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Quantum Powered Employee Transport and Agri-Logistics Optimization

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Abstract— **Logistics involves managing how resources are acquired, stored, and transported to their final destinations along the supply chain in a cost-effectively manner. Logistics problems are NP-hard combinational optimization problems involving searching for the best solution in a large solution space. Recent studies have demonstrated the capability of quantum methods to solve such combinatorial optimization problems. Consequently, this paper presents the application of quantum computing methods for two real-world logistics problems, namely, a) Employee transport route optimization and b) Agri-tech logistics optimization. The main goal of this paper is to present the evaluation of the results of the experiments executed on quantum gate-based variational algorithms and quantum annealers. Given the current limitation of quantum hardware, we had to simplify the problem and use case specific decomposition techniques such as distance based clustering to reduce the search space and size of the problem before executing them on quantum computers. The method has been elaborated in this paper. The results were benchmarked with classical exact solvers.**

Keywords— Vehicle routing problem, Variational quantum algorithms, D-Wave Ocean, Quantum annealer, Quadratic Unconstrained Binary Optimization (QUBO), Logistics

I. INTRODUCTION

The logistics process involves complex physical flows and the integration of different elements. In today's competitive world, managing logistics cost-effectively is the key to business success. The logistics scope covers the entire supply chain flow from suppliers, manufacturers, warehouses, distribution centres, raw materials, and finished products between these facilities, all the way to end customers. Logistics optimization involves picking the optimal number, location, and size of the facilities and determining the best logistics network flow in the supply chain that is most cost-effective by considering a wide range of constraints such as delivery time constraints, customer demands and facilities' maximum capacity.

From a wide range of logistics optimization problems, we have selected two industry-relevant use cases; which are related to the vehicle routing problem. In the employee transport route optimization use case, with a set of available vehicles, we have to determine the best routes to service various customer locations from office (depot) ensuring the vehicles are optimally utilized. The distance traveled by the vehicles are also minimum. Agri-tech logistics optimization use case is another variant of the vehicle routing problem in which farmers load their commodities on trucks using a set of available vehicles and deliver them to the regional hub. This problem has an additional segregation constraint where there is a restriction on certain commodities from getting transported together in a vehicle.

The key objective for both these use cases is to find the optimum utilization of vehicles and determine the optimal route for employee transportation/distribution of commodities to target locations by considering a wide range of constraints such as vehicle capacity constraints, depot constraints, and customer demands. The complexity of the problem increases as the number of employees, commodities, and target locations increases.

The above use cases are NP-hard [1] combinatorial optimization use cases. There are multiple possible solutions that increase with the size of the data. Exact approaches can be applied to the smaller dataset to get an optimal solution to the problem. But, for large data instances, approximate methods such as meta-heuristics techniques must be used to decrease the search space so that we can get near-optimal solutions in a reasonable computation time. Recent research in quantum computing [2]–[5] , shows the potential of quantum methods to solve complex combinatorial optimization problems.

In this paper, for the above-mentioned real-world applications, we modeled the problem using quantum technologies and presented the results of the experiments executed on quantum gate-based variational algorithms and quantum annealers. Due to the hardware limitation of the quantum gate-based model, we had to simplify the problem and run a small instance of a problem on IBM Qiskit's [6] gate-based variational algorithms like variational quantum eigensolver (VQE) [7] and quantum approximate optimization algorithm (QAOA) [8]. The larger instance of the problem was modeled and executed on D-Wave's quantum annealers [9]. The purpose of D-Wave systems is to solve difficult combinatorial optimization problems. The current Advantage system [10] of D-Wave comes with 5000 qubits and an improved topology, precision, and inter-connectivity, making it suitable for handling largescale combinatorial optimization problem. We have used a hybrid quantum and classical approach for solving the above problems, which has been elaborated on in this paper. The results were benchmarked with one of the classical solvers called CPLEX [11].

The rest of the paper is organized as follows, Section II covers the relevant literature on the problem statement, a brief about quantum mechanics, and the two branches of quantum computing, namely gate-based quantum computers and annealing based quantum computers. Section III presents the use case of employee transportation route optimization, solution methodology, and the experiment results. Section IV discusses the use case of Agri-tech logistics optimization. Section V covers the conclusion, our learning, and potential future research.

II. Optimization Using Quantum

Quantum computing consists of applying the laws of quantum mechanics such as superposition, entanglement, and interference, which gives the system greater computing power and can solve NP-hard problems faster and more efficiently [13], [14]. There are two significant types of quantum computing systems: quantum annealers and gate-based quantum computers.

A. *Annealing-based Quantum Computers*

Quantum annealing is a notion used by quantum annealers, and it works on the principle of adiabatic theorem [15]. The problem is mapped so that it can be easily encoded into qubits and gradually evolved (annealed) to the optimal (or near optimal) state under the influence of a magnetic field. At the end of this process, the quantum annealer outputs a distribution of results with different probabilities. To get the desired answer, it has to be iterated multiple times. The solution to the problem is the result with the highest probability. D-Wave Annealer [9] employs quantum annealing to compute the minimum of an energy landscape defined by the biases and couplings applied to its qubits as a Hamiltonian [17]. The Hamiltonian of a system specifies its total energy. To solve the problem by sampling, the problem is formulated as an objective function or problem Hamiltonian, usually in Ising or quadratic unconstrained binary optimization format (QUBO) [19], then these are embedded onto the actual D-Wave hardware. This mapping to the Quantum Processing Unit (QPU) topology of the D-Wave system is known as minor embedding. Classical solvers do not require embedding, but quantum classical hybrid solvers embed parts of the problem on the QPU while solving the rest with classical techniques on CPUs or GPUs. D-Wave system provides various annealers as well as hybrid samplers (quantum hybrid-classical solvers) such as Binary Quadratic Model (BQM) solvers, Constrained quadratic Model (CQM) solvers and Discrete Quadratic Model (DQM) solvers [16] for solving optimization problems. A simple working of an annealing based quantum computer is shown in Fig. 1.

B. *Gate based Quantum Computers*

Variational algorithms such as the variational quantum eigensolver (VQE) [7] and the quantum approximate optimization method (QAOA) are used in gate-based models [8]. Quantum variational algorithms work by executing external parameterized quantum circuits on quantum machines to effectively sample from massive, parameterized distributions.

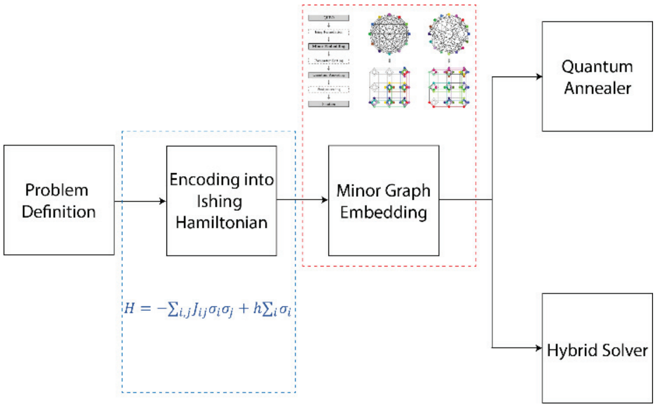

Fig. 1. Quantum workflow on Quantum Annealer.

When tackling combinatorial optimization problems, the quantum machine is utilized to generate a utility function of the optimization problem (cost Hamiltonian) [17] for a given parameterized quantum state. The given utility function is optimized over the rotation parameters using a classical approach. On modern quantum devices, variational algorithms can yield acceptable heuristic solutions if the parameterized circuit, also known as an Ansatz, represents states close to the problem Hamiltonian's ground state. Workflow for a gate-based quantum computer is shown in Fig. 2

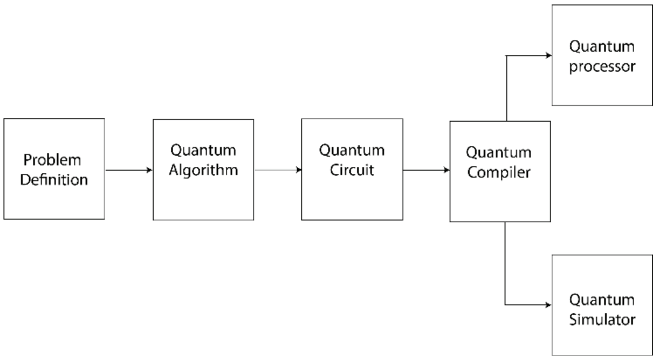

Fig. 2. Quantum Workflow in gate-based mode.

We employed IBM Qiskit's [6] gate-based variational algorithms, such as VQE and OAOA, and D-Wave's hybrid solvers to solve our problems.

III. Employee Transport Route Optimization

A. *Problem Statement*

The objective of the employee transport route optimization problem was to find the best way to use heterogeneous vehicles to drop employees from the office (depot) to various locations, minimizing the total distance traveled by the vehicles. We've considered vehicles of different capacities. As the instance size increases, the amount of time needed to solve the issue increases exponentially. We used real-world data from a large IT company to model this problem, which includes information on multiple serving locations, customer details, and vehicle types. The objective function is to minimize the total distance traveled by all vehicles, with all constraints stated as follows:

1) Each employee should be served precisely once and by precisely one vehicle.

2) The vehicle's route is continuous and does not finish at any serving location, which simply means that a vehicle must leave if it reaches at a node, thereby ensuring route continuity.

3) Each vehicle should start from the office, and each vehicle should end its route at the office.

4) Total employees to be picked up should be less than the vehicle capacity.

5) With a specific subset of customer locations, vehicle 'v' shouldn't form closed loops. When the number of arcs between any subset of customer locations across all vehicles equals the number of customer locations in that subset, a closed-loop (also known as a sub-tour) is initiated. As a result, we restrict the total number of arcs to one less than the total number of customer locations. This is known as the sub-tour elimination constraint [18]. We did not used MTZ approach [18] because it involves continuous variables, and it is challenging to convert continuous variables problems into QUBO.

B. Solution Methodology / Approach

1) Gate Based Model: We perform preprocessing on the data and identify the client locations. The pairwise distances are calculated. In this instance, the Euclidean distance is the most direct distance to consider. Initially, the relaxed combinatorial problem (only with equality constraints) is transformed into a QUBO [19], and then the resulting problem is mapped into an Ising Hamiltonian [17]. We choose the depth of the circuit, the set of controls for the circuit to make a trial function. Finally, cost is evaluated by sampling the outcomes. In later stages, a classical optimizer is used to optimize the set of controls, and the process is repeated till we reach a minimum. The feasible solution generated using mathematical model is then converted into table form for the ease of the user. The entire workflow is also shown in Fig. 3.

2) Annealing-based Model: The objective function is formed up by the total costs of travel from the depot to their first destinations, the sum of all costs for the last part of the route, that is, returning to the depot and the sums of cost of all the inter-node travel from one customer to the other. To solve the VRP and its real-world equivalent, Capacitated Vehicle Routing Problem (CVRP), we worked on two-hybrid methods, DBSCAN Solver (DBSS) and Solution Partitioning Solver (SPS) [20]. Both methods have significant classical components; however, DBSS allows us to apply a quantum approach in conjunction with a classical algorithm. This algorithm was inspired by recursive DBSCAN. [21]. DBSS uses recursive DBSCAN as a clustering algorithm with a limited size of clusters. VRP is then solved individually for each cluster. But DBSS can only solve CVRP problem with vehicles of equal capacity. To solve CVRP with different vehicle capacities, the SPS algorithm is used. It splits the VRP solution generated by DBSS into consecutive intervals, which are the solution for CVRP having unequal vehicle capacities.

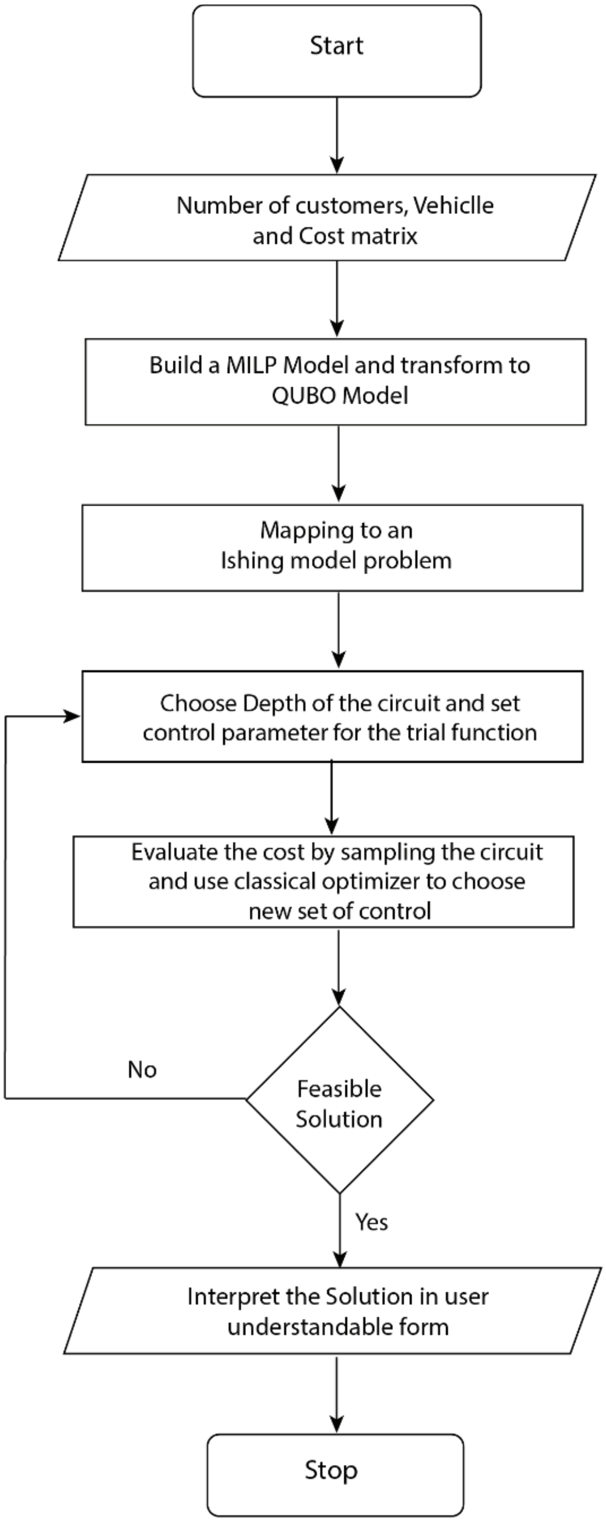

Fig. 3. Flowchart of Employee transport route optimization

C. Results

Experiment 1 : In this experiment, we have solved the problem for n = 4 and k = 2, where n is the number of customers and k is the number of vehicles. To encode the problem, we used $4 \times 3 = 12$ qubits. We are limited by the quantum hardware of a gate-based quantum computer to further solve this problem for an extensive dataset or including all the constraints at once. As we increase the number of variables, the computational cost and time increases considerably. So for our experiment purpose, we have worked with a relatively minor data set of 4 customers and 2 vehicles and have considered the first three constraints. The result is shown in the Table. I.

TABLE I.

COMPARISON OF CLASSICAL AND QUANTUM RESULTS.

# Customers and Vehicles	Vars.	Cost		Obj. Value Deviation (%)
		CPLEX	*CQM*	
(6, 3)	144	1499.23	1499.31	0%
(9, 1)	90	60.65	60.66	0%
(8, 1)	72	98.90	98.90	0%
(6, 2)	84	349.80	349.81	0%
(9, 2)	180	34.84	34.84	0%

We ran it on IBMs Qiskit's [6] qasm simulator.

1) Experiment 2 : We employed the SPS algorithm [20] for the Employee Transport Management System (ETMS) dataset to solve the heterogeneous capacity constraint problems on D-Wave's [9] quantum annealer. The cost by QPU is provided in the Table. II. This experiment follows all the constraints mentioned in Sec. III-A

TABLE II.

EXECUTION RESULT FOR QUANTUM SPS

# Customers and Vehicles	Variables	Cost
(106, 37)	11236	14383

2) Experiment 3 : Table III shows the experimental output and compares the results between CPLEX [11], BQM, DQM and CQM [11]. BQM and DQM did not provide feasible solutions in any combination. So, as per Table III CQM and CPLEX outperform BQM and DQM in any given combination of (n, k). We used a distance-based clustering [23] approach to solve the problem since CQM could not handle the big dataset at once.

TABLE III.

COMPARISON OF CLASSICAL AND QUANTUM RESULTS.

# Customers and Vehicles	Vars.	Cost		Obj. Value Deviation (%)
		CPLEX	*CQM*	
(4, 2)	24	30148.00	30148.00	0%
(5, 2)	40	30152.00	30152.00	0%
(9, 2)	144	318631.10	318631.10	0%

IV. AGRI-TECH LOGISTICS OPTIMIZATION

A. Problem Statement

In the Farm producer organizations Management System (FMS), harvest is scheduled for suppliers (farmers/vendors) whose plots/commodity is ready for harvest. Once in this status, one or more than one vehicle is assigned along with a harvester to harvest, load, and bring the material to the collection centres for further processing under some defined conditions. In this problem statement, transportation cost is one of the high costs that we try to reduce by the optimal utility of the vehicles and finding the optimal route of the vehicles. We modeled this business problem statement as a capacitated vehicle routing problem [24]–[27] where the objective is to minimize the total distance traveled by all vehicles, and maximize utilization of vehicles subject to their weight and volume capacity, with all constraints stated as follows

1) The total weight of the commodities for each vehicle should not be greater than the loading capacity provided for the vehicle.
2) The total volume of the commodities must be less than equal to the given volumetric capacity of the vehicle.
3) Some selected commodities should not be loaded together in a single vehicle. This is the segregation constraint.
4) If needed, multiple vehicles can be assigned to a farmer.

This model does not only minimize the distance traveled, but it also decides on the number of heterogeneous capacitated vehicles to use while following all the mentioned constraints. This use case is similar to the ETMS use case (CVRP) but with extra segregation constraints. We are solving CVRP in the Agri-tech industry.

B. Solution Methodology / Approach

We pre-processed the above optimization model before handing it to the quantum solver. Since there is currently a limitation in quantum hardware, we decomposed our main problem into sub-problems by using clustering based on distance. Then we solved each sub-problem separately to find the output of the actual problem.

To solve the above optimization problem in quantum first, we convert this binary constraint optimization problem into QUBO and then solve this QUBO by using a quantum annealing based CQM solver. The feasible solution generated using mathematical model is then converted into table form for the ease of the user. The workflow is presented in Fig. 4.

C. Results

We used the real-world data set from an Agri-tech company throughout the experiments. The actual problem statement has the following parameters :

Number of farmers' location= 38, number of available vehicles = 15, number of commodities = 52. To solve this in quantum, we created five clusters based on the distance and then solved each sub-problems concerning each cluster. Finally, by combining the output of each cluster, we found the result of our actual problem.

Table IV clearly shows that the Quantum CQM solver provides comparable results compared to the classical CPLEX results.

TABLE IV.

COMPARISON OF CLASSICAL AND QUANTUM RESULTS.

# Customers and Vehicles	Vars.	Cost			Obj. Value Deviation (%)
		CPLEX	*VQE*	*QAOA*	
(4, 2)	12	124.87	124.87	124.87	0%

V. CONCLUSIONS AND FUTURE WORK

Due to the current limitation of quantum hardware, we have solved a simplified version of the employee transport route optimization by taking a subset of data serving only one office location for a single trip, without time window constraints.

In the future, we intend to extend this to multiple facilities, multiple depots, multiple trips, and time-window constraints.

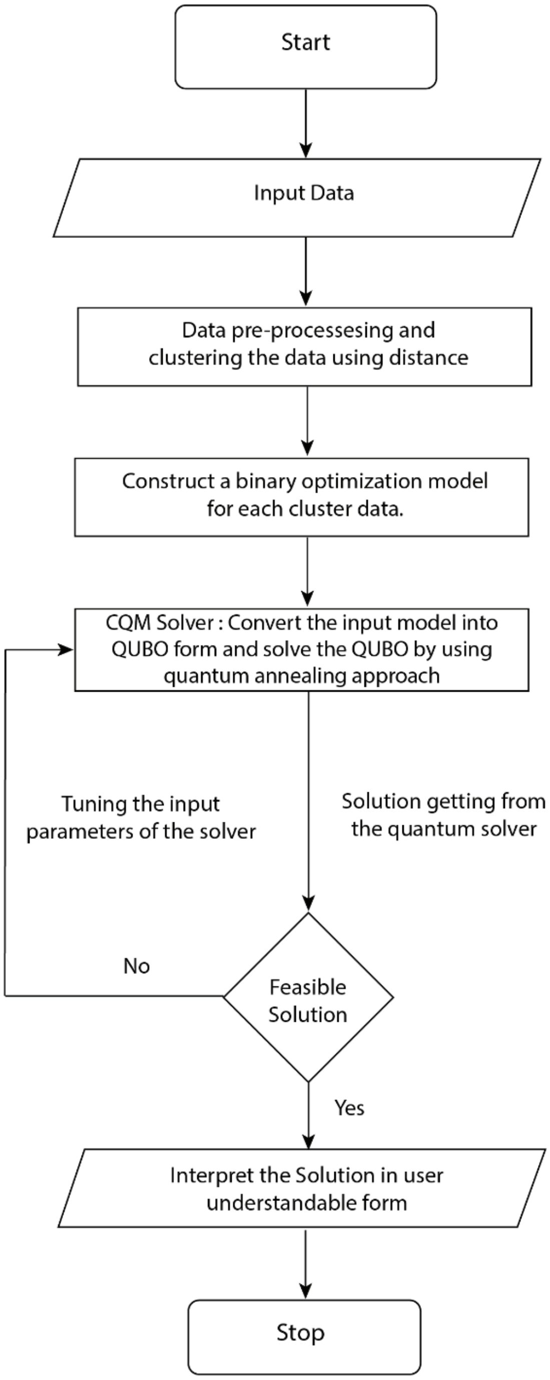

Fig. 4. Flowchart of Agri-tech logistics optimization

The same is the case with the Agri-tech logistics optimization problems. The complexity of the problem can be increased by incorporating additional constraints such as time windows and multiple distribution centers. We intend to cover all these additional parameters and complexity in our future work and look for creative ways to formulate and solve the problem on quantum computers. We will continue to focus on solving real-world problems employing quantum algorithms.

Furthermore, we find that these optimization problems are well-suited for D-Wave systems. Also, over the last couple of years, there has been a significant improvement in the topology [28], the number of qubits [29], precision [30], connectivity of the qubits [31], and performance of D-Wave QPUs. Soon, we expect to solve larger, more complex real-world problems.

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