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Quantum Noise Assessment in Quantum Machine Learning Models for Equipment Failure Modes Diagnosis

Lavínia Maria Mendes Araújo[a], Isis Didier Lins[a], Caio Bezerra Souto Maior[a], Márcio das Chagas Moura, Enrique Lopez Droguett[b], Rafael Chaves Souto Araújo[c], Askery Alexandre Canabarro[d], Andre Juan Ferreira Martins de Moraes[d]

[a] *Center for Risk Analysis and Environmental Modeling, Department of Industrial Engineering, Federal University of Pernambuco, Brazil*
[b]*University of California, Los Angeles, United States of America*
[c] *International Institute of Physics, Federal University of Rio Grande do Norte, Natal, Brazil*
[d] *Department of Physics, Federal University of Alagoas, Arapiraca, Brazil*

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In Prognostics and Health Management, diagnostics involves identifying and detecting existing failures or anomalies in a system. Its primary objective is to promptly identify and report any deviations from normal operation, providing crucial information regarding the current health status of the system (Barraza et al., 2022). Recently, there has been significant research interest in the potential of Quantum Computing (QC) and related quantum technologies, which offer parallel processing capabilities. Quantum algorithms aim to enhance the computational speed and efficiency of solving complex problems challenging for classical computers (Kavitha and Kaulgud, 2022). Quantum devices have the potential to address these limitations and improve various ML applications. Consequently, quantum properties have been incorporated into machine learning models, resulting in Quantum Machine Learning (QML) techniques (Biamonte et al., 2017).

In the literature, two papers explored the application of Quantum Machine Learning (QML) in rotary machines. (Correa-Jullian et al., 2022) used quantum kernel methods for wind turbine fault detection. (Maior et al., 2023) performed different QML models to evaluate available literature databases, using parameterized quantum circuits (PQC). Therefore, the present study represents an advancement in the research conducted by (Maior et al., 2023), as we will address the impact of quantum noise on quantum neural network models. Simulating quantum noise is particularly important because it helps assess the models' performance under realistic conditions, considering the inherent noise associated with quantum systems.

Quantum computers experience noise, which arises from various sources such as the surrounding environment, fabrication imperfections, Tunneling Two-Level Systems (TLS) effects, and even cosmic rays (Broughton et al., 2020). As of now, large-scale error correction remains a challenge, requiring today's algorithms to function reliably despite noise. Therefore, testing algorithms under noisy conditions is crucial to validate their suitability for current quantum computers. The presence of noise in a quantum computer impacts the measurement of bitstring samples. One way to conceptualize noise is as the random "insertion," "deletion," or "replacement" of gates within the quantum circuit.

We tested a rolling bearing fault database using vibration signals obtained from Case Western Reserve University (CWRU, 2020). The database includes data from the normal state and nine different failure modes. The tested circuit consists of 5 qubits with a circuit structure composed of Euler rotations (rotation in y, rotation in z, rotation in y) in terms of three angles (a, b, c) and iSWAP entanglement gates. In practice, it is nearly impossible to know all the ways a circuit can fail and their exact probabilities. Therefore, we used a simplifying assumption that after the rotation operations in the circuit, there is some kind of channel that captures approximately how this operation can go wrong. In this case, we added a depolarization channel of 0.01 on all qubits before measurement, as shown in Figure 1 (D0.01).

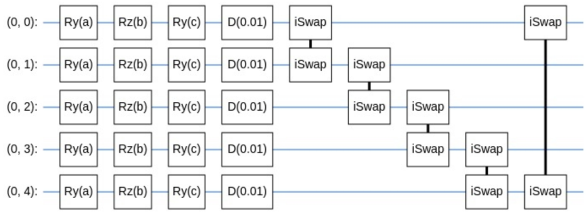
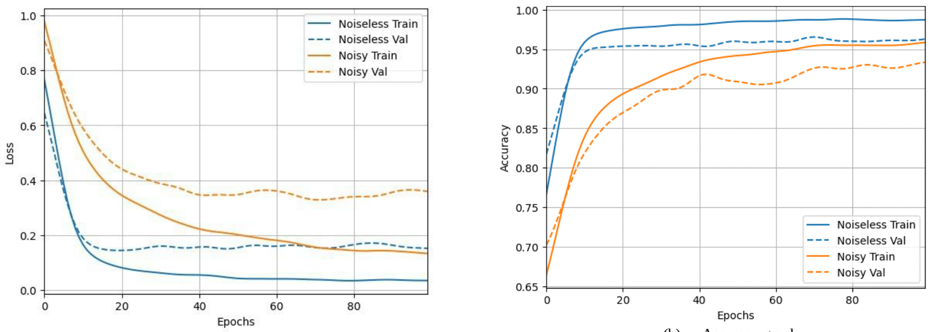


Fig. 1. Noisy circuit visualization.

The analyses were performed using the TensorFlow-Quantum library and the Cirq simulator (developed by Google). Comparing the training and validation, the noisy simulation was more time-consuming (1555.10s) than the noise-free one (74.14s). The loss (Figure 2a) and accuracy (Figure 2b) graph below show the training results. The test data resulted in an accuracy of 0.9655 for the model without noise. For the noisy model, the value was 0.9464.



(a) Loss graph

(b) Accuracy graph

Fig. 2. Models results in graphs.

In the presented scenario, the noisy model still managed to train under some mild depolarization noise, thus supporting the robustness of the model already used by (Maior et al, 2023). The continuation of this study involves experimenting with different noise models to understand how and when training might fail. By studying the effects of quantum noise, we can gain insights into the QML techniques' resilience and adaptability, providing valuable information for future quantum computing applications in risk and reliability.

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