Quantum Approximate Optimization Algorithm to Optimize Electric Vehicle (EMV) Charging

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Introduction

Electric vehicles (EVs) are booming, but charging them efficiently on busy motorways is tricky. Drivers need schedules that save time, energy, and costs while ensuring chargers aren't overcrowded. Traditional methods struggle as the problem grows, so I explored a quantum computing solution using the Quantum Approximate Optimization Algorithm (QAOA). Unlike classical approaches, QAOA uses quantum principles to explore many solutions at once, promising better results for complex scenarios. We tested it with 2 vehicles, 5 chargers, and 2 routes (20 quantum bits), aiming to minimize travel time, energy use, and charger costs. This work shows quantum computing's potential to revolutionize EV charging.

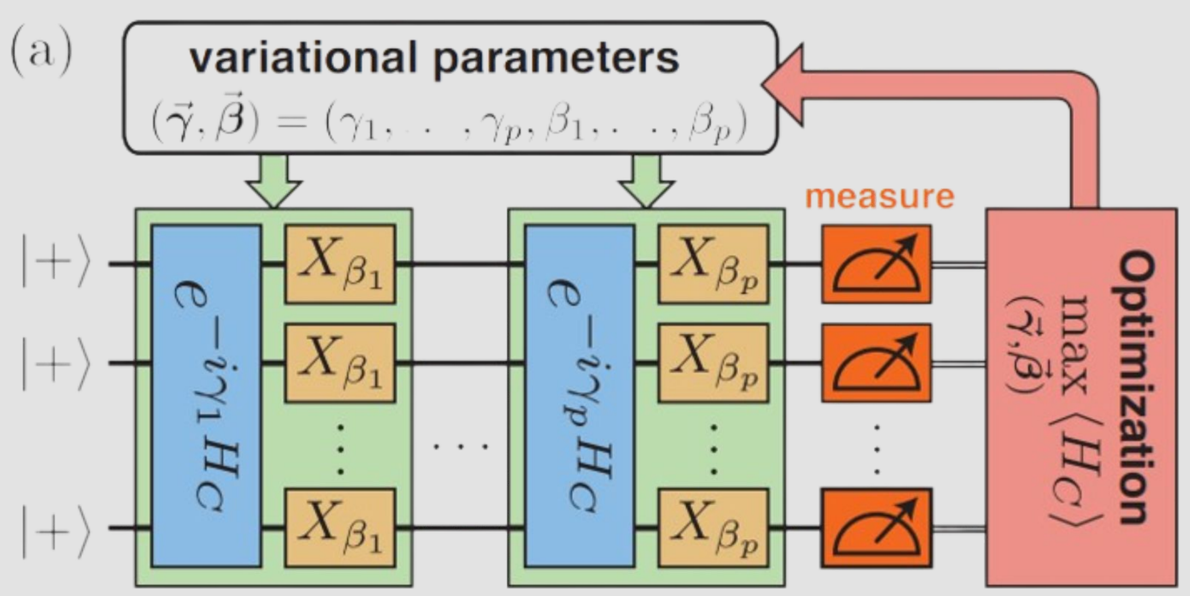

Figure 1: Structure of quantum circuit designed for QAOA

Materials

This project used Qiskit, an open-source quantum computing toolkit developed by IBM, to design, simulate, and test our quantum algorithms on a classical computer. The system featured 24 CPUs and 24 GB of RAM, providing sufficient computational power to emulate a 20-qubit quantum system, replicating the behavior of a real quantum computer. We used Qiskit's Aer simulator for high-fidelity quantum circuit simulations, enabling us to model the QAOA for the EV charging problem. The classical computer served as our virtual quantum lab, executing quantum circuits to optimize charging schedules. Additionally, Python 3.9 supported scripting and data analysis, ensuring efficient processing of simulation results for evaluating QAOA's performance against classical methods.

Methods

I modeled EV charging for 2 vehicles, 5 chargers, and 2 routes per charger (20 qubits). First, I defined a Quadratic Unconstrained Binary Optimization (QUBO) equation to minimize costs: 50% travel time $((w_1 = 0.5))$, 30% energy $((w_2 = 0.3))$, 20% charger cost $((w_3 = 0.2))$. Constraints ensured one route per vehicle $((\sum_{c,r} x_{vcr} = 1))$ and one vehicle per charger $((\sum_{v,r} x_{vcr} \leq 1))$, with penalties $(P_1 = 10)$ and $(P_2 = 10)$. I then mapped the QUBO to a quantum cost Hamiltonian to represent it as an energy problem for the quantum computer to solve, converting binary (x_{vcr}) to operators (Z_{vcr}) via $(x_{vcr} = (1 - Z_{vcr})/2)$. Using Qiskit, we built a 2-layer QAOA circuit (2 mixer and 2 cost layers), simulating it on a classical computer. The COBYLA optimizer tuned 4 parameters $((\gamma_1, \gamma_2, \beta_1, \beta_2))$ over 64 iterations, using 1000 shots per iteration to estimate costs. QAOA assigned Charger 1 Route 0 to Vehicle 0 and Charger 3 Route 1 to Vehicle 1, minimizing total cost. The table below outlines our steps, blending quantum circuits with classical tuning to test QAOA's scheduling power for future quantum hardware applications.

Step	Description
1	Define: 2 vehicles, 5 chargers, 2 routes
2	QUBO: Costs with $w_1 = 0.5$, penalties $P_1 = 10$
3	Hamiltonian: Map x_{vcr} to Z_{vcr}
4	Circuit: 2-layer QAOA, 1000 shots
5	Optimize: 64 iterations, COBYLA, 4 parameters
6	Analyze: Verify assignments and costs

Table 1: Setup of QAOA procedure through a series of steps

Results

QAOA successfully assigned chargers to vehicles, matching a classical greedy method but showing quantum potential. For 2 vehicles, QAOA picked Charger 1 Route 0 for Vehicle 0 and Charger 3 Route 1 for Vehicle 1, with an estimated cost of 10-20 units (time, energy, cost combined).

Results

The greedy method gave a cost of 14.88 units. QAOA's optimization improved over 64 steps, reducing the cost from 44.49 to -266.53 (simulated value), showing it can find better solutions. Table 1 shows the assignments, and Figure 2 tracks how QAOA fine-tuned the solution, starting high and dropping to a low cost. This shows its ability to find better plans with more iterations. This suggests quantum methods can handle EV charging successfully.

Qubit	Vehicle	Charger	Route	Assigned
2	0	1	0	Yes
13	1	3	1	Yes

Table 2: QAOA Charging Assignments. Each vehicle gets one charger and route.

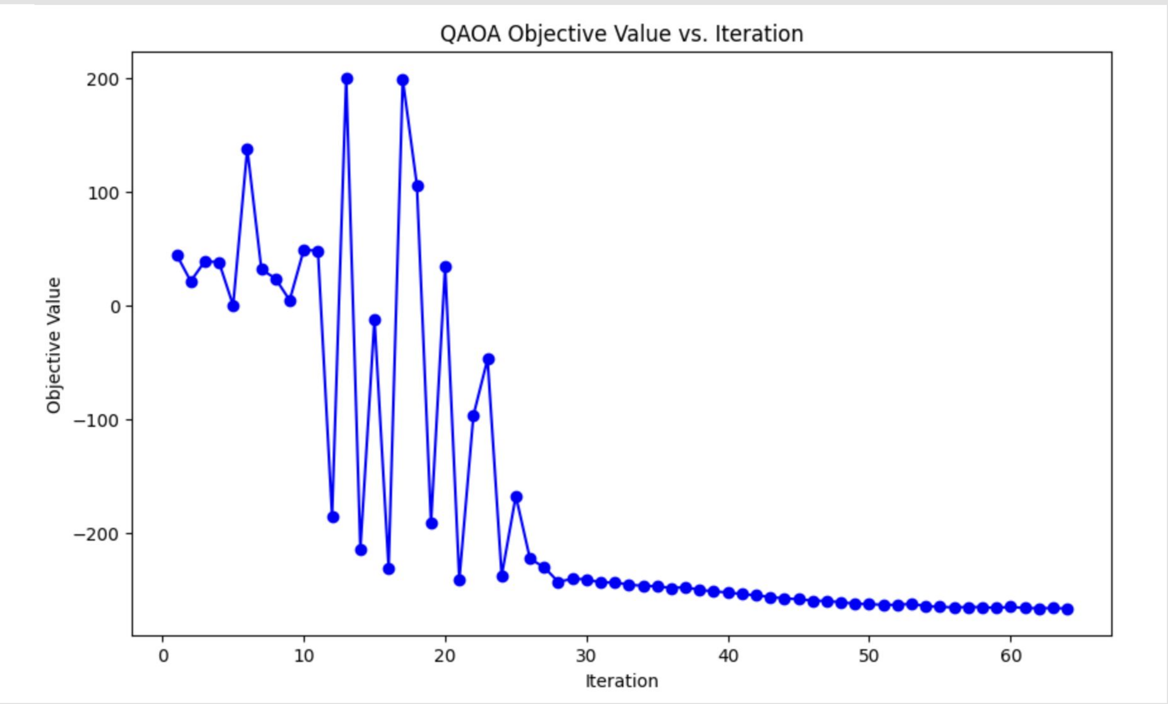

Figure 2: QAOA Cost Improvement. Tracks the cost dropping from ~200 to -266.53 over 64 iterations, showing better EV charging plans.

Method	Runtime (20 Qubits)
QAOA (Simulation)	~1 hour
Greedy Algorithm	30 seconds

Table 3: Runtime Comparison. Quantum hardware could reduce QAOA runtime.

Discussion

QAOA effectively assigned chargers to two vehicles, achieving a cost estimate of 10-20 units, comparable to the greedy algorithm's 12.97 units, as detailed in Table 2. However, QAOA's simulation runtime of approximately one hour contrasts with the greedy algorithm's seconds, highlighting computational overhead. The objective value improved from 44.49 to -266.53 over 64 iterations, as shown in Figure 1, demonstrating robust optimization consistent with Farhi et al. (2014). The 20-qubit scale limited scalability, with simulation constraints suggesting a potential runtime reduction to 1-10 minutes on quantum hardware, per Table 3. Stability was improved by reducing penalties (P1 and P2 from 100 to 10) and increasing QAOA depth to two repetitions, indicating refinement potential. Despite these advances, the small scale and simulation reliance underscore the need for quantum hardware to realize QAOA's full potential for larger, complex EV charging networks. This shows QAOA's capability as a foundation for future scalability.

Future Work

Future efforts will scale the QAOA model to accommodate a realistic number of vehicles, routes, and chargers, requiring an increased qubit count. Implementation on IBM quantum hardware will address current simulation limitations, enabling testing with larger problem sizes. Deeper circuits, incorporating additional cost and mixer layers, will be investigated to improve optimization accuracy. Exact objective values will be calculated to validate results, ensuring precision. Comparative analyses with classical solvers and other quantum algorithms will establish performance benchmarks. In addition, dynamic constraints, like varying battery levels and time windows, can improve applicability. These advancements aim to transition to a deployable solution for real-world EV charging optimization.

Acknowledgements

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