

Quantum optimization algorithms in battery adaptive charging

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Quantum Computing (QC) has the potential to revolutionize battery research by not only offering computational advantages over classical computers but aspiring at a potential paradigm shift in computational approaches. Potential research applications of high impact are in material discovery, electrolyte design, reaction kinetics, molecular dynamics, and optimization of charging algorithms.

This work aims at providing an overview of these applications but focuses on optimisation of charging algorithms. Optimization of charging algorithms for batteries is an essential aspect of battery management and energy storage system design. The goal is to maximize the efficiency, performance, and lifespan of batteries while ensuring safe charging operations. Long term scientific progress may arise by simulations of the complex physical and chemical processes, including ion diffusion, electrochemical reactions, and thermal management but also in other domains such as rapid testing of multiple charging algorithms, safety considerations and grid integration. The goal of this research is to introduce an application for QC for adaptive charging where the quantum algorithm could adapt a prohibitively large number of charging parameters in real-time based on the battery's current state. For example, if the battery is showing signs of heating or increased internal resistance, the algorithm could automatically reduce the charging rate and voltage to prevent overheating and extend the battery's life. Conversely, when the battery is in optimal conditions, it could allow faster charging to meet user demands. The scope of application goes beyond traditional battery systems and can be applied for optimisation of complex real-life large power grids where electrical vehicles (EVs) are relying on for charging. Such systems as whole are described by a large number of parameters and their optimisation is a topic of ongoing research [8,1].

Reducing the problem to a combinatorial optimisation issue, the preliminary results point at Quantum Variational Algorithms (QVA) [9], specifically the Quantum Approximate Optimization Algorithm (QAOA) for approximating the solutions to combinatorial optimization problems. Compared to Quantum annealers, basic Grover's algorithm, and Quantum Adiabatic optimization, preliminary results point to QAOA as the first candidate for modeling such combinatorial optimization problems due to its hybrid nature and other characteristics [2].

The broad family of Quantum Variational Algorithms, other than the QAOA also includes many more methods and tools like Variational Quantum Eigensolver, Quantum Variational Classifier, Variational Quantum Thermalizer, Quantum Kernel Estimator, Quantum Neural Networks and Quantum-Assisted Helmholtz Machines - each worth exploring for battery applications beyond charging optimization. Most QVAs are noise resilient due to their iterative nature using a classical optimizer making them suitable for real quantum hardware that tends to be prone to errors and decoherence. That very reliance on classical optimisers may push them on 'barren plateaus' where the gradient of the optimization landscape becomes very flat making it difficult for classical optimizers to find the minimum, leading to potential issues with scalability as required by complex battery systems. Beyond the straightforward definition of a QAOA, it can also be easily tested in systems of IBM through Qiskit [5] and Xanadu through PennyLane [6].

This work also stresses that QC is still in its early stages, and practical applications are limited by the current state of quantum hardware, which may not yet offer a significant advantage over classical computers for many optimization problems. However, as quantum technology continues to advance, it is expected that quantum optimization algorithms will find broader application in energy research. In order to illustrate the complexity of such developments, this work also presents the overview of a state-of-the-art atomic system and points to a quantum processor based on Rydberg-interacting qubits [10] with mention to a state-of-the-art project led by the ArQuS Lab [3,4,7].

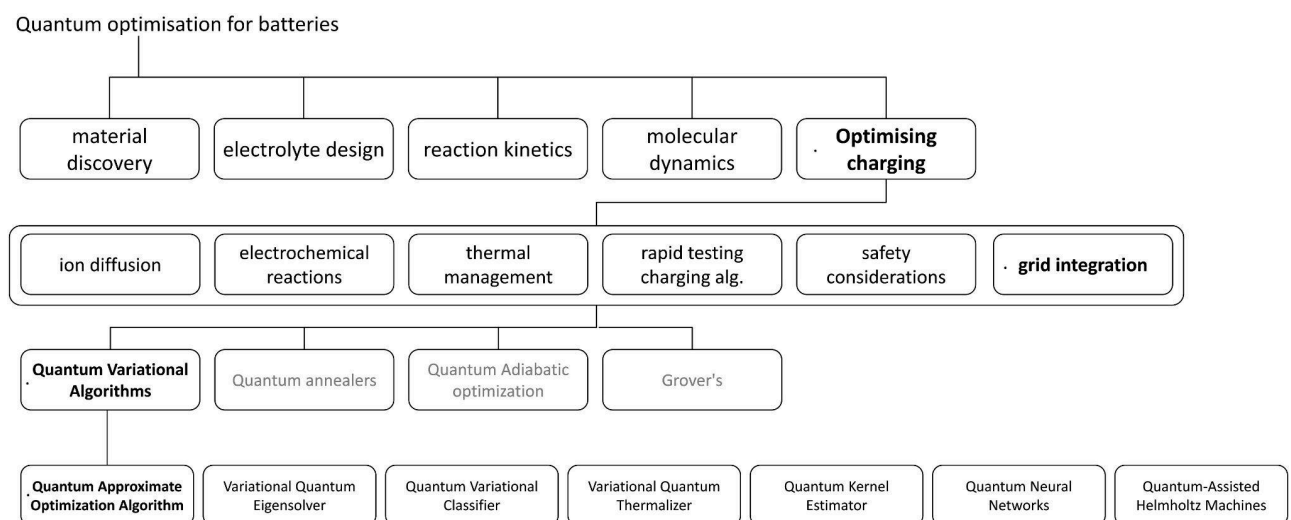


Figure 1. Quantum optimization for batteries. Highlighted in bold a potential application of the QAOA quantum variational algorithm for optimising charging through in grid integration problems.

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