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Quantum Intelligence in Beyond 5G Networks: Current Progress, and Open Avenues

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Abstract: The emergence of fifth-generation (5G) wireless technologies leads to enlarging network complexity as a result of massive data generation, exhaustive operating costs, time, energy, and the burdens of planning and management. Artificial intelligence (AI) has been demonstrated to have a vital role in improving data analytics and decision-making in massive 5G networks. On the other hand, Quantum Computing is an evolving technology for handling exponential expansion in the data dimensions and calculating linear algebra quicker and more proficiently than traditional computers implying reduced computational costs and energy consumption. The unification between these disciplines engenders the concept of "Quantum Intelligence", which is an innovative and quite promising field with the possibility of unbounded capabilities for the 5G network. Beyond centralized learning, our discussions extend to debate the potentials of quantum intelligence to improve the distributed (federated) learning scenarios over several quantum computers, aiming to drastically enhance computational efficiency and energy consumption. Multiple simulation experiments are performed to evaluate and compare the performance of quantum intelligence on classical and quantum datasets. Finally, this article outlines the major technical and research challenges and open problems for future research on quantum intelligence in 5G wireless networks.

Keywords: Artificial intelligence, Quantum computing, Beyond 5G networks, ultra-reliable low-latency communications.

1. Introduction

The emergence of beyond 5G (B5G) networks is expected to bring about a paradigm shift in the telecommunications industry, with unprecedented opportunities for faster data speeds, lower latency, and increased network capacity. However, to fully realize the potential of B5G networks, it is essential to address the challenges that come with the increased complexity of network management and optimization [1]. This is where machine learning (ML) comes in, as it offers a promising approach to tackle the complexity and enable efficient operation of B5G networks. One of the primary role of ML in B5G networks is in network management and optimization. With the large amounts of data generated by B5G networks, ML algorithms can be used to analyze this data and identify patterns, predict network behavior, and automate network management tasks [2]. ML can also be used for fault detection and diagnosis, enabling quick identification and resolution of network issues. Additionally, ML can assist in resource allocation, optimizing network performance by predicting demand and allocating resources accordingly [3].

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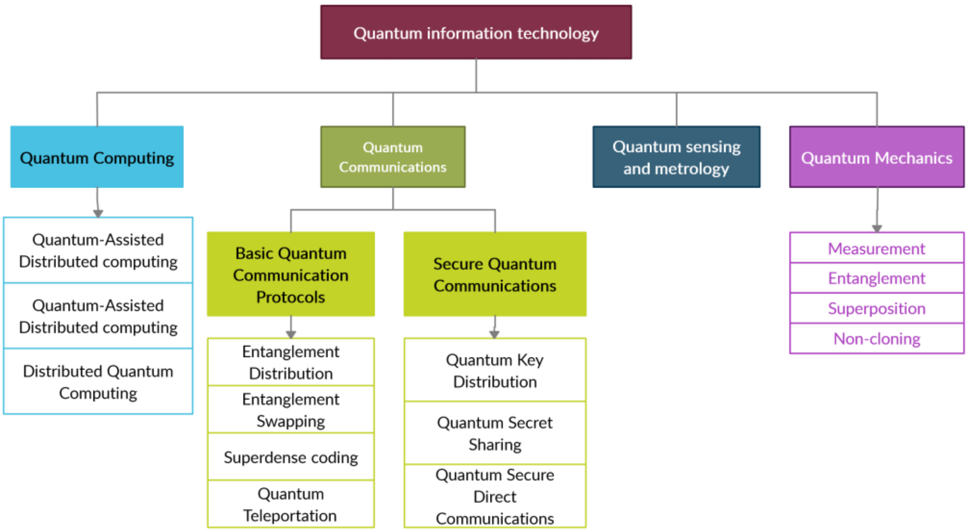

Fig. 1. Categorization of quantum technologies in B5G wireless communications. [5]

Quantum computing (QC) , is defined as an evolving computational paradigm that exploit the principles of quantum mechanics to perform computations that usually exceed the abilities of traditional computers. A part from classical bits representing info in from of $0\ or\ 1$, quantum bits (also called qubits) can occur in manifold states concurrently, which can be attributed to the superposition phenomena. This intrinsic parallelism makes the quantum computers capable to solve some computing problems exponentially faster than traditional computers. In addition, entanglement comes into sight as another inherent attribute of quantum systems, allowing the qubits to interrelate with each other in a way that the state of one qubit promptly impacts the state of another, irrespective of the how they far from each other. This, in turn, render the QC as a promising tool for revolutionizing different fields, including telecommunications, cryptography, and optimization [4].

When it comes to B5G networks, QC has an essential role in transforming network infrastructure, processes, and security. This can be significantly demonstrated with recently developed quantum-based algorithms for solving common problems in B5G networks, counting ultra-reliable low-latency communications (URLLC), high dependability, and massive machine-type communications (mMTC) [5]. For network optimization problem, Quantum Approximate Optimization Algorithm (QAOA) demonstrated an extraordinary ability to improve resource distribution, traffics routing, and network management [6]v. However, there are still several technical and practical challenges that need to be addressed before QC can be fully integrated for optimizing B5G networks. On the security side, QC empower the B5G networks with an enhanced set of security protocols that help protecting sensitive data from possible cyber threats. For example, Quantum key distribution (QKD) protocols made use of the ideologies of quantum mechanics to found safe communication channels with unreserved security assurances. With the integration of QKD, B5G networks become equipped with secure and tamper-proof communication [7].

The convergence of QC with artificial intelligence (AI) into B5G solutions leads to the rise to the concept of Quantum Machine Intelligence (QMI), as transformative tool for advancing abilities of B5G networks. This revolutionary power of QMI stem from the deep integration of intelligence and decision-making capabilities of ML and computing power of QC, helping the networks to adapt, optimize, and evolve in real-time. QMI represent a step forward to address composite challenges, such as dynamic resource allocation, network optimization, and anomaly detection. Some QMI algorithms like quantum neural networks (QNNs) and quantum reinforcement learning (QRL), can analyze vast streams of network data and unconventionally adapt network configurations, which enable meeting the diverse and growing demands of B5G applications.

To this end, this article studies the opportunities of applying QMI challenges and effects of applying quantum mechanics for enhancing computational capability in a B5G wireless network. Particularly, we present some fundamental knowledge about QC—superposition, entanglement, and inference principles — required to interpret the distinctions between conventional intelligence and QMI. Follow, the discussion cover QMI methods as a crucial way to learn from quantum information without the contravention the standards of quantum technology. Finally, we figure out the open research challenges and the promising research direction.

The remainder of this work is organized as follows. Section 2 provide a detailed background about the concepts of QC. Following, we discuss the role of AI in B5G concepts in section 3. Then, we explore of the current progress in the quantum intelligence in section 4. Section 5 explore the quantum federated learning (FL). The open research avenues are debated in section 6. Finally, the concluding remarks are summarized in section 7.

2. Background and Literature

QMI is envisioned to revolutionize to offer an intelligent approach for solving computing paradigm that can solve classic intractable computational problems in B5G environments [8]. It is noteworthy that user can contains operative mobile networks equipped with a computational module distributed between the two layers. Based on type of application and required resources, the computation can be performed on either devices or core [9]. It is noteworthy that on-device activities would enhance the performance with respect to delays for classical calculations across the network. On the other hand, quantum processes need more resources in order to collect a sizable amount of data, particularly when dealing with real-time jobs [10]. In addition to providing high-convergent, data-intensive learning, a better comprehension of augmented and virtual reality, and improved interaction with the potential configurations of the systems, QMI algorithms can solve problems with traditional computing. Data partitioners, which are able to separate the data into quantum and conventional parts to aid in the adoption of better models and provide an idea of resource utilisation in QMI, are another aspect to consider. A definitive response to the applications' demand for either classical or quantum computing would be necessary in the data splitting sector. However, intelligent devices are anticipated to be competing for resources—which QMI algorithms may better manage—in B5G applications.

A. Qauntum Computing

QC is a kind of high computation that operates on a quantum computer and can't operate on conventional computing. The main unit of quantum is qubit or quantum bit which is like a bit in classical computers. Where in classical computers the data is stored either in zeros or ones as a binary formula into bits on a hard drive. The qubit has two main states $|0> \ and \ |1>$. The qubit $|\psi>$ is broader than the classical bit. Furthermore, the qubit can deal with any combinations of binary formulas based on superposition property. So, super classical computers don't have a memory to hold numerous combinations of problems. Also, traditional computation analyzes each combination one by one which consumes time. The quantum computing is depending on quantum properties such as superposition, entanglement, and interference.

Superposition indicates that a qubit can present many combinations of states at the same time, not like a bit in classical computers. These qubits are integrated together permanently to act the same as a system based on entanglement property. So, the quantum state (QS) of each element can't be described individually from other states. Lastly, Inference is also named cancelation which mange the QS by amplifying signals that indicate the correct answer "Constructive Interference" and canceling the signals which indicate the wrong answer" Destructive Interference". In conventional computing, the gates such as AND, OR gates do irretrievable operations, where the input can't be retrieved from the output.

B. Types of Qauntum Computers

Quantum computing encompasses diverse architectures tailored to different computational tasks and requirements.

First, quantum annealer (QA) is the easiest to implement and the most limited one. But recently conventional computers have a broken QA in normal operations. On the other hand, QA can successfully perform operations by exploiting the quantum fluctuations effect to solve high computation problems such as discrete search domains with many local minima as optimization issues. The D-wave platform was the first depending on the QA pattern in its kernel processing [11]. Second, analog quantum computer (AQC) is more robust than the conventional computer by imitating the interactions between quantum systems. AQC can have from 50 to 100 qubits. It's not a global purpose computer but can identify certain issues in quantum physics [12]. Third, Universal Quantum Computer (UQC) is the highest powerful one among the three kinds. It's difficult to implement and more globally. Can involve 100,000 qubits for operations such as cryptography, quantum chemistry, optimization, searching, etc. The UQC requires a very low temperature which is highly expensive to offer this technology. Also, it's hard to implement reliable qubits and integrate them [13]. In more fine-grained way, quantum technology has been a taxonomized into different quantum technologies and their apps as shown Figure 1. It can be noted that this taxonomy comprises quantum sensing, quantum communication, quantum computation, and quantum simulation [5].

3. Artificial Intelligence

Artificial Intelligence is a field of computer science that has revolutionized the way of performing daily life tasks using machines with limited human interference to promote automated and intelligent conduct. Machine Learning (ML) and Deep Learning (DL) are rapidly evolving subfields of AI that achieve an extraordinary level of performance when learning to solve progressively complicated computational data-driven or data-free problems, making them crucial for the upcoming development of human civilization. The complexity of AI solutions has recently improved to such a level that roughly no human interference is necessary for their building and deployment. This in turn renders the AI as key enabler for the realization of B5G wireless communications in real-world [1]. Moreover, AI enabled wireless communications are being deployed in extremely sensitive policy areas (i.e., recidivism forecast in the criminal justice system, or the face recognition in police system), and in fields with variety of societal and political authorities. Hence, now, AI solutions are integrated into a broad range of decision-making activities in almost all life sectors. Accordingly, the attention of science and policy communities has been positioned toward the extent to which AI can help standardize the design of B5G networks soon [2].

4. Quantum Intelligence

Quantum computing easily lends its concepts to the realm of AI and therefore there has been effective research on striving to use standards of quantum technology to enhance the computational efficacy and representation power of traditional AI algorithms. Quantum expansions to conventional AI challenges have been gaining great significance for the B5G community in recent times. The key differences between quantum intelligence and classical intelligence are parallel computation. The new research direction aims to combine classical ML or DL algorithms with quantum computing. This will lead to complex quantum states with high-dimension particles and many entangled quantum degrees. It is considered to be challenging to rebuild an experimental structure that generates it. In this part, we break down the quantum intelligence elements of learning under a quantum context.

Input representation: In conventional computing, the NN computations are done in one direction to the output where computations are irretrievable. In contrast to quantum computing where its computations are retrievable conversion to derive the input from the output. In a QNN the output can be achieved by appending an ancillary bit to the input. In a multi-class situation, where one qubit can't indicate the output, the $O\ (logN)$ can be given to indicate the class where N is several classes in Hilbert space.

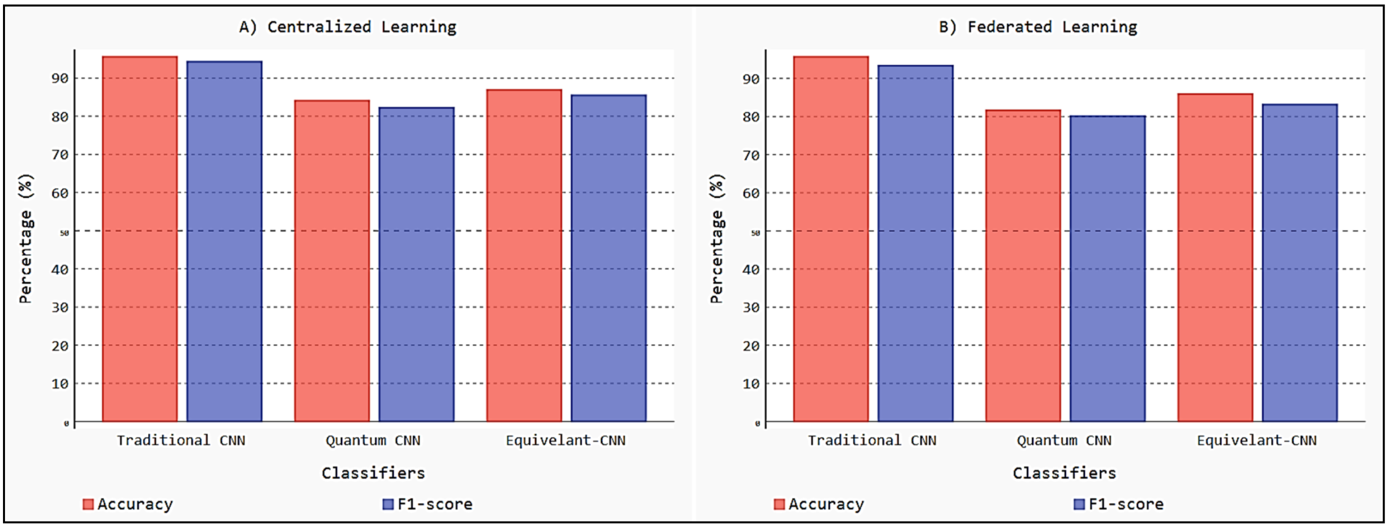

Fig.2. Comparison of classification performance of quantum CNN and traditional CNN under A) centralized learning and FL on MNIST dataset using classical data.

The input to QNN can be the conversion of classical data or quantum data into the form of states $\psi > (1,\ldots,s)$ where its a superposition 2^s. the get reliable quantum data to implement QNN networks, the mainstream concerned studies convert their considerations to obtain QNNs on classical data. the conversion of traditional data to a QS, many famous techniques have been proposed. Such as binarizing independent elements based on threshold and representing each binary domain regarding qubit outcomes. In parallel work, many contributions have been introduced in [3] the continuous-variable platforms, which transform traditional input using a continuous degree of freedom to QS. This technique reduces the information loss during uniform continuous inputs, but with high complexity [10].

Modeling: Generally, the QNN is modeled using a variational quantum circuit (VQC) [4]. VQC is the technique to achieve approximations to the lowest energy eigenstate (ES) or ground state. In another word, VQC can be trained by classical approaches to drive queries on quantum computers. In this step, the encodings are given to the VQC which involves parameterized gates and then reduces the loss to optimize the model task. The permutation matrix transforms which is the common way of conversion. Also, the unitary matrix can find the conversion, based on free parameters. Some contributions implement linear and non-linear conversions [3].
Extracting the output: the final step depends on estimating the parity of the output. It's challenging to get a single value from superposition qubits. The quantum output is relying on QS or bias. the aim is to identify p^y from the combined output state, regarding the final qubit in the last quantum computing achieve after the unitary process.
The fidelity [7] is the estimation of clones between two QS. If the output is not computationally biased, the fidelity can be easily altered as the output state is combined. In another word, fidelity indicates the probability that one state will pass a test to identify as the other. To measure the cost function, the Pauli operator is computed. Pauli operators are logical operators or gates that are appended to input states to identify the impacts of the environment on a QS.

Learning network parameters: As in traditional NN on conventional computing, The QNN parameters aim to reduce the loss function based on the first-order and second-order optimization approaches, which provides a general flow of QDL.

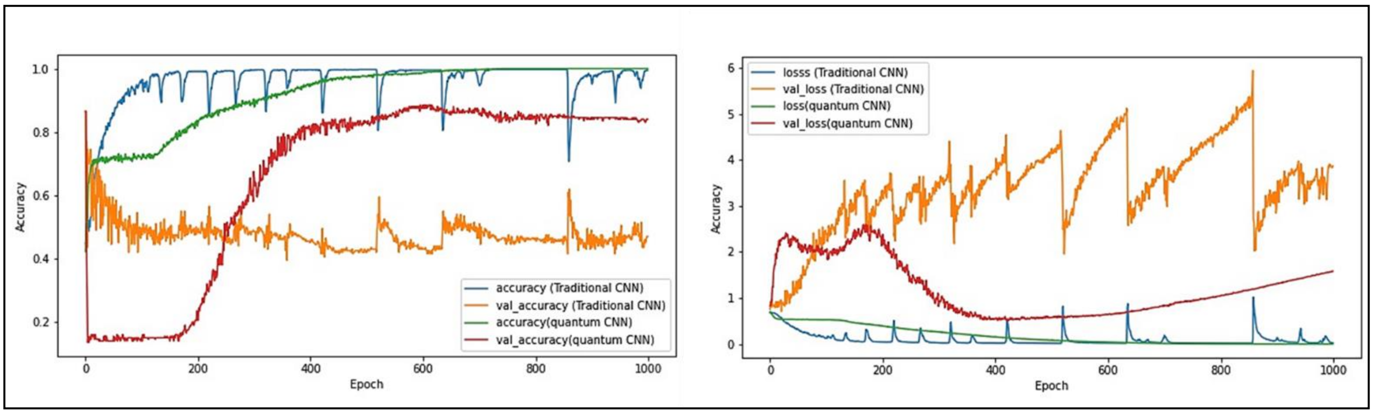

Fig. 3. The training curves in terms of A) accuracy curves and B) loss curves using quantum relabeled on MNIST dataset.

Quantum Feedforward Deep Neural Networks (QFFDN): One exciting contribution will be the studies depending on [6]. This contribution is pioneered in using the encoding of a non-discrete valued array instead of binary formula. This is like obtaining gray-level images instead of binary images. Furthermore, the probability of linking many quantum layer perceptrons together. The model could be completely developed on quantum computing and would efficiently form an FFDN [7].

Quantum Convolution neural network (QCNN): QCNNs were first proposed in [8] inspired by the classical CNNs. Convolutions are processes achieved on vicinity couples of qubits. As in VQC, Convolutions are parameterized unitary rotations. The next pooling layers are achieved by evaluating a subset of the qubits and using the outcomes of the evaluation to manage following process. The fully connected analog layer is a various qubit process on the remaining qubits before the last evaluation. During training whole parameter value is assessed. QCNNs is classifying quantum states, as in the traditional CNN that differentiates among various topological forms. QCNNs can also classify classes just like in conventional computing.

Quantum Recurrent neural network (QRNN): The classical RNN has an effective impact on many DL tasks such as speech recognition, machine translation, etc. The QRNN cell is made up of parametrized quantum neurons depending on VQC to generate non-linearity to input if it is combined with amplitude amplification. Then measure the output for every step-in class perdition [9].

Quantum Autoencoder (QAE): An effective variational quantum approach for quantum data compression by its capability to obtain low-dimensional patterns from QS being in the high-dimensional space based on eigenvalues computations.

Quantum Reinforcement Learning (QRL): The state (action) in classical RL is seen as the ES in QRL. The state (action) set can be introduced as a quantum superposition state and the ES can be achieved by randomly monitoring the simulated QS regarding the fall hypothesis of quantum measurement. The possibility of ES is determined by the probability amplitude, which is upgraded correspondingly to rewards and value functions. Therefore, it becomes a great balance between exploration and exploitation and can increase learning speed also.

5. QUANTUM FEDERATED LEARNING

Traditional centralized quantum intelligence is not quite applicable for B5G networks as they require transferring the data to a central location where learning is performed, which involves high computing, storage, and communication overhead and also could be unfeasible due to the failure to gain entree private data [7]. Therefore, distributed intelligence come to be essential requirement to learn from such private data locally by communicating only the parameter of local AI models to a cloud coordinator. This greatly helps reduce the network resource and energy consumption and increases the responsiveness of AI solutions in latency-sensitive applications. FL [8] is an evolving decentralized approach that is especially cognizant of these challenges, involving privacy and resource limitations. It employs the on-device processing capability and private data by implementing the model training in a decentralized fashion [8].

As with QDL, the integration of FL and quantum intelligence leads to quantum FL (QFL), which is a key enabler for distributed and privacy-preserved learning in B5G networks. On the other hand, most present QML models depend on centralizing the training data. As a result, more feasible QFL solutions adapted to upcoming quantum intelligence architecture should be considered. Due to, the delicate nature of computing qubits and its conversion challenge process, establishing QFL frameworks for quantum networks is crucial. In addition to its practical importance, QFL enables quantum learning to be distributed by utilizing the wireless network [9].

In the nutshell, the design of the QFL solution can be implemented through the following phases:

Phase 1: Initialisation. The cloud coordinator initialized the training hyper-parameters of the quantum intelligence model such as batch size, number of iterations, Optimizers, learning rates, number of communication rounds, number of layers, and number of participating quantum computers.

Phase 2: local training of the quantum model. The designated quantum computers download the preliminary hyper-parameters and begin executing the local training using local quantum data.

Phase 3: securing the model. Prior to uploading the local updates to the central aggregator in the cloud. Each quantum computer calls a specific procedure for protecting the privacy of the model and associated training data. This procedure may be differential privacy, parameter encryption, etc.

Phase 4: global aggregation, the cloud coordinator aggregates local quantum updates from participating quantum computers and averages them to calculate the global model parameters.

Phase 5: the process from phase 1 to phase 4 repeats until the model converges or the training ends.

6. SIMULATIONS AND ANALYSIS

This article develops a quantum CNN to classify images of handwritten digits from the MNIST dataset [14]. The classification performance of this quantum CNN is evaluated on such classical data (non-quantum) and compared against traditional CNN. To make the comparison fair, the quantum CNN is further compared to its equivalent traditional CNN i.e., with the same number of parameters (see figure 2). The simulation is also extended to train both traditional and quantum CNN under FL scenarios using traditional MNIST data. The findings show that regardless of the structure of the quantum intelligence model or its learning strategy it cannot overcome its traditional counterparts on classical datasets [13-15]. The CNN models above are implemented using TensorFlow 2.0. The implemented quantum convolutional layers used quantum circuits operating on qubits to perform convolution operations, in which quantum inputs are handled with quantum gates (like Hadamard gate and the CNOT gate) extracting features in a quantum-mechanical method. The implementation of this part is performed using Cirq framework, which simulate and execute quantum circuits on classical computers. The model architecture consists of 8 convolutional layers followed by 3 linear layers, with max-pooling layers spread to perform spatial downsampling. It also includes batch normalization, and ReLU activation functions. The model training is performed with initial learning rate of 0.001, with batch size of 64, and Adam optimizer. We use cross-entropy as a loss, and dropout rate of 0.5.

In addition, the previous simulations are performed again but on the quantum version of data generated from MNIST data via quantum (see Figure 3). By observing the training behavior of both quantum CNN and traditional CNN in terms of loss and accuracy curves, we could find that the quantum CNN can overcome the existing with large margins. In the same way, the federated training of both variants of model show similar training behavior and close results. This in turn support our hypothesis that quantum intelligence can afford powerful learning capabilities while maintaining high computational efficiency.

7. OPEN AVENUES

In this section, we elaborate on several directions of quantum intelligence in wireless communication. while QMI show a promising role in revolutionizing computational speeds in B5G, it still encounters many limitations. For instance, the present state of quantum hardware still in its early phases of development and is disposed to to errors and noise. QML algorithms needs a robust error correction technique to mitigate these challenges, posing computational overhead and complexity. Additionally, the limited scalability of QMI stem from the number of qubits and quantum gates [15]. Furthermore, the practical implementation of QMI often necessitates noteworthy computational resources and expertise, impeding widespread adoption and deployment. Studying these challenges and other be crucial for unlocking the open avenue in QMI and realizing its transformative impact on various applications [16].

Measuring quantum algorithms speed: this issue is solved on individual bias cases only. This problem is extended to QDL also, which requires general theorems and standards for certain structures and learning approaches [11].

Vanishing gradient problem: Because QNN employs the same gradient descent approach to train their parameters as classical NN, they face the same challenge. Classical DL models tackle this problem by using an adequate activation function, however QDL does not, hence a different solution will be required later [12].

Noisy intermediate-scale quantum (NISQ) indicates fewer qubits and a much computational error of near-term quantum devices. Not all quantum approaches work under this context but are predictable to be applied in the future. such as Shor's algorithm that needs a minimum of thousands of qubits without an error correction operation. Recent quantum computers have only ten's number of qubits which high error rate percentage. Though, during the comparatively short circuit depth and qubit conditions, VQC and quantum intelligence depending on them are tolerant to these environmental restrictions. However, to improve the data processing capacity of quantum intelligence, it is required to study near-term device compatibility [16].

Quantum supremacy: The illusion that quantum approaches are always superior to conventional approaches performing the same purpose may arise because of quantum advantage. However, under some conditions, gains can only be obtained by thoughtful algorithms. It is vital to argue the advantages of a new QDL algorithm over the comparable classical models while creating it.

More DL inspiration algorithms: QDL is still in its early stages. The present method case is to put the same strategy training network with a QNN from the existing DNN, but there are many cases of various approaches concepts from classical RL, LSTM, GAN Attention mechanism research. The quantum computing advantages can be achieved through QNN in a case of great computational complexity via the complex Markov decision method environment [16-18].

8. CONCLUSION

In this article, we define and explain the fundamentals of research on the emerging field of quantum intelligence for tackling some of the challenges in 6G wireless networks. Quantum intelligence is an emerging learning solution, tailored for centralized and distributed scenarios, that seek to address the computational cost, energy, latency, and decision-making in wireless communications by performing decentralized model training. An approachable introduction is given to figure out quantum intelligence and related salient principles. Then, we show up multiple applications of quantum intelligence in wireless communication, covering from terminal to the main network. Simulations have been conducted to validate the applicability of quantum intelligence and the results imply that quantum intelligence can approach the performance of the conventional AI under centralized and federated training scenarios. The article ends by discussing the state-of-the-art challenges and open research topics that necessitate further technical research efforts.

Supplementary Materials

Not applicable.

Author Contributions

All authors contributed equally to the manuscript.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Institutional Review Board Statement

Not applicable.

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