Investigating Essential Technologies and Applications of Quantum Computing in Finance

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Abstract. Quantum computing, even though it is still in its early stages, holds the potential to revolutionize the finance sector by providing efficient solutions to complex problems. This potential is evident in the direct correlation between key financial issues and the principles of quantum mechanics, such as the mathematical connection between the Black-Scholes-Merton formula and the Schrödinger equation. Nevertheless, quantum computing also brings about significant risks, notably threats to cybersecurity that could endanger systems like Blockchain. Financial institutions in the Netherlands, along with others worldwide, are beginning to contemplate these implications, making efforts to forecast the progress of quantum computing in order to adapt their operational strategies accordingly. This paper delves into the impact of quantum computing on finance, from the advantages in portfolio optimization, arbitrage, credit scoring, and fraud detection, to the challenges concerning the security of payment systems and the integrity of Blockchain. Additionally, potential solutions to these challenges are explored. The evolution of quantum computing necessitates a shift in focus towards less popular yet highly desirable applications that exhibit inherent complexity. These are the areas where quantum computers are anticipated to make a significant impact.

Keywords: Quantum computing, Blockchain, Quantum machine learning, Cryptography, Finance

1 Introduction

While quantum computing is still in its early stages of development, its potential for solving complex problems efficiently has led to a surge of academic papers and articles. These pieces suggest that it holds significant transformative power for the finance sector. Some well-recognized financial problems can be directly framed within the context of quantum mechanics. For example, the Black-Scholes-Merton formula can be mathematically connected to the Schrödinger equation, representing the arbitrage relationships that informed its creation. Furthermore, the entirety of the financial market can be envisioned as a quantum process, where foundational financial quantities, like the covariance matrix, emerge naturally [1].

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However, the potential of quantum computing also introduces new risks. The possible dangers posed by quantum-enabled cyberattacks are expected to loom over the many benefits that quantum computing can offer the financial industry. Specifically, concerns about future quantum decryption capabilities may counterbalance the potential improvements in computational efficiency and precision that quantum computing could bring to finance. In 2015, the Dutch General Intelligence and Security Service issued warnings to owners and managers of essential infrastructure in the Netherlands about the rise of quantum computing and its associated threats. Consequently, Dutch financial institutions started to monitor the advancements in quantum computing and strived to understand its implications for their interbank business operations. Despite the continuous nature of these developments, banks and payment institutions can proactively anticipate the path of quantum computing and adjust their strategies accordingly. In addition, the progression of quantum computing threatens the current Blockchain System. Blockchain, a computational data structure, provides an open and distributed ledger with various fascinating applications, including digital currencies. However, this ledger's security depends on the computational challenge presented by specific cryptographic problems, which could be undermined by the prospective capabilities of quantum computing [2]. In summary, this paper explores how key technologies in quantum computing can provide benefits and opportunities in areas such as portfolio optimization, arbitrage, credit scoring, and fraud detection. Moreover, potential challenges associated with the advent of quantum computing in finance are examined. These include the potential to undermine the security of current payment systems and the impact on the Blockchain System.

2 Relevant Theories

2.1 Blockchain System

The Blockchain System is a protocol for recording data in a way that makes unauthorized alteration, access, or manipulation extremely difficult or even impossible. It operates through a distributed ledger that duplicates and disseminates transactions across the network of computers involved in the blockchain. This system presents multiple advantages such as decentralization, robustness, privacy, and traceability.

The Blockchain System is an openly accessible ledger containing an ever-growing list of records, known as blocks, which are securely linked using cryptographic hashes. When employed within a business network, it can enhance trust, security, transparency, and traceability of data, ultimately leading to cost savings due to improved efficiency. This technology for businesses uses a shared and immutable ledger that can only be accessed by authorized participants.

Backed by mathematical theories like cryptography and hash tables, the Blockchain system has already found applications in the field of finance, particularly in risk management and cryptocurrency operations. One of the most promising future possibilities of blockchain technology is in the realm of smart contracts. As shown in

Table 1. Through these, the blockchain enables the execution of validated agreements and transactions without exposing sensitive information between the parties involved. This eradicates the necessity for intermediaries such as distributors or online car rental platforms in managing payments or supervising the process [3].

Table 1. Correlation table

Layer	Main Contents	Features
Application Layer	Programming Languages, Programming Interfaces, Application Cases	Realized Specific Functions
Protocol Layer	Virtual Machines, Scripts, and Docker Containers	Provided Third-Party Applications Access to Ports and Platforms Applications
Consensus Layer	Incentive Mechanism, Consensus Algorithm	Sorted Transactions, Guaranteed Data Consistency
Network Layer	Point-to-Point Communication, Verification Mechanism, Propagation Machine	Built a Decentralized Network
Data Layer	Hash-Merkle Tree, Transaction Model, Digital Signatures and E-Wallets	Realized Efficient Data Transfer

2.2 Cryptography

Modern Cryptography involves various mechanisms for ensuring integrity, techniques for exchanging keys, user authentication protocols, electronic voting, and encryption, among others. It is pivotal that communications are constructed based on untrusted mediums, like the internet. There are three main types of cryptographic algorithms: Secret Key Cryptography, Public Key Cryptography, and Hash Functions.

Secret Key Cryptography uses a single key for both encryption and decryption, while Public Key Cryptography employs one key for encryption and another key for decryption. Hash Functions, on the other hand, apply a mathematical process to encrypt data in a manner that cannot be reversed. They operate without the need for a key, calculating a fixed-length hash value based on the input data. This makes it infeasible to retrieve the original plaintext or its length. Hash Functions are widely used to generate a "digital fingerprint" of a file's content, serving as a means to verify that the file has remained unchanged and un-tampered with by unauthorized individuals or malicious software. Various operating systems frequently employ hash functions to encrypt passwords, making them instrumental in ensuring the integrity of files and providing a level of security. Hash functions excel in maintaining data integrity, as any alteration to the message content will result in the recipient computing a different hash value from the one initially generated by the sender. Given the slim probability of two distinct messages yielding the same hash value, there is high confidence in preserving data integrity [4].

2.3 Quantum Machine Learning

Quantum machine learning, meanwhile, is the integration of quantum algorithms into machine learning systems. Classical machine learning has already exhibited a wide array of practical applications in fields that require handling of large volumes of pre-collected pairs of input and output data, such as Google's PageRank algorithm, spam email filters, consumer behavior analysis, risk assessment in the financial sector, and more. Though traditional machine learning algorithms are skillful at processing vast amounts of data, quantum machine learning exploits the potential of qubits, quantum operations, and specialized quantum systems to boost computational speed and data storage within program algorithms.

One approach for enhancing classical machine learning through quantum information processing involves using amplitude amplification techniques founded on Grover's search algorithm. This algorithm has shown a quadratic acceleration in resolving unstructured search problems compared to classical algorithms. The use of these quantum procedures is relevant to learning algorithms that involve unstructured search tasks, like the case of the k-nearest neighbors algorithms.

Blockchain relies on the computation of hashes to ensure the integrity of past blocks and protect against unauthorized modifications. The security of the blockchain stems from its distributed nature, which makes it resistant to widespread modification, and the computational effort required to recalculate the blockchain [5].

3 Challenges

3.1 The impact of quantum computing on blockchain security

When considering the impact of quantum computing, two factors arise that could jeopardize the security and reliability of blockchain technology. First, quantum computers could significantly decrease the computational difficulty associated with inverting hashes. This change would threaten both the authenticity of the entire blockchain and the integrity of individual entries. As previously discussed, Grover's algorithm could hasten the search for the pre-image of a function value compared to traditional methods.

Additionally, Shor's algorithm, another quantum computing method, poses a risk to blockchain systems because of its ability to break RSA encryption. Shor's algorithm is a significant advancement in the efficiency of factoring large numbers, and can therefore be used to exploit RSA encryption and related cryptographic challenges. In contrast to the general number field sieve, currently the most efficient known factoring algorithm with superpolynomial complexity (running time longer than any polynomial over input length but shorter than exponential over input length), Shor's algorithm exhibits polynomial complexity with respect to input length, resulting in approximately exponential acceleration. In practice, this means that RSA keys of 4096 bits, which are virtually impervious to classical computation, become susceptible to quantum computation [6].

Quantum computing presents two serious threats to the integrity of blockchain. First, if a quantum computer can efficiently perform hash inversions, the presumption about their computational difficulty becomes invalidated. This undermines the authenticity of the main blockchain and the integrity of its entries. Grover's algorithm exacerbates this problem by swiftly targeting function preimages, thereby surpassing classical brute force methods.

Grover's algorithm compromises blockchain in two ways. It enables hash collision search, allowing blocks to be swapped without disrupting the blockchain's integrity. This opens a door for malicious actors to insert fraudulent blocks undetected. Additionally, Grover's algorithm accelerates nonce generation, facilitating the quick recreation of modified but consistent hash chains. This jeopardizes the integrity of the blockchain by enabling the creation of fraudulent chains. In both cases, the algorithm identifies the original input for functions that are difficult to invert. Furthermore, components of blockchain that rely on public and private key cryptography are exposed to an additional threat from quantum computers. The computational power of quantum computers could penetrate the security of encryption schemes used for information exchange and digital signatures. These invasions further compromise the integrity and confidentiality of the blockchain system [7].

3.2 Quantum computing challenge the financial system

While the model acknowledges the potential risks associated with the widespread breaking of encryption due to quantum computing, it fails to consider the possibility of a quantum-enabled cyber incident. Such an incident could significantly amplify the overall impacts, adding to the concerns surrounding quantum computing. The potential risks associated with quantum-enabled cyberattacks may overshadow the numerous advantages that quantum computing can offer to the financial sector. The possibility of quantum decryption in the future could outweigh the benefits of enhanced computational efficiency and accuracy in finance.

A quantum-enabled hack disrupting the Fedwire interbank payment system would severely impact the targeted institution and connected banks, spreading negative effects through contagion channels. This poses a self-perpetuating risk to the broader financial system, potentially leading to a collapse of the US economy. Targeted attacks on critical interbank network nodes, as shown in quantum scenarios, would cause a significant systemic shock, resulting in economic losses beyond the targeted institution and financial network. This report highlights the triggering of an internal liquidity crisis and escalating liquidity and solvency risks throughout the vulnerable RTGS system network [8].

The negative credit conditions described in our scenario would have a direct impact on consumption, business and residential investment, leading to lower stock and housing prices. This, in turn, would have some impact on mortgage liabilities in the housing sector. The liquidity traps created by the Fedwire hack would spread throughout the financial system, spread throughout the economy, and have side effects.

4 Opportunities

4.1 Fraud detection and credit risk scoring

Currently, machine learning has already been widely applied in finance in the field of fraud detection and credit risk scoring. The utilization of machine learning has seen a growing application in the identification of fraudulent transactions. However, the majority of existing systems for such applications are capable of detecting deceitful activities only after they have taken place, rather than in real-time or close to it. Due to the fact that fraudulent transactions are significantly less common than legitimate ones, the presence of highly imbalanced data presents a major challenge in fraud detection. This calls for alternative approaches to address the issue beyond conventional machine learning methods. In the subsequent paragraph, the utilization of quantum-enhanced feature space in a basic binary classification task will be explored. One method to establish quantum-enhanced feature space is called the variational quantum classification (VQC), which finds the best hyperplane that is able to linearly separate the embedded data. In VQC, the data x, belonging to Rd, undergoes a mapping process known as the feature map circuit UΦ(x), which implements the function Φ(x). The binary decision is made by measuring the quantum state in the computational basis, resulting in z ∈ {0,1}n, and then combining the measurement results linearly. $\mathrm{m}=\sum_{\mathrm{z}\in\{0,1\}x^{\mathrm{n}}}\mathrm{m}(\mathrm{z})|\mathrm{z}\rangle\langle\mathrm{z}|$, noticed that $\mathrm{m}(\cdot)\in\{-1,1\}$. The provided quantum circuit encompasses the implementation of the quantum feature map and the variational classifier. The probability of observing the outcome z can be expressed as follows.

$$|\langle \mathrm{z}|\mathrm{W}(\theta)|\Phi(\mathrm{x})\rangle|^2=\langle\Phi(\mathrm{x})|W^\dagger\ (\theta)|\mathrm{z}\rangle\langle \mathrm{z}|\mathrm{W}(\theta)|\Phi(\mathrm{x})\rangle \tag{1}$$

After linearly combining the two measurement results, z and m, the function f(x) is achieved.

$$\mathrm{f(x)}=\langle\Phi(\mathrm{x})|\ \mathrm{W}^\dagger\ (\theta)\ \mathrm{m}^{\mathrm{W}}\ (\theta)|\Phi(\mathrm{x})\rangle+\mathrm{b} \tag{2}$$

The hyperplane (w, b) is now represented by the parameterization θ, and each element of w(θ), denoted as w_i(θ), is computed as w_i(θ) = tr($W^\dagger$ (θ) m^{W} (θ)P_i, where P_i is a diagonal matrix with zeros in all elements except for the ith row and column, which is set to 1. Similarly, the ith element of Φ(x), denoted as Φ_{i}(x), is calculated as Φ_{i}(x)= ⟨Φ(x)| P_i|Φ(x)⟩.

The process of determining the optimal θ involves minimizing the empirical risk R(θ) in relation to the training data S, which consists of pairs of the form {(x1, y1), (x2, y2), ..., (xmS, ymS)}. Consequently, the empirical risk can be reduced to

$$R(\theta) = \frac{1}{|S|}\sum_{i\in[mS]} |f(x_i) - y_i| \tag{3}$$

The process of effectively converting discrete features into a quantum-enhanced feature space is particularly important in financial models that work with structured data. A recent study has suggested the use of quantum random access coding, or QRAC, as a potential strategy to achieve this conversion. When QRAC is utilized, the training process can be expedited, leading to improved classification accuracy. This benefit is due to the decreased number of necessary qubits and hyperparameters in models using variational quantum classification, often abbreviated as VQC. The proposed methodology includes dividing the encoding of the feature vector, known as x, into discrete and continuous elements. These are represented as x(b) for the discrete parts and x(r) for the continuous parts. The discrete elements, x(b), are obtained from categorical features using methods such as one-hot encoding, while ordinal features are converted into integer values.

A synthetic dataset was created to analyze credit card transactions, consisting of 100 records of purchasing transactions. Each transaction, referred to as xi, contains information like transaction time, transaction amount, method of transaction, location of the transaction, and Merchant Category Code, often abbreviated as MCC. The transaction time and amount are displayed as real numbers, whereas the remaining data points are categorical. The method of transaction has three categories, and there are ten distinct locations and MCCs. Each transaction is tagged as either fraudulent (with a label of yi = -1) or normal (with a label of yi = 1). A different study, conducted on the same dataset, explored the use of variational quantum Boltzmann machines as an alternative to models using variational quantum classification or quantum kernel estimation (referred to in the original text as QKE) [9].

Apart from the aforementioned, Quantum machine learning (QML) has attracted a lot of interest due to its computational capabilities and potential to solve critical problems. However, formulating problems in the required QUBO format for quantum computing is challenging and comes at a high cost. Therefore, identifying the most important areas of application of QML is essential to justify the expenses incurred and potential efficiency gains [10]. However, for non-time series data, traditional machine learning continues to play a key role as a more cost-effective and efficient solution until quantum computing achieves significant breakthroughs. It is worth noting that the QML system in this study exhibits an extremely high detection rate, approaching real-time results.

4.2 Risk Management

Financial risk management encompasses the protection of a company's financial value by managing various forms of financial risks effectively. These risks include operational risk, credit risk, market risk, among other related categories. The primary objective of financial risk management is to mitigate potential hazards and safeguard the economic value of the company. To estimate the financial risk, contemporary methods involve the use of models and simulations. The level of accuracy of these models and simulations can have a direct impact on the profits that companies or individuals yield. One common risk metric that is extensively utilized to measure the magnitude of potential financial losses within a company, investment portfolio, or specific position during a predetermined period is known as "Value at Risk" or VaR.

When dealing with a random variable X, VaR alpha relates to the value at which the loss distribution of Y, where Y equals negative X, reaches the 1-alpha quantile. In simpler terms, VaR represents the smallest value of gamma for which the probability of X exceeding gamma is alpha.

$$\mathrm{Va}R\alpha(\mathrm{X}): = -\inf \{\gamma \text{ such that } \mathrm{F}x(\gamma) > \alpha\} \tag{4}$$

The equation utilizes the cumulative distribution function, denoted as F subscript X of x, to compute Value at Risk (VaR). However, VaR has a limitation in that it fails to adequately capture the impact of extreme losses in the tail of the distribution. To address this shortfall, the Conditional Value at Risk (CVaR), also known as expected shortfall, is often used as an additional risk measure. CVaR subscript alpha represents the average value of all losses up to the Value at Risk at the alpha level. In the context of the financial services challenges discussed in the rest of this article, the assumption is that the market operates under the regulations outlined in Basel Three. Monte Carlo simulations are the preferred method for calculating Value at Risk and Conditional Value at Risk. These simulations involve constructing a model and generating the loss or profit distribution for a large number, denoted as M, of model input parameter realizations. Multiple iterations are necessary to get a comprehensive representation of the loss or profit distribution. Traditional methods to enhance performance include variance reduction or quasi-Monte Carlo techniques. Variance reduction aims to decrease the constants without altering the asymptotic scaling, while quasi-Monte Carlo techniques improve the asymptotic behavior, albeit being more effective for problems with low dimensions.

Estimating Value at Risk is typically a computationally demanding task that involves classic Monte Carlo simulation. However, quantum Amplitude Estimation provides a quadratic speedup to achieve the same outcome. This technique can be applied to a portfolio consisting of K assets, where the multivariate random variable represents the potential losses associated with each asset. The expected value of the total loss, denoted as L equals the summation from k equals 1 to K of L subscript k, is calculated as E of L equals the summation from k equals 1 to K of E of L subscript k. The Value at Risk, which corresponds to the minimum total loss with a probability greater than or equal to a given confidence level alpha, where alpha is an element of the interval from 0 to 1, can be determined using Amplitude Estimation. Amplitude Estimation can be used in estimating the Economic Capital Requirement for a loan portfolio. By utilizing Amplitude Estimation, a quadratic speedup is achieved compared to classical Monte Carlo simulations. This example further underscores the dependency of the required quantum circuit for implementing operator A on the specific task. Therefore, to extend this approach to other financial simulation tasks, it is necessary to design task-specific quantum circuits to implement operator A.

5 Conclusion

The advancements in quantum computing have initiated a new epoch in the field of finance, bringing forth a variety of opportunities as well as challenges that demand careful deliberation. Opportunities presented include the capabilities for swift and accurate fraud detection, enhanced credit risk scoring, and improved risk management.

However, the challenges are significant too, such as potential detrimental impacts on the security of blockchain technology and the financial system at large. As this study strives to accomplish significant milestones in demonstrating the quantum advantage in industrial applications, it becomes critical to deviate from the traditionally adopted and manageable machine learning implementations. Our focus must instead be directed towards exploring applications that, while highly desirable, are less popular due to their intrinsic complexity. This study anticipates that it is within this space where quantum computers can bring substantial benefits to machine learning. Merely achieving a quantum speed-up does not suffice. If the chosen machine learning applications can be effectively solved using traditional machine learning methods with a high degree of accuracy, then the number of qubits required to approach large-scale industrial applications may well exceed the capacity of near-term quantum devices.

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