ARTIFICIAL INTELLIGENCE AND QUANTUM COMPUTING MODELS FOR FORECASTING PROCESSES IN POWER SUPPLY SYSTEMS

Shevchenko Vladyslav
ORCID ID: 0009-0004-5507-5293
PhD Student
Department of Software Engineering and Management Intelligent Technologies
National Technical University "Kharkiv Polytechnic Institute", Ukraine

Scientific advisor: Shmatko Oleksandr
ORCID ID: 0000-0002-2426-900X
Ph.D., Associate Professor, Associate Professor
Department of Digital Technologies and Project Analytical Solutions
Technical University "Metinvest Polytechnic" LLC, Ukraine

INTRODUCTION. Accurate forecasting of power supply parameters is one of the most fundamental tasks in modern energy system management [1]. The increasing penetration of renewable energy sources, the variability of consumer demand, and the transition to decentralized smart grids have introduced unprecedented complexity into the operation of power systems. Traditional forecasting methods, including statistical regression, time series analysis, and classical machine learning algorithms, often struggle to capture the nonlinear and transient dynamics of such systems.

Quantum computing, a rapidly evolving field, offers fundamentally new approaches to data representation and processing based on the principles of superposition and entanglement. Quantum Neural Networks (QNNs) integrate quantum computing with machine learning, allowing simultaneous processing of multiple states and enabling more efficient learning in complex multidimensional spaces [2-6]. This study explores the application of QNNs to short-term forecasting tasks in power supply systems, demonstrating how quantum resources can enhance the efficiency and adaptability of forecasting models.

METHODOLOGY. The proposed research introduces a hybrid quantum–machine learning approach to predict short-term variations in power supply parameters such as load, voltage, and frequency. The study investigates two distinct QNN architectures tailored to the physical dynamics of power systems.

The first, the Sinusoidal-Friendly QNN (SFQ), is designed to model oscillatory phenomena in voltage and current waveforms typical of electromechanical transients. The second, the Polynomial-Friendly QNN (PFQ), is optimized for approximating nonlinear dependencies in load fluctuations. Both models employ Variational Quantum Circuits (VQCs) with parameterized quantum gates, ensuring hardware compatibility with near-term quantum processors.

Training data were generated using simulation models of two benchmark systems: the Single Machine Infinite Bus (SMIB) and the Western Systems Coordinating Council (WSCC) three-machine configuration. Each dataset included between four and nineteen input parameters representing voltage magnitudes, rotor angles, active power, and system frequency variations under dynamic load changes.

The quantum models were trained using noiseless quantum simulators to emulate the operation of future quantum devices. The optimization process employed gradient-based parameter updates and fidelity-based loss functions. For comparison, a classical Recurrent Neural Network (RNN) was implemented using identical datasets and evaluated against the same performance metrics. These included mean squared error (MSE), the number of training epochs to convergence, and the total number of parameters.

All simulations were executed under consistent experimental conditions, with model parameters and training configurations standardized to ensure comparability. The goal was to assess the relative advantages of quantum neural computation in terms of accuracy, convergence speed, and model complexity.

RESULTS. The experimental findings demonstrate that QNNs can accurately forecast short-term variations in power supply parameters, achieving superior performance compared to traditional RNN-based approaches. In the best-performing models, the mean squared error did not exceed 10^{-5}, corresponding to a high level of approximation accuracy.

Quantum models exhibited parameter efficiency, requiring approximately 30–40% fewer trainable weights than classical RNNs. Furthermore, convergence analysis revealed that the QNNs reached stable accuracy levels two to three times faster, reducing the number of epochs necessary for effective learning.

An important observation was the robustness of QNN models to problematic input features that commonly lead to overfitting in classical architectures. This robustness can be attributed to quantum entanglement and superposition, which allow the QNN to encode and learn interdependencies more effectively without requiring explicit parameter expansion.

Both SFQ and PFQ architectures demonstrated consistent generalization performance across simulated datasets. SFQ achieved slightly better results in modeling oscillatory transients, while PFQ outperformed in nonlinear load forecasting scenarios. These results suggest that specialized QNN architectures can be tailored to specific energy system behaviors to maximize forecasting precision.

CONCLUSION. This study demonstrates the feasibility and potential of quantum neural networks in forecasting processes within power supply systems. The combination of quantum computation and artificial intelligence enables efficient modeling of nonlinear and transient behaviors that are difficult to capture using classical methods. The experimental results confirmed that QNNs achieve higher forecasting accuracy, reduced model complexity, and faster convergence while maintaining robust generalization across diverse operating conditions.

The research provides a foundation for developing quantum-assisted control and forecasting systems for future intelligent power grids. These systems will operate on principles of adaptability, predictability, and self-optimization, contributing to the transition toward more resilient and sustainable energy infrastructures. Quantum neural computation thus represents not only a technical innovation but also a paradigm shift in how forecasting and optimization are approached in the field of energy systems.

References:

1. Mirzayev, S. N. O. G. L., & Esonov, T. B. O. G. L. (2024). Forecasting the urban electricity supply system. Oriental renaissance: Innovative, educational, natural and social sciences, 4(5), 558-563.
2. Küçükkara, M. Y., Atban, F., & Bayılmış, C. (2024). Quantum-Neural Network Model for Platform Independent Ddos Attack Classification in Cyber Security. Advanced Quantum Technologies, 7(10), 2400084.
3. Hafeez, M. A., Munir, A., & Ullah, H. (2024). H-QNN: A hybrid quantum–classical neural network for improved binary image classification. AI, 5(3), 1462-1481.
4. Innan, N., Behera, B. K., Al-Kuwari, S., & Farouk, A. (2025). Qnn-vrcs: A quantum neural network for vehicle road cooperation systems. IEEE Transactions on Intelligent Transportation Systems.
5. Basha, R., Pathak, P., Sudha, M., Soumya, K. V., & Arockia Venice, J. (2025). Optimization of Quantum Dilated Convolutional Neural Networks: Image Recognition With Quantum Computing. Internet Technology Letters, 8(3), e70027.
6. Hong, Y. Y., Lopez, D. J. D., & Wang, Y. Y. (2024). Solar irradiance forecasting using a hybrid quantum neural network: A comparison on gpu-based workflow development platforms. IEEE Access, 12, 145079-145094.