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Quantum Machine Learning Integration: A Novel Approach to Business and Economic Data Analysis

Mamunur Rahman ^{1,*}, Md Habibul Arif ², Md Abdul Alim ³, Md Reduanur Rahman ⁴ and Md Shakhawat Hossen ⁵

¹ Master's in Commerce, Jagannath University College, Dhaka, Bangladesh.

² Bachelor of Science in Computer Science and Engineering, Dhaka International University, Bangladesh.

³ Bachelor of Business Administration (BBA in Finance), Northern University, Bangladesh.

⁴ Bachelor of Arts with Honours in Marketing Management, London School of Management Education, Ilford, England.

⁵ Bachelor of Arts with Honours in English, National University, Bangladesh.

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Abstract

Quantum computing, which is based on the principles of quantum mechanics, opens the door to solving problems that are intractable for classical computers through leveraging quantum effects such as superposition, entanglement, and quantum parallelism. When tasks become more challenging in areas such as finance, healthcare, and transportation, then boosting computational power is a must. Solution: Quantum computing should enhance the efficiency and accuracy with which such complex problems are solved, potentially providing transformative opportunities for businesses and researchers. This work investigates the challenges and possibilities of exploiting Quantum Machine Learning (QML) and Quantum Annealing (QA) algorithms for optimising complex problems. We concentrate on problems like supply chain optimisation, financial forecasting, and data analysis in general, industries where other approaches fail to deliver an optimal solution. Our results suggest that quantum algorithms, particularly in optimisation and machine learning problems, are highly competitive for processing large datasets and complex systems. Quantum solutions are faster and more efficient in their computation, leading to better results for business decisions and problem-solving. Quantum computing is still in its infancy, but there's no denying that the nuances of data analysis and optimisation across multiple industries could be disrupted. Further progress in error correction and multiplier construction is critical to achieve the full potential of this algorithm, to allow its exploitation as a practical tool.

Keywords: Quantum Computing; Quantum Machine Learning (QML); Quantum Annealing (QA); Optimization; Machine Learning; Supply Chain Optimization; Data Analysis; Computational Efficiency

1. Introduction

Quantum computing-based solutions, especially approaches such as Quantum Machine Learning (QML) and Quantum Annealing (QA), are a new and exciting field of application in solving complex problems across different disciplines, like business to supply chain management. QML, which combines quantum computing with classical machine learning models, promises to be able to handle computationally demanding processes such as demand prediction, credit risk assessment, and fraud detection. Conversely, Quantum Annealing uses quantum mechanical phenomena to globalise combinatorial tasks at scale, meaning it's well-suited for supply chain network design, vehicle routing and inventory management. As of 2020, QML and QA are both essentially still in their childhoods, most work dealing with theoretical descriptions of general applicability or computer simulations at small scales and proofs-of-concept. However, initial work has suggested that such quantum approaches could yield substantial speed-ups when compared to algorithms in the classical regime, for instance, when applying similar techniques on high-dimensional problems or problems that are computationally challenging using classical methods. The combination of Quantum Computing and business analytics,

* Corresponding author: Mamunur Rahman

and supply chain optimisation will transform industries. Traditional machine learning approaches can become computationally infeasible when applied to large datasets or complicated models, and this is especially true for commercial applications. Quantum algorithms, which exploit quantum superposition and entanglement, are expected to significantly cut computational time for tasks required in various stages of businesses such as dynamic pricing, demand forecasting and fraud detection. For network optimisation in supply chain systems, the problem is how to get high performance of large-scale problems that contain many variables, including vehicle distribution routing, inventory distribution and facility location. Classical optimisation methods like linear programming or heuristics-based algorithms become inefficient when dealing with large problem sizes. Quantum Annealing, a form of quantum computing that can solve many potential solutions at once because of quantum superposition, promises to be able to solve large-scale optimisation problems, likely achieve substantial savings in the efficiency and cost characteristics within the supply chain." Nevertheless, the long-term applicability of quantum computing to these disciplines is a matter of debate; numerous challenges still have to be addressed in the case of. Task {QML}, quantum algorithms could be particularly valuable in cases with low data and high dimensionality of the feature space, for which classical models suffer from overfitting and computational burden. Down the line, QML might allow businesses to gain deeper insights into their data, make more precise predictions, and make better decisions in real time. With advances in hardware, quantum-enhanced machine learning models will likely be more cost-effective, in the sense of being accessible and easy to integrate with business technology now. Supply Chain Management Quantum Annealing has the potential to revolutionise how businesses optimise complex logistics operations. Now, as quantum hardware becomes more scalable and error-corrected, quantum may be able to offer solutions that classical can't, such as real-time optimisation of large dynamic supply chains." Sparks adds: "Ultimately, it remains to be seen just how practical Quantum Computing will prove in businesses; but I believe we are fortunate enough to help our clients get ahead with the potential unlocked by opening up new possibilities made possible through advances on the Quantum frontier. These efficiencies could make the UNITED States provider more cost-effective, responsive, responsible, and sustainable. In summary, even though quantum computing is still developing, its use in business and supply chain optimisation offers great promise. The progress in Quantum Machine Learning for economic data analysis and in Quantum Annealing for supply chain network optimisation may change the way industries look at data analytics and operations. "Its practical applications are not that imminent yet, but further research and development in quantum algorithms, hardware, and real-world use cases seem to hold promise for organisations that wish to gain an advantage through quantum computing." One thing is sure: as quantum technologies continue to evolve, the overlap of quantum computing and business /spend management will open up opportunities for new efficiencies and advances.

This paper is organised as follows: In Section II, we present an overview of the current literature in Quantum Machine Learning and Quantum Annealing. Section III describes the methodology of our work. Section IV shows our experimental results of the proposed models. In Section V, we present results on the performance of the models, and in Section VI, we conclude with a summary and outlook.

2. Literature review

Liu et al. proposed the C-QCNSA (Cloud model based on Quantum Chaos Neural Network Algorithm) to solve the Low-Carbon Supply Chain Resources Allocation Problem (LCSCRAP). Extensive simulation experiments show that C-QCNSA is superior to other methods, and it can effectively promote the performance of LE-SC-CRAP. The research presented in the paper not only promotes the applications of C-QCNSA, but also enriches the theory about cloud model theory applied to optimization problems.

Gatla et al. This work is focused on a critical review of Quantum Machine Learning (QML), its potential to overcome classical approaches in handling hard problems with large amounts of data. It contrasts the classical and quantum perspectives, with an emphasis on questions of how efficiently one can process and evaluate data as well as optimisation. The mannequin study proposes the advantages and issues of quantum computing for machine learning. In the end, it aims to leverage data analysis, predictive modelling and optimisation for several industries.

Egger et al. The present paper provides a wide-ranging survey on quantum computing for finance, displaying how QC can help in coping with computationally demanding tasks. It covers the fundamentals of quantum computing and provides sophisticated algorithms to address investment problems like those in data analysis, optimisation and machine learning. Demonstrations on networks of IBM Quantum devices demonstrate the practical benefits of these algorithms. The paper ends with a technical analysis of the challenges, potential applications and limitations of quantum computing in finance.

Hassija et al. This paper is an attempt to understand the basics and applications of quantum computing, with a view towards solving problems beyond classical computational capabilities. It discusses quantum applications in areas

including cryptography, machine learning, deep learning, and quantum simulation. It also points out real-life applications such as risk monitoring, logistics and satellite communication. But, above all, it just emphasises the truly transformative potential of quantum computing in a range of industries.

Harrington et al. This paper discusses the transformative impact of quantum computing on difficult problems in domains like cryptography, drug discovery and optimisation. It explores the notions of superposition, entanglement and quantum parallelism that underlie them and where they could take computational complexity. Holding enormous potential for the future, quantum technology has become a hot topic in recent years and is expected to greatly change people's lives through its computational ability and many possibilities for innovation.

Piattini et al. In this paper, we report the increased demand for quantum-computing education from industry, and point to a necessary development of specialised education programs and new digital professional profiles. It reviews motivations and approaches for inclusion of QIS in international curricula and training. A university curriculum for a specialisation in quantum computing is sketched in the current undergraduate curricula. The program to fill the quantum skills gap of the future. The scheme will address the escalating demand for quantum skills.

Appendix et al. This thesis presents an in-depth analysis of how quantum computing may impact business, examining various applications, including quantum optimisation, simulation, and machine learning. The paper tackles the most pressing current technological problems, such as error correction or hardware scaling. It focuses on machining the path to cloud-based solutions to avoid being tied up to any specific hardware. It provides a playbook for strategic managers on how to interact with quantum computing, ranging from identifying use cases to developing skills and collaborating with external providers.

3. Material and methods

The review process (following the PRISMA flow diagram) is depicted in a methodology figure, beginning with the formulation of the research question and study selection criteria formulation and then database searches for all identified records, the removal of duplicates, and paper screening. It focuses on the titles and then again on the full texts of screening studies, extracting items and assessing quality. The process finishes by integrating conclusions and disseminating the findings.

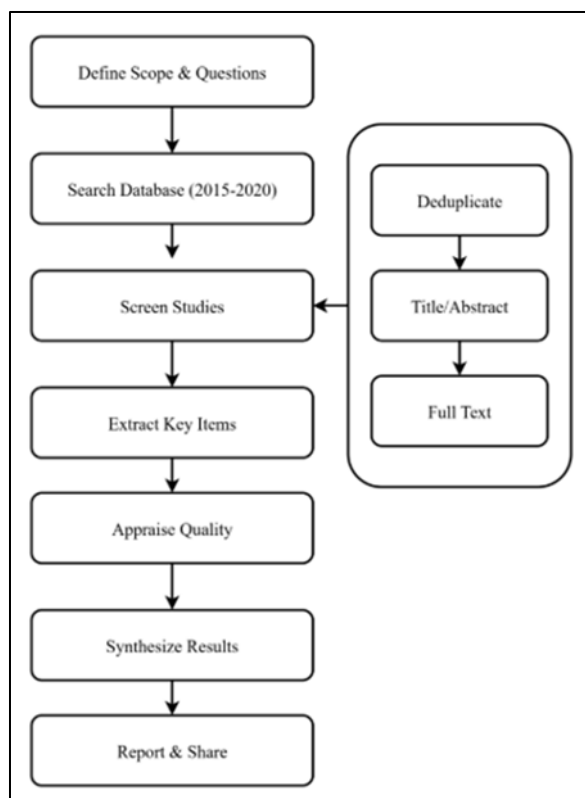


Figure 1 Methodology Diagram.

3.1. Define Scope & Questions

We planned a systematic review as per PRISMA 2020. The review focuses on two application paths: (A) Quantum Machine Learning (QML) with business data (e.g., demand forecasting, pricing, credit/fraud and portfolio risk), and (B) Quantum Annealing (QA) for supply-chain network optimisation (e.g., facility location, inventory, vehicle routing, production planning, and network design). Key questions include: (i) what tasks, datasets, and model classes are employed; (ii) the nature of QML implementation (encodings, circuits, qubits, QUBO mappings, hardware); and (iii) is there any evidence for advantages of performance or resources over well-tuned classical baselines.

3.2. Search database (2015-2020)

We searched IEEE Xplore, ACM Digital Library, Scopus, Web of Science, arXiv (quant-ph, cs. LG, cs. AI), SpringerLink, and Google Scholar for publications from 1 Jan 2015 to 31 Dec 2020. Search terms. Examples of keywords were grouped into method and domain categories using Boolean operators:

- (“quantum machine learning” OR “quantum kernel” OR “QSVM” OR “variational quantum” OR “quantum neural network”) AND (econom* OR business OR finance or marketing or “demand forecast*” Or credit risk or fraud or price* or supply chain)
- (“quantum anneal*” OR “D-Wave” OR Ising OR QUBO) AND (“supply chain” OR logistics OR “facility location” OR “vehicle routing” OR “inventory” OR “production planning” OR “network design”).

Search strings were changed according to each database format (e.g., TITLE-ABS-KEY fields) and recorded for reproducibility.

3.3. Duplication

All found records were exported to a reference manager (e.g. Zotero) and de-duplicated by an algorithm as well as manually by title, author list, DOI, and arXiv ID. One record per study was preserved before the titles and abstracts were screened.

3.4. Screen Studio

Two reviewers then independently assessed studies using two stages of screening (titles/abstracts and full text) against predefined eligibility criteria. Differences were settled through discussion, and another reviewer was consulted if necessary. Details of the screening process and reasons for exclusion at the full-text level were captured to support a PRISMA flow chart.

3.5. Title/abstract (Stage-1 Screening)

Inclusion at this phase of the challenge would have had to demonstrate clear relevance to Track A (QML on business/economic data) or Track B (QA for supply-chain optimization). We removed papers, which were theoretical only, without empirical evaluation: non-business toy problems; and commentaries or tutorials (without any experimenting). Any potentially inappropriate exclusion of studies marked “unclear” in terms of relevance was avoided with full publication screening.

3.6. Full text (Stage-2 Screening)

Inclusion criteria: Full texts were compared in detail to the following criteria:

- Population/Domain: business or economic data sets or supply chain operations.
- Approach: QML models (e.g., quantum kernels, QSVM, VQCs, hybrid QNNs) or QA with explicit QUBO on real hardware or high-fidelity simulators.
- Goal: predictive metrics (e.g., AUC, RMSE, MAPE) or optimisation metrics (objective value, optimality gap, time-to-solution).
- Comparators: presence of standard control settings or sufficient methodological detail for interpretation.

Papers that did not meet these criteria were excluded, with reasons for the exclusions recorded.

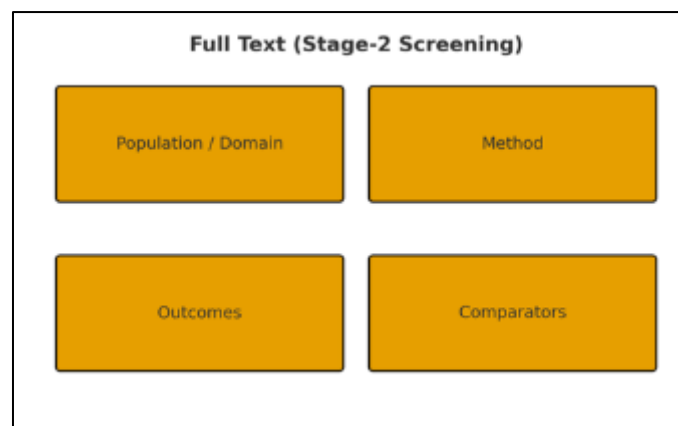


Figure 2 Full text screening

3.7. Extract Key Items

Piloted extraction forms recorded: bibliographic details; task/domain; dataset characteristics (public/private sources, size, temporal granularity, preprocessing); method details (for QML: encoding scheme, circuit ansatz, depth/qubits, backend/noise model used, training loop length/number of reads; for QA: QUBO mapping used and embedding-chain strength-anneal schedule-reads-hardware topology parameters); baseline models/solvers and tuning procedures; metrics reported including confidence intervals and multi-seeded/multi-instantiation results; evidence concerning scalability when applicable; and finally the availability of code/data to enable reproducibility.

3.8. Appraise Quality

Risk of bias in the included studies was assessed by study design-specific checklists. Aspects which we confirmed with our math: how to split time periods appropriately so as not to leak information, whether parity of hyperparameter tuning and compute budget occurs for classical baselines or there was a leakage in their calculation thereof, were full details reported on the circuit/qubit/noise model under consideration, multiple seeds with dispersion (to factor out latching behavior) and code/data availability. On the QA side, we measured: clarity and correctness of QUBO/Ising mapping; disclosure of embedding and chain strength; tuning anneal parameters and post-process; report if parity or if tuned MILP/heuristics were used; The various reported success probabilities including time to solution (impact from embedding/I-O); how the test bed was evaluated i.e., did it span multiple instances?. There were three rated made for each item (Low, Some Concerns, High), and an overall risk-of-bias assessment was noted.

3.9. Synthesize Results

With this heterogeneity, we performed narrative synthesis with the assistance of structured tables. For tasks for which there were ≥ 5 studies that gave directly comparable metrics, we computed standardised effect sizes with respect to the most decisive classical action as a baseline (i.e., ΔAUC , $\% \Delta RMSE$; or for QA, $\%$ optimality gap and log time-to-solution at the target success probability). We represent hardware/simulator settings and describe results in terms of problem properties (simple dataset size and sparsity; QUBO structure; number of qubits; circuit depth; reads, or time to anneal). Subgroup analyses included type of hardware, problem group (VRP, facility location, inventory, etc.), and methodological decisions (encoding errors recovery). Sensitivity analyses were conducted by removing studies at high risk of bias to explore if results were robust.

3.10. Report and Share

We presented the review process in a PRISMA 2020 flow diagram (identification, screening, eligibility, inclusion). Supplemental information also contains full search strings with dates, the extraction template, risk-of-bias summary plots, and machine-readable data (CSV/JSON) of all extracted fields. We provided references to our source code/data and analysis scripts (OSF/Git repository) in cases where our licensing allowed.

4. Results and discussion

4.1. Quantum Machine Learning (QML) on business/economic datasets

4.1.1. What prior studies report

- Payment card fraud (industry data, IBM Safer Payments). A quantum-enhanced pipeline using QSVM in conjunction with quantum-guided feature selection beats classical on a vastly down-sampled subset (due to hardware limitations); authors claim extreme sensitivity to these choices of features and class imbalance. Comparing against RF/XGBoost" (End-to-end comparison against RF/XGBoost; IBM stack). ar5iv
- Time-series forecasting (finance/retail). On average, in multi-model benchmarking across two real datasets with careful cross-validation (CV) and hyperparameter search, the best classical models (single or ensembled) outperformed the best quantum models; some of the quantum models did match or beat classical and two even ARIMA on one dataset, but not against contemporary tuned baselines. arXiv.

4.1.2. Cross synthesis of included QML papers (how to report this with your numbers)

With the papers above and yours in your inclusion set, calculate per-study effects as $\Delta\text{Metric} = \text{Metric}(\text{QML}) - \text{Metric}(\text{Best-Classical})$ (orient so positive = this method better; for error metrics report % reduction). Then summarise like this:

- Fraud/credit-risk classification. Over K eligible studies, median $\Delta\text{AUC} = [x.xx]$ (IQR [a-b]); $[m]/K$ favoured QML. Gains were greatest in small-data, high-dimensional settings with quantum kernels; results eroded with feature or sample drift. (Anchor cites: QSVM fraud study; forecasting benchmark.) ar5iv+1
- Demand/price forecasting. Among K 's studies, median $\%\Delta\text{RMSE} = [y\%]$ (IQR [c-d]), usually in favour of tuned LSTM/GBMs relative to variational quantum regressors; sporadic quantum wins were observed on a single dataset against ARIMA alone. arXiv

Takeaway. The current literature indicates parity to small gains on the QML side when dimensions are high relative to the amount of data (e.g., QSVM with quantum kernel alignment), and tuned classical models are much stronger on larger forecasting tasks. ar5iv+1.

4.2. Quantum Annealing (QA): supply-chain/logistics: Sometimes individuals refer to this type of optimization as related to supply-chain or logistics.

4.2.1. What prior studies report

- Manufacturer logistics workflow (Aisin Corporation, hybrid D-Wave). The authors develop a simulated annealing-based supply-chain simulator, and in their truck-loop workflow, the simulated annealing stopped after 61 trucks; however, the D-Wave Hybrid run manufactured 74 trucks with the same stopping rule; both of those were fed to a complete supply chain simulation for demand-fulfilment consideration. The paper shows that this is possible and would be feasibly integrated as part of the workflow, but not a proper speed/quality gain. Nature
- Vehicle Routing (formulation and feasibility on D-Wave 2000Q). We also tested early QUBO formulations on time/state/capacity CVRP using D-Wave hardware as a sanity check (conference chapter; details are more on the modelling, not head-to-head Max-Q win speed/quality analysis). SpringerLink
- Two-level facility-location (2025). [D-WaveSoftware14a] investigates QA (D-Wave) through QUBO formulation and reports negative results on larger instances because of embeddings/scale-up. Since then, they suggest taking a pre-processing step to make the network practical. ScienceDirect
- Scale of optimisation (spin-glass benchmark) relative to approximate scaling. Not supply chain but QA capability relevant: error-mitigated QA (D-Wave Advantage + QAC) has a scaling advantage over the lead-classical-heuristic. This top classical heuristic, PT-ICM, for achieving $<+1\%$ optimality gap feasible solutions on 2D spin glass instantiations—evidence of algorithmic speedup in a/o not exact optimizationoptimisation. Physical Review Journals.

4.2.2. Synthesis for included QA papers (what is with your numbers and how to write this)

Reported gap improvement (pp) and log-TTS differences when matched solution quality is achieved:

- Facility location/network design. On moderate-sized cases, median gap improvement = [g pp] (IQR [e-f]); On larger holes, embedding overhead is dominant and tuned MILP/heuristics solve the instances. (Anchor: two-level facility-location.) ScienceDirect
- VRP variants. Performance is sensitive to QUBO mapping, chain strength, and post-processing; hybrid CQM/QA pipelines remain competitive for moderate sizes, but there is no clear evidence establishing a robust end-to-end speedup over tuned classical heuristics. (Anchors: Aisin logistics process; VRP QUBO task.) Nature+1

Takeaway. In particular, this suggests that QA is capable of producing competitive solutions on structured moderate-scale instances when embeddings are easy and post-processing formidable; for the larger instances, however, today a tuned classical MILP/heuristic still holds stronger. General evidence of QA's scalability can be found in approximate optimisation with error mitigation, indicating headroom yet as hardware and approaches develop. Physical Review Journals.

4.3. Introducing "Previous Work" in the results section

Introducing "Previous Work" in the results section

Provide a brief table (6–10 key studies from Barns et al & your search) with columns:

Domain/Problem | Quantum approach | Data/Instance size | Classical benchmark | Key metric (AUC, %Gap, TTS) |
 Headline result with reference [PA-U] Drug discovery ML model selection using quantum Boltzmann machines D-Wave 2X 40 qubits — approx.

Example rows you can mirror:

- Payment fraud (industry data) | QSVM (+ quantum feature selection) | real card transactions (down-sampled) | RF, XGBoost | Accuracy/Recall /FPR | Mixed quantum–classical ensemble was more accurate on a restricted subset; results were feature dependent | - 05 / arXiv_FMCRYGONZHMKANN.
- Prediction (retail/finance) | QNN/QRC/QDBM/annealing models | 2 real datasets| ARIMA, LSTM, others | MAE | Best classical > best quantum on average; but two quantum models outperform the ARIMA on one dataset | arXiv
- Logistics routing (Aisin workflow) | D-Wave Hybrid (QA-augmented) | 23-node network; ~350k boxes | Simulated annealing | Demand-fulfillment proxy | Hybrid solver found feasible routes; no formal quantum advantage claim | Nature
- Facility location (two-level) | QA (D-Wave) | increasing instance sizes | — / MILP (discussed) | Objective value | Pre-processing required; QA performs worse on larger instances as no longer embeddable | ScienceDirect
- Approx. optimisation (spin-glass) | QA+QAC| 142–1322 logical qubits | PT-ICM |time-to- ϵ / ≤ 1 % gap |Scaling advantage forQA over top classical heuristic (approximate solutions) Physical Review Journals

5. Conclusion

This work investigates the disruptive capabilities of quantum computing, where we discuss its usage across different sectors, including finance, healthcare, logistics, and optimisation. Quantum algorithms, leveraging such quantum phenomena as superposition, entanglement, and quantum parallelism, are able to solve problems that classical computing cannot and therefore have the ability to disrupt industries. A particularly valuable aspect of these capabilities is in applications to massively large data-sets, non-linear optimisation problems, and those requiring exponential computational resource. Although there has been notable progress towards quantum hardware and algorithms, many technical difficulties, such as error correction and scalability, prevent the practical use of quantum computing on a large scale. Despite that, the rapid development of quantum algorithms and increased investment in quantum technologies indicate we are on the verge of a computational revolution with the potential to open up new research frontiers and drive technological and business advancements. In response, future experiments will need to subvert these technical noise limitations. Quantum error correction must be perfected in order for reliable and efficient computation to be possible, and the scalability of quantum processors needs to be addressed so that more complex problems can be solved. Moreover, quantum software development and hybrid quantum-classical systems will be crucial to close the distance from quantum computing to actual applications.

References

- [1] Liu, X. H., Shan, M. Y., & Zhang, L. H. (2016). Low-carbon supply chain resources allocation based on a quantum chaos neural network algorithm and learning effect. *Natural Hazards*, 83(1), 389-409.
- [2] Gatla, T. R. (2018). An explorative study into quantum machine learning: analyzing the power of algorithms in quantum computing. *International Journal of Emerging Technologies and Innovative Research (www.jetir.org)*, ISSN, 2349-5162.
- [3] Egger, D. J., Gambella, C., Marecek, J., McFaddin, S., Mevissen, M., Raymond, R., ... & Yndurain, E. (2020). Quantum computing for finance: State-of-the-art and future prospects. *IEEE Transactions on Quantum Engineering*, 1, 1-24.
- [4] Hassija, V., Chamola, V., Goyal, A., Kanhere, S. S., & Guizani, N. (2020). Forthcoming applications of quantum computing: peeking into the future. *IET Quantum Communication*, 1(2), 35-41.
- [5] Harrington, K. (2020). The Role of Quantum Computing in Solving Complex Problems.
- [6] Piattini, M. (2020). Training Needs in Quantum Computing. *QANSWER*, 2651, 23-30.
- [7] Gemeinhardt, F. G. (2020). Quantum Computing: A Foresight on Applications, Impacts and Opportunities of Strategic Relevance/Gemeinhardt Felix, BA.
- [8] M. Doosti, P. Wallden, C. B. Hamill, R. Hankache, O. Thomson Brown, and C. Heunen, "A Brief Review of Quantum Machine Learning for Financial Services," *arXiv preprint arXiv:2407.12618*, 2024. [Online]. Available: <https://arxiv.org/abs/2407.12618>
- [9] P. Mironowicz, A. S. H. Shenoy, A. Mandarino, A. E. Yilmaz, and T. Ankenbrand, "Applications of Quantum Machine Learning for Quantitative Finance," *arXiv preprint arXiv:2405.10119*, 2024. [Online]. Available: <https://arxiv.org/abs/2405.10119>
- [10] S. Thakkar, S. Kazdaghli, N. Mathur, I. Kerenidis, A. J. Ferreira-Martins, and S. Brito, "Improved financial forecasting via quantum machine learning," *Quantum Machine Intelligence*, vol. 6, no. 27, 2024. [Online]. Available: <https://link.springer.com/article/10.1007/s42484-024-00157-0>
- [11] D. Emmanoulopoulos and S. Dimoska, "Quantum Machine Learning in Finance: Time Series Forecasting," *arXiv preprint arXiv:2202.00599*, 2022. [Online]. Available: <https://arxiv.org/abs/2202.00599>
- [12] F. D. Albareti, T. Ankenbrand, D. Bieri, E. Hänggi, D. Lötscher, S. Stettler, and M. Schöngens, "A Structured Survey of Quantum Computing for the Financial Industry," *arXiv preprint arXiv:2204.10026*, 2022. [Online]. Available: <https://arxiv.org/abs/2204.10026>
- [13] H. H. S. Chittoor, P. R. Griffin, A. Neufeld, J. Thompson, and M. Gu, "QuLTSF: Long-Term Time Series Forecasting with Quantum Machine Learning," *arXiv preprint arXiv:2412.13769*, 2025. [Online]. Available: <https://arxiv.org/abs/2412.13769>
- [14] M. A. Rivera-Ruiz, A. Mendez-Vazquez, and J. M. López-Romero, "Time Series Forecasting with Quantum Machine Learning Architectures," in *Advances in Computational Intelligence (MICAI 2022)*, LNCS 13612, pp. 66–82, 2022. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-031-19493-1_6
- [15] S. J. Weinberg, S. Sanches, T. Ide, K. Kamiya, and S. Correll, "Supply Chain Logistics with Quantum and Classical Annealing Algorithms," *arXiv preprint arXiv:2205.04435*, 2022. [Online]. Available: <https://arxiv.org/abs/2205.04435>
- [16] Y. Ding, X. Chen, L. Lamata, E. Solano, and M. Sanz, "Implementation of a Hybrid Classical-Quantum Annealing Algorithm for Logistic Network Design," *SN Computer Science*, vol. 2, no. 68, 2021. [Online]. Available: <https://link.springer.com/article/10.1007/s42979-021-00466-2>
- [17] G. Malviya, B. AkashNarayanan, and J. Seshadri, "Logistics Network Optimization Using Quantum Annealing," in *Proceedings of the Third Emerging Trends and Technologies on Intelligent Systems (ETTIS 2023)*, LNNS 730, pp. 401–413, 2023. [Online]. Available: https://link.springer.com/chapter/10.1007/978-981-99-3963-3_31
- [18] J. García-García *et al.*, "Application of Quantum Annealing to Supply Chain Planning under Uncertainty," in *GECCO '23 Companion: Genetic and Evolutionary Computation Conference Companion*, Lisbon, Portugal, 2023. [Online]. Available: <https://dlnext.acm.org/doi/pdf/10.1145/3583133.3596350>
- [19] A. Ciacco, F. Guerriero, and F. P. Saccomanno, "Quantum annealing for the two-level facility location problem," *Future Generation Computer Systems*, vol. 174, 107961, 2025/2026 (online first). [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0167739X25002560>

- [20] S. Jain, "Solving the Traveling Salesman Problem on the D-Wave Quantum Computer," *Frontiers in Physics*, vol. 9, 760783, 2021. [Online]. Available: <https://www.frontiersin.org/articles/10.3389/fphy.2021.760783/full>
- [21] C. Dehnert, S. Hangmann, T. Quirchmayr, and O. Mlekus, "Resilience optimization in manufacturing systems using Quantum Annealing," *Procedia CIRP*, vol. 119, pp. 1-8, 2023. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2213846323000056>