continuous port reconfiguration. In response, this article proposes quantum graph learning (QGL) as a key enabler toward the goal of near-zero latency wireless operation in FAS. By representing the wireless network as a unified relational structure, QGL captures signal information and topological connections while leveraging the inherent parallelism of quantum processing. Subsequently, this article demonstrates how a FAS network can be transformed into a quantum graph representation, establishing a robust framework for more advanced QGL models. This article also identifies some pivotal research directions, charting a roadmap for QGL to drive FAS evolution in the near and long term.**

***Index Terms*—Fluid antenna systems, graph representation, quantum machine learning, hyper-reliable low-latency communication.**

I. Introduction

THE RAPID evolution of next-generation communication networks requires real-time operations, in which systems must sense, process, and respond to environmental changes within extremely tight temporal constraints. Such networks prioritize deterministic performance, such as low latency, high reliability, and precise synchronization. This focus underpins the IMT-2030 vision for hyper-reliable low-latency communication (HRLLC), a paradigm designed to deliver negligible end-to-end delay and failure rates without compromising on higher area traffic capacity or connection density. These stringent requirements are essential for time-critical applications that rely on seamless monitoring, prediction, and analysis. In such environments, the network does more than transport data, it actively engages with its environment, supporting a continuous feedback loop that integrates communication and control. Hence, real-time optimization at the antenna interface becomes a critical system-level constraint.

In recent years, driven by the rapid advancement of wireless systems, reconfigurable and movable antennas have garnered significant attention for their superior adaptability. Fluid antenna system (FAS) introduces a paradigm in which radiating elements dynamically reposition within a confined physical boundary. Functionally, FAS enables the antenna to move across multiple spatial ports, selecting optimal positions to mitigate fading, interference, and channel variation. This capability ensures reliable real-time link quality while minimizing physical footprint. Such a feature is particularly advantageous for small, resource-limited devices, where maintaining connectivity under strict energy, space, and mobility constraints is critical. Recent articles, such as [1], provide comprehensive discussions of FAS principles and applications across multiple classification frameworks. However, the flexibility offered by FAS expands the configuration space that must be explored in real time. These challenges are compounded in multi-user and multi-port settings, where inter-port and user interactions induce spatial correlations that are difficult to model analytically. Even when convex relaxation techniques are employed, computational complexity increases rapidly with the number of ports and users, as both the dimensionality of the optimization variables and the number of required iterative updates grow with the network size. This can further contribute to latency in dynamic FAS environments, depending on system configuration [2]. This observation motivates the search for structured and scalable alternatives to the existing optimization pipelines.

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Graph-based learning has recently been explored to manage the relational complexity inherent in FAS environments. By modeling FA ports, users, and environmental factors as interconnected nodes in a unified graph. This approach allows the learning model to capture not only wireless network conditions but also the topological dependencies within the environment. Specifically, graph neural network (GNN) architectures have demonstrated the ability to generalize across multiple domains while maintaining manageable computational complexity. Although graph learning-based methods demonstrate relatively low computational complexity, their performance becomes increasingly expensive to represent explicitly within classical architectures. Addressing this limitation, quantum machine learning (QML) complements GNN by exploiting quantum principles such as superposition and entanglement. Such integration is apparent in quantum graph learning (QGL), which extends GNNs' capabilities to non-Euclidean domains, where data are relational and represented as graph structures [3]. Applied to FAS, QGL captures spatial dependencies among FAS ports, user terminals, and propagation environments. Various studies, such as [4], highlight potential speedup benefits of QGL over classical machine learning counterparts.

Recent progress in both wireless communication and QGL has garnered growing research on flexible antenna systems and quantum-enabled optimization tasks. Existing studies on FAS span performance analysis, optimization frameworks, and integrated system design. For example: [5] establishes that adaptive port selection in multi-user FAS mitigates interference and delay; [6] tackles the joint optimization of antenna position and precoding under electromagnetic exposure constraints. [7] demonstrates that fluid-port mobility maintains spectral efficiency even in backscattering-based sensing environments. Concurrently, QGL is gaining traction in modeling complex relational systems. Notable advances include [8], which developed a temporal-spatial quantum graph model combining topology with time evolution using quantum-mechanical formulations, and [9], which shows that quantum circuits can accurately model particle interactions and physical dynamics over graph topologies Yet, a clear gap remains in bridging QGL with FAS, specifically in developing a unified framework. Therefore, this article focuses on the QGL application for dynamic port selection that exploits quantum-enabled relational modeling to optimize FAS for HRLLC wireless operations.

To drive this vision forward, this article charts forward-looking research directions positioning QGL as a cornerstone of HRLLC wireless applications. The main contributions are threefold as illustrated in Fig. 1: (i) We articulate the theoretical underpinnings of QGL, detailing how its graphical representation empowers model learning. Section II formalizes these foundations and maps their relevance to the flexible antenna environment. (ii) We identify near-term opportunities where QGL can augment FAS intelligence and efficiency. Section III details specific pathways to accelerate the integration of QGL into deployable wireless architectures. (iii) We assess how QGL can strengthen FAS adaptability to meet the rigorous demands of next-generation wireless networks. Developed in Section IV, this analysis examines the broader implications and potential benefits of QGL-enabled optimization. Finally, Section V concludes the article by distilling key insights and outlining prospective studies toward realizing the era of quantum-intelligent antenna systems.

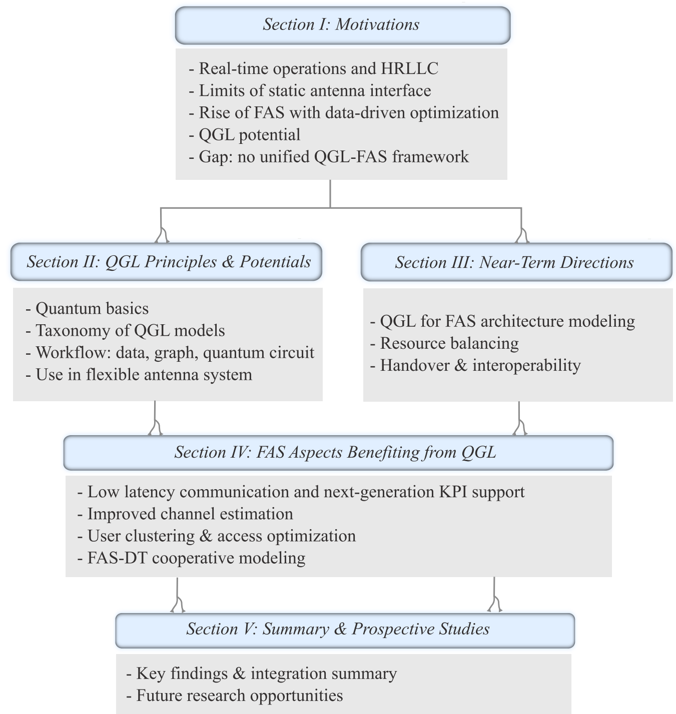


Fig. 1: Organization of this article, illustrating the logical progression from QGL foundations and workflow (Sec. II) to near-term architectural integration (Sec. III) and advanced performance optimization for next-generation FAS (Sec. IV).

II. Principles and Potentials of Quantum Graph Learning

A. Fundamentals of Quantum Graph Learning

The rapid maturation of quantum hardware has repositioned quantum computing from a theoretical novelty to a potent engine for processing high-dimensional wireless data. Unlike classical computation, which is built upon binary logic, quantum computation harnesses the physics of qubits. By exploiting quantum superposition and entanglement, qubits can exist as linear combinations of the orthonormal bases $|0\rangle$ and $|1\rangle$, establishing deep correlations across the system. These properties unlock inherent parallelism, improve representational effectiveness, and thus enable the modeling of multi-scale dependencies with significantly reduced computational complexity. QGL extends these principles to graph-structured data, where vertices and edges represent entities and their interdependencies (related to users, antennas, network elements, or channel interactions) within the environment, marking a potential advancement in QML. This allows QGL to learn simultaneously across multiple network configurations, while capturing global dependencies and nonlinear correlations often overlooked by conventional learning models.

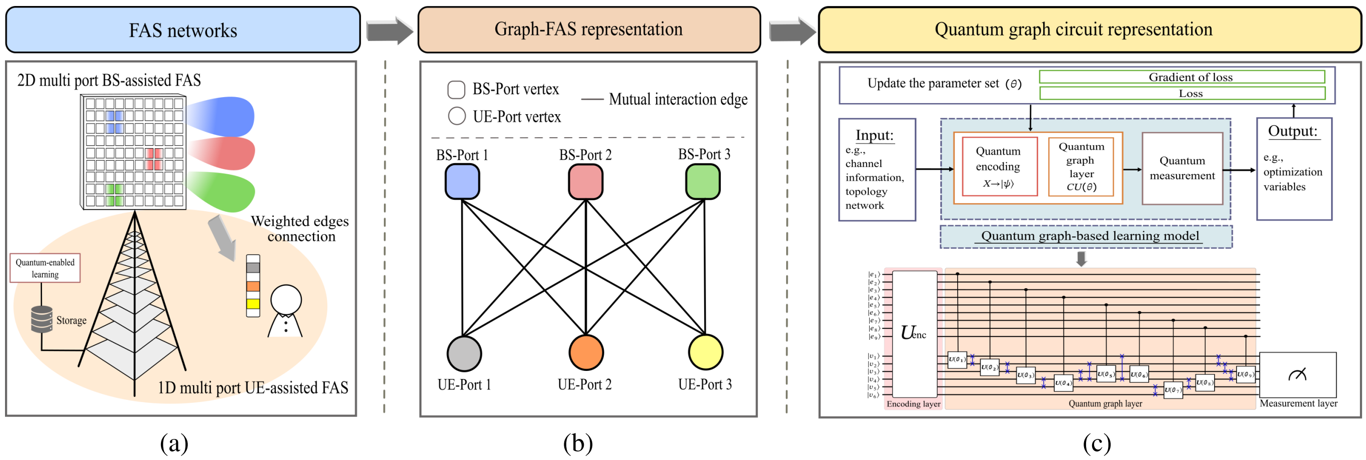


Fig. 2: Mapping (a) a FAS environment to (b) its graphical representation, and embedding it into (c) a quantum graph circuit.

B. Classifying Quantum Graph Learning

The relationship between graph theory and quantum mechanics in QGL is realized through the Hamiltonian, which encodes the graph's topology into the temporal evolution of the quantum system. Mathematically, this Hamiltonian generates the unitary operator that determines the quantum circuit, simulating information propagating across the graph. Functionally, the quantum circuit acts as a dynamic representation of the graph, with quantum states evolving according to its connections. Each vertex and edge corresponds to a qubit, with pairwise interaction representing the graph structure as energy terms that imply the system's dynamics. On near-term quantum devices in the noisy intermediate-scale quantum (NISQ) era, this can be realized effectively through parameterized unitary gates, composed of single-qubit rotations and controlled operations. The field of QGL encompasses several architectural families, based on how quantum computation is integrated into graph learning: (i) quantum-inspired models, which simulate quantum operations for ML tasks on classical hardware, involving central processing units (CPUs) or graphics processing units (GPUs); (ii) hybrid quantum-classical models, which leverage parameterized quantum circuits (PQCs) on near-term quantum processors with classical optimizers, enabling rich local feature extraction while using a classical optimizer for global learning; (iii) fully quantum models, execute all learning processes within the quantum domain, offering improved expressiveness. Collectively, these QGL-based approaches are particularly relevant for joint beamforming optimization in MIMO systems, port selection in FAS, and channel extrapolation of FA-aided systems to predict channel state information (CSI).

C. Constructing a Quantum Graph Learning Workflow

To realize the end-to-end QGL workflow, a hybrid quantum-classical framework illustrates how quantum and classical resources can be combined for efficient graph-based learning. The process, comprising three steps, begins with transforming the FAS network into a graphical representation, then formulates a QGL circuit modeling this graph, and finally computes the loss based on the output from the QGL, as illustrated in Fig. 2. The FAS network in Fig. 2 (a) consists of a set of vertices and edges, connected to each other. The vertices form a quantum set whose cardinality equals the number of entities in the FAS networks. Each vertex is represented by a dedicated qubit to enable direct mapping, thus preserving the interoperability of network entities. The edges define the connections between these vertices, representing interactions such as antenna-port correlation and signal interference, which can be expressed in an adjacency matrix $\mathcal{E}$. This matrix encodes the structure of these relationships, where each element $e_{i,j}$ characterizes the link between vertices i and j based on the physical parameters of the FAS environment. This formulation is visualized in Fig. 2 (b) and integrated into QGL as a learning model.

The QG circuit is composed of two quantum registers: the vertex register and the edge register. This circuit is organized into three primary layers as shown in Fig. 2 (c). The number of qubits required mainly depends on the FAS wireless environment. For example, with 10 ports, approximately 35 qubits would be needed to represent the graph. First, the encoding layer serves as a preprocessing stage that maps classical input data into quantum states. Since the input data originates in the classical domain, this layer transforms it into a suitable quantum representation using single-qubit rotation gates. For example, pertinent input data, e.g., received signal strength, can be embedded through controlled or single-qubit rotations onto the corresponding edge qubits, with the same approach applied to the vertex qubits. This layer typically contains no trainable parameters, serving solely to prepare the quantum registers for subsequent processing in the QG circuit. Next, the QG layer, in which the underlying graph structure is translated into the quantum states. This layer employs controlled-unitary gates with learnable parameters, denoted by ($\mathsf{CU}(\theta)$). Each gate is controlled by an edge qubit to apply a parameterized unitary operation to the corresponding vertex-qubit pair.

Since modifying or replacing entangled qubits during computation can disrupt encoded quantum information, a "swap" gate (which facilitates necessary state exchanges without collapsing the superposition) is incorporated within the $\mathsf{CU}(\theta)$ to preserve the graph topology in the FAS environment. The

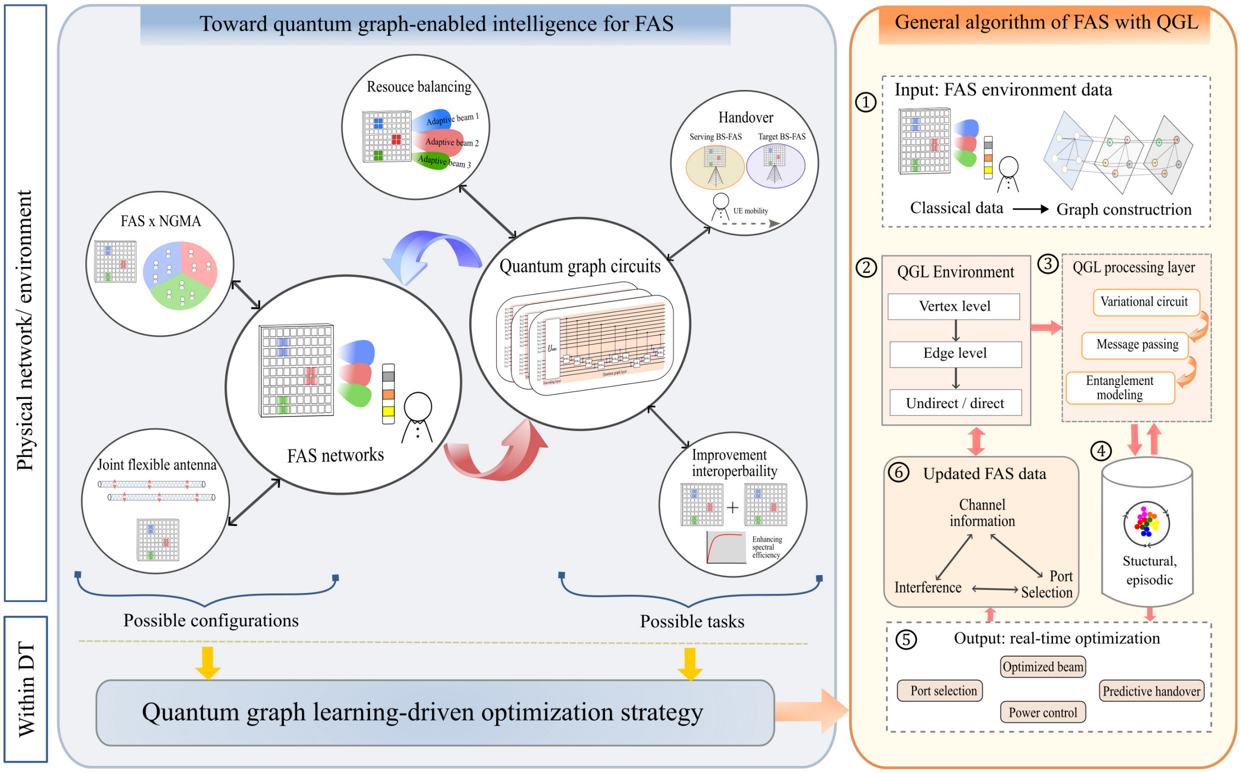


Fig. 3: Illustration of the integration between QGL and FAS within a digital twin environment. Representative FAS configurations and associated tasks are shown together with a general FAS optimization algorithm.

swap gate exchanges states between affected qubits without collapsing their superposition. In this wise, “swap” gates are used when the circuit requires reordering qubit interaction to match adjacency relationship, while preserving the encoded quantum state. Such a mechanism provides QGL with a consistent quantum representation of the wireless network environment, allowing the model to learn not only from the encoded input data but also from the information embedded within the graph topology. Following the QG layer, we proceed to the quantum measurement layer, where quantum states are projected onto the classical outcomes. These measurement outcomes correspond to the pertinent objective variable used in the learning process. In unsupervised learning, the aim is to discover correlations within the graph-encoded data without relying on labeled targets. The loss function is typically derived from a statistical similarity or divergence measure. A concrete example in wireless optimization is maximizing the achieved sum rate, which is particularly relevant in resource allocation problems. Gradients of the loss with respect to QG circuit parameters are computed using the parameter-shift rule, which enables direct gradient estimation on quantum hardware without classical backpropagation.

III. Near-Term Directions

This section investigates the immediate synergies arising from FAS-QGL cooperation. Fig. 3 summarizes the roadmap of the proposed QGL-enabled FAS framework, connecting representative network configurations with the corresponding optimization tasks, along with a generalized QGL-based FAS optimization algorithm. The discussion begins with the evolution of FAS applications for next-generation multiple access (NGMA), followed by its role in balancing resource and computational load under dynamic network conditions. It extends to the discussion of using QGL to improve handover efficiency and interoperability between FAS and static interface antennas, particularly MIMO systems.

A. *QGL for FAS and NGMA*

Emerging antenna technologies such as FAS can manipulate radiated EM field waves to produce programmable signal patterns, enabling precise control over directionality and coverage. In parallel, NGMA departs from traditional orthogonal access schemes by embracing non-orthogonal and adaptive connectivity, allowing multiple users to share spectrum intelligently under fluctuating conditions. Together, this programmed capability of FAS builds a “smart radio environment” that naturally complements NGMA’s flexible access paradigm.

Integrating QGL with FAS introduces a way to model and optimize the NGMA architectures, where the FAS networks can be seen as an undirected graph whose structures evolve with port behavior and channel condition. Suitable models for this architecture include QGNNs [10], which adopt QGL by mapping the FAS environment into a quantum-enhanced graph representation, encoding the spatial structure of port behavior and signal interactions within the quantum state space. In addition, QGNNs can explore multiple grouping and access configurations simultaneously, while graph-guided unitaries preserve the relational structure essential for NGMA.

Moreover, QGL in this setup can extend the idea of classical graph learning optimization, such as greedy coloring for channel allocation among small cells, improving spectrum efficiency in NGMA. In this respect, the QGL model alleviates the need for exhaustive combinatorial searches, allowing it to adjust the parameters and learn optimal access patterns that maintain communication quality under changing conditions. This approach aligns with the broader advancement of QGL, where similar principles have been applied to large-scale optimization and communication network design, including scenarios combining FAS with other flexible antennas.

B. QGL for Resource and Computational Load Balancing in FAS

Since resource management and computational load are precious and limited in wireless communication, balancing them is a pressing issue in FAS-enabled real-time operation. Unlike static antenna interfaces, each FA port needs to update its operating state based on channel conditions. Frequent reconfiguration, especially when the number of ports and users increases, can directly affect the interference, throughput, and computational burden. Hence, these problems are highly combinatorial and resemble minimizing the "energy-level" shaped by the interactions among the network. A quantum graph Hamiltonian learning (QGHL) aligns with this particular structure, since they encode the graph's topology directly into a Hamiltonian operator, whose quantum evolution captures the global dependencies that govern resource interactions. Once this Hamiltonian operator is constructed based on the graph structure, it is embedded into the unitary operation with variational parameters and trained so that its evolution approximates the desired, target Hamiltonian. By learning trainable, variational parameters that shape this Hamiltonian, QGNN seeks the lowest-energy configurations to yield efficient balancing of resource and computational load across distributed FA ports. The Hamiltonian can further emphasize a specific target, such as minimizing mutual interference, equalizing computational load across ports, or preserving performance fairness among user terminals. In contrast with the classical models that approximate over vast decision spaces, this QGHL-based approach accelerates the search for near-optimal solutions and reduces the reliance on iterative local heuristics, which may become unstable in rapidly changing FAS environments. The potential of QGHL is further emphasized in related developments, such as [11], highlighting its suitability for learning and optimizing non-Euclidean graph data structures, aligned with the optimization problems in FAS systems.

C. QGL for Improved Handover Interoperability Between FAS and MIMO Systems

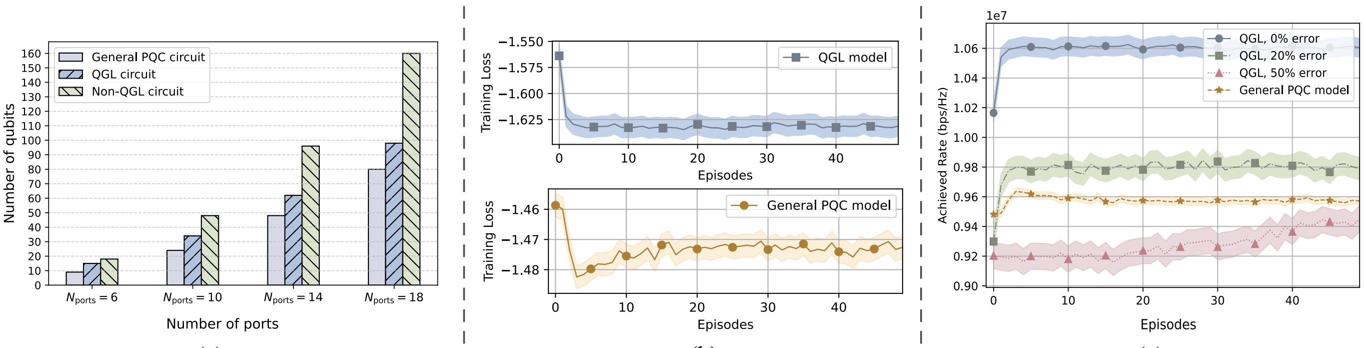
In current static cellular networks, handover remains a problem, particularly as network deployments grow denser and more complex. Conventional MIMO systems often operate within fixed coverage regions and cell boundaries, simplifying the handover decision process. FAS-equipped BSs, however, provide dynamic, programmable coverage footprints that respond to instantaneous channel conditions. While this flexibility enhances adaptability, it complicates mobility management, increases CSI acquisition overhead, and makes user association less predictable. As a result, handover decisions need to reflect not only user movement but also the shifting coverage zones induced by FA port reconfiguration. A promising direction is the adoption of quantum graph-walking learning (QGWL), following a concept similar to that explored in [12], where the handover process is modeled as the evolution of a quantum walker over a unified graph capturing FAS and static-MIMO nodes.

In this context, the constructed graph may incorporate FA ports, static-MIMO nodes, and candidate neighboring base stations (BSs) as vertices, allowing the quantum walk to evaluate transition stability across intra- and inter-cell paths. The graph is then embedded into the quantum state space, where a quantum walk is carried out from the user's current serving point. Using this approach, the quantum walker appears in all possible handover paths in the topology. Each vertex receives a probability amplitude that reflects the stability that can be reached from the current serving point. The searching process then ranks candidate serving areas according to vertex connectivity strength. This enables the BS to assess interoperability between FAS and conventional MIMO systems, ensuring that port reconfiguration strategies remain compatible with static-MIMO operation. When the FAS activates a new port or the user's trajectory shifts, both the graph topology and the quantum state change, prompting the walk dynamics to adjust immediately in real-time. Exploiting QGWL's ability to evaluate multiple handover candidates at once, the BS can identify the transition paths that minimize the risk of service interruption and mitigate the handover ping-pong effect.

IV. Aspects of FAS Benefiting from Quantum Graph Learning

A. Leveraging FAS to Satisfy HRLLC Requirements

Aligning FAS with the rigorous demands of HRLLC requires a paradigm shift in optimization speed and accuracy. Unlike classical models that rely on sequential evaluation, QGL leverages quantum superposition to interrogate multiple candidate antenna configurations concurrently. This inherent parallelism substantially reduces the latency required to identify reliability-preserving port positions. Furthermore, the high expressivity of entangled quantum states empowers QGL to capture intricate spatio-temporal dependencies (ranging from interference correlations to rapid fading) that, if unaccounted for, will destabilize HRLLC links. Structurally, the variational nature of QGL allows for rapid parameter updates in response to abrupt environmental changes, safeguarding latency targets. Crucially, specific HRLLC metrics, such as tail-distribution failure probabilities and worst-case SINR, are directly embedded into the learning workflow's loss function, steering the optimization explicitly toward ultra-high reliability. In the QGL representation, the wireless environment is modeled as a graph, where vertices may represent network entities such as FA ports, BS, or users, while edges may capture their



(a) (b) (c)

Fig. 4: Comparison of (a) quantum resource requirements, (b) training behavior, and (c) achieved throughput demonstrates that the QGL framework delivers efficient scaling and improved performance within a FAS network.

mutual interactions (for example, channel information, channel gains, or interference). While the required number of qubits naturally increases with the number of ports and users (as these entities determine the size of the vertex and edge registers in the QGL circuit), recent advances in quantum hardware show steady growth in available logical qubits and improved circuit reliability. These trends indicate QGL's potential to facilitate FAS optimization as quantum processors mature.

B. Parametric Channel Estimation in FAS

Recent findings [13] highlight a fundamental challenge in FAS channel estimation: the breakdown of classical sampling theory. This is not due to the estimation itself, but because of the sampling structure dictated by the FAS hardware. As each FA port only observes the electromagnetic field over a finite region, the channel is effectively no longer band-limited, causing spectral leakage and rendering the conventional half-wavelength sampling criterion insufficient. Reliable channel reconstruction thus requires a minimum number of estimated channels, which drives computational cost as the FA surface expands. The QGL framework helps alleviate this burden, stemming from dense sampling requirements, by learning the underlying structure that governs channel variations across the surface. Its learning objective is designed such that the reconstructed channel remains consistent with sampled-port observations, while remaining aligned with the spatial relationships encoded in the graph. QGL thus supports accurate reconstruction and stable performance across the FA ports, even with a limited number of sampled ports.

C. User Clustering in FAS

As highlighted in [14], a key challenge in FAS-enabled multiple access is coordinating multiple users to remain compatible under shared port configurations in both the BS and user equipment (UE). Activating a set of BS ports can affect the interference seen by all users, and determining the suitable BS requires balancing performance indicators, not only for the intended user but also for the other users in the network. Classical optimization approaches, which treat port selection and user clustering separately, may overlook the joint dependencies and become impractical as the number of users increases. QGL addresses this aspect by learning the structure of the multi-user system directly. Rather than clustering based on instantaneous channels, QGL aggregates representative information from all users into a unified learning workflow. This workflow produces decisions regarding which users remain consistently distinguishable under BS-port switching and which user combinations repeatedly trigger interference. Consequently, the QGL's objective is formulated to reward user clustering that preserves low interference across multiple BS-port pairs, while penalizing clustering combinations that fail when the port configuration changes. In addition, QGL can be designed to remain effective even when BS-port switching occurs extremely fast, e.g., on the order of microseconds, by preparing its graph representation during an offline phase. Once the learning model is trained, the online phase becomes computationally less complex, allowing the estimation of port assignment and multi-user clustering to approach real-time performance.

D. Joint FAS-DT Cooperative Graph Modeling

The integration of FAS with DT transforms the network into a sophisticated cyber-physical system, introducing a new tier of system intelligence. In this joint architecture, the digital representation of the wireless network, such as user mobility and network condition, is continuously synchronized with physical environment, as discussed in [15]. The physical FAS entities and their corresponding DTs evolve on different timescales, each conveying different information at any particular time frame. Bridging this gap requires a coordination strategy that can harmonize real-time physical changes with predictive DT insights. Within this context, QGL provides a natural mechanism to link physical FAS networks with their digital representations, as illustrated in Fig. 3, where DT information can be incorporated into the graph-based optimization process. Since QGL models the networks as graphs, each digital representation can be treated as a "virtual" version within the digital world. By jointly evaluating both representations, QGL can detect when the predictions made by DT are still trustworthy and when they begin to diverge from real-time behavior. Predictions that align with the current FAS state are reinforced, while those showing misalignment trigger adjustments to the port decisions. This allows FAS to be guided by both immediate physical information and DT's predictive insight, thereby improving reliability and preventing unexpected interference.

To validate the proposed framework, Fig. 4 presents a concrete performance analysis of QGL within a representative FAS setting. All experiments are carried out using the Qiskit Aer Simulator with a shot-based simulation model, where each circuit evaluation uses 1024 measurement shots. 'Non-QGL' refers to a PQC that directly encodes each FA port channel interaction into qubits without exploiting graph structure. First, regarding resource scalability (Fig. 4 (a)), the required qubit count naturally scales with the port density. Crucially, QGL occupies a strategic middle ground, where it requires significantly fewer qubits than the naive 'Non-QGL' approach (which inefficiently maps qubits separately) while maintaining growth comparable to general PQCs. For the performance evaluation in Figs. 4(b) and (c), a FAS configuration with two fixed BS antennas and three FA ports at the user terminal is considered. Second, in terms of learning dynamics (Fig. 4 (b)), QGL demonstrates superior convergence velocity and reduced variance compared to the general PQC baseline. This stability confirms that encoding the graph topology provides a strong inductive bias, guiding the optimizer through the solution space more effectively. Finally, Fig. 4 (c) evaluates robustness against channel uncertainty. Here, quantum noise is modeled using a bit-flip error channel applied to qubits with varying error probabilities. Even under severe conditions (up to a 50% chance that quantum error affected the system), the QGL-assisted FAS maintains high spectral efficiency, with only moderate degradation, and performance remains competitive despite the noise.

These observations corroborate broader trends in quantum machine learning, particularly studies demonstrating the efficacy of embedding topological priors directly into quantum models. Structured quantum circuits, particularly walk-based and message-passing approaches, have been shown to offer similar benefits in stability and parameter efficiency when the underlying physical topology can be expressed as a structured graph. In addition, graph-embedded quantum learning has been reported to improve convergence and robustness even in unstructured variational circuits [11]. Collectively, these findings confirm that QGL's structural isomorphism, where the circuit mirrors the antenna network, allows it to scale gracefully and withstand dynamic spatial reconfiguration.

V. Summary and Prospective Studies

This article establishes QGL as a promising approach for the intelligence and adaptability required by FAS. We have systematically demonstrated the integration of FAS within a quantum graph framework, mapping near-term opportunities across access, resource, and mobility domains, while quantifying the performance gains that strengthen FAS capabilities. Although QGL-enabled FAS is nascent, this paradigm lays the groundwork for real-time, resilient, and structure-aware operation under strict HRLLC constraints. Looking forward, a promising frontier lies in the heterogeneous integration of FAS with other reconfigurable architectures, such as pinching antenna systems (PASS). Specifically, deploying PASS at the BS to serve FA-equipped user terminals may offer benefits such as adapting to blockages and maintaining strong line-of-sight links. Such an opportunity also opens the opportunity of cooperative control among different reconfigurable antennas. In particular, under severe blockage conditions, two or more pinching antenna waveguides can jointly transmit to an FA-equipped user terminal, ensuring link reliability.

Nevertheless, realizing this vision requires navigating practical challenges stemming from current quantum hardware limitations (e.g., NISQ) and the computational demands of rapid port reconfiguration. Current quantum computing platforms are constrained by a limited qubit count, circuit depth, and noise tolerance, while the dynamic nature of FAS demands concurrent graph updates. Addressing this challenge calls for maintaining a consistent quantum encoding as FA ports adjust their positions, which can be addressed via an adaptive graph-update mechanism that preserves relational structure with minimal circuit and processing resources. From a long-term perspective, an intriguing direction involves developing a quantum-native representation of wireless environments, allowing QGL models to predict, extract, secure, and optimize FAS behavior at the quantum level. Beyond improving reliability and reducing latency, such integration may also facilitate secure coordination among distributed network entities that exchange control information for dynamic antenna configuration. Early progress along this path is apparent in quantum secure direct communication, where quantum information exchange mechanisms facilitate closed-loop quantum information transfer among network vertices. Such advances would allow QGL and FAS to evolve together: improved quantum models guide more capable FAS technology, whereas the resulting wireless interactions provide richer structure for subsequent QGL development, which ultimately enables adaptive, resilient, and real-time operation under HRLLC constraints.

Acknowledgments

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