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***Abstract*—Applying quantum computing to real world applications to assess the potential efficacy is a daunting task for non-quantum specialists. This paper shows an implementation of two quantum optimization algorithms applied to portfolios of trade finance portfolios and compares the selections to those chosen by experienced underwriters and a classical optimizer. The method used is to map the financial risk and returns for a trade finance portfolio to an optimization function of a quantum algorithm developed in a Qiskit tutorial. The results show that whilst there is no advantage seen by using the quantum algorithms, the performance of the quantum algorithms has no statistically significant degradation. Therefore, it is promising that in the future, with expected improvements in quantum hardware, the theoretically superior processing speeds, and data volumes that quantum offers, will also be applicable to trade finance.**

Keywords—quantum computing, credit, trade finance, supply chain finance.

I. Introduction

This paper shows the application of existing quantum computing algorithms to optimise a trade finance portfolio for supply chains. Like a portfolio of stocks, an optimal trade finance portfolio will maximise the returns while minimising the risk. However, the risk in this case is based on the likelihood of defaulting on the payback of the financing, for example a letter of credit. Determining the best mix for a trade finance portfolio is currently a highly manual and skilled job and market experts estimate that only 10% of the global available marketplace are satisfied with Supply Chain Finance (SCF) solutions [1]. The current market size for SCF is estimated to be at around US$ 3 trillion globally [1] and is expected to expand strongly in the coming years at a rate between 10% to 20% [2]. The driving forces behind the rapid growth of SCF solutions are an increase in supply chain risks due to globalisation, liquidity and cash flow management, and suppliers' growing requirements for better access to finance along with lower financing costs. Furthermore, IoT in manufacturing is generating vast amounts of data which could be used in decision-making models, allowing the supply chain ecosystem to act with the timely insight needed to optimize finance, resource management and logistics. For financing supply chain portfolios, more precise estimates of credit exposures should lead to better optimization decisions. More broadly, capital allocation across a range of corporate finance activities can also be improved by insights into the size and materiality of risks.

Quantum computing has been applied to finance over the past few years [3], in particular for areas such as option pricing, risk management, client and product management, and portfolio optimisation showing potential advantages such as a quadratic speed up of Monte Carlo simulations over classical machines [4]. However, there are still issues that do not allow the advantages to be exploited today, such as loading data into quantum states and the low quality of quantum hardware. Progress on quantum computer hardware continues at a good pace with significant research and investment by many companies around the world, for example IBM announced a new quantum computing milestone, with a Quantum Volume of 64 [5]. Furthermore, interest is growing in major banks such as Goldman Sachs, JPMorgan and Citigroup having set up quantum computing initiatives [6]. Any non-deterministic and computationally intense process with a large set of variables is a candidate for improvement by quantum computing in the future. This paper explores the accuracy of two quantum algorithms in selecting a number of corporates to finance by comparing three models (one classical and two quantum) to that of an experienced underwriter.

II. Approach

Quantum computing algorithms are complex and time-consuming to create, requiring specialised knowledge outside the capability of most underwriters. However, there are already many algorithms existing for many types of problems [7]. Furthermore, IBM Quantum Services provides tools and tutorials showing examples of using certain quantum algorithms [8] which can be implemented in their Qiskit development environment [9]. It was decided to leverage the stock portfolio optimisation tutorial [10] as a basis for exploring trade finance portfolio optimisation.

The overall objective of any portfolio optimisation is to maximise returns whilst minimising risk. One main difference for our use case is that the risk for the portfolio is captured by the likelihood of defaulting rather than the volatility of stock prices. Another difference is that the return is not simply a stock price difference but is the interest paid and fees charged for the financing. Optimising the portfolio is achieved by introducing a constraint on the acceptable risk level, q, and then maximize the return under this constraint by the best selection of assets (i.e. companies to finance). In the tutorial the value of $q=0.5$ is for a balance of risk to returns for illustration. For different values of q, we expect to find different selections. For example, $q=0$ is considered risk-neutral and the optimal solution would only maximize the expected return independent of the risk. As q increases, the solution becomes more and more risk-averse and possibly reduce returns. Solving the problem for a reasonable set of q leads to the so-called efficient frontier of risk and return, i.e. for every risk level, we get the maximum expected return that can be achieved. In other words, q is an implicit way to control the risk taken in the optimal solution of the resulting optimization problem.

The stock portfolio algorithm is a mean-variance optimization problem for n selections. In this paper the main selection shown is 6 companies out of 10 in total using 20 performance parameters. A covariance matrix of the scoring of the company's performance is calculated and input to the quantum algorithms along with the return equivalent values, and the risk factor. The overall process flow used is to pre-process the base data, load the data into the optimisation algorithms and then analyse the results (Fig. 1).

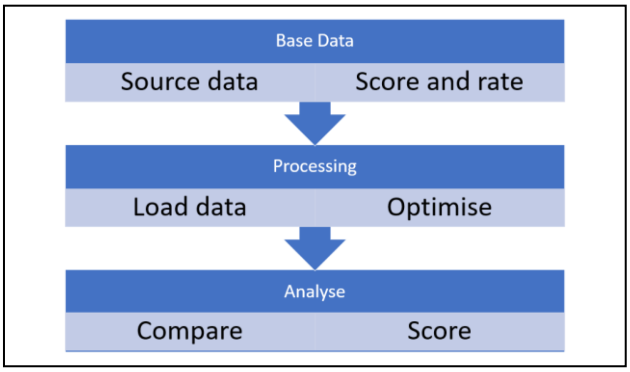

Fig. 1. Overall data preparation and processing flow.

A. Base Data

Performance parameters used were collected from the following sources:

- **Annual report and quarterly filings** – including Financial Highlights, Chairman's Statement, CEO's Statement, Operations Review, Board of Directors and Key Management, Corporate Information, etc.
- **Manually underwriting** - a section of the annual report including: Financial Statements, Statements of Financial Position, Consolidated Statement of Profit or Loss and Other Comprehensive Income, etc.
- **Country Risk evaluation parameters** – including economic and political risks, core fundamentals such as demographics and infrastructure

These were finalised into 20 parameters for counterparty financial metrics and sector country risk, broadly categorized under:

- Liquidity position
- Business performance
- Fundamental solidity
- Sector risk constraints

The 10 companies chosen were across 2 sectors and diversified across geographies:

Department Stores: Woolworths Group Ltd *(ASX: WOW)*, Walmart Inc *(NYSE: WMT)*, Tesco PLC *(LON: TSCO)*, Shoprite Holdings Ltd *(JSE: SHP)***,** Avenue Supermarts Ltd *(NSE: DMART)*.

Steel Manufacturing:

Nippon Steel Corp *(TYO: 5401)*, JSW Steel Limited *(NSE: JSWSTEEL)*, ArcelorMittal SA *(AMS: MT)*, Novolipetsk Steel PAO *(NCX: NLMK)*, Hoa Phat Group JSC *(HPG.HM)*.

B. Data Processing

The performance parameters of each company were weighted and summed in Microsoft Excel to give a weighted score:

$$S = \sum(s * w) \tag{1}$$

Where s is a value between 0 and 100, mapped to the actual metric value and w is the relative importance weight of the metric compared to other metrics, as decided by the underwriter and applied to all companies. The summation of the individual scores combined with the weights provide an output in the form of a rating which serves as a tool for the underwriter to decide on the companies to pick, vis-à-vis the returns expected from each company.

Pandas software library was used to extract the data from the Excel file and import into Python lists. The covariance was calculated using standard Python NumPy functions. The covariance along with the financing interest rate, as the equivalent return, were loaded into the optimization algorithms.

C. Optimization Algorithms

Three algorithms were used to determine the optimum selection: a classical Minimum Eigenvalue Algorithm, Variational Quantum Eigensolver (VQE) and Quantum Approximate Optimization Algorithm (QAOA). Each algorithm was executed for ten risk values from q=0.0 to q=1.0 in steps of 0.1 for the same returns and covariance matrix.

The code in the tutorial [10], to solve the mean-variance portfolio optimization problem for n stocks, was modified for n companies' financing. The problem to optimize for now becomes:

$$\min q x^T \sum x - \mu^T x \tag{2}$$

For $x \in \{0,1\}^n$ indicating which company to pick (x=1) or not to pick (x=0) with the constraint that the number of selected companies equals the total budget, B, available. Also, it is assumed that all financing amounts are the same for all companies (i.e. $1^T x = B$). μ is a vector of interest rates for financing the companies, Σ is the covariances between the company metrics, and q is a factor for the risk appetite of the decision maker and is always >0.

The equality constraint $1^T x=B$ is mapped to a penalty term $(1Tx-B)^2$ which is scaled by a parameter and subtracted from the objective function. The resulting problem can be mapped to a Hamiltonian function whose minimum energy ground state corresponds to the optimal solution.

The classical Minimum Eigenvalue Algorithm works on the principal that eigenvectors represent the directions of the spread or variance of data and the corresponding eigenvalues are the magnitude of the spread in these directions. This optimization algorithm finds the eigenvalue in generalized eigenvalue problems.

The Variational Quantum Eigensolver (VQE) is used for optimization applications harnessing energy states to calculate the function of the variables it needs to optimize. In financial services, the VQE has been used in stock portfolio optimization in the tutorial.

The Quantum Approximate Optimization Algorithm (QAOA) is a hybrid quantum-classical variational algorithm designed to address combinatorial optimization problems. A quantum circuit is created to prepare a quantum state according to a set of variational parameters and is executed. The measurement outputs of the quantum circuit are then read by a classical computer and used to further optimize the parameters feeding back to the quantum machine in a closed loop.

The three algorithms compute a minimum eigenvalue for an operator implementing the same programming interface allowing the different algorithms to be used interchangeably.

To evaluate the performance of the algorithms, we have used the IBM Qiskit framework accessing the quantum systems and simulators available in the IBM Quantum network. All the experiments were executed on quantum simulators to remove variations from hardware noise.

D. Scenarios and analysis

The first trial scenario was to select 2 companies out of a total of 4 to confirm the functions were executing as expected. The results seemed promising and the selection was expanded to 10 companies out of 25 but the processing time increased to greater than 12 hours, too slow to be practical. Finally, 6 out of 10 companies were chosen from 2 sectors: retail and steel and with geographical diversity.

Each company's credit worthiness and potential equivalent return was assessed by an underwriter and the portfolio manually compiled for each risk value from 0.0 (risk neutral) to 1.0 (risk adverse). The asset selections of the algorithms were found for each risk value and compared to the manual selections of the underwriter. An accuracy scores was calculated by summing the number of times the selection of an algorithm matched that of the underwriter.

To further analyze the behavior of quantum algorithms the number of selected companies out of the total 10 was decreased and accuracy scores measured.

III. Results

Results shown here are for selecting 6 out of 10 companies across 2 sectors and diversified for geography. The first observation was that the asset selections ("1" in cells shaded in green in Table. I) for differing risk appears relatively stable for the classical algorithm with more variation for VQE and even more for QAOA. Also, the QAOA algorithm does not always select 6 assets, for example with q=1.0 only has 3 selections, q=0 has 7 selections and q=0.5 has 5 selections. It is not clear where the variation arises from and is an area that can be further explored.

To check on the stability of the results and to explore possible differences in accuracy with the number of selections, it was decided to reduce the number of companies to select from 6 to 1 and re-run the experiments for all values of q. Results show the accuracy increasing with the number of selections for all algorithms (Fig. 2). The accuracy for the classical algorithm appears above those of the quantum algorithms (blue line on Fig. 2) and has a higher average (Table III) and lower variance. This is even clearer if only selections of 3 to 6 are statistically analysed (not shown). However, a one-way analysis of variance (ANOVA) shows that there are no significant differences in the distributions of three algorithms ($F(2,15)=0.96$, $p=0.40$) (Table IV), i.e. they all exhibit the same behavior.

TABLE I. SIX COMPANIES SELECTED BY CLASSICAL, VQE AND QAOA ALGORITHMS COMPARED TO MANUAL.

	Manual										Classical									
q	SH	AV	WO	WA	TE	NO	HO	NI	JS	AR	SH	AV	WO	WA	TE	NO	HO	NI	JS	AR
0.0	1	1	1			1	1		1				1	1	1			1	1	1
0.1	1	1	1			1	1		1				1	1	1	1			1	1
0.2	1	1	1			1	1		1				1	1	1	1			1	1
0.3	1	1	1			1			1	1		1	1	1	1	1				1
0.4	1	1	1					1	1	1		1	1	1	1	1				1
0.5	1	1	1					1	1	1		1	1	1	1	1				1
0.6	1	1	1					1	1	1		1	1	1	1	1				1
0.7		1	1	1	1			1		1		1	1	1	1	1				1
0.8		1	1	1	1			1		1		1	1	1	1	1				1
0.9		1	1	1	1			1		1		1	1	1	1	1				1
1		1	1	1	1			1		1		1	1	1	1	1				1

	VQE										QAOA									
q	SH	AV	WO	WA	TE	NO	HO	NI	JS	AR	SH	AV	WO	WA	TE	NO	HO	NI	JS	AR
0.0			1	1	1	1			1	1		1	1	1	1			1	1	1
0.1		1	1	1		1			1	1		1	1	1	1			1	1	
0.2		1	1	1	1			1		1		1	1	1	1				1	1
0.3		1	1	1				1	1	1		1	1	1			1	1		1
0.4		1	1	1	1			1		1		1	1	1	1			1		1
0.5	1	1	1	1	1				1		1					1	1	1		1
0.6	1	1	1	1	1				1			1		1			1	1		1
0.7		1	1	1			1	1		1	1						1	1		1
0.8		1	1	1	1		1		1				1		1	1	1	1	1	1
0.9		1	1	1	1	1	1	1			1		1		1	1			1	
1		1	1	1	1	1	1	1							1		1		1	

TABLE II. ACCURACY SCORES FOR COMPANIES SELECTED THE ALGORITHMS COMPARED TO MANUAL.

	Manual										Classical									
q	SH	AV	WO	WA	TE	NO	HO	NI	JS	AR	SH	AV	WO	WA	TE	NO	HO	NI	JS	AR
0.0	1	1	1			1	1		1		0	0	1	0	0	0	0	0	1	0
0.1	1	1	1			1	1		1		0	0	1	0	0	1	0	0	1	0
0.2	1	1	1			1	1		1		0	0	1	0	0	1	0	0	1	0
0.3	1	1	1			1			1	1	0	1	1	0	0	1	0	0	0	1
0.4	1	1	1					1	1	1	0	1	1	0	0	0	0	0	0	1
0.5	1	1	1					1	1	1	0	1	1	0	0	0	0	0	0	1
0.6	1	1	1					1	1	1	0	1	1	0	0	0	0	0	0	1
0.7		1	1	1	1			1		1	0	1	1	1	1	0	0	0	0	1
0.8		1	1	1	1			1		1	0	1	1	1	1	0	0	0	0	1
0.9		1	1	1	1			1		1	0	1	1	1	1	0	0	0	0	1
1		1	1	1	1			1		1	0	1	1	1	1	0	0	0	0	1

	VQE										QAOA										Accuracy Score		
q	SH	AV	WO	WA	TE	NO	HO	NI	JS	AR	SH	AV	WO	WA	TE	NO	HO	NI	JS	AR	Classical	VQE	QAOA
0.0	0	0	1	0	0	1	0	0	1	0	0	1	1	0	0	0	0	0	1	0	2	3	3
0.1	0	1	1	0	0	1	0	0	1	0	0	1	1	0	0	0	0	0	1	0	3	4	3
0.2	0	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	3	2	3
0.3	0	1	1	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0	0	1	4	4	3
0.4	0	1	1	0	0	0	0	1	0	1	0	1	1	0	0	0	0	1	0	1	3	4	4
0.5	1	1	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	1	3	4	3
0.6	1	1	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	1	3	4	3
0.7	0	1	1	1	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	1	5	5	2
0.8	0	1	1	1	1	0	0	0	0	0	0	0	1	0	1	0	0	1	0	1	5	4	4
0.9	0	1	1	1	1	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	5	5	2
1	0	1	1	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	5	5	1
																				Sum	41	44	31

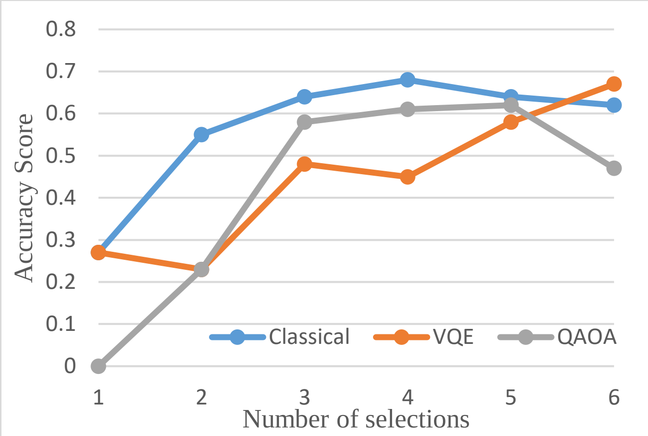

Figure 2. Accuracy scores for varying number of selections.

IV. DISCUSSION

As there is no statistical difference between the accuracy of VQE and QAOA quantum algorithms to classical algorithm in the results we cannot conclude that there is any advantage in using quantum algorithms with this data. However, as there is no difference then there is also no disadvantage. Hence, it is hopeful that when quantum computing can be scaled up with improved hardware, the amount of data that can be processed should also be able to also scale efficiently. This would allow the finance industry to be better equipped to deal with the higher data volumes and more features. For this use case there are over 200 more data points that could be explored from other financial metrics in the P&L, Balance Sheet and Auditor's notes of companies as well as transaction data analysis & payment track records. Also, macroeconomic data relating to sector, economy, and country or region could also be included. Using all this data with efficient quantum algorithms could lead to improved trade finance portfolio optimization.

This is just the beginning and future work will include selecting more companies out of larger total numbers of companies and using more performance parameters with the algorithms. Executing on quantum hardware would also be necessary to prepare for when quantum computing is sufficiently developed, and the algorithms can be practically implemented. Uses of these algorithms would complement the skills and experience of underwriters showing possible optimal combinations for large numbers of financing opportunities. It is most likely that first uses would be in the food and beverage services and credit insurance industries where the data volumes are high and contract values are low.

TABLE III. CUMMULATIVE ACCURACY

Groups	*Count*	*Sum*	*Average*	*Variance*
Classical	6	3.4	0.566667	0.022947
VQE	6	2.68	0.446667	0.029387
QAOA	6	2.51	0.418333	0.063337

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TABLE IV. STATISTICAL ANALYSIS OF OPTIMISATION SCORES

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.074411	2	0.037206	0.964958	0.403435	3.68232
Within Groups	0.57835	15	0.038557			
Total	0.652761	17				