IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

The Comparison of Supply Chain Management using Quantum Computing and Classical Computing

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Abstract: The aim of this paper is to review and compare the Quantum and classical computing models for Supply chain Management. Full-scale optimization problems of practical significance that can have numerous variables and complex objective functions are almost uniformly incompatible with noisy intermediate-scale quantum (NISQ) gear. As a result, there is an expanding body of research that uses scaled-down versions of operations research-related problems to test quantum algorithms. Instead of using this method, we study a challenge with significant commercial value: multi-truck-vehicle routing for supply chain logistics and the back-order prediction. By employing a hybrid workflow strategy, we are able to get around this problem by iteratively allocating routes for trucks by creating a new instance of a binary optimization problem, one truck at a time. It is impossible to completely implement such a task on any foreseeable quantum hardware or simulator. Each instance has about 2500 quadratic binary variables, which is within NISQ quantum computing's capability. After putting the vehicle paths and order predictions suggested by these runs into a very realistic classical supply network simulation, we further reveal similar performance for the entire supply chain.

Index Terms - Quantum Computing, Classical Computing, Vehicle Routing Problem, Back-Order Prediction, QUBO, Quantum, NISQ.

I. INTRODUCTION

For tackling significant issues like integer tracking and quantum mechanical simulation, quantum algorithms have the potential to significantly outperform known classical algorithms. The current state of quantum hardware, however, is still too immature for any existing quantum device to provide useful computational benefit, despite incredible effort and money. A quantum computer has recently been used to execute calculations that are faster than classical computing, although these calculations do not resolve any practical problems.

Given these facts, heuristic algorithms often of a mixed classical-quantum nature have received a lot of attention in research. They strive to provide computing advantages even with problematic hardware. Although it has not been established that these algorithms for the noisy intermediate-scale quantum era (NISQ) offer complexity advantages over conventional techniques, they have the potential to be a haven on the arduous path to the development of large-scale fault-tolerant quantum computers.

Numerous industries looking for ways to increase the effectiveness of their operations have taken notice of NISQ algorithms and the rapid development of quantum technology. It is typical practice to start with a complex problem, locate a downsized version of the problem that can be solved using a NISQ quantum algorithm, and then test the potential of NISQ algorithms in the specific use case. For instance, many operations research-related issues can be reformulated as QUBO (quadratic unconstrained binary optimization) issues. The quantum approximation optimization approach (with simulated or actual hardware) can be used to reduce the size of these problems, and then they can be solved.

Such studies unquestionably have importance, but they also have significant flaws. Problem instances must be reduced to tiny dollhouse replicas that hardly capture the genuine nature of real-world issues. schematic diagram Even on simulators, it is currently impossible to evaluate quantum algorithms with many more variables than 30 binary ones. Due to embedding issues, quantum annealers can become complicated at a few hundred variables. Where limited to such narrow use cases and when the quality of the solution and runtime is almost certainly going to be easily exceeded by classical algorithms using widely accessible hardware, private companies might not be eager to sponsor quantum computing investigations.

In this study, we create a different method for solving downsizing issues in commercial research. We start with a practical car routing issue that occurs in a business' operations. Instead of simplifying the mathematical issue and creating a version with a minimal number of variables, we employ a hybrid workflow approach and use NISQ algorithms to iteratively create small QUBO instances that are appropriate for use with current technology. While offering a route for a single truck, solutions to these tiny examples do not offer a solution to the complete and extremely complex vehicle routing problem. We update the remaining unmet demand using that channel before repeating the process. We feed the routes into a highly realistic simulation of the flow of all trucks and carried boxes after we have found solutions for each truck, taking into consideration a number of constraints that are challenging to include in QUBO instances. The end result is a workable answer to the complete routing problem that can be compared to answers discovered by using other techniques.

It is not a novel concept to develop a heuristic solution to a complex problem using iterative methods. The construction we provide, however, is specifically designed to work with the hardware required for near-term quantum computing. Each step's issue instances are QUBO instances with no more than a few thousand variables. These QUBO instances are suitable for quantum hardware with a few thousand noisy qubits in circuit models. D-Wave Systems already has quantum annealing hardware that can optimize QUBO instances with hundreds of variables, therefore this issue is more urgent. However, due to the difficulties of incorporating QUBO connection graphs, our instances are just slightly too large for direct application on D-Wave annealers.

The method outlined in this paper gives a workable quantum-classical solution to a particular issue of significant commercial significance. We focus on the issue of back-order prediction and vehicle routing problem in supply chain. We stress, however, that the broad approach of using quantum algorithms on small problem instances to build up a hybrid solution to full-scale commercial applications is important well outside of the context of supply chain optimization. In fact, such ap-proaches may be the first ways that quantum computing will be used outside of a research setting.

II. Related Work

In this section we will explain the back-order prediction and the Vehicle Routing problem as in cooperation with the Supply chain Management.

A. Back-Order Prediction

First, A backorder is a purchase order for a good or service that cannot be fulfilled right away owing to a shortage of stock. Although the product might not be in the company's current inventory, it might still be in production, or the company might need to continue producing more of the item. Backorders are a sign that a company's product is in higher demand than it can meet. The company's backlog is another name for them.

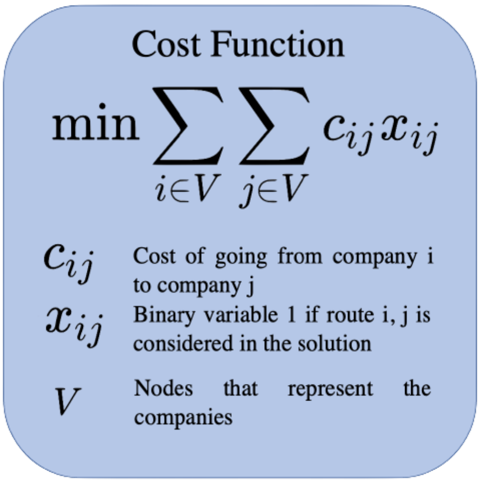
B. Vehicle Routing Problem (VRP)

The vehicle routing problem (VRP) is concerned with finding the best combination of routes to serve a specific group of clients, all of whom start and terminate at the same node (referred to as the depot). Planning a fleet of vehicles' delivery routes is the procedure known as routing. By reducing the distance traveled and the amount of time spent traveling, the most economical route can be found.

These are the related problems that need to be solved. These problems will make a full solution for supply chain management.

C. QUBO Model

It is necessary to represent an issue as a quadratic unconstrained binary optimization (QUBO) problem in order to encode it as the Vehicle Routing Problem on a quantum computer. The objective function's constraints are added as a penalty to the cost function in the QUBO form, which also includes linear and cubic components for the cost function. the subsequent purpose. In this work, demonstrated the VRP's objective function in the figure below:



To constrain this problem in this work applied some constraints as follows:

Constraints

$$\sum_{i \in V} x_{ij} = 1 \quad \forall j \in V \setminus \{0\}$$

$$\sum_{j \in V} x_{ij} = 1 \quad \forall i \in V \setminus \{0\}$$

Ensure one route entering company i and leaving company j

$$\sum_{i \in V} x_{i0} = K$$

$$\sum_{j \in V} x_{0j} = K$$

Constraints associated with K vehicles leaving the deposit and returning to it.

$$\sum_{i \notin S} \sum_{j \in S} x_{ij} \geq r(S), \quad \forall S \subseteq V \setminus \{0\}, S \neq \emptyset$$

$$x_{ij} \in \{0,1\} \quad \forall i, j \in V$$

Impose the routes must be connected

The terms of the above equations are:

Cij : We take into account the cost connected to a certain route ij as a combination of distance, traffic, and other anticipated terms connected to the drawbacks of using the specific route on a given day.

K: We find the solution for 3 trucks.

D. Quantum Computing

These computers can answer problems up to 100 million times quicker than conventional ones thanks to quantum computing, which uses the power of quantum physics to analyze data in fundamentally new ways. The majority of modern computers transfer data using binary code, which is a series of ones and zeros. Quantum computers, however, use quantum bits, sometimes known as "qubits," to carry out the same tasks. QC, in contrast, employs numbers that are neither one nor zero but rather oscillate on a spectrum in a liquid, non-binary state. This quantum uncertainty principle enables the computer to take into account all likely scenarios. Instead of needing to individually change each scenario, results are supplied instantly.

Applying Quantum computing to the problems identified will help to optimize the solution as the classical computing or conventional machine learning models won't be able to do so in given conditions.

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III. METHODS AND IMPLEMENTATION

1. *Backorder Prediction*

The Data set:

Obtaining data is the initial stage in any machine-learning project, and selecting the appropriate dataset for the task is crucial since it can have a significant impact on your model and strategy.
We used the dataset that is freely available on the specified GitHub repository to acquire this data. This dataset contains certain variables with 7% data gaps and an unbalanced distribution where one class makes up 81% and the other 19%.

Data analysis:

Prior to thinking about creating a prediction model for this project, it was essential to identify, emphasise, and analyse the data set in light of its characteristics and limitations. The historical data for the eight weeks preceding the week we are attempting to anticipate are contained in the data file. The dataset includes 23 variables, such as

The first action that had to be completed for using both methodologies was to preprocess, clean, and transform the data into a format that could be used.
Different approaches were taken in this study to compare the outcomes for the backorder dataset. The various approaches are demonstrated as follows:

A. Classical Computing Methods

In this paper, we compare both classical and quantum computing. To do this, we've trained a number of models based on various backorder prediction methods. Additionally, by merging various algorithms, a machine-learning pipeline was built. Here are a few machine learning models built on traditional computing.

1. Logistic Regression
2. SGD
3. KNN
4. Decision Tree
5. Random Forest
6. Gradient boosting
7. Ada-boost
8. Naive Bayes

9. Light GBM

In this work also deep learning models are also used for generating results on the backorder prediction problem. A fine-tuned neural network was created and trained on the backorder dataset with following architecture:

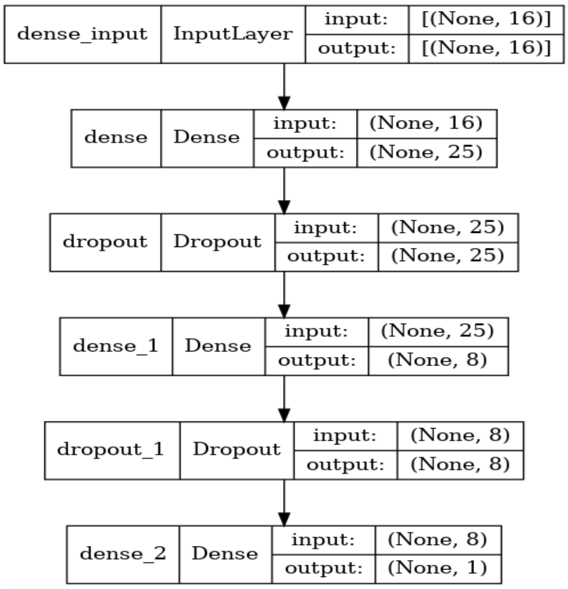
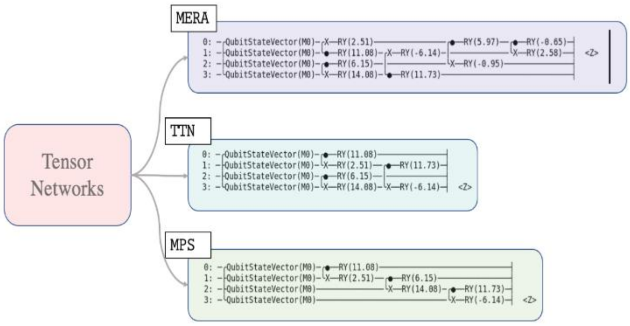


Fig. 1. Architecture of Neural Network

However, all traditional machine learning models were being severely overfit due to the sparse distribution between the two target classes. Another method of skimming the data was used to address this problem and produce some acceptable results.

B. Quantum Computing Methods

Data must be contained in the quantum circuit models' supported format in order to work with quantum models. We examine various size data models from the backorder's dataset using a special case of 15647 samples for training and 5216 samples for validation. This will act as a case study for a scenario in which no findings are provided.
Using Tensorflow and Keras, the QNN built in Pennylane is evaluated against a traditional neural network.



The ansatz encoding:

The following system is constructed for each experiment in the quantum computing case and has three distinct analogues based on three tensor networks (TN): MERA, TTN, and MPS. The amplitude embedding was constructed with just 16 variables, one layer per TN.
For the three different ansatzes depicted in the preceding figures, several architectures were tried using the Penny Lane templates. Four different architectures—1 layer, 2 layers, 4 layers, and 1 layer with a conventional scaler—were trained for the MERA architecture.
In the MPS and TTN examples, 1-, 2-, and 4-layer architectures were tested.

2. Vehicle Routing Problem

Once the backorders predictions are solved, we choose a few of them to optimise the optimal path for a group of K trucks using the Vehicle Routing Problem (VRP).

Setting the problem:

- We select a selection of 10 businesses from which it was anticipated that some products would be on backorder.
- There is always a relationship between the warehouse, where we gather all the merchandise, and each business.

- The merchandise will be collected by 3 trucks.
- When the Euclidean distance falls below a certain threshold, connections between companies are chosen.

To solve this problem first we are encoding the data into QUBO representation.

A. *Classical approach of the QUBO model*

We obtain the solution to the above-described problem using docplex, the Python implementation of the optimization solver cplex.

B. *Quantum approach of the QUBO model*

Once we obtain our model's quadratic programme. We may convert it into its QUBO representation using the qiskit optimization library. In this situation, we have inequality restrictions, which typically call for additional variables, or "slack variables." In this scenario, the inequality restrictions are represented by an increase in the number of variables from 68 to 196.
The number of qubits we can simulate is another limitation. The best solution for simulating programmes with more than 20 qubits without a supercomputer is to use IBM's qasm simulator in runtime mode. With the qasm simulator, 32 qubits are the most that can be simulated. Similar issues arise when dealing with real equipment because we can only do research on a 7 qubits device (ibm_oslo, ibm_lagos) to which we have access.

By selecting the best answer for the slack variables, we can reduce the number of variables by using the prior solution. In two scenarios, we choose the optimal solution for part of the variables that represent the routes of company I to company j and leave the quantum computer to find the optimal solution for the remaining variables:

1. 7 variables are used, and the best answer is used to replace the others. Out of the remaining 7 variables, 3 are optimally solved as 1 and 4, respectively (testing local machine and ibm lagos runtime).
2. 15 variables are used, and the best result is used to replace the others. When testing the qasm simulator runtime, the optimal solutions for the variables 5 and 10 are both identical to 1 from the variables on the left.

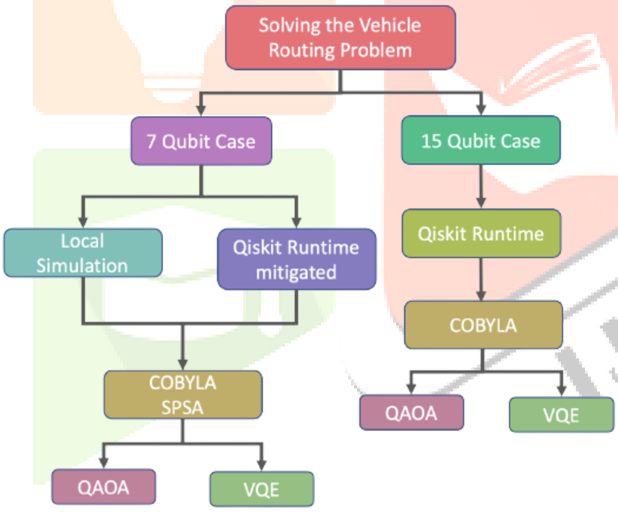


Fig. 4 *Solution Flow of VRP using Quantum Computing*

IV. RESULTS AND DISCUSSION

This specificity suggests that quantum computing will works with the equivalant accuracy to other classical computation. The following are the results obtained from the comparison of different models of classical computing and Quantum computing.

A. *Results of Classical Computing*

1. *Back-Order Prediction*

We tried many machine learning algorithms for the backorder problem using the classical method, and after comparing their accuracies, it was discovered that the neural network model performed the best of all of them. We were able to generate an accuracy of about 75% by employing the quantum models, which had an accuracy of 85% on both the training and testing data sets. The model that performed the best was the MERA model.

I. RESULTS OF BACK-ORDER USING CLASSICAL COMPUTING

Sr. No.	Model Description		
	Model Name	***Accuracy***	***ROC-AUC***
1.	Logistic Regression	0.8598543	0.85895346
2.	SGD	0.8425997	0.84109661
3.	KNN	0.8604294	0.85875817
4.	Decision Tree	0.8995399	0.85965803
5.	Random Forest	0.891296	0.89787216
6.	Gradient Boosting	0.891296	0.8901947
7.	Ada Boost	0.866181	0.86509219
8.	Naive Bayes	0.8013804	0.8058268
9.	Light GBM	0.6157975	0.62030692

2. Vehicle Routing Problem (QUBO Model)

We obtain the solution to the above-described problem using docplex, the Python implementation of the optimization solver cplex. The graph representation of the solution is shown in the figure below, where the edges are the relationships between the businesses that minimize the cost function and adhere to all constraints. This answer will be used throughout the rest of the notebook as the best answer.

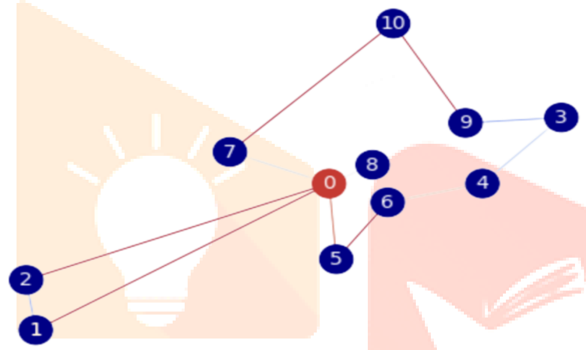


Fig. 2. *Optimal Solution for VRP using QUBO Model*

B. *Results of Quantum Computing*

1. *Back-Order Prediction*

Different architectures were tried using the templates created by Pennylane for the three different ansatzes described in above in alternative architectures, including 1 layer, 2 layers, 4 layers, a layer with a standard scaler, and a layer with 0.2 depolarizing noise, were trained for the MERA architecture. The structures tested in the cases of MPS and TTN were 1, 2, and 4 layers. The outcomes were contrasted with those of a 640 parameter classical neural network. The MERA and one layer combination produced the greatest results out of all the examined architectures. As there is a larger class with variables than the other, recall, pressure, F1 score, and ROC AUC should be taken into account for the unbalanced dataset rather than accuracy. When examining the confusion matrix, it can be seen that class 1—which makes up about 18% of the test set—is mostly correctly classified.

In nearly every statistic shown in the table below, the MERA architecture, which has only 10 parameters, performs better than the top performance achieved by a classical neural network, which has 684 parameters. The ability of MERA 1 layer to lower false positives, which can lead to overstocking, is crucial. Another plus is that the 1 layer model can still predict well even in the presence of considerable noise, as evidenced by the confusion matrices below.

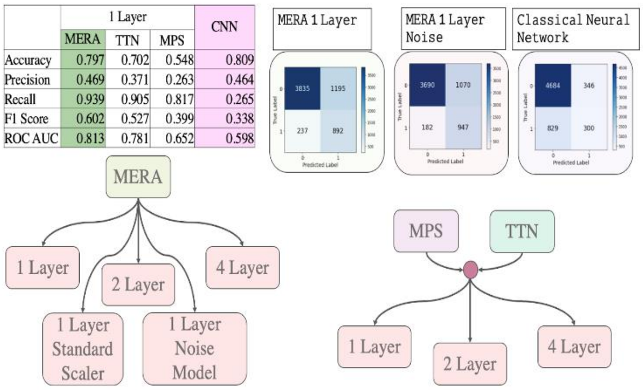


Fig. 3. *Results of Back-Order Prediction using Quantum Computing*

2. *Vehicle Routing Problem*

7 Qubit Results:

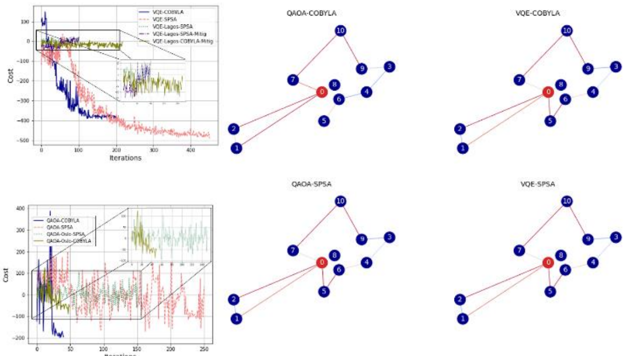


Fig. 5 *Results of VRP QUBO using 7 Qubit Case*

15 Qubit Results:

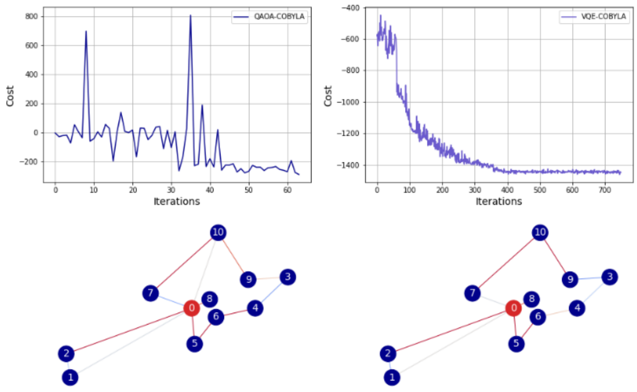


Fig. 6. *Results of VRP QUBO using 7 Qubit Case*

V. Conclusions

For particular workloads, quantum algorithms are known to offer computational advantages over traditional computing. This specificity suggests that quantum computing will most likely be employed as a component of hybrid classical-quantum work-flows when dealing with difficult problems of practical consequence, even when quantum hardware improves. This project's methodology is an illustration of a hybrid process. We were able to create small issue instances as subroutines that can be addressed by NISQ quantum algorithms, even for the incredibly difficult task of routing trucks in a genuine supply chain.

The smaller issues in our investigation of a commercial supply chain are binary optimization issues with approximately 2500 binary variables, a scale that is suitable for both near-term quantum annealing and slightly near-term circuit model quantum computing. We discovered workable solutions for the whole supply chain when we ran our workflow with solvers like simulated annealing and the D-Wave hybrid solver, proxies used in place of more developed quantum technology.

Because NISQ quantum optimization techniques like quantum annealing and QAOA are heuristics without meaningfully proven guarantees, we do not assert that our approach provides a demonstrable performance benefit over classical algorithms. Although it is NP-hard, the individual truck routing binary optimization problem can still be a performance constraint. It makes sense to use quantum algorithms to address these bottlenecks, and this strategy will be successful if NISQ quantum optimization algorithms are discovered that outperform classical computing.

ACKNOWLEDGMENT

Thanks to Prof. Rakesh Pandey & Dr. Sharda A. Chhabria, Bot Lab In-charge (Centre of Excellence) for guiding us throughout the whole process of building the project and for the discussions on Supply chain management and different techniques to build a research-oriented project.

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