Quantum Battery Optimization through Quantum Machine Learning Techniques

Vu Tuan Hai[1], Vo Minh Kiet[2], Le Vu Trung Duong[1], Pham Hoai Luan[1], Le Bin Ho[3, 4], and Yasuhiko Nakashima[1]
[1] Nara Institute of Science and Technology, 8916–5 Takayama-cho, Ikoma, Nara 630-0192, Japan.
[2] University of Information Technology, Vietnam National University, Ho Chi Minh, Vietnam.
[3] Frontier Research Institute for Interdisciplinary Sciences, Tohoku University, Sendai 980-8578, Japan.
[4] Department of Applied Physics, Graduate School of Engineering, Tohoku University, Sendai 980-8579, Japan.
Email: vu.tuan_hai.vr7@naist.ac.jp

Abstract— **Quantum batteries are a promising technology that could surpass their classical counterparts and play a critical role in the advancement of quantum technologies. In this work, we develop a quantum machine learning algorithm to improve the charging power of quantum batteries. To model an N-cell quantum battery, we use a quantum circuit with N quantum bits. During the charging process, we apply a set of quantum gates with trainable parameters to the circuit. Next, we evaluate the power extraction and optimize it using a classical computer. We find a remarkable maximum power when increasing N. Our work has the potential to create sustainable and scalable energy storage technologies in the future**

Qaantum computing; quantum machine learning, quantum battry

I. INTRODUCTION

Quantum machine learning (QML) is the intersection of quantum computing and artificial intelligence, which presents an exciting new frontier with transformative potential across various research fields [1]. One such field is the optimization of quantum batteries, which are hypothetical energy storage devices that use quantum phenomena to enhance their performance [2]. By combining principles from quantum mechanics and machine learning algorithms, QML promises novel approaches to address complex optimization challenges inherent in designing and managing quantum batteries [3], [4]. Through the use of quantum states, optimization algorithms, data processing techniques, and simulation capabilities, various works aim to gain insights into quantum battery behaviors. These insights will help drive advancements toward efficient energy storage solutions for future quantum technologies.

Recently, many attempts have been made to improve the performance of quantum batteries by optimizing their ergotropy [5] and charging time [6]. The charging process in quantum batteries is carried out using a charged Hamiltonian, which is also crucial to the battery's performance. However, the Hamiltonian itself has still not been optimized. In this study, we address this issue by using a QML approach to optimize the charged Hamiltonian. To model a quantum battery with N cells, we use a quantum circuit with N quantum bits (qubits). During the charging process, we apply a set of quantum gates with trainable parameters to the circuit. Power extraction is evaluated and optimized by a classical computer. We investigated batteries with cell sizes from 2 to 5 and found that size plays a significant role in determining the maximum power output. Our research has the potential to enable sustainable and scalable energy storage technologies in the future.

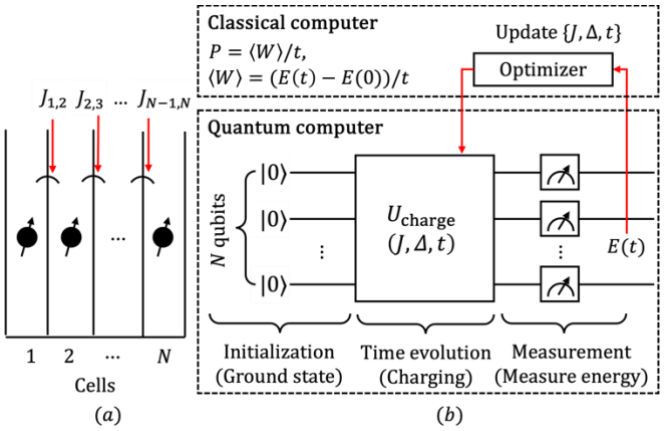

Figure 1. (a) A model of N- cell quantum battery. (b) A quantum machine learning algorithm for optimizing battery's power.

II. PREPARE YOUR PAPER BEFORE STYLING

A. Overview architecture

We consider a quantum battery consisting of N cells, where each cell is a qubit, as shown in Fig. 1 (a, b). At the beginning, the battery is given in the ground state of a Hamiltonian

$$\boldsymbol{H_0}(h) = -h \sum_{j=1}^{N} Z_j \tag{1}$$

where $\{X, Y, Z\}$ are Pauli matrices and h is an external field. To charge the battery, we turn off the external field h and switch on the interaction between cell j^{th} and $(j+1)^{\text{th}}$. The charging Hamiltonian is given by

$$H_{\text{charge}}(J, \Delta, \gamma) = \sum_{j=1}^{N-1} J_j h(1+\gamma) X_j X_{j+1} + (1-\gamma) Y_j Y_{j+1} - \sum_{j=1}^{N-1} \Delta_j Z_j Z_{j+1} - h \sum_{j=1}^{N} Z_j \tag{2}$$

TABLE I. Experimental result with $\Delta t = 50$ (ms), $t \in [0, 5]$.

N	J_{opt}	$t_{\text{opt}}(ms)$	$E_{\max}(J)$	$P_{\max}(W)$
2	[78.54]	15	2	227.61
3	[8.39, 156.68]	7.5	0.99	453.63
4	[156.44, 24.32, 156.44]	7.5	3.88	896.85
5	[156.89, 4.08, 156.76, 8.58]	7.5	2.98	908.01

where J, Δ, γ are battery's coefficients. The total Hamiltonian gives $H = H_0 + H_{\text{charge}}$. After charging, the battery will store a certain amount of energy

$$\langle W \rangle = \langle \psi(t)|H_0|\psi(t)\rangle - \langle \psi(0)|H_0|\psi(0)\rangle, \quad (3)$$

where t is the charging time, $|\psi(t)\rangle = e^{-itH}|\psi(0)\rangle$, and $|\psi(0)\rangle$ is the initial ground state. To evaluate the preferment of the battery, we calculate its power as $P = \langle W \rangle / t$. With a conventional quantum battery, we must determine the optimal time t_{opt} at which the power P is maximized ($P_{\max}$).

In this work, we aim to find the best of $P_{\max}$ via optimizing the battery's coefficients $\{J, \Delta, \gamma\}$ using QML model as shown in Fig. 1 (b). In our QML model, we utilize a quantum circuit with N qubits to simulate an N - cell battery. The circuit begins in state $|\mathbf{0}\rangle$, which is also the ground state of H_0, we then apply unitary $U_{\text{charge}}(J, \Delta, \gamma) = e^{-itH}$ to the circuit, with the external field turned off ($h = 0$). In the quantum circuit, we decompose $U_{\text{charge}}(J, \Delta, \gamma)$ into single- and two-qubit quantum gates, with the coefficients $\{J, \Delta, \gamma\}$ being trainable. Once the battery has been charged, we measure the final circuit and calculate the expected energy $\langle W \rangle$, the probability of success P , and the maximum probability of success $P_{\max}$. To find best $P_{\max}$, we choose $\mathcal{L}(J, \Delta, \gamma) = -|P_{\max}|$ as a loss function. Since $P_{\max} > 0$ then, we have

$$\nabla \mathcal{L} = -\left(\frac{\partial P_{\max}}{\partial J_0}, \frac{\partial P_{\max}}{\partial J_1}, \dots, \frac{\partial P_{\max}}{\partial \Delta_0}, \frac{\partial P_{\max}}{\partial \Delta_1}, \dots\right)^{\intercal} \quad (4)$$

where $\frac{\partial P_{\max}}{\partial J_j} = i\left[t_{\text{opt}}\langle \psi(t_{\text{opt}})|(G_j^{\dagger} H_0 - H_0 G_j)|\psi(t_{\text{opt}})\rangle\right]$ with $G_j \in \{X_j X_{j+1}, Y_j Y_{j+1}, Z_j Z_{j+1}, Z_j\}$ is the corresponding Pauli term. Then, {J, Δ, γ} are updated via Gradient Descent or Adam optimizer. We repeatedly update $\{J, \Delta, \gamma\}$ until obtaining the optimal value of $P_{\max}$.

III. EXPERIMENT

For numerical calculation, we consider an XX spin chain model, where $\Delta = 0$ and $\gamma = 0$ as

$$H_{\text{charge}} = \sum_{j=1}^{N-1} J_j \left(X_j X_{j+1} + Y_j Y_{j+1}\right) \quad (5)$$

We conduct the experiment from N = 2 to 5 cells with setting as Tab. I, and the results are shown in Fig. 2. In Fig. 2 (a, b), we illustrate the change in loss function and power across different numbers of iterations. After a certain point, these values reach their optimum levels, indicating that the model is trainable. In Fig. 2 (c, d), we analyze the energy and power as they vary with charging time. The energy exhibits oscillatory behavior while the power reaches its maximum value after a short charging time. Remarkably, as the number of cells increases, the battery receives more power.

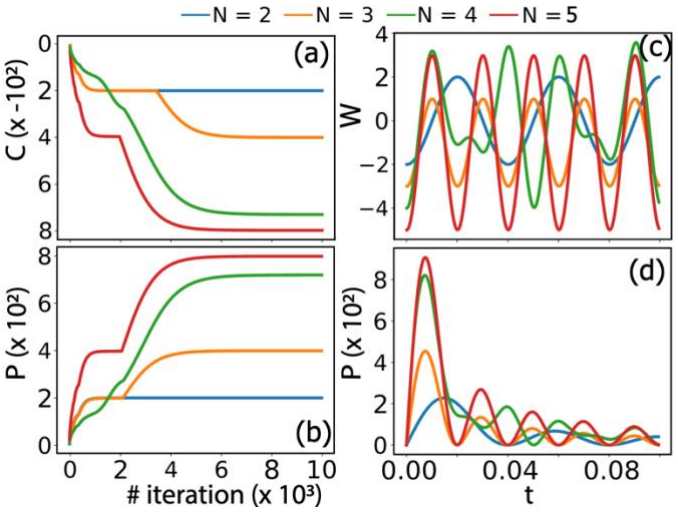

Figure 2. (a) Plot of loss function versus the iteration. (b) Plot of power versus the iteration. (c) Energy as a function of time. (d) Power as a function of time.

IV. CONCLUSION

Optimizing quantum batteries using quantum machine learning is a new frontier in energy storage. By using quantum computing techniques and machine learning algorithms, we unlock the maximum potential of quantum batteries. This research will advance quantum power and revolutionize energy storage. Future technological advancements in QML will lead to efficient, reliable, and sustainable quantum batteries, prov- ing the transformative potential of QML at the intersection of quantum computing and energy science

ACKNOWLEDGMENT

This work was supported by JST-ALCA-Next Program Grant Number JPMJAN23F5, Japan. The research has been partly executed in response to support of JSPS, KAKENHI Grant No. 22H00515, Japan.

REFERENCES

[1] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum machine learning," Nature, vol. 549, no. 7671, pp. 195-202, Sep 2017. [Online]. Available: https://doi.org/10.1038/nature23474

[2] F. Campaioli, S. Gherardini, J. Q. Quach, M. Polini, and G. M. Andolina, "Colloquium: Quantum batteries," 2023.

[3] D. Rossini, G. M. Andolina, D. Rosa, M. Carrega, and M. Polini, "Quantum advantage in the charging process of sachdev-ye-kitaev batteries," Phys. Rev. Lett., vol. 125, p. 236402, Dec 2020. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevLett.125.236402

[4] D. T. Hoang, F. Metz, A. Thomasen, T. D. Anh-Tai, T. Busch, and T. Fogarty, "Variational quantum algorithm for ergotropy estimation in quantum many-body batteries," Phys. Rev. Res., vol. 6, p. 013038, Jan 2024. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevResearch.6.013038

[5] S. Juli`a-Farr´e, T. Salamon, A. Riera, M. N. Bera, and M. Lewenstein, "Bounds on the capacity and power of quantum batteries," Phys. Rev. Res., vol. 2, p. 023113, May 2020. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevResearch.2.023113

[6] J.-Y. Gyhm, D. Rosa, and D. ˇSafr´anek, "Minimal time required to charge a quantum system," Phys. Rev. A, vol. 109, p. 022607, Feb 2024. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevA.109