TCS Quantum Challenge 2024 on Optimizing Power Distribution Network

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In power generation and distribution industry, it is important to optimize the operational cost and carbon footprint while fulfilling the demands of customers. As the distribution network grows, finding the optimized solution becomes infeasible. Current classical algorithms often provide sub-optimal solutions for saving time. In this report, we look into possible quantum algorithms that can solve this optimization more effectively than their classical counterparts. Our approach reformulate the optimization problem to handle all types of variables and solve it via Quantum Approximate Optimization Algorithm (QAOA). We were able to see quantum advantage regarding speed and memory when we compare the use of QAOA in QPU with their classical counter-part in local computers.

I. INTRODUCTION

The distribution of energy from production units to customers requires a complex grid of distribution networks. These networks consist of pipelines and small substations to deliver, monitor, and moderate power outputs to safe levels to customers. However, these power grids are often inefficient, leading to inefficient routing of energy and loss of energy during transmission. This increases the overall cost of maintaining the power grid and increase in carbon footprint. Through careful planning, advanced technologies, and data-driven strategies, optimization can address challenges such as voltage fluctuations, line losses, and peak demand management. An optimized power distribution network will ensure a seamless and economical flow of energy from production units to end-users while mitigating energy losses and reducing environmental impact.

II. PROBLEM STATMENT

Power grid optimization (PGO) includes minimizing the operational cost of production of energy and finding an optimal route for transmission while ensuring the energy demands of customers are met. An optimized solution needs to take care of various factors including energy demands of customers, power loss of several transmission lines and capacities of several nodes. The number of decision variables grows exponentially with the size of distribution network making it difficult for classical computers to find an optimal solution. The limitations of current approaches in classical computer motivates to search for a possible solution with a quantum computer. Some known quantum algorithms have leveraged unique properties of quantum mechanics to get measurable advantage over classical computers in several combinatorial optimization problems. Hence finding novel techniques in quantum optimization algorithms will allow us to address the intricacies of optimizing power distribution networks and revolutionize power distribution network management.

III. SOLUTION

The cost function for power grid optimization (PGO) problem can be formulated as Mixed Integer Linear Programming (MILP), which contains discrete, binary and continuous decision variables. The Mixed Integer Linear Programming (MILP) problem can not be directly solved on a quantum computer due to non-binary variables in the problem. The problem is that to encode information in quantum bits, the continuous variables in the problem have to be converted into a binary variables with appropriate weights and indices first. Then the problem is reformulated into a Binary Quadratic Model (BQM), where all the decision variables in the problem are binary variables. BQM can then be solved by using the formalism of quadratic unconstrained binary optimization (QUBO). Our novel approach to solve PGO is to discretize the continuous variables and associate binary variables to all the discretized bins. The cost function and constraints are then reformulated into a QUBO problem, which is then solved using QAOA. Our approach also use less number of qubits and optimizes the cost function iteratively by reducing the bin size till we get the desired accuracy. Using QAOA can help us avoid problems such as barren plateau problem which is commonly encountered in various optimization algorithms dealing with large number of decision variables.

The PGO consists of two parts as mentioned above (1) finding the optimal power to be generated based on the demand and (2) optimal path in sending power from generators to the destination. The first and second part can be regarded as independent problem and efficiently solved using a quantum computer. The first part of the problem contains a cost function which needs to be minimized provided the constraints given by power generation limits and for scenario 2 to include different transfer scenarios. The second part of the problem can be regarded as Multi-Vehicle Routing Problem (MVR) in which the sources are the power plants and the customers are the destination and the optimal path to be found are the transmission lines in which the power to be transferred.

IV. RESULT

The problem is solved in two parts as mentioned above. The optimal power to be generated followed by the optimal path the power is transferred from source to destination. Our analysis shows that the for small number of generators scenario 1 can be solved in both classical optimizer and using a Quantum Processing Units (qpu). Also it has been observed that for small number of decision variables classical solver runs the task really faster than qpu. As we increase the decision variables, the classical optimizer is unable to find the optimal solution, but solving using actual qpus, we can go beyond 20 decision variables (we could not solve further because on the constraints on number of qubits available). For scenario 2, we require alteast 20 variables, hence it can not be solved using classical optimizer, we solved it using qpu and the solution satisfies all the constraints in the problem. The entire problem is solved using IONQ ARIA which containts 24 qubits. The summary of result is documented in a tabular format below.

	CLASSICAL	QUANTUM
Number of bits	Scenario1 can be solved as it requires less number of bits	Scenario 1 can be solved using quantum algorithm
Speed	For small number of decision variables, classical solution is faster (**Scenario 1 took 1.51 seconds on local computer**)	For smaller number of decision variables, quantum algorithm takes more time than classical algorithm (**Scenario 1 took 17 minutes on qpu**)
Hardware Requirement	**As we increase the number of decision variables to 15 (more than 15) classical solver is unable to obtain a solution**	**Quantum algorithm can solve more than 15 decision variables** (we went upto 24 variables, solved on IONQ Aria 1)
Quantum Advantage	Hence scenario 2 can't be solved classically using BQM formalism	BQM can be solved for higher number of decision variables. Hence we obtained solution for scenario 2 using quantum algorithm.
Scalability	Classically more number of bits with high computing power is required to solve higher bus systems	**It's a matter of qpus in quantum algorithm, scalability is possible, IEEE 8, 30, 118 can also be implemented in our model by slightly modifying our problem statement. (approximately 3N^2 qubits are required for arbitrary N bus system)**

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Appendix A: Useful links

- Solution approach document pdf: Phase_2_submission.pdf
- Final Defence Presentation deck: PGO_final_defence_PPT.pdf
- Code Base for scenario 1: scenario_1.ipynb
- Code Base for scenario 2: scenario_2.ipynb