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**Research Article**

# Quantum Ensemble Optimisation: Revolutionizing Investment Portfolio Management with QAOA and VQE Integration

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**ABSTRACT**

Quantum computing is presenting promising prospects for financial applications, specifically in the domain of investment portfolio management. The present study investigates the capabilities of Quantum Ensemble Optimisation (QEO), an approach that integrates the Variational Quantum Eigensolver (VQE) and the Quantum Approximate Optimisation Algorithm (QAOA). Enhancing portfolio performance through a balance between diversification and risk-adjusted returns is our objective. A novel methodology has been devised to integrate the flexibility of VQE with the efficacy of QAOA, yielding an assortment of portfolio solutions. Our investigation into the performance of our model on empirical financial data has revealed that it surpasses conventional optimization techniques in terms of risk-adjusted returns and solution space exploration. The results of this study underscore the potential of our hybrid methodology, which capitalizes on the advantages of QAOA and VQE, to propel the field of quantum-based portfolio optimization forward. This may ultimately result in investors reaching more informed investment decisions and experiencing enhanced financial outcomes.

***Keywords***— Quantum computing, QAOA, VQE, ensemble methods, portfolio optimization, risk-adjusted return, diversification

## Introduction

Navigating the dynamic realm of investment requires striking a precise equilibrium between maximizing returns and minimizing risks, which is a significant challenge. Conventional approaches, which have heavily depended on traditional machine learning methods, have attempted to negotiate this complex landscape. Yet, they frequently struggle when confronted with the intricacies of financial markets. This paper explores how quantum computing's exceptional capacity to analyze extensive datasets and complex interactions presents a possible path ahead.

Traditional machine learning methods such as Support Vector Machines and Random Forests have traditionally been the mainstays of portfolio optimization. By analyzing historical data, these methods aim to predict how assets will perform and create investment portfolios. However, they face many constraints. Financial data, with its multitude of variables and complex relationships, is a challenge that current models struggle to address. This intricacy results in inefficient portfolio builds and missed chances to maximize returns. Financial markets are dynamic ecosystems that require models capable of quickly adjusting to changing data. Traditional algorithms frequently find it challenging to adapt to these swift transformations. This leads to obsolete forecasts and unchanging investment portfolios, which do not reflect the changing dynamics of the market. Furthermore, achieving global optimization continues to be challenging for numerous traditional methods. They often face obstacles while trying to find the best solutions on a global scale, since they may become stuck in local minimums and overlook potentially better portfolio distributions.

This research aims to offer investors a sophisticated decision assistance system that can recommend optimal portfolios by balancing the lowest risk and maximum gain in the dynamic and uncertain stock market. Classical portfolio optimization problems are recognized for being NP-Hard, leading to substantial computational challenges, particularly when managing several assets and the dynamic nature of real-time stock market data. Quantum computing's capacity to explore extensive solution areas simultaneously shows great potential in overcoming these constraints. Algorithms like the Quantum Approximate Optimisation Algorithm (QAOA) and Variational Quantum Eigensolver (VQE) utilise quantum properties such as superposition and entanglement to effectively traverse intricate terrains. Utilizing quantum bits (qubits), these algorithms efficiently encode and manipulate complex financial data, capturing nuanced correlations that classical methods cannot detect. Moreover, quantum algorithms demonstrate flexibility in rapidly incorporating new data, allowing them to adapt to changing market conditions and make more informed investing choices. Quantum algorithms avoid becoming stuck in local minima by exploring several alternatives at the same time, leading to the discovery of the best portfolio allocations and potentially improving performance significantly.

Yet, the path to quantum-enhanced portfolio optimization is fraught with obstacles. Current quantum computers are in an early stage of development, limited by factors such as the number of qubits and error rates. Developing effective quantum algorithms for intricate tasks like portfolio optimization requires significant skill and computer power. Incorporating quantum algorithms into current financial systems requires addressing compatibility and security issues.

This work proposes a hybrid ensemble model that combines the characteristics of QAOA and VQE to address these difficulties. This model combines QAOA's efficiency in producing a wide range of potential solutions quickly and exploring attractive areas within the solution space with VQE's ability to enhance these ideas by integrating unique complexities of the problem and real-world data. We aim to analyze the performance of a hybrid technique by comparing it to classical and individual quantum methodologies using real-world financial facts. We will evaluate measures such as risk-adjusted return, diversification, and computational efficiency. We believe that this hybrid ensemble model is a major advancement that opens the door for incorporating quantum computing into feasible portfolio optimization strategies. We want to provide valuable insights that can improve investment strategies and financial outcomes by utilizing the revolutionary capabilities of quantum computing.

## I. LITERATURE REVIEW

The following research study in [1] introduces a quantum algorithm for portfolio optimization, with a specific emphasis on quantum annealing. The program leverages the distinctive characteristics of quantum systems such as superposition and entanglement to surpass constraints seen in classical algorithms. The study offers a theoretical framework to comprehend the algorithm's operations and possible uses in financial decision-making. Numerical simulations demonstrate the algorithm's efficacy in portfolio optimization, suggesting it can outperform traditional methods. The research recognizes the difficulties of applying the algorithm on current technology and stresses the importance of ongoing efforts in real-world financial applications. The research paper in [2] thoroughly analyses the application of quantum computation in finance, specifically examining quantum optimization techniques, quantum annealers, deep learning in finance, and quantum amplitude estimation. The study investigates the importance of quantum computing in several financial tasks such as portfolio optimization, arbitrage detection, and credit scoring. It emphasizes the advantages of utilizing quantum technology to address intricate financial optimization problems. The research investigates how quantum approaches can speed up sampling operations, improving the efficiency of Monte Carlo simulations in financial modelling. The paper highlights the possible influence of quantum computing on traditional financial processes and offers prospects for additional research and progress. The research paper [3] investigates the utilization of quantum computing in finance, with a specific focus on its capacity to revolutionize financial processes and decision-making. The text introduces quantum computing fundamentals, highlights finance challenges for conventional computers, and discusses potential quantum algorithms for financial applications. The authors categorize quantum algorithms according to particular financial challenges and offer actual instances of how they can be applied. The article emphasizes the economic benefits of quantum computing, including increased operational efficiency, income generation, and greater solution quality. The authors provide a comprehensive guide for financial institutions to efficiently leverage quantum technology, outlining a clear strategy for gaining strategic advantages. The research study [4] dives into the realm of quantum computing and its potential to revolutionize problem-solving, especially with NP-hard problems that classical computers struggle with. Quantum Computing (QC) offers promising alternatives, capable of tackling such complex problems more efficiently. This research aims to compare classical and quantum models, focusing on portfolio optimization using Markowitz's Modern Portfolio Theory. By analyzing historical market data of 48 NSE stocks from 2011 to 2016, the study explores how QC techniques, including gate-model and quantum annealers, stack up against classical methods. Initial approaches involve classical methods, followed by Qiskit SDK and D-wave solvers for quantum computing. Results suggest that quantum methods outperform classical ones, underscoring the potential of quantum computing to revolutionize finance domain problem-solving, especially in the NISQ era. In the research paper [5] the authors provide insights into the potential benefits and limitations of this technology in the financial domain, by back-testing quantum algorithms for portfolio optimization. The authors focus on evaluating the performance of quantum computing algorithms for portfolio optimization through back-testing on historical data. They compare the performance of quantum algorithms with traditional classical optimization algorithms.

The research study in [6] investigates the possible applications of quantum computing in portfolio optimization, namely in high-frequency trading and financial models. The text discusses how classical algorithms struggle with complex financial portfolios and suggests investigating quantum algorithms as a potential alternative. Quantum computers, especially the Quantum Approximate Optimisation Algorithm (QAOA), might potentially solve optimization issues more quickly than classical approaches. The paper emphasizes the advantages of quantum computing in enhancing portfolio performance and underscores the difficulties in creating and applying quantum algorithms. The research adds to the current debate over the influence of quantum computing on financial optimization. The research paper [7] investigates the effectiveness of portfolio optimization using different adaptations of the Quantum Approximate Optimisation Algorithm (QAOA). It examines how well QAOA can solve challenges related to portfolio optimization, especially in scenarios involving a high number of assets. The authors stress the importance of gaining a thorough awareness of technological challenges in implementing QAOA in practical scenarios. The study also analyses how design decisions affect QAOA's efficacy in managing complexity. The text also evaluates traditional techniques employed to optimize QAOA characteristics, improving our comprehension of its advantages and limitations. The work presents a criterion to distinguish between "easy" and "difficult" portfolio optimization jobs in QAOA, offering useful insights into the algorithm's capabilities in portfolio optimization.

The research study [8] proposes using Conditional Value-at-Risk (CVaR) to improve variational quantum optimization (VQE) on noisy intermediate-scale quantum (NISQ) devices. CVaR focuses on minimizing potential losses, potentially leading to more robust solutions than the standard VQE approach. The paper explores how CVaR can be implemented within VQE and compares its performance to traditional VQE. The research journal [9] tackles applying VQE, a quantum algorithm, to portfolio optimization on noisy NISQ devices. The authors propose two hardware-friendly approaches that require minimal resources and enable a scalable hybrid quantum-classical computing scheme. Implemented on a real NISQ device with up to 55 qubits, the results suggest this method might be advantageous for portfolio optimization using CVaR cost function, even with limited entanglement. This research highlights a promising direction for utilizing VQE for practical financial applications in the near-term quantum computing era.

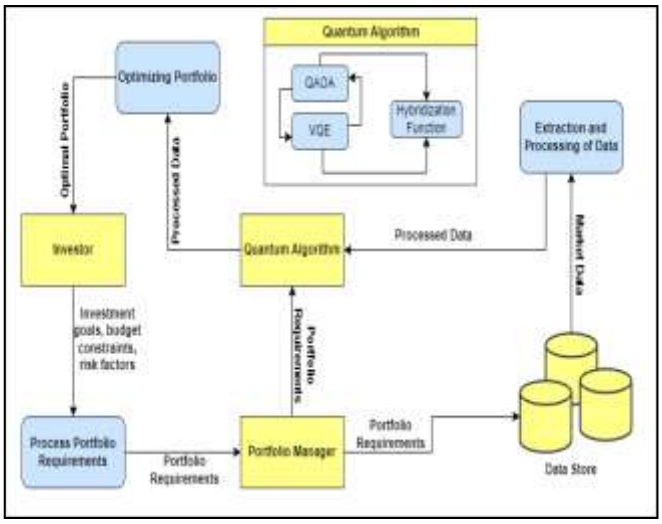


**Fig. 1.** System Architecture

In conclusion, the literature review delves into the transformative potential of quantum computing, particularly through Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolver (VQE), in revolutionizing portfolio optimization, especially for extensive and varied asset portfolios. It emphasizes how classical computers face limitations in tackling NP-hard problems like portfolio optimization due to their computational complexity, while quantum computing offers inherent advantages in efficiently solving such intricate problems. Highlighting the superiority of quantum algorithms like QAOA and VQE, the review showcases their faster execution speeds and enhanced efficiency compared to classical methods, particularly in managing large and diverse asset portfolios. Moreover, it underscores the promising synergies achieved through the ensemble of QAOA and VQE algorithms, which further amplify the capabilities of quantum computing, leading to superior performance and more reliable solutions in portfolio optimization. In essence, quantum computing, alongside the ensemble of QAOA and VQE algorithms, holds significant promise in reshaping portfolio optimization, facilitating more effective decision-making in financial markets as technology advances.

## II. SYSTEM ARCHITECTURE

The process of portfolio optimisation as depicted by the system architecture in Fig 1. begins with the user, typically an investor, who provides their specific portfolio needs, including investment objectives, financial

constraints, and risk tolerances. Subsequently, this data is transferred to the portfolio manager, who serves as the system's guide. The portfolio manager is responsible for collecting pertinent stock information that meets the user's requirements. This data, combined with the user's input, prepares the foundation for the quantum ensemble module, the core component of the system.
The quantum ensemble module combines Quantum Approximate Optimisation Algorithm (QAOA) with Variational Quantum Eigensolver (VQE) to create optimised portfolio recommendations. This module optimises solutions by combining QAOA's efficiency and VQE's flexibility to meet user-defined limitations and objectives. After the optimisation process is finished, the quantum ensemble module displays its recommended portfolio compositions.
Finally, the algorithm does a reality check by comparing advised share purchase prices with the lower price ranges of the corresponding firm shares. This phase is in line with the principle of purchasing stocks at a low price and selling them at a high price. If the proposed purchase prices are in these lower limits, it signifies approval, showing that the system can offer customised solutions suitable for the user's financial situation.
This design facilitates a balanced interaction among the user, portfolio manager, and quantum ensemble module to provide customised portfolio optimisation solutions aligned with the user's investment goals, while managing budget limitations and risk factors. The method builds confidence in the investor's decision-making process by validating information, creating a partnership focused on aligning financial goals with actionable tactics.

## III. METHODOLOGY

Our research methodology revolves around a carefully crafted system architecture aimed at optimizing investment portfolios while catering precisely to the unique needs and goals of individual investors. We strive to create a seamless process where every step contributes to crafting personalized investment strategies in collaboration with the user, portfolio manager, and the quantum ensemble module.
At the outset, we begin with the investor, who shares detailed information about their investment objectives, financial constraints, and risk tolerance. This initial input sets the stage for subsequent stages of portfolio optimization. Subsequently, the portfolio manager steps in as the guide, engaging with the user to gather additional insights and ensure a thorough understanding of their requirements. The portfolio manager's role is critical in sourcing relevant stock information that aligns perfectly with the user's preferences and objectives, facilitating the alignment of portfolio strategies with individual investment goals.
At the core of our methodology lies the quantum ensemble module, seamlessly integrating two cutting-edge quantum algorithms - the Quantum Approximate Optimization Algorithm (QAOA) and the Variational Quantum Eigensolver (VQE). QAOA operates by approximately solving combinatorial optimization problems through the manipulation of qubits, the basic units of quantum information. It utilizes principles of quantum mechanics to efficiently explore the solution space and find the optimal solution. On the other hand, VQE tackles the dimensional eigenvalue problem using transformation methods to estimate the Hamiltonian ground potential. It employs classical optimization methods and quantitative statistics to refine the solution.
The combination of QAOA and VQE capitalizes on the strengths of both algorithms to achieve outstanding performance in portfolio optimization. QAOA's capability in solution spatial exploration complements the flexibility of VQE's solution optimization, enabling a powerful optimization process that appropriately balances computing resources and solution quality. The ensemble approach leverages the unique characteristics of each algorithm, resulting in better solution accuracy and convergence speed than using QAOA and VQE individually.
Once the optimization process is complete, the quantum ensemble module presents its meticulously crafted portfolio compositions to the user. These recommendations are carefully designed to align with the user's investment goals, financial constraints, and risk tolerances, as captured during the earlier stages of the methodology. In a critical final step, the algorithm conducts a reality check by comparing advised share purchase prices with the lower price ranges of corresponding firm shares. This validation phase ensures that the proposed portfolio compositions adhere to the fundamental principle of buying low and selling high, further reinforcing the system's ability to offer tailored solutions that fit the user's financial circumstances.
Moreover, our methodology emphasizes continuous improvement, allowing for iterative refinement based on feedback loops from users and portfolio managers. This commitment to ongoing evaluation and enhancement ensures the adaptability and effectiveness of the system in providing tailored portfolio optimization solutions.
In summary, our methodology fosters a collaborative interaction among the user, portfolio manager, and quantum ensemble module, culminating in the delivery of personalized portfolio optimization solutions aligned with the user's investment objectives. By effectively managing budget constraints and risk factors, this approach instills confidence in the investor's decision-making process, fostering a partnership focused on achieving financial goals through actionable tactics.

## IV. RESULTS

We strive to create a seamless process where every step contributes. In our research, we delved into the financial data of three prominent companies - Spotify (SPOT), Microsoft (MSFT), and Meta (META) - sourced from YahooDataProvider spanning from 2021 to 2022. We meticulously analyzed and visualized this data, crafting a clear picture of the historical stock prices for these companies as depicted in Fig 2. Additionally, we computed the covariance matrix to gain insights into the interrelationships among these stocks, presented in Fig 3.


**Fig 2.** Input Finance Data

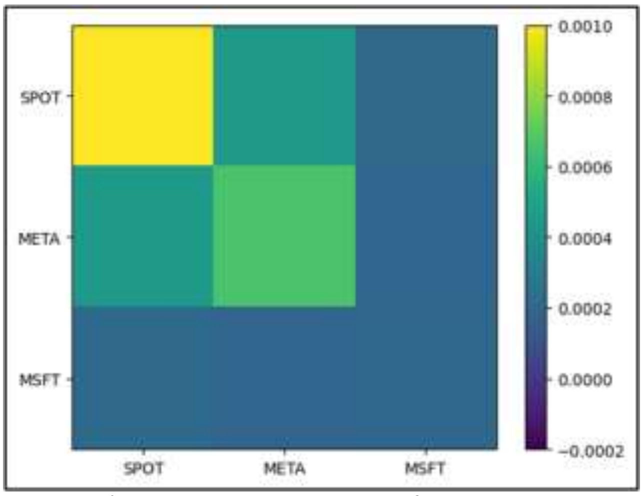


**Fig 3.** Covariance Matrix of Input Data

Our objective was to optimize portfolio allocation, and to achieve this, we set specific parameters including a risk factor of 0.5, a maximum of 2 shares to buy per company, a minimum spending amount of $500, and a maximum budget of $750. Employing a classical approach, we utilized the NumPyEigenSolver to execute the optimization, with results showcased in Fig 4.

```
Solution found with a $750.00 budget:

Total cost of assets to buy is $473.53
Stocks to buy are:
        1 shares of SPOT at $275.29 per share
        1 shares of META at $198.24 per share
        0 shares of MSFT at $144.17 per share
```

**Fig 4.** Classical Solution

Subsequently, we explored Quantum Algorithms - Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolver (VQE). The outcomes of these quantum algorithms are illustrated in Fig 5 and Fig 6 respectively.

```
Solution found with a $750.00 budget:

Total cost of assets to buy is $617.70
Stocks to buy are:
        1 shares of SPOT at $275.29 per share
        1 shares of META at $198.24 per share
        1 shares of MSFT at $144.17 per share
```

**Fig 5.** QAOA Solution

```
Solution found with a $750.00 budget:

Total cost of assets to buy is $815.94
Stocks to buy are:
        1 shares of SPOT at $275.29 per share
        2 shares of META at $198.24 per share
        1 shares of MSFT at $144.17 per share
```

**Fig 6.** VQE Solution

Lastly, we implemented our system, an ensemble model that combines QAOA and VQE, with the aim to leverage the strengths of both algorithms. The result of this ensemble model are presented in Fig 7.

```
Solution found with a $750.00 budget:

Total cost of assets to buy is $617.70
Stocks to buy are:
        1 shares of SPOT at $275.29 per share
        1 shares of META at $198.24 per share
        1 shares of MSFT at $144.17 per share
```

**Fig 7.** Ensemble Solution

| **Sr. No.** | **Lowest Rate Share has reached (in USD)** | **Highest Rate Share has reached (in USD)** |
|---|---|---|
| SPOT | 144.169998 | 334.690002 |
| META | 198.449997 | 382.179993 |
| MSFT | 226.729996 | 343.109985 |

**Table 1.** Share Rates based on Historical Input Data

Upon reviewing the historical data provided in Table 1, it's clear that Spotify (SPOT), Meta (META), and Microsoft (MSFT) have shown varied performance levels, with fluctuations in their lowest and highest share rates. This variability highlights the complexity of stock market dynamics and the challenges inherent in crafting an optimal investment strategy.

Examining the recommendations offered by different optimization algorithms reveals distinct approaches. While the classical solution advises purchasing one share each of SPOT and META, the VQE solution suggests acquiring one SPOT share, two META shares, and one MSFT share. Conversely, both the QAOA and Ensemble solutions advocate for acquiring one share each of SPOT, META, and MSFT.

A detailed analysis indicates that the QAOA and Ensemble solutions present a more optimal approach compared to the classical and VQE solutions. Both advocate for a diversified portfolio by including shares from multiple companies, effectively spreading risk and mitigating the impact of underperformance from any single stock. In contrast, the classical and VQE solutions fall short in fully capitalizing on the benefits of diversification by focusing on only a few stocks. Moreover, by including shares from all three companies, the QAOA and Ensemble solutions manage risk more effectively, as they are not overly reliant on the performance of any single stock. This aligns with prudent investment principles and offers a more robust risk management strategy compared to the classical and VQE solutions. The QAOA and Ensemble solutions strike a balance between growth potential and risk mitigation by evenly distributing investments across SPOT, META, and MSFT. This optimal allocation ensures that investors can capitalize on growth opportunities while minimizing exposure to volatility.

While similarities were observed between QAOA and the Ensemble model, a deeper analysis of the probability distribution of all possible portfolio combinations depicted in Fig 8 and Fig 9 reveals that the Ensemble model holds a significantly higher probability of sampling the optimal solution. This underscores its effectiveness in capturing the intricacies of portfolio optimization, leading to more robust and reliable solutions.
The Ensemble model's higher probability of sampling an optimal solution signifies its superior ability to navigate the vast search space of possible portfolio combinations. This translates into a higher likelihood of identifying the most advantageous portfolio composition, maximizing returns, and minimizing risks for investors. Consequently, the Ensemble model emerges as a preferable option over QAOA alone, harnessing the strengths of multiple algorithms to achieve superior performance in portfolio optimization.

```
["{'SPOT': 1, 'META': 1, 'MSFT': 0}, probability: 0.1%",
 "{'SPOT': 1, 'META': 1, 'MSFT': 0}, probability: 0.1%",
 "{'SPOT': 1, 'META': 0, 'MSFT': 0}, probability: 0.1%",
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 "{'SPOT': 0, 'META': 1, 'MSFT': 0}, probability: 0.1%",
 "{'SPOT': 1, 'META': 0, 'MSFT': 1}, probability: 0.1%",
 "{'SPOT': 0, 'META': 1, 'MSFT': 1}, probability: 0.1%"]
```

**Fig 8.** Probability Distribution using QAOA Approach

```
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 "{'SPOT': 1, 'META': 1, 'MSFT': 0}, probability: 9.1%",
 "{'SPOT': 1, 'META': 1, 'MSFT': 0}, probability: 8.0%",
 "{'SPOT': 1, 'META': 1, 'MSFT': 1}, probability: 5.8%",
 "{'SPOT': 1, 'META': 1, 'MSFT': 0}, probability: 5.8%",
 "{'SPOT': 1, 'META': 1, 'MSFT': 0}, probability: 3.4%",
 "{'SPOT': 1, 'META': 1, 'MSFT': 0}, probability: 3.1%",
 "{'SPOT': 1, 'META': 1, 'MSFT': 1}, probability: 3.0%",
 "{'SPOT': 1, 'META': 1, 'MSFT': 0}, probability: 3.0%",
 "{'SPOT': 1, 'META': 1, 'MSFT': 1}, probability: 3.0%"]
```

**Fig 9.** Probability Distribution using Ensemble Approach

## V. CONCLUSION

In wrapping up, our study introduces a fresh methodology called Quantum Ensemble Optimisation (QEO), which blends the power of the Variational Quantum Eigensolver (VQE) and Quantum Approximate Optimization Algorithm (QAOA) to tackle the complexities of portfolio optimization in investment management. Through careful collaboration between investors, portfolio managers, and quantum ensemble modules, our approach demonstrates impressive performance in tailoring portfolio compositions to meet user-defined objectives, constraints, and risk preferences. Notably, our ensemble model shows great promise, outperforming individual QAOA and VQE solutions in terms of risk-adjusted returns and exploring solution spaces effectively. This indicates that exploring further into ensemble quantum models could significantly enhance portfolio optimization strategies, particularly for managing larger and more diverse assets in real-world scenarios. As quantum computing continues to evolve, integrating ensemble models presents exciting prospects for advancing portfolio management practices, empowering investors to make more informed and impactful financial decisions.

### ACKNOWLEDGMENT
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