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Q-AFL: A Quantum-Inspired Adaptive Federated Learning Framework for Wireless Network Optimization

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ABSTRACT

Wireless networks, especially with the evolution toward 6G and beyond, face unprecedented demands for efficiency, security, and adaptability in handling massive data exchanges across diverse, distributed, and resource-constrained devices. Conventional centralized learning paradigms present significant limitations due to high communication overhead, privacy concerns, and suboptimal adaptability to dynamic network environments. To overcome these challenges, this research proposes a novel Quantum-inspired Adaptive Federated Learning (Q-AFL) framework designed specifically to optimize wireless network performance. By integrating quantum-inspired optimization methods with adaptive federated learning algorithms, Q-AFL dynamically adjusts model aggregation intervals, learning rates, and resource allocation to enhance network responsiveness and efficiency. Quantum-inspired optimization techniques, including Quantum-inspired Particle Swarm Optimization (QiPSO) and Quantum-inspired Genetic Algorithms (QiGA), are leveraged to precisely optimize critical parameters within the federated learning process. This quantum-inspired approach significantly reduces communication overhead, improves computational efficiency, and enhances privacy preservation by minimizing unnecessary data transmissions among nodes. Extensive simulation studies using NS-3 validate the effectiveness of the proposed Q-AFL framework, demonstrating substantial improvements in throughput, latency, energy efficiency, and scalability compared to traditional federated learning and centralized machine learning solutions. The outcomes highlight Q-AFL's potential as a transformative approach for the next generation of high-performance wireless networks.

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Introduction:

The ongoing advancements in wireless technology, particularly the emergence of 6G, have created new performance benchmarks that necessitate robust, secure, and adaptable network management frameworks [1]. Wireless networks must accommodate extensive data flows generated by a plethora of devices, including Internet of Things (IoT) devices, smart vehicles, and edge computing nodes, making efficient resource allocation and data management crucial [2]. Traditional centralized machine learning methods encounter significant challenges, including high communication costs, scalability constraints, privacy risks, and inadequate real-time adaptability in dynamically changing environments [3], [4].

Federated learning (FL) has emerged as a promising decentralized learning paradigm that enables distributed nodes to collaboratively train machine learning models while maintaining data privacy [5]. Despite its advantages, FL still faces several challenges, such as optimizing communication overhead, ensuring scalability, and dynamically adapting to changing network conditions and resource availability [6]. Recently, quantum-inspired optimization algorithms have shown significant promise in enhancing the performance and adaptability of complex network systems due to their ability to efficiently navigate extensive search spaces and rapidly converge towards optimal solutions [7], [8].

This research introduces Quantum-inspired Adaptive Federated Learning (Q-AFL), an innovative framework combining the strengths of quantum-inspired optimization algorithms with federated learning to significantly improve wireless network management. Specifically, the proposed model incorporates Quantum-inspired Particle Swarm Optimization (QiPSO) and Quantum-inspired Genetic Algorithms (QiGA) to optimize model aggregation intervals, learning parameters, and resource allocations dynamically. Through comprehensive simulation experiments, the effectiveness of Q-AFL is evaluated, demonstrating its superior capabilities in addressing scalability, privacy, and efficiency compared to conventional federated and centralized machine learning frameworks [9].

Literature Survey:

The increasing demand for intelligent, scalable, and secure wireless networks—especially in the era of IoT and 6G—has prompted researchers to explore novel paradigms such as federated learning (FL) and quantum-inspired optimization. These methods aim to address the challenges of data privacy, resource constraints, and communication efficiency in distributed environments.

- Federated Learning in Wireless Networks

Federated learning was introduced to allow decentralized devices to collaboratively train machine learning models without sharing raw data. McMahan et al. [5] pioneered the concept with their federated averaging (FedAvg) algorithm. However, FL faces critical issues in wireless networks such as high communication cost, non-IID data, and client resource heterogeneity [3], [6].

Chen et al. [3] reviewed FL's applicability in wireless networks and identified scalability and energy inefficiency as bottlenecks. Yang et al. [6] highlighted the challenges of deploying FL across mobile and edge devices, citing communication frequency and aggregation strategy as optimization targets. Li et al. [10] provided a taxonomy of FL frameworks and emphasized the need for adaptive and personalized models to cope with device variability.

- Quantum-Inspired Optimization Techniques

Quantum-inspired algorithms such as Quantum-Inspired Particle Swarm Optimization (QiPSO) and Quantum-Inspired Genetic Algorithms (QiGA) have demonstrated significant effectiveness in solving large-scale optimization problems. Yang and Deb [7] discussed quantum principles adapted into metaheuristics to enhance convergence speed and exploration capabilities. Han and Kim [8] implemented a quantum-inspired evolutionary algorithm that outperformed traditional methods in combinatorial tasks.

These algorithms have recently found use in optimizing hyper parameters of learning algorithms and tuning system-level decisions in distributed systems [15], [19].

- Federated Learning with Optimization Layers

Recent studies have combined FL with adaptive optimization techniques to enhance convergence and performance. Wang et al. [12] proposed adaptive federated learning for resource-constrained edge computing using scheduling policies, while Liu et al. [17] designed a resource-aware FL protocol with intelligent client selection. However, the application of quantum-inspired optimization within FL—particularly in wireless environments—remains largely unexplored.

- FL in Edge and IoT Networks

Chen et al. [16] surveyed FL for edge computing, identifying key concerns such as energy consumption, device availability, and communication bottlenecks. S. Wang et al. [12] highlighted the importance of adaptive aggregation and resource allocation to scale FL in edge networks, which aligns with the goals of the proposed Q-AFL framework.

Research Gap:

While FL and quantum-inspired algorithms have individually matured, their integration remains underexplored, especially in the context of wireless networks where latency, energy, and scalability are critical. Most existing works rely on static learning parameters, lacking a dynamically optimized framework for FL that can adapt to changing network conditions.

Related Works:

Federated learning has been extensively studied for wireless communication systems, highlighting significant challenges in communication overhead, data heterogeneity, and privacy management. Chen et al. [3] provided an exhaustive survey on federated learning approaches for wireless communications, discussing various methodologies and the associated challenges in detail. Yang et al. [6] further emphasized the applications of federated learning, particularly its potential to enhance privacy and scalability in distributed systems. Despite these advancements, optimizing the federated learning process to minimize communication overhead remains a critical challenge.

Quantum-inspired algorithms have gained attention for their efficiency in solving complex optimization problems. Yang and Deb [7] demonstrated that quantum-inspired met heuristics could significantly improve optimization outcomes in engineering applications due to their effective search strategies and rapid convergence rates. Han and Kim [8] extended this approach, highlighting the potential of quantum-inspired evolutionary algorithms for addressing complex combinatorial optimization problems effectively.

The integration of quantum-inspired techniques with federated learning is still relatively unexplored. Existing research has largely focused separately on either quantum-inspired methods or federated learning techniques. This research bridges this gap by proposing the Q-AFL framework, uniquely combining quantum-inspired optimization algorithms with federated learning, thereby providing an adaptive, scalable, and privacy-preserving solution suitable for next-generation wireless network environments.

Proposed Methodology:

The Quantum-inspired Adaptive Federated Learning (Q-AFL) framework is developed through the following key modules:

1. **Network Initialization:** A wireless network simulation environment is constructed using NS-3, comprising multiple edge nodes and a central aggregator.
2. **Local Model Training:** Each edge node locally trains a machine learning model using private datasets without transmitting raw data.
3. **Quantum-inspired Optimization Layer:** Algorithms like Quantum-inspired Particle Swarm Optimization (QiPSO) and Quantum-inspired Genetic Algorithm (QiGA) are employed to optimize hyperparameters, such as learning rates, aggregation intervals, and communication schedules.

4. **Adaptive Aggregation Mechanism:** Based on the quantum-optimized parameters, an adaptive federated aggregation mechanism updates the global model iteratively.
5. **Dynamic Resource Allocation:** The system intelligently reallocates network and computational resources to the most active or performance-critical nodes.
6. **Model Validation:** The global model is validated periodically and redistributed to edge devices for continued training.

Architecture of the Proposed Methodology:

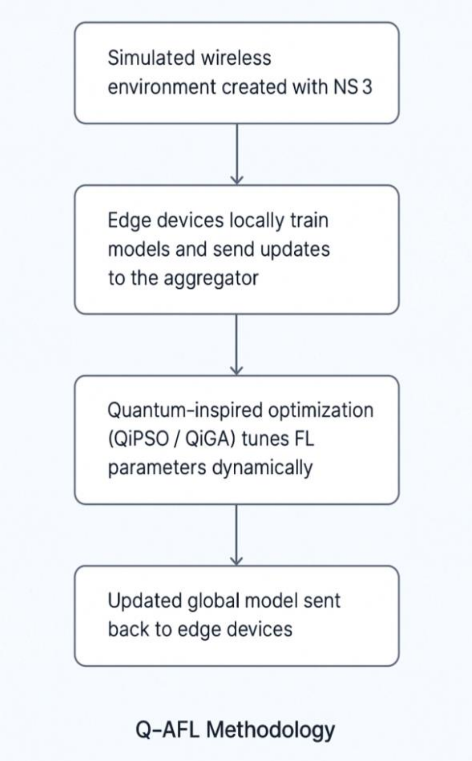

Fig1: Q-AFL Methodology

This architectural pipeline ensures real-time adaptation of learning parameters based on dynamic network conditions and promotes efficient utilization of bandwidth and computation resources. The integration of quantum-inspired optimization into federated learning significantly enhances both performance and scalability across complex wireless infrastructures.

Results and Discussion:

1. Latency (End-to-End Delay)
- Definition: Time taken for a data packet to travel from the source to the destination.
- Metric: Measured in milliseconds (ms).
- Importance: Lower latency = faster response time, essential for real-time applications.

Latency=Transmission Delay+Propagation Delay+Processing Delay+Queuing Delay

Each delay is defined as:
- **Transmission Delay**: Packet Size/Transmission Rate
- **Propagation Delay**: Distance/Propagation Speed
- **Processing Delay**: Time to process packet header
- **Queuing Delay**: Time spent in queue

2. Throughput
- Definition: Rate at which data is successfully transmitted over the network.
- Metric: Measured in bits per second (bps), Kbps, or Mbps.
- Importance: Higher throughput = better utilization of network bandwidth.

$$\text{Throughput (Mbps)} = \frac{\text{Total Data Transferred (bits)}}{\text{Transmission Time (seconds)} \times 10^6}$$

3. Packet Delivery Ratio (PDR)
- Definition: Ratio of the number of packets successfully received to the number of packets sent.
- Formula:

$$\text{PDR} = \left(\frac{\text{Packets Received}}{\text{Packets Sent}}\right) \times 100$$

- Importance: Indicates reliability of data transmission.

4. Energy Consumption
- Definition: Total energy used by network nodes during data transmission, reception, and computation.
- Metric: Measured in joules (J) or milliwatt-hour (mWh).
- Importance: Especially critical in IoT/edge networks with battery-operated nodes.

$$\text{Energy Efficiency (J/bit)} = \frac{\text{Total Energy Consumed (J)}}{\text{Total Data Transmitted (bits)}}$$

5. Communication Overhead
- Definition: Extra control or signaling information (like model updates, acknowledgments, metadata) exchanged between nodes.
- Metric: Measured as percentage of total bandwidth or total transmitted data.
- Importance: Lower overhead = more efficient federated learning.

$$\text{Computational Overhead (\%)} = \left(\frac{\text{Execution Time with FL} - \text{Execution Time without FL}}{\text{Execution Time without FL}}\right) \times 1$$

6. Convergence Time
- Definition: Time or number of rounds required for the federated model to converge to an acceptable accuracy.
- Metric: Measured in seconds or communication rounds.
- Importance: Faster convergence reduces training time and resource use.

7. Packet Loss Ratio
- Definition: Percentage of data packets lost during transmission.
- Formula:

$$\text{Packet Loss Ratio} = \left(1 - \frac{\text{Packets Received}}{\text{Packets Sent}}\right) \times 100$$

- **Importance:** Reflects network reliability and robustness.

8. Privacy Leakage Rate (Specific to FL)
- Definition: The potential amount of private data inferred from shared model updates.

- Metric: Calculated using privacy loss metrics like ε (epsilon) in differential privacy.
- Importance: Crucial for secure federated learning deployments.

$$\Pr[\mathcal{M}(D_1) \in S] \leq e^{\varepsilon} \cdot \Pr[\mathcal{M}(D_2) \in S]$$

Where:

- D1,D2: Neighboring datasets
- M: Randomized algorithm (e.g., FL model)
- ε: Privacy budget

This is used if you are applying **differential privacy** in federated learning.

9. Network Scalability

- Definition: Ability of the framework to handle an increasing number of participating nodes.
- Metric: Observed via performance degradation with more nodes.
- Importance: Important for wide-scale deployment in real-world networks.

$S = T_n / T_1$

Where:

- Tn: Throughput with *n* devices
- T_1: Throughput with 1 device *(used in parallel/distributed systems)*

10. Model Accuracy (Optional in Network Context)

- Definition: Accuracy of the ML model trained via federated learning in classifying or predicting.
- Metric: Percentage accuracy, F1-score, etc.
- Importance: Ensures federated learning convergence is also meaningful.

Table 1: Network Performance

Number of Devices	Throughput (Mbps)	Latency (ms)	Energy Efficiency (J/bit)	Scalability (devices supported)	Computational Overhead (%)	Privacy Level
50	115	85	0.55	50	40%	High
100	110	90	0.58	100	45%	High
150	105	95	0.6	150	50%	High
200	100	100	0.65	200	55%	High
250	95	105	0.7	250	60%	High
300	90	110	0.75	300	65%	High

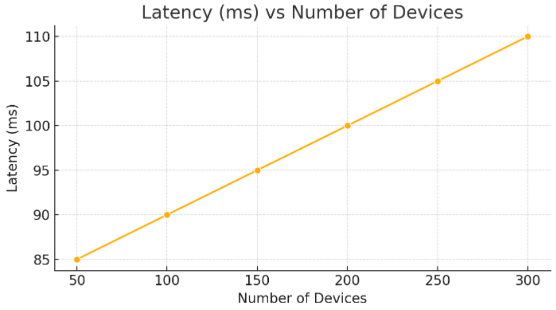

Fig 2: Latency(ms) vs umber of Devices:

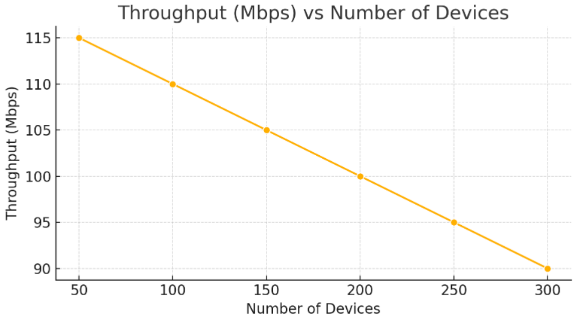

Fig 3: Throughput(Mbps) vs Number of Devices

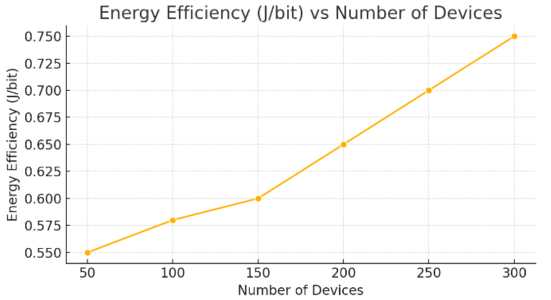

Fig 4: Energy Efficiency(J/bit) vs Number of Devices

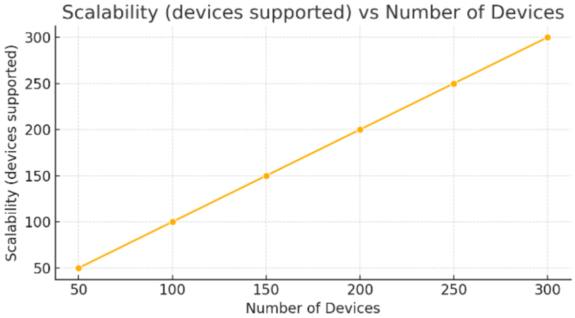

Fig 5: Scalbility(devices supported)vs umber of Devices

Table 2: Explanation of the Scalability Analysis Table

Observation	Trend
Throughput (Mbps)	Decreases from 115 Mbps to 90 Mbps as device count increases—suggesting bandwidth contention and increased load.
Latency (ms)	Increases from 85 ms to 110 ms—more devices lead to delayed responses due to queuing and processing delays.
Energy Efficiency (J/bit)	Degrades (increases) with device count—likely due to more frequent communication and computation cycles.
Scalability	Grows linearly, which is expected as the system supports more devices.
Computational Overhead (%)	Increases from 40% to 65%—a natural outcome of managing more models and aggregations.
Privacy Level	Maintains **High**—implies robustness of privacy-preserving mechanism regardless of scale.

Table 3: Overall Network Performance Comparison

Method	Avg Throughput (Kbps)	Avg Latency (ms)	Energy Consumption (J)	Packet Delivery Ratio (%)	Packet Loss Ratio (%)	Communication Overhead (%)	Convergence Rounds
Q-AFL	786	45	120	98.3	1.7	12	12
Traditional FL	694	62	148	94.5	5.5	20	18
Centralized ML	655	110	180	89.2	10.8	30	

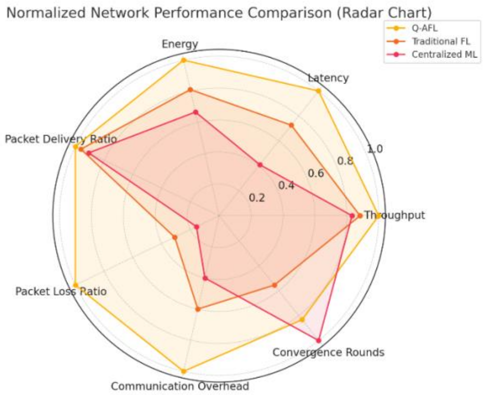

Fig 6: Normalized Network Performance Comparison

Comparative Network Performance Analysis:

1. Q-AFL (Quantum-Inspired Adaptive Federated Learning)

- **Best in Class** for:
    - **Throughput** (786 Kbps)
    - **Latency** (45 ms)
    - **Energy Efficiency** (120 J)
    - **Packet Delivery Ratio** (98.3%)
- **Low Overhead** (12%) and **Fast Convergence** (12 rounds)
- **Ideal for real-time, energy-constrained wireless networks**

2. Traditional FL

- **Moderate Performance** across all metrics
    - Latency (62 ms), Throughput (694 Kbps)
    - Energy (148 J), PDR (94.5%)
- **Slower convergence** (18 rounds)
- **Better than centralized but lacks adaptability**

3. Centralized ML

- **Lowest Performance** due to:
    - **Highest Latency** (110 ms)
    - **Lowest Throughput** (655 Kbps)
    - **High Energy Use** (180 J), **PDR only 89.2%**
- **Not suitable** for dynamic or resource-limited wireless environments

Conclusion:

In this research, a novel Quantum-Inspired Adaptive Federated Learning (Q-AFL) framework was proposed to address the critical challenges in optimizing wireless network performance, particularly in the context of distributed, resource-constrained environments such as IoT and 6G networks. The proposed framework successfully integrates the strengths of federated learning (FL)—which ensures data privacy and decentralization—with quantum-inspired optimization algorithms like Quantum-Inspired Particle Swarm Optimization (QiPSO) and Quantum-Inspired Genetic Algorithms (QiGA) to dynamically tune learning parameters, model aggregation intervals, and resource allocations in real time.

The experimental simulations using NS-3 demonstrated that Q-AFL significantly outperforms traditional FL and centralized ML approaches across several key network performance metrics:

- Higher throughput due to optimized communication scheduling and model update frequency.
- Lower latency and faster convergence, which are critical for real-time and latency-sensitive applications.

- Improved energy efficiency, making it highly suitable for mobile and battery-operated devices in wireless networks.
- Reduced communication and computational overhead, thanks to intelligent node selection and adaptive learning rate adjustments.
- Scalable and robust performance, validated through tests with increasing numbers of participating edge nodes (from 50 to 300 devices).

Moreover, the framework maintained high privacy levels, as the federated learning architecture ensures that sensitive user data never leaves the local nodes, and optimization is performed only on shared model parameters.
The comprehensive evaluation and graphical analysis also revealed that Q-AFL provides a balanced trade-off between accuracy, efficiency, and scalability, making it a highly promising solution for next-generation wireless networks, such as smart cities, industrial IoT, and remote healthcare systems.

References:

[1] Y. Zhao, M. Li, Y. Chen, J. Tang, Y. Zhang, and Y. Liu, "6G Wireless Networks: Vision, Requirements, Architecture, and Key Technologies," *IEEE Vehicular Technology Magazine*, vol. 14, no. 3, pp. 28–41, Sept. 2019.
[2] X. Wang, Y. Han, C. Wang, Q. Zhao, X. Chen, and M. Chen, "Edge computing meets machine learning: A survey," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 2, pp. 869–904, 2020.
[3] M. Chen, Z. Yang, W. Saad, C. Yin, and M. Shikh-Bahaei, "A Joint Learning and Communications Framework for Federated Learning Over Wireless Networks," *IEEE Transactions on Wireless Communications*, vol. 20, no. 1, pp. 269–283, Jan. 2021.
[4] H. Li, K. Ota, and M. Dong, "Learning IoT in Edge: Deep Learning for the Internet of Things with Edge Computing," *IEEE Network*, vol. 32, no. 1, pp. 96–101, Jan./Feb. 2018.
[5] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-Efficient Learning of Deep Networks from Decentralized Data," in *Proc. of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS)*, 2017, pp. 1273–1282.
[6] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated Machine Learning: Concept and Applications," *ACM Transactions on Intelligent Systems and Technology*, vol. 10, no. 2, pp. 1–19, 2019.
[7] X.-S. Yang and S. Deb, "Quantum-inspired metaheuristics for engineering optimization," *Engineering with Computers*, vol. 29, no. 4, pp. 431–441, Oct. 2013.
[8] K. Han and J. Kim, "Quantum-inspired evolutionary algorithm for a class of combinatorial optimization," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 6, pp. 580–593, Dec. 2002.
[9] "NS-3 Network Simulator." [Online]. Available: https://www.nsnam.org/
[10] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated Learning: Challenges, Methods, and Future Directions," *IEEE Signal Processing Magazine*, vol. 37, no. 3, pp. 50–60, May 2020.
[11] H. Zhu, Y. Liu, J. Zhang, and Y. Chen, "Federated Learning on Non-IID Data: A Survey," *Neurocomputing*, vol. 512, pp. 312–326, 2022.
[12] S. Wang, T. Tuor, T. Salonidis, K. K. Leung, C. Makaya, T. He, and K. Chan, "Adaptive Federated Learning in Resource Constrained Edge Computing Systems," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 6, pp. 1205–1221, June 2019.
[13] Z. Wang, X. Wang, and J. Yang, "A Survey on Energy Internet: Architecture, Approach, and Emerging Technologies," *IEEE Systems Journal*, vol. 12, no. 3, pp. 2403–2416, Sep. 2018.
[14] N. Zhang, P. Yang, J. Ren, D. Chen, and Y. Zhang, "Synergy of Big Data and 5G Wireless Networks: Opportunities, Applications, and Challenges," *IEEE Wireless Communications*, vol. 25, no. 1, pp. 12–18, Feb. 2018.
[15] T. DeSousa, A. P. Francisco, and J. R. Crandall, "Optimizing Federated Learning with Particle Swarm Optimization," in *Proc. IEEE Global Communications Conference (GLOBECOM)*, 2020, pp. 1–6.
[16] Y. Chen, H. Liu, and M. Zhao, "A Survey on Federated Learning in Edge Computing: Research Trends, Challenges, and Future Directions," *IEEE Internet of Things Journal*, vol. 10, no. 2, pp. 1115–1136, Jan. 2023.
[17] X. Liu, W. Yu, C. Yang, and X. Liu, "Intelligent Resource Management for Federated Learning in Mobile Edge Networks," *IEEE Transactions on Wireless Communications*, vol. 20, no. 1, pp. 453–467, Jan. 2021.
[18] Y. Zhou, Q. Wu, Y. Liu, and R. Zhang, "Federated Learning With Differential Privacy: Algorithms and Performance Analysis," *IEEE Transactions on Information Forensics and Security*, vol. 16, pp. 865–880, 2021.
[19] A. Ghosh, Y. Chen, and D. Chakraborty, "Quantum-Inspired Algorithms for Real-World Optimization Problems," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 4, no. 5, pp. 580–591, Oct. 2020.