A QAOA-based solution for routing optimization for optical networks in 6G

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Identifying an optimal packet route while fulfilling Quality of Service criteria is a prominent optimization problem belonging to the NP-Hard problem category. In addition, with the development of 6G and Beyond networks, packet routing will become more challenging. In this paper, we propose a Hybrid Quantum-Classical Algorithm-based solution for the pathfinding problem named Quantum Approximate Optimization Algorithm. We describe our approach to network modeling then we will explain how this algorithm can be applied to solve pathfinding problems, what is the equivalent implementation of a network model in quantum computing and what are the main advantages of using it compared to classical methods (i.e. Dijkstra and classical machine learning).

Introduction

Routing is a combinatorial optimization problem that falls under Non-deterministic Polynomial-time Hard (NP-Hard) problems. Moreover, in the 6G era, it is expected that the network topology's scale and complexity will increase, with extremely heavy computational applications such as VR/AR, V2X, and Massive-IoT [1]. Therefore, solving routing problems in 6G mobile networks will become more complex. Classical Machine Learning algorithms need a heavy learning process that requires huge computing capabilities [2]. Moreover, with the massive amount of data that is expected to be processed by 6G use cases (i.e. connectivity density for M-IoT is expected to reach $10^7\ d/km^2$ and a pick data rate $> 1Tbps$), high computing power and computational time capabilities are required. In this case, the lack of these requirements may negate the benefits and advantages of having 6G (ultra-low latency, high throughput, high reliability…). Moreover, routing is considered one of the pilar functions in networking, and normally, the performance of a network is defined based on the quality and the accuracy of the routing decisions. Many techniques such as legacy routing protocols (i.e., OSPF, BGP…), Linear programming algorithms (i.e. Dijkstra…), and ML algorithms (i.e. Reinforcement Learning) were applied in order to optimize the routing decisions [3]. However, these techniques fail when the size of the network becomes larger and denser. In this regard, Quantum Computing (QC) can be used in order to accelerate ML algorithms. This combination between QC and ML is known as Quantum Machine Learning (QML) [4]. Since its appearance, QML proved that it can provide better performance regarding real-time and heavy computational applications. QML is considered a potential candidate that can reduce or even break the complexity of NP-Hard problems. In this context, we propose a QML-based algorithm for routing optimization entitled Quantum Approximate Optimization Algorithm (QAOA). In section II, we provide a general overview of QC and QML. In section III we explain our QAOA-based solution for routing optimization. Finally, section IV, reports the conclusions.

Quantum Machine Learning and Approximate Optimization Algorithm

QC is a field of study that utilizes quantum physics to build powerful processors able to execute certain types of computations better than a conventional computer. QML is combining ML algorithms with QC techniques. The main idea behind QML is to translate the classical data and algorithms into a quantum-manageable language to exploit the quantum properties (superposition, entanglement, and parallelism) of quantum processors. Normally, known as Noisy-Intermediate Scale Quantum computers (NISQ) [5]. The number of qubits and quantum gates in NISQ is limited and these qubits are significantly sensitive to noise which makes them collapse in a relatively short time. In this regard, a new class of hybrid algorithms has been developed especially for the NISQ era, known as Variational Quantum Algorithms (VQA) [5]. The main idea behind the VQAs is to use the quantum computer for computing and measuring the result, while the classical computer is used in to correct some of the noise generated from using the NISQ processors and optimize the results. One of the well-known VQAs is Quantum Approximate Optimization Algorithm (QAOA).

QAOA is a variational quantum-heuristic algorithm that was proposed in 2014 by Edward Farhi [6], as a solution for combinatorial optimization problems. The problem is divided into two parts: one to be solved by a quantum computer, and the other by a classical one, as depicted in Fig 1. Therefore, it consists of: a Variational Quantum Circuit (VQC), containing a set of quantum gates: Hadamard, Cost, and mixing Hamiltonian gates, that are prepared and measured on a quantum computer/simulator. The main role of the Hadamard gates in the circuit is to set the qubits into an equal superposition. Followed by a layer of cost and mixing Hamiltonians, parametrized respectively by γ and β, which are defined according to the objective function. A Hamiltonian in quantum physics represents the total energy of the quantum system. Then the classical optimizer uses the outcome of the measurement to decide on the new set of parameters that may lead the quantum computer to produce a new optimized objective function. Those parameters are provided as a new input to the VQC and the process again is repeated until the cost function converges to its meaning (maximization or minimization).

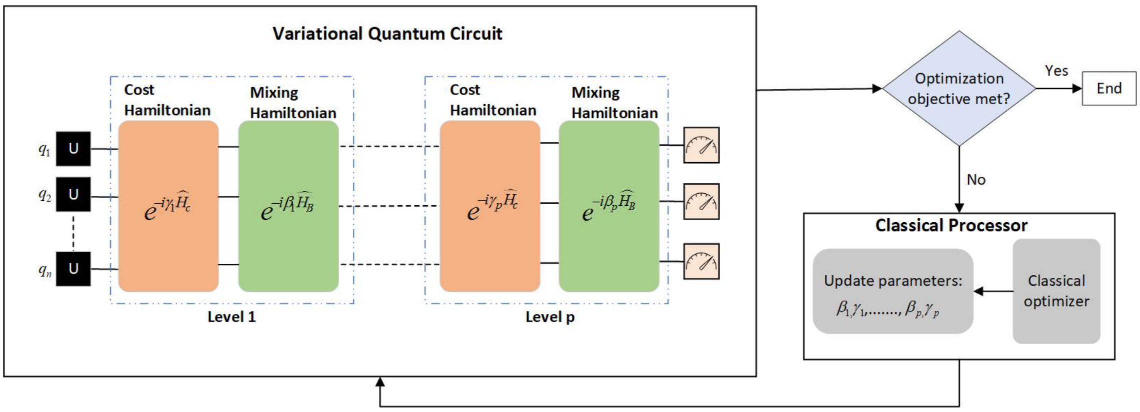

Figure 1: Quantum Classical loop of QAOA

In QC, the optimal solution to an optimization problem corresponds to the ground energy state of the system, therefore, in order to solve an optimization problem using quantum computers, we have to convert it into a problem of characterization of quantum Hamiltonian[7] [8].

Quantum Approximate Optimization Algorithm for Routing

The first step that we did in the process of applying QAOA for routing optimization is to convert a simple undirected graph $G = (V, E)$ into a quantum circuit, where V represents the vertices and E are the edges of the graph, Fig 2.
The qubits in our case will play the role of the vertices of the graph. The first layer in our circuit corresponds to the Hadamard gates we apply to put our qubits/vertices in an equal superposition.

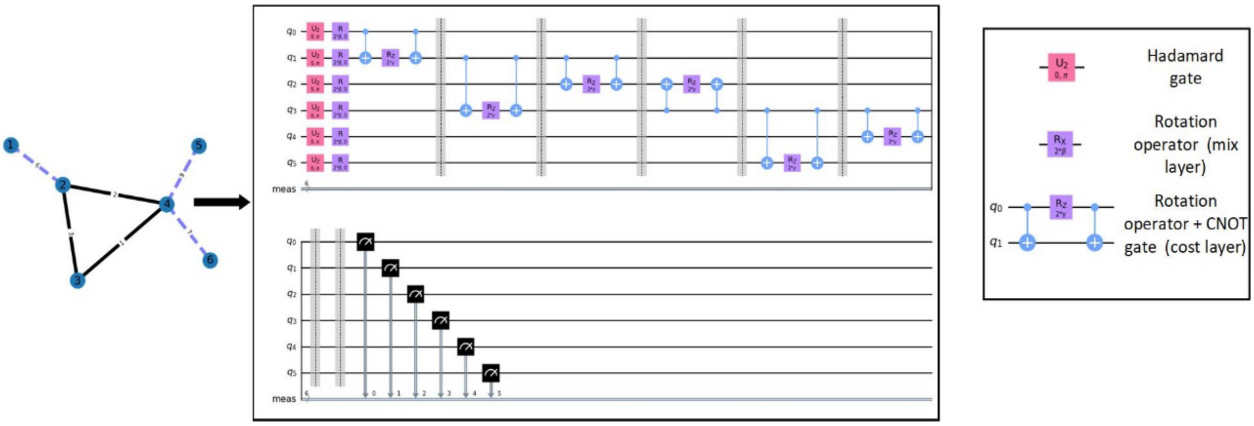

Figure 2: the equivalent VQC of a network

The second layer represents the mixing Hamiltonian characterized by the parameter β that we mentioned above. This layer consists of the rotation operator R_x which is a single qubit rotation around the x-axis through the angle of rotation β. Usually, β takes a value between [0, π] [6]. The third layer of the circuit represents the cost Hamiltonian and it consists of two types of quantum gates: R_z and the controlled-NOT (CNOT) gates. R_z is a single qubit rotation around the z-axis through the angle of rotation γ. Usually, γ takes a value between [0, 2π] [6]. The CNOTs are two-qubit operations, where the first qubit acts as the control and the other one as the target qubit. This gate creates an entanglement of two qubits if and only if the control qubit is in superposition (for that we implemented the Hadamard gates in the first place). A combination of one R_z and two CNOT gates, in our case, represents the edge between the vertices of the graph. In Fig 2, we separate each edge of the graph with a gray barrier to facilitate understanding of the circuit component. Finally, in the last layer, we measure in the computational basis to get a bitstring bitstrings samples $x_i \in \{0, 1\}^n$ correspond to the optimal solutions of the routing problem.

The circuit in Fig 2 represents a QAOA circuit of depth p=1, we can adapt the depth of the circuit as we want, meaning that we cascade the mix and cost layers, and it will be just a repetition of the same circuit multiple times behind each other, and supposedly higher-depth QAOA will provide better performance regarding the accuracy compared to the low-depth implementations [7]. However, this is not always the case as this system is affected by the noise generated from the quantum gates, and at higher depth QAOA the noise becomes larger, which affects at the end the accuracy of the solution. Moreover, a level-p QAOA has 2p parameters that need to be optimized classically (for each mix/cost layer we add, we will have a different β and γ), and as p increases, parameter optimization becomes passive due to the curse of dimensionality [9].

The second part of the hybrid loop of the QAOA is the classical optimizer (see Fig1, right side), the main role of this entity is to improve the guess of the VQC and correct some of the noise generated from the "noisy" quantum gates. Thus choosing a classical optimizer that fits the problem is very important for the success of the QAOA [10]. An example of the classical optimizers that is supported by the Qiskit framework are COBYLA, ADAM, and SPSA [11].
In future works, we need to integrate the weights of the graph into the quantum circuit. The weights are going to be the parameter multiplied by the angle of rotation of the cost Hamiltonian γ. Moreover, we need to develop a mathematical formulation of the routing optimization based on the QAOA that will help to solve the problem even faster than the current best-routing algorithms.

Conclusion

Routing is considered one of the most important functionalities in networking and normally, it defines the performance of a network, thus ensuring the optimality of packet route while fulfilling QoS criteria is a very important task that needs to be addressed. In this regard, this paper proposed a hybrid quantum algorithm entitled QAOA for routing optimization. The proposed hybrid QC-based approach provides a high computational efficiency in terms of computation time and accuracy, by utilizing the unique features of both classical and quantum computers. We expect that the QAOA will be a well-suited solution for routing optimization in the NISQ era.

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