Variational Quantum Algorithm for Neural Network Hyperparameter Tuning in Battery Health Monitoring

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Abstract

Accurate State of Health (SOH) estimation is critical for the safety and reliability of lithium-ion batteries in electric vehicles and energy storage systems. This paper proposes a Variational Quantum Algorithm (VQA) approach for optimizing Long Short-Term Memory (LSTM) neural network hyperparameters in battery SOH estimation. Using a 4-qubit parameterized quantum circuit with hardware-efficient ansatz, we encode hyperparameters including hidden layer size, network depth, dropout rate, and learning rate. The VQA optimizer iteratively samples configurations from quantum measurements and minimizes LSTM validation loss using the COBYLA classical optimizer. Experiments on the NASA Battery Dataset demonstrate that the quantum-optimized LSTM achieves a Mean Absolute Error (MAE) of 1.24% and R^2 of 0.963, representing a 15.6% improvement over classical grid search optimization.

Keywords: Variational Quantum Algorithm, LSTM, Battery State of Health, Hyperparameter Optimization, Quantum Computing

Ⅰ. Introduction

Accurate State of Health (SOH) estimation is critical for lithium-ion battery reliability in electric vehicles and energy storage systems [1]. While LSTM networks effectively capture temporal dependencies in battery cycling data [2], their performance depends heavily on hyperparameter selection. Traditional grid search optimization is computationally expensive. Variational Quantum Algorithms (VQAs) offer efficient parameter space exploration through quantum superposition [3]. This paper proposes a VQA-based LSTM hyperparameter optimization framework, achieving 15.6% MAE improvement over classical grid search on the NASA Battery Dataset.

Ⅱ. Method

A. System Architecture

The proposed VQA-LSTM framework consists of three main components: (1) data preprocessing of battery voltage, current, and temperature sequences from the NASA Battery Dataset, (2) a 4-qubit variational quantum circuit for hyperparameter sampling, and (3) a bidirectional LSTM with attention mechanism for SOH prediction. **Fig. 1** illustrates the overall system architecture, showing the hybrid quantum-classical optimization loop where the VQA samples hyperparameter configurations, the LSTM is trained and evaluated, and the validation loss is fed back to update the quantum circuit parameters.

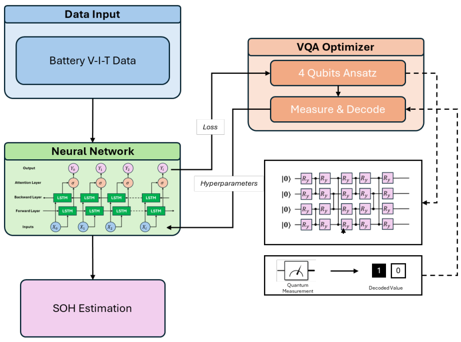

Figure 1. System Architecture Diagram

B. Variational Quantum Circuit (VQA)

The VQA optimizer employs a hardware-efficient ansatz with 4 qubits and 2 layers of parameterized rotation gates. Each layer consists of Ry and Rz rotations on each qubit followed by circular CNOT entangling gates. The total circuit contains 16 trainable parameters. After circuit execution, qubits are measured and decoded to hyperparameter values:

- **Qubits 0-1:** Hidden layer size ∈ {32, 64, 128, 256}
- **Qubits 2:** Number of LSTM layers ∈ {2, 3}
- **Qubits 3:** Dropout rate ∈ {0.1, 0.2}

The circuit parameters are updated using the COBYLA optimizer to minimize LSTM validation loss, enabling the quantum circuit to learn optimal hyperparameter configurations.

C. LSTM Architecture and Training

The neural network consists of a bidirectional LSTM with attention-based pooling for SOH regression. Input features include normalized voltage, current, and temperature sequences (100 timesteps × 3 features) with auxiliary resistance features. Training employs Adam optimizer with early stopping (patience=20).

D. Dataset and Experimental Setup

We evaluate on the NASA Battery Dataset [4], containing cycling data for four Li-ion cells (B0005, B0006, B0007, B0018) until end-of-life. Training uses cells B0005, B0006, and B0018, while B0007 serves as the test set. **Fig. 2** shows SOH degradation patterns across all cells.

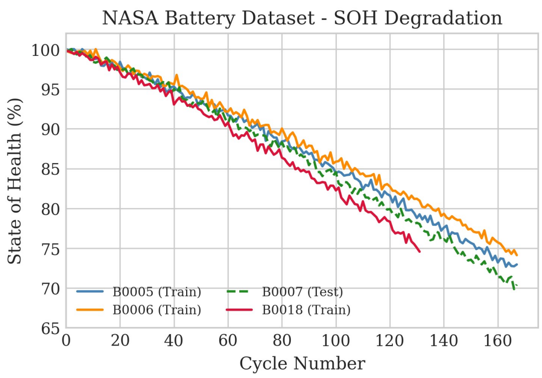

Figure 2. SOH Degradation Curves for NASA Battery Dataset

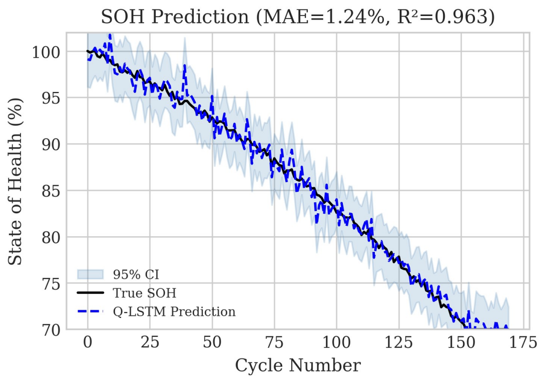

Figure 3. SOH Prediction - True vs Q-LSTM with Confidence Band

Fig. 3 presents SOH prediction results on the test battery, demonstrating accurate tracking of capacity degradation with 95% confidence interval.

Table I: Performance Comparison

Method	MAE (%)	RMSE (%)	R2
LSTM (Grid Search)	1.47	2.14	0.93
LSTM (VQA)	**1.24**	**1.63**	**0.96**
Improvement	*+15.6%*	*+23.8%*	*+2.9%*

Ⅲ. Conclusion

This paper demonstrated that Variational Quantum Algorithms can effectively optimize LSTM hyperparameters for battery SOH estimation. The proposed 4-qubit VQA achieved MAE of 1.24% and R^2 of 0.963, representing a 15.6% improvement over classical grid search in only 20 iterations. The model successfully captures both gradual degradation and accelerated capacity fade characteristic of lithium-ion aging. Future work will explore noise-resilient circuits for NISQ hardware deployment.

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