

Quantum-Assisted Identification of Inverter-Based Resource Dynamics in Weak Grids: A Hybrid Quantum Convolutional Neural Network

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Introduction and Objectives

- Inverter-based resources (IBRs) now dominate grid dynamics; in weak power grids, they switch abruptly among normal/grid-support, current-limited, and low-voltage ride-through (LVRT) modes.
- Vendor-proprietary control logic hides the switching thresholds; operators observe terminal behavior but not the internal operating mode.
- Proposal targets** (held-out): mode-classification **Accuracy** ≥ 0.70 ; trajectory error $\leq 10\%$;
- Scope**: build and validate the quantum classification stage plus a systematic “QCNN Configuration Selector.”

Results

- Stable training (**Fig. 1, top left**): loss **0.67** $\rightarrow$ **0.478** (train)/accuracy plateau $\approx$ **76–77%** (**Fig. 1, top right**); train and validation track closely $\rightarrow$ good generalization.

Methods

- **Data**: 3,758 terminal-measurement windows $\times$ 2,000 features; binary mode label; min–max normalized.
- **Dimensionality reduction**: PyTorch autoencoder 2000 $\rightarrow$ 512 $\rightarrow$ 64 $\rightarrow$ 8 (matches the 8-qubit register).
- **Encoding**: angle embedding — one feature sets one R_x rotation per qubit.
- **QCNN**: hierarchical convolution (conv2, 15 params, Ising XX/YY/ZZ couplers) + pooling (pool2, 9 params) (**Fig. 2 bottom**); register 8 $\rightarrow$ 4 $\rightarrow$ 2 $\rightarrow$ 1; $\langle Z \rangle$ readout; ≈ 513 trainable parameters.

Conclusions & Path Forward

- Delivered a reproducible, simulator-validated hybrid quantum convolutional neural network (QCNN) pipeline plus a transferable configuration-search method for IBR mode identification.
- Precision $>$ recall $\rightarrow$ the model is conservative on the current-limited/LVRT mode; threshold and class-weight tuning planned.
- Next**: integrate a physics-informed neural ODE for parameter estimation; noise-robustness ablation on IBM hardware; matched classical neural ODE baseline.

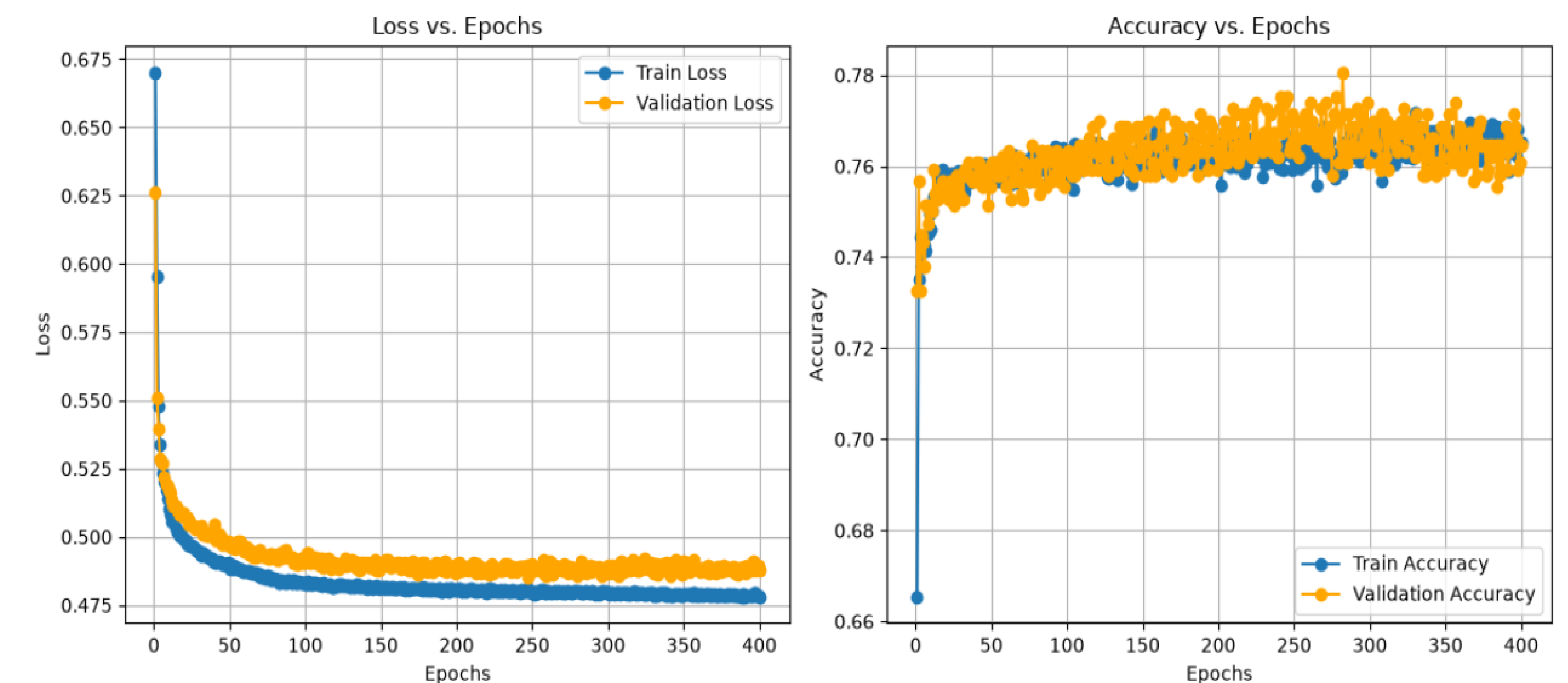
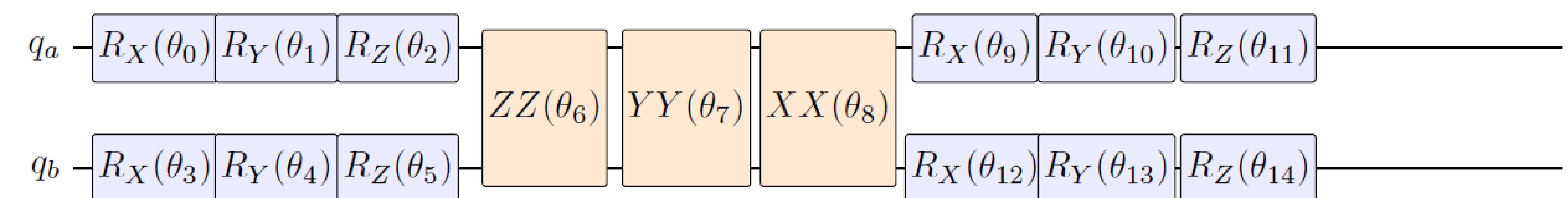
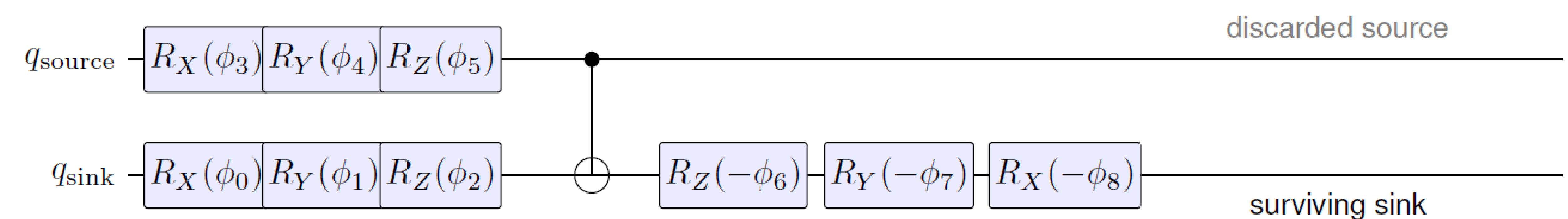


Fig 1. The performance of the proposed algorithm.



(a) conv2: 15-parameter two-qubit convolution



(b) pool2: 9-parameter pooling block

Fig 2. The proposed convolution layer.

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