Literature Survey:
Quantum Gated Recurrent Units

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Literature Survey

A Variational Approach to Quantum Gated Recurrent Units. Authored by Andrea Ceschini, Antonello Rosato, and Massimo Panella (2024), this study proposes a foundational architecture for a hybrid QGRU to address the computational bottlenecks of Quantum LSTMs (QLSTMs). The authors designed a cell where the three classical gating operations (reset, update, and candidate) are replaced by three Variational Quantum Circuits (VQCs). A key architectural choice in this work is the use of shared classical fully connected layers (FC_{in} and FC_{out}) sandwiching the VQCs to manage dimensionality while minimizing parameter count. The study evaluated the model on time-series tasks including sine waves, sunspots, and wind power forecasting. The key finding is that this QGRU architecture requires 25% fewer quantum parameters than a QLSTM while achieving superior accuracy (e.g., 46% lower Mean Squared Error than classical GRU on sine waves) and 25% faster training times, establishing it as a computationally efficient alternative for Noisy Intermediate-Scale Quantum (NISQ) devices.

Evolving Hybrid Quantum-Classical GRU Architectures for Multivariate Time Series. Authored by Francesca De Falco, Leonardo Lavagna, Andrea Ceschini, Antonello Rosato, and Massimo Panella (2024), this research builds upon the variational approach to extend the QGRU architecture to the domain of multivariate time-series forecasting, a complex task requiring the correlation of multiple input variables. The authors employed a hybrid structure—using VQCs for the reset and update gates flanked by classical layers—to process multidimensional datasets such as energy transformer temperatures (ETTh1) and meteorological data. The study compared the QGRU against Bi-LSTMs and QLSTMs. The key finding is that the QGRU consistently outperformed both classical and quantum baselines in Mean Squared Error (MSE) on datasets like SACRAMENTO and ELIZABETH, demonstrating that the hybrid QGRU can effectively capture correlations in multivariate data while maintaining a significantly lower parameter count (46% fewer than classical LSTM).

Quantum Recurrent Neural Networks with Encoder-Decoder for Time-Dependent Partial Differential Equations. Authored by Yuan Chen, Abdul Khaliq, and Khaled M. Furati (2025), this paper introduces a structural innovation by embedding QGRU and QLSTM cells within a classical Encoder-Decoder framework to solve high-dimensional Partial Differential Equations (PDEs). Unlike direct processing, this architecture uses a classical encoder to compress high-dimensional spatiotemporal data into a low-dimensional latent space, where the QGRU then predicts the temporal evolution. The key finding is that the QGRU model achieved the highest accuracy in solving the Burgers' equation (MAE of 2.981×10^{-4}) and the 3D Michaelis-Menten system, effectively demonstrating that QGRUs can operate efficiently in latent spaces to model complex non-linear dynamics that are computationally prohibitive for traditional numerical methods.

Quantum Recurrent Neural Networks: Predicting the Dynamics of Oscillatory and Chaotic Systems. Authored by Yuan Chen and Abdul Khaliq (2024), this study focuses on the internal operations of the quantum circuit to investigate the performance of QGRUs on chaotic dynamical systems such as the Van der Pol oscillator and the Lorenz system. The authors introduced an operational novelty by modifying the VQC data encoding strategy, utilizing sine and cosine functions for rotation gates (R_y and R_z) rather than the standard arctangent encoding. The key finding is that this specific encoding allowed the QGRU to capture chaotic dynamics with exceptional precision, reducing the Mean Absolute Error (MAE) on the Lorenz system to approximately half that of the QLSTM and one-fourth that of the classical LSTM, validating the QGRU's superior stability in modeling chaos.

Short-term Photovoltaic Power Forecasting Based on Hybrid Quantum Gated Recurrent Unit. Authored by Seon-Geun Jeong, Quang Vinh Do, and Won-Joo Hwang (2024), this work proposes a "Hybrid QGRU" (HQGRU) specifically optimized for solar power forecasting. In terms of design, this model diverges from the shared-layer approach by employing a specific "Quantum Convolutional Filter" ansatz and, crucially, using separate, independent classical linear layers for each gate's VQC to maximize expressivity. The authors tested this architecture against L-QLSTM (Linear-layer enhanced QLSTM) on real-world weather data from Korea. The key finding is that the HQGRU achieved the highest prediction accuracy (R^2 of 0.961) with fewer parameters (971 vs. 1131 for L-QLSTM), proving that independent gate optimization in QGRUs is highly effective for renewable energy tasks.

Quantum Gated Recurrent GAN with Gaussian Uncertainty for Network Anomaly Detection. Authored by Wajdi Hammami, Soumaya Cherkaoui, Jean-Frederic Laprade, Ola Ahmad, and Shengrui Wang (2025), this paper integrates the QGRU into a generative adversarial framework (QWGAN) for anomaly detection. The primary architectural contribution is the implementation of "Successive Data Injection" (SuDal), a technique where input features are injected progressively across the depth of the quantum circuit rather than all at once, allowing high-dimensional data to be loaded onto limited qubits. The model was trained to output Gaussian distribution parameters (μ, σ) rather than point estimates. The key finding is that this generative QGRU achieved a high Time-aware F1 score (0.89), outperforming classical RNNs, and was successfully deployed on real IBM Quantum hardware with high fidelity, validating the SuDal approach for practical quantum implementation.

Reservoir Computing via Quantum Recurrent Neural Networks. Authored by Samuel Yen-Chi Chen, Daniel Fry, Amol Deshmukh, Vladimir Rastunkov, and Charlee Stefanski (2022), this study explores a different training paradigm called Reservoir Computing (RC), where the QGRU is treated as a fixed dynamical system. In this design, the parameters of the VQCs within the QGRU are randomly initialized and frozen (untrained), and only the final classical output layer is optimized. This approach was tested on function approximation and time-series benchmarks. The key finding is that the QGRU-RC achieved performance comparable to fully trained quantum models but with drastically reduced training time and complexity, offering a highly efficient strategy for utilizing QGRUs on NISQ devices where gradient calculation is expensive.

Application of Quantum Recurrent Neural Network in Low-Resource Language Text

Classification. Authored by Wenbin Yu, Lei Yin, Chengjun Zhang, Yadang Chen, and Alex X. Liu (2024), this paper targets Natural Language Processing (NLP) and proposes the "Parameter Non-shared Batch-Uploading QGRU" (PN-BUQGRU). The design addresses the bottleneck of loading large word embeddings by splitting vectors into batches and uploading them sequentially into the VQC (Batch Uploading), while also assigning independent classical layers to each gate (Parameter Non-sharing). The model was evaluated on Bengali sentiment analysis datasets. The key finding is that the PN-BUQGRU achieved state-of-the-art accuracy (85.3% on Book-Reviews), surpassing both standard QGRUs and classical baselines, confirming that batch uploading prevents information loss better than classical compression for NLP tasks.